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From Condition Monitoring to Maintenance Management in Electric Power System Generation with focus on Wind Turbines

Peyman Mazidi

UNIVERSIDAD PONTIFICIA ICAI ICADE COMILLAS MADRID

TU Delft Delft University of Technology

KTH VETENSKAP OCH KONST

From Condition Monitoring to Maintenance Management in Electric Power System Generation with focus on Wind Turbines

Peyman Mazidi

Doctoral thesis supervisors:

Main Supervisor
Prof. Dr. Miguel Ángel Sanz Bobi, Universidad Pontificia Comillas,
Supervisor in HEI2
Prof. Dr. Lina Bertling Tjernberg, KTH Royal Institute of Technology,

Members of the Examination Committee:

Prof. Dr. Adolfo Crespo Márquez,	University of Seville, Examiner and Chairman
Asso. Prof. Dr. David Flynn,	University of Heriot-Watt, Examiner
Asso. Prof. Dr. Hans Edin,	Kungliga Tekniska Högskolan, Examiner
Prof. Dr. Gerard J.W. van Bussel,	Technische Universiteit Delft, Examiner
Asso. Prof. Dr. Pedro Sánchez Martín,	Universidad Pontificia Comillas, Secretary
Asso. Prof. Dr. Javier García González,	Universidad Pontificia Comillas, Opponent

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door

Peyman MAZIDI
Electirc Power System Engineer
Jawaharlal Nehru Technological University, India

geboren te Aliabad, Golestan, Iran

This dissertation has been approved by the promotor:

Prof. Dr. Paulien M. Herder

Composition of the doctoral committee:

Prof. Dr. Adolfo Crespo Márquez,	University of Seville, Examiner and Chairman
Asso. Prof. Dr. David Flynn,	University of Heriot-Watt, Examiner
Asso. Prof. Dr. Hans Edin,	Kungliga Tekniska Högskolan, Examiner
Prof. Dr. Gerard J.W. van Bussel,	Technische Universiteit Delft, Examiner
Asso. Prof. Dr. Pedro Sánchez Martín,	Universidad Pontificia Comillas, Secretary
Asso. Prof. Dr. Javier García González,	Universidad Pontificia Comillas, Opponent

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The Erasmus Mundus Joint Doctorate in **Sustainable Energy Technologies and Strategies**, SETS Joint Doctorate, is an international programme run by six institutions in cooperation:

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This Thesis is a part of the examination for the doctoral degree.

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Abstract in English Language

Author: Peyman Mazidi
Affiliations: Universidad Pontificia Comillas, KTH Royal Institute of Technology, Delft University of Technology
Title: From Condition Monitoring to Maintenance Management in Electric Power System Generation with focus on Wind Turbines
Language: English
Keywords: Anomaly Detection, Condition Monitoring, Maintenance Management, Performance Evaluation, Data Analytics, Mathematical Modeling, Optimization

With increase in the number of sensors installed on sub-assemblies of industrial components, the amount of data collected is rapidly increasing. These data hold information in the areas of operation of the system and evolution of health condition of the components. Therefore, extracting the knowledge from the data can bring about significant improvements in the aforementioned areas.

This dissertation provides a path for achieving such an objective. It starts by analyzing the data at the sub-assembly level of the components and creates four frameworks for analysis of operation and maintenance (O&M) for past, present and future horizons at the component level. These frameworks allow improvement in operation, maintenance planning, cost reduction, efficiency and performance of the industrial components. Next, the dissertation evaluates whether such models can be linked with system level analysis and how providing such a link could provide additional improvements for system operators. Finally, preventive maintenance (PM) in generation maintenance scheduling (GMS) in electric power systems is reviewed and updated with recent advancements such as connection to the electricity market and detailed implementation of health condition indicators into the maintenance models. In particular, maintenance scheduling through game theory in deregulated power system, for offshore wind farm (OWF) and an islanded microgrid (MG) are investigated.

The results demonstrate improvements in reducing cost and increasing profit for the market agents and system operators as well as asset owners. Moreover, the models also deliver an insight on how direct integration of the collected operation data through the developed component level models can assist in improving the operation and management of maintenance for the system.

Abstract in Spanish Language

Autor: Peyman Mazidi
Afiliación: Universidad Pontificia Comillas, KTH Royal Institute of Technology, Delft University of Technology
Título: Desde la supervisión de estado a la gestión de mantenimiento en la generación de sistemas de energía eléctrica con especial atención a las turbinas eólicas
Lingua: Inglés
Palabras claves: Detección de Anomalías, Supervisión de Estado, Gestión de Mantenimiento, Evaluación de Rendimiento, Análisis de Datos, Modelado Matemático, Optimización

Debido al creciente número de sensores instalados en subconjuntos de componentes industriales, la cantidad de datos recogidos está aumentando rápidamente. Estos datos contienen información en áreas como la operación del sistema y la evolución del estado de salud de los componentes. Por tanto, extraer el conocimiento de los datos puede conllevar mejoras significativas en las áreas mencionadas.

Esta tesis proporciona un camino para alcanzar tal objetivo. Se comienza analizando los datos en el nivel del subconjunto de los componentes y se crean cuatro marcos para el análisis de la operación y mantenimiento (O&M) para horizontes pasados, presentes y futuros a nivel de componente. Estos marcos permiten mejorar la operación, la planificación de mantenimiento, la reducción de costes, la eficiencia y el rendimiento de los componentes industriales. A continuación, la tesis evalúa si dichos modelos pueden enlazarse con el análisis a nivel de sistema y cómo proporcionar tal enlace podría proporcionar mejoras adicionales para los operadores del sistema. Finalmente, se revisa y actualiza el mantenimiento preventivo (PM) en la programación del mantenimiento de generación (GMS) en sistemas de energía eléctrica con avances recientes como la conexión al mercado eléctrico y la implementación detallada de indicadores del estado de salud en los modelos de mantenimiento. En particular, se investiga la programación de mantenimiento a través de la teoría de juegos en un sistema de energía desregulado, en un parque eólico offshore (OWF) y una Microgrid aislada (MG).

Los resultados demuestran mejoras en la reducción de costes y el aumento de beneficios para los agentes del mercado y operadores de sistemas, así como los propietarios de activos. Además, los modelos también ofrecen una visión de cómo la integración directa de los datos de la operación recopilada a través de los modelos desarrollados a nivel de componentes puede ayudar a mejorar el funcionamiento y la gestión del mantenimiento.

Abstract in Swedish Language

Författare: Peyman Mazidi
Aansluiting: Universidad Pontificia Comillas, KTH Royal Institute of Technology, Delft University of Technology
Titel:Underhållsstyrning med tillståndskontroll för elkraftsystem med fokus på vindturbiner
Språk: Engelska
Nyckelord: feldetektering, tillståndskontroll, underhållsstyrning, underhåll, data analytics, matematisk modellering, optimering.

Med ökningen av antalet sensorer installerade på industrikomponenter ökar mängden data som samlas snabbt. Dessa data innehåller information om systemets funktion och utvecklingen av komponenternas tillstånd. Att extrahera kunskapen från data kan därför medföra betydande förbättringar inom dessa områden.

Denna avhandling ger en väg för att uppnå ett sådant mål.Först analyseras data på komponenternas delkomponentnivå och fyra modeller föreslås för analys av drift och underhåll (O&M) för; tidigare, nuvarande och framtida horisonter på komponentnivå. Dessa modeller möjliggör förbättring av drift, underhållsplanering, kostnadsminskning, effektivitet och prestanda för industrikomponenterna. Därefter utvärderar avhandlingen om sådana modeller kan kopplas till systemnivåanalys och hur ett sådant samband kan ge ytterligare förbättringar för systemoperatörer. Slutligen studeras förebyggande underhåll för planerat underhåll för elgenerering i elkraftsystemet. Detta görs med avseende på nya metoder med tillgång till information från elmarknaden och detaljerad information om komponenters tillstånd i underhållsmodeller. Speciellt undersöks underhållsplanering genom spelteori i avreglerade elkraftsystem, för en havsbaserad vindkraftpark (OWF) och ett isolerat mikrogrid (MG).

Resultaten visar förbättringar i att sänka kostnaden och öka vinsten för marknadsaktörer och systemoperatörer samt tillgångsägarna. Dessutom ger modellerna även en inblick i hur direkt integration av insamla operationsdata förmodeller på komponentnivå kan hjälpa till att förbättra driften och hanteringen av underhållet för systemet.

Abstract in Dutch Language

Auteur: Peyman Mazidi
Aansluiting: Universidad Pontificia Comillas, KTH Royal Institute of Technology, Delft University of Technology
Titel: Van conditiebewaking naar onderhoudsmannengent in generatoren in het elektriciteitssysteem met de focus op windturbines
Taal: Engels
Trefwoorden: Anomalie detectie, conditiebewaking, onderhoudsmanagement, performance evaluatie, data analyse, windkundig modelleren, optimalisatie

Met de toename van het aantal geïnstalleerde sensoren op subassemblage van industriële componenten neemt de hoeveelheid verzamelde gegevens snel toe. Deze gegevens bevatten informatie over de werking van het systeem en de ontwikkeling van de gezondheid van de componenten. Door deze gegevens om te zetten in kennis, kunnen daarom aanzienlijke verbeteringen op de hiervoor genoemde gebieden tewerkstellingen.

Dit proefschrift biedt een weg voor het bereiken van een dergelijk doel. Het begint met het analyseren van de data op het subassemblage niveau van de componenten en creëert vier kaders voor de analyse van de bediening en het onderhoud (O&M) voor de voorbije, huidige en toekomstige tijdshorizon op het componentniveau. Deze kaders maken verbeteringen op het gebied van onderhoudsplanning, kostenreductie, efficiëntie en prestatie van de industriële componenten mogelijk. Vervolgens wordt in dit proefschrift beoordeeld of dergelijke modellen gekoppeld kunnen worden aan een systeemniveauanalyse en hoe het maken van een dergelijke link extra verbeteringen kan bieden voor netbeheerders. Ten slotte wordt het doen van preventief onderhoud (PM) in de onderhoudsplanning van generatoren (GMS) in het elektriciteitsnet beoordeeld en aangepast. Recente ontwikkelingen, zoals de aansluiting op de elektriciteitsmarkt en de gedetailleerde implementatie van gezondheidsindicatoren in de onderhoudsmodellen zijn in het preventieve onderhoud geïmplementeerd. Met name wordt de onderhoudsplanning aan de hand van speltheorie in een gedereguleerde elektriciteitsmarkt, voor een windpark op zee (OWF) en een microgrid in eiland bedrijf (MG) onderzocht.

De resultaten tonen een kostenbesparing en een verhoging van de winst aan voor handelspartijen, netbeheerders en de eigenaars van de generatoren. Bovendien geven de modellen ook inzicht in hoe de directe integratie van de verzamelde operationele data via de ontwikkelde componentmodellen kan bijdragen aan het verbeteren van de uitvoer en het beheer van het onderhoud.

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List of Abbreviations

ABAO	As-bad-as-old
AD	Anomaly detection
AGAN	As-good-as-new
AI	Anomaly index
AP	Active power output of wind turbine
AT	Ambient temperature
BHF	Baseline health condition function
BLAT	Lower bearing temperature
BLOAT	Upper bearing temperature
BLP	Bi-level optimization problem
BPR	Behavior pattern recognition
CAIDI	Customer average interruption duration index
CF	Covariates function
CI	Condition indicator
CMC	Condition monitoring chain
CMS	Condition monitoring system
DA	Data analysis
DER	Distributed energy resource
DS	Deviation signal
DT	Decision tree
EDNS	Expected demand not supplied
EENS	Expected energy not supplied
ENS	Energy not served
FOR	Forced outage rate
GCV	Voltage of converter
GENCO	Generation company

GF	Generator frequency
GMS	Generation maintenance scheduling
GT	Gearbox temperature
GWT	Generator winding temperature
HC	Health condition function
HCWT	Additive health condition function
HGP	Hydraulic group pressure
HGT	Hydraulic group temperature
HNCUC	Hourly network constraint unit commitment
IM	Imperfect maintenance
IMGO	Independent microgrid operator
ISO	Independent system operator
ISP	Initial state probability
KKT	Karush–Kuhn–Tucker
KL	Kendall measure
kNN	k-nearest neighbor
LOL	Loss of load
LOLE	Loss of load expectation
LOLP	Loss of load probability
MAE	Mean absolute error
MC	Markov chain
MG	Microgrid
MI	Mutual information
MILP	Mixed-integer linear programming
MMRR	Maintenance management and risk reduction
MNA	Maintenance analysis
MOA	Mid-term operation analysis
MSE	Mean squared error
MTBF	Mean-time-between-failure
MTBM	Mean-time-between-maintenance
MTTF	Mean-time-to-failure
NaN	Not-a-number
NBM	Normal behavior model

NE	Nash equilibrium
NN	Neural network
NT	Nacelle temperature
O&M	Operation and maintenance
OC	Operation cost
OWF	Offshore wind farm
PA	Pitch angle
PAAD	Performance analysis and anomaly detection
PAME	Performance and maintenance evaluation
PC	Pearson correlation
PCA	Principal component analysis
PHM	Proportional hazards model
PLP	Production loss profit
PM	Preventive maintenance
PRA	Performance analysis
QP	Reactive power
RAP	Rotor active power
RCA	Root-cause analysis
RCAM	Reliability centered asset management
RCM	Reliability-centered maintenance
RES	Renewable energy sources
RI	Risk indicator
RMSE	Root mean squared error
RReliefF	Regressional ReliefF algorithm
RS	Rotor speed
SAE	Sum absolute error
SAIDI	System average interruption duration index
SAIFI	System average interruption frequency index
SCADA	Supervisory control and data acquisition
SLP	Single-level optimization problem
SMSOMG	Strategic maintenance scheduling of microgrid
SMSOWF	Strategic maintenance scheduling of offshore wind farm
SOM	Self-organizing maps
SP	Spearman measure

SSE	Sum squared error
SSR	Sum of squares of reserve
TOG	Temperature of oil in gearbox
TPM	Transition probability matrix
WS	Wind speed
WT	Wind turbine

1 Introduction

This chapter motivates the topic of this dissertation, defines the objectives, and presents the outlines. Illustrations are used to display the motivations, objectives and structure of the dissertation.

1.1. Motivation

The current infrastructure of electric power systems is old [1] and the cost of an unexpected failure of a critical component in the system is significant. The companies cannot afford to continue with traditional maintenance strategies (e.g. routine time-based, fixed-age replacement) and would like to reduce cost and risk simultaneously. Therefore, the companies would like to move towards utilization of condition-based maintenance and this type of maintenance requires information on the health condition of equipments.

The conventional electric power system provided only low level of automation (e.g. in substations) with little data about the system behavior due to few number of monitoring devices and measured signals (e.g. only current, voltage and power in the substations). This resulted in little or no knowledge of power consumption behavior (e.g. at individual customer level) and system behavior in case of any anomaly.

As the numbers of installed sensors and measurement devices in different parts of the power system (load, substation, distribution, transmission, generation and distributed generation) increase, more data become available in the new smart grid, Figure 1.1. These newly emerged data inherently contain information about the system and its behavior in different conditions which can provide useful information on the operation of the system. By analyzing these data, a new door opens to the evaluation of the electric power system which holds a great deal of economic potential in forms of savings, operation and investment in this new smart environment. As the collected data from condition monitoring system (CMS) intrinsically carry information and knowledge, it is of great importance to obtain methods for:

- extracting this knowledge,
- finding approaches to use the extracted knowledge,
- studying the impact of the obtained changes after applying the new knowledge and

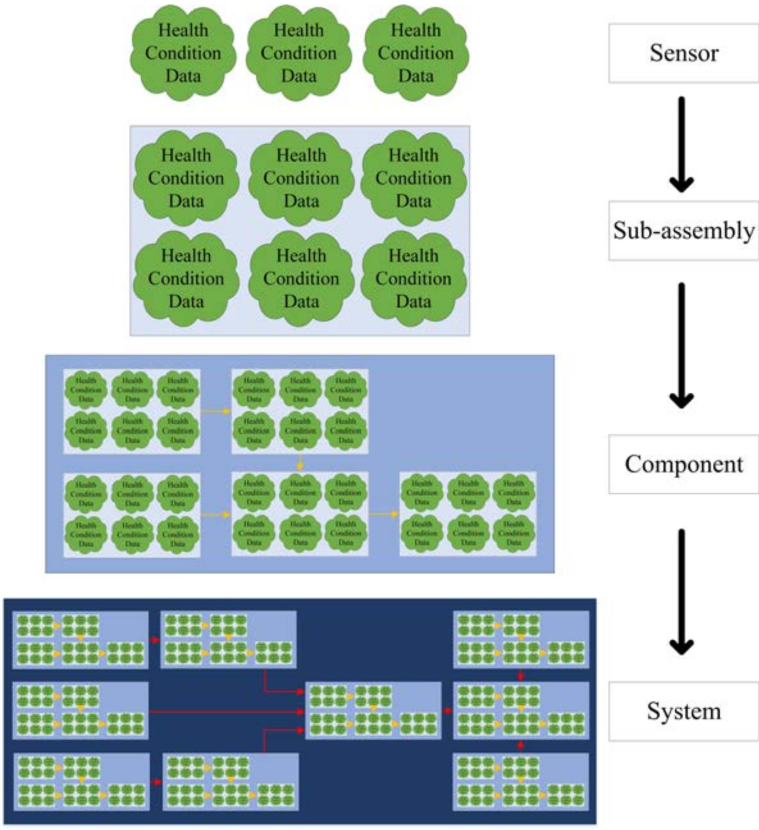


Figure 1.1: Motivation diagram of the dissertation

- improving this process through feedback and with the goal of automation.

Recent studies, particularly after emergence of distributed generation have shown that the power system reacts in different ways to anomalies in various situations which endanger the rest of the system. These situations and impacts are not known thoroughly. Thus, it is believed that assessment and analysis of the information available in these collected large data sets will be of great assistance in overcoming such obstacle. It can teach us the behavior of the system in case of abnormalities (before, during and after), which can educate us on how to better treat them and deal with them (or prevent them). It can also result in new achievements in reinforcement of the grid.

1.2. Dissertation Objective

Traditionally, the power system analyses are based on consideration of random failure events. This dissertation proposes analysis of the power systems from a new perspective. It tries to understand under what conditions the health of some components or system could affect the n-1 criterion and operation and maintenance (O&M) decisions. This is performed by integrating condition variations of some of the critical components that maintain this criterion. With this regard, this dissertation intends to address three main objectives through the definition of condition monitoring chain (CMC). The CMC starts from any data related with the life of a component or system obtained from sensors installed at the component level and concludes at O&M decisions in the management level of the system, Figure 1.2.

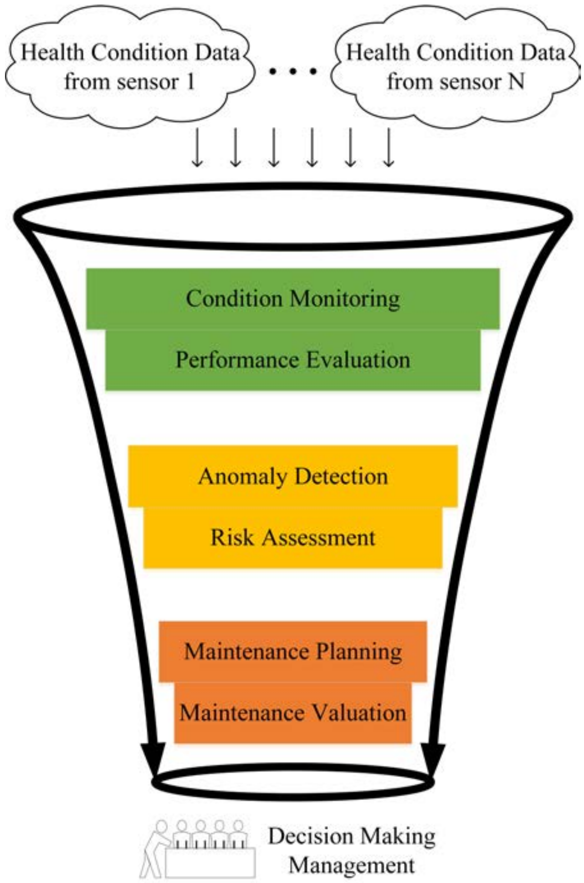


Figure 1.2: Overall objective of the dissertation in form of CMC

- The first objective is to account for the large operation and condition data collected at the component level and create data-driven models to improve O&M of the assets. This objective is achieved by delivering performance, stress, risk and health condition indicators for the components in three perspectives of short-term, real-time and medium-/long-term analyses where they provide insight on past, current and future operations.
- The second objective is to link the newly developed data-driven component level models to the system operation and update the indicators based on the observed condition of the components. This link is a medium that facilitates a decision-making step by providing information from the conditions of the assets. Hence, such a link and model provide anomaly detection (AD) and risk assessment opportunities.

- The third objective is to improve system level traditional preventive maintenance (PM) scheduling models by linking them to the (electricity) market, evolution of condition of equipment and to analyze the strategic operation of the agents.

The fully connected CMC can provide several contributions. It updates the traditional failure rate reliability analysis of power systems and transforms it into the observed condition-based analysis. It introduces new tools to implement the observed condition into the analysis with possibility of detecting anomalies and assessing their impacts on the component and the system. Finally, it proposes new strategies for PM scheduling based on the developed health condition models and consideration of the electricity market.

1.3. Dissertation Outline

The dissertation is divided into six chapters as follows, Figure 1.3:

Chapter 1 This chapter presents the motivation and objective of the dissertation.

Chapter 2 This chapter presents a thorough literature review of related topics connected with this dissertation by pointing out the scientific gap in the O&M field. These topics are detection of abnormal behavior and performance assessment in wind turbine (WT), integration of condition monitoring and risk in power system operation, and PM scheduling in power system generation.

Chapter 3 This chapter presents four data-driven methodologies to address improvements in component level analyses. Each methodology has a generic framework and each framework includes a model based on the objective of the framework. It discusses approaches that assist in increasing efficiency of the performance of the component by interpreting health condition data that are recorded at the sub-assembly level in components.

Chapter 4 This chapter presents one model to discuss the possibilities of improvements in O&M in power system generation in system level analyses by integrating health condition data from the sub-assemblies of components and data-driven component level models into the operation.

Chapter 5 This chapter presents three generic models for preventive maintenance scheduling. The models are applied in the power system generation context and are based on game-theory, offshore wind farms and microgrids. The models also compare centralized and decentralized frameworks in preventive maintenance planning.

Chapter 6 This chapter presents concluding remarks and directions for future works in line with the research performed in this dissertation.

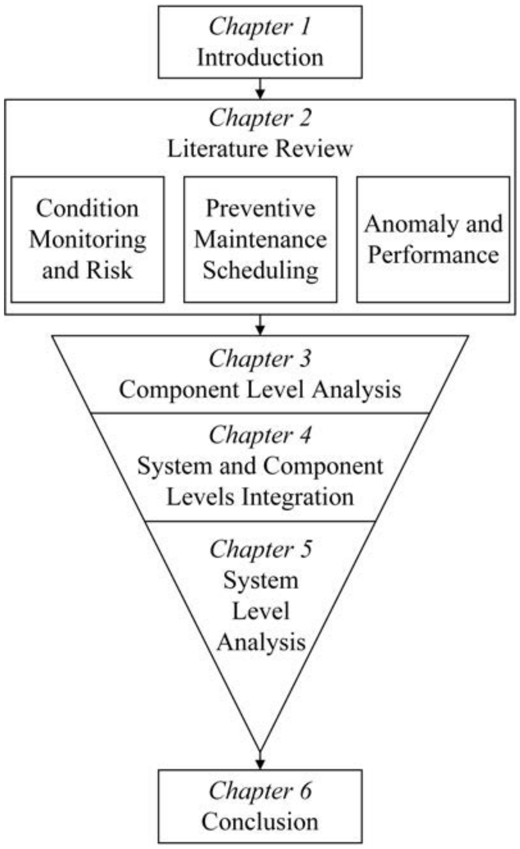


Figure 1.3: Structure of the dissertation

2 Literature Review

2.1. Introduction

This dissertation deals with topics of abnormality detection, condition monitoring, modeling of normal behavior, performance assessment and maintenance management under the operation and maintenance (O&M) field. Therefore, these topics related to power system generation are covered for the review of the state-of-the-art research studies. It should be mentioned that due to the vast topics involved, in each area, solely studies with connection to the considered topics are reviewed. After the thorough review, the scientific gaps are identified. The proposed methodologies in this dissertation at each area address these specific gaps. While this chapter mentions the related studies in literature, the critical view of every study is presented in the introduction section of each individual chapter where detailed analysis on a particular issue is carried out.

2.2. Anomaly Detection and Performance Assessment in Wind Turbines

In this dissertation, wind turbine (WT)s are considered as particular components to be thoroughly investigated with regard to their health condition developments and their impacts on power systems. The main reason is accessibility of the authors to detailed information from operating condition of the WTs. Moreover, due to the continuous monitoring of the WTs around the world, many information are becoming available on the WTs.

This section considers several aspects with respect to the studies on WTs. At first, it distinguishes among studies that consider sub-assemblies (e.g. generator, gearbox, blades, pitch system) as individual systems or consider the whole WT as a system. Next, for each considered system, a model is created. The model can be non-parametric, parametric or simulation based. With respect to anomaly detection (AD), the model can use a static or dynamic threshold to detect anomalies. Finally, some studies take into account performance evaluation and maintenance management of the considered systems into the analysis. Table 2.1 shows the key points that have been selected as references for reviewing the literature. These key points are selected as they have shown prominent impact in the O&M field. Hence, analysis of impact of these points on improving O&M from component level is the addressed scientific gap in chapter 3.

[2] proposes a conceptual simulation model to replicate WT failures from historical failure data. Then, it introduces a delay-time model to integrate maintenance actions where performance of the WT is not considered. [3] proposes a parametric Weibull model to predict the output power of a WT without addressing maintenance. [4] compares several parametric models in term of output power prediction. The models are classified into two main categories of “fundamental equations of available power in wind” and “power curve concepts”. The first category uses variables such as wind speed (WS), air density and mechanical conversion efficiency. It is concluded that calculation of output power through this category of models is difficult and does not provide high accuracy. The second category is more interesting as it could be linked to the performance of the WT. Among the models in the second category, some models consider a fixed (linear, non-linear) relationship between the WS and the output power. Although this makes the model simple, it does not provide high accuracy. Some other models use the power curve cut-in and cut-out speeds and define particular models for each WT. These models require additional techniques to estimate unknown parameters in the models. It is also shown that different parameter estimation techniques such as least square or cubic spline interpolation, despite passing the previous category in replicating the output power of the WT, have different performances. In a similar study, [5] concludes that exponential and cubic equations provide better results than polynomial and approximate cubic when energy density error is considered. [6, 7] continue the analysis and add non-parametric models where they show great potential in this area for future developments.

In general, an anomaly can be defined as deviation of the system from its expected normal behavior, where a deviation signal (DS) is the measured difference. In this dissertation, the anomaly is considered in the context of WTs and then its impact on the WT and the power system is assessed. Therefore, an anomaly is defined as any event that causes the WT deviate from its expected normal operation. The anomaly in a WT can be due to external factors such as human errors, malfunctioning of a sub-assembly, wear and fatigue or failure of a sub-assembly. In general, AD is carried out by first developing a normal behavior model (NBM) for the WT. Next, the real-time operation is monitored and then whenever a deviation is occurred between the output of the NBM and the actual operation (observed through DS), an anomaly is detected. To ignore the error in the results which is due to the model itself or external reasons, a threshold is generally developed as not all the deviations can be considered as anomalies and only the deviations above this threshold value are selected as anomalies. [8] creates a parametric model for gearbox of the WT and a condition indicator to predict the remaining useful life of the gearbox. Then, from experience, it sets a static threshold on the indicator to avoid failures.

[9, 10] develop parametric models for a WT and its sub-assemblies from supervisory control and data acquisition (SCADA) centers to evaluate the performance of the WT where the link to maintenance is not considered. [11] proposes a condition based maintenance strategy for maintenance optimization by considering failure data from four sub-assemblies of rotor, bearing, gearbox and generator. Similarly, [12] proposes an opportunistic based maintenance strategy for maintenance optimization. The model

is time-based and a static reliability threshold is considered as to when a maintenance action should be carried out. Similar to previous studies, the relation to maintenance is disregarded.

[13] proposes a Copula based method to evaluate the performance of a WT. It only requires WS and active power output of wind turbine (AP) as variables and it suggests the use of Copula for performance degradation studies. [14] simulates a frequency analysis tool for AD in WTs through monitoring the drive-train system. Validation of the method on full-size WTs in the field are considered as the future work. [15, 16] focus on the bearing sub-assembly and develop models on failure detection. [16] mentions that since the number of failure data are little, accuracy of the static threshold is not certain. [17] develops a fault detection system for a WT by building an NBM through neural network (NN) and applies an experienced based static threshold. Perfect and imperfect maintenance policies are considered in [18] for opportunistic maintenance optimization of the WTs and a static threshold is set on the age of components. [19] proposes a linear regression model for the temperature of generator. [20] uses the generator stator current homopolar component to develop an ensemble-empirical mode decomposition-based bearing-failure-detection model which does not need training sequence.

[21] develops a model based on the relation between different SCADA data parameters where the performance of the WT is assessed over monitoring of these relations under various operating conditions. It concludes that AD is easier before the time when the WS reaches the rated WS of the WT due to the nonlinear control effects of the pitch system. In a similar study, [22] considers several temperature-related variables such as gearbox, rotor, oil and converter and compares the evolution of the changes in their relation with the AP. [23] proposes a fault detection method of rolling element bearing based on multiwavelet denoising technique with data-driven block threshold. [24] proposes two regression-based load-independent diagnostic fault-sensitive parameters that are for long-term monitoring of bearings. [25] proposes an approach to improve the reliability of a gearbox by choosing the right preventive maintenance (PM) interval based on maintenance cost and availability. [26] updates failure mode and effects analysis with sub-assembly downtimes, failure costs and rates. It applies the analysis to WTs by testing it on a gearbox and bearings. Future research is considered to focus on integrating maintenance into the failure mode and effects analysis model.

[27] develops an NBM for a WT. It analyzes different characteristics and structures of a NN to find the most suitable one and evaluates the impact and sensitivity of the model based on various parameters. The model is then tested with some anomaly data in the WT where the future work considers to address a root-cause analysis. [28] continues the study by adding principal component analysis (PCA) and evaluating the extracted abnormal behavior where it mathematically concludes that the pitch system is the cause of an observed abnormal behavior. [29] develops NBMs for 48 WTs through NNs and Gaussian Process. The extreme value statistics threshold is calculated using the evolutionary optimization algorithm of differential evolution. Adding extra features (other than power-curve) to the model and classification of the observed failures are considered as future works. [30, 31] use the benchmark model in [32] and a testbed for

simulation to develop condition monitoring and fault diagnosis in a gearbox and blades where the connection between performance and maintenance is not considered. [33–35] propose parametric models to analyze the maintenance in sub-assemblies of WTs. The model in [33] optimizes maintenance times based on the age or degradation state in bearings. In a similar study, [34] considers the cracks in the blades. The future works can include a system level model for the WT and integration of dynamic threshold on a performance model.

[36] uses labeled condition monitoring data to determine occurrence of an alarm and its type where future study can link the alarms to performance and maintenance. [37] proposes a model to optimize short-term maintenance schedules for several WTs considering constraints such as number of technicians. Integration of condition monitoring into the model can be considered as future work. [38] proposes a performance and maintenance evaluation framework for WTs. At first, it creates NBMs of WTs through NNs. Next, it extracts the different behavior patterns in the operation of the WTs through unsupervised learning technique of self-organizing maps (SOM). Then, from the extracted patterns, it creates a Markov chain (MC) model for each WT to evaluate the performance of the WT and proposes maintenance schedules. [39] uses SCADA data and proposes a stress condition monitoring and maintenance management approach for WTs. At first, it uses several statistical techniques to evaluate the relation between several variables in the data. Next, an NBM model through NNs is created. Then, a parametric stress model is developed which mathematically has the form of proportional hazards model (PHM). Finally, the model is assessed through O&M data where it can detect the under-performance in a WT and suggest for improvement in the maintenance strategies.

With failure data from bearings, [40] develops a failure state prediction model through Bayesian method. Prediction of WT condition for specific events is considered as future works. [41] considers a cost function where the remaining useful life is incorporated into it. The real-time condition monitoring data update the remaining useful life function and correspondingly the cost function where dynamic maintenance scheduling is carried out in the end. In [42], an extreme learning machine algorithm is optimized using the genetic algorithm to train a single hidden-layer feed-forward NN to detect faults in a gearbox. [43] proposes a procedure to detect faults in a pitch system by detailed analysis of various parameters and performance curve of the WT. Therefore, it does not require any training data and the process is based on a set of predefined rules over operation of each variable. [44] develops a parametric model for health condition monitoring of WTs. At first, it creates NBMs for a number of variables from SCADA data. Next, through nonlinear regression technique, it produces parametric models for each variable. Finally, through an additive model, a WT parametric model is constructed where real-time measurements of each variable is also incorporated. Moreover, a dynamic threshold is derived where it detects abnormal behaviors in the performance of the WT. Due to its parametric form, this model can address adaptability and scalability issues that are currently available in this field.

Table 2.1: Summary of reviewed literature on wind turbine condition monitoring

References		Wind Turbine	Sub-assembly	Non-Parametric Model	Parametric Model	Simulation Model	Static Anomaly Threshold	Dynamic Anomaly Threshold	Performance	Maintenance
[2]		✓	✓			✓				✓
[3–5]		✓			✓					
[6, 7]		✓		✓	✓					
[8]			✓			✓	✓			
[9]		✓			✓				✓	
[10]		✓	✓		✓				✓	
[11, 12]		✓	✓		✓		✓			✓
[13]		✓		✓						
[14]		✓				✓	✓			
[15, 16]			✓	✓			✓			
[17]		✓		✓			✓			
[18]		✓	✓		✓			✓		✓
[19]			✓		✓					
[20]		✓				✓				
[21]			✓		✓		✓		✓	
[22]			✓		✓				✓	
[23]			✓		✓			✓		
[24]			✓		✓		✓			
[25, 26]			✓		✓					✓
[29]		✓		✓			✓		✓	
[30, 31]			✓			✓				
[33–35]			✓		✓		✓			✓
[36]		✓		✓					✓	
[37]		✓			✓					✓
[40]			✓	✓	✓		✓			✓
[41]		✓			✓		✓			✓
[42]			✓	✓					✓	
[43]			✓		✓		✓		✓	
[27]	Chapter 3	✓		✓			✓		✓	
[28]		✓		✓			✓		✓	
[38]		✓		✓			✓		✓	✓
[39]		✓		✓	✓		✓		✓	✓
[44]		✓	✓	✓	✓		✓	✓	✓	✓

2.3. Condition Monitoring and Risk in Electric Power System Operation

The electric power system is comprised of generation, transmission and distribution hierarchical levels. In the traditional power system, the power flows from generation to consumers where there is only a one-way communication link from the generation to the consumers. However, this is changing due to the developments in the power system towards creating a smarter system. One aspect that the new smart grid is different from the traditional power system, and is addressed in this dissertation, is the existence of a two-way communication between multiple parts of the system. This communication is particularly considered to carry information on health condition of the assets. With this regard, Table 2.2 shows the key points that have been selected as references for reviewing the literature. These key points are selected as they have shown prominent impact in the O&M field where the gap is the missing communication link. Hence, analysis of impact of these points on improving O&M from component and system levels is the addressed scientific gap in chapter 4. They address how the operation of the system can be affected from cost and risk perspectives when this two-way communication link is provided.

Currently, fossil fuels (e.g. coal and natural gas) have the highest share among the sources of electricity generation and produce large amounts of greenhouse gas emissions. With the increasing electricity demand, the electric grid is the largest contributor to the climate change. In order to mitigate the climate change impacts and maintain the balance between the increasing demand and supply, the traditional electric power system requires significant changes in various parts.

Integration of renewable energy sources (RES) such as wind and solar in the generation level, addition of distributed generation in the distribution level, consumer engagement as demand side management, two-way communication among all levels, deregulation of the power system and installation of numerous measuring devices on components transform the conventional electric power system to a smart grid. All these changes bring about new opportunities and challenges [45]. One of the challenges, which is the basis of this dissertation, is the delay in updating the current equipment and investing in new ones when most of the assets are old. The opportunity that this transition can provide is to improve the infrastructure and intelligence of the system in order to decrease the vulnerability of the system in presence of abnormalities and failures [46]. This can also lead towards the self-healing concept [47]. This dissertation in particular considers availability of the new health condition related data from components (recorded by measuring devices) in addition to the integration of RES in the power system and tries to take advantage of these new opportunities and provide some solutions for some of the challenges.

One of the first ideas to realize the potential capability of a smart grid is the effort to utilize the recorded data. The data can help to mitigate the impact of failures in components which can cause power outages and cascaded events [48–50]. While the most common conception of the data collection in a smart grid is the readings from smart meters from different types of customers, the data can also include health condition information from critical components such as generators and transformers, where this is the main focus of this dissertation. The intelligence in such a system then comes from the real-time interaction among the components in various situations where the objective is to optimize the operation of the system. It can be considered that the smart grid is not responsible for clearing any abnormal event, rather assist the system in these times to act more intelligently and if possible, avoid the unwanted events [51]. In other words, each component has a number of sensors and can evaluate its state where it also communicates with its neighboring components, and a centralized system if possible. If the component is having abnormalities or approaching a failure, the components can communicate with each other, taking into account the overall state of the system, and act based on the defined set of rules to maintain the stability of the system.

To evaluate the reliability of a grid, primarily, the operating reserve is generally performed by considering the N-1 criterion where the outage of the largest unit is considered [52, 53]. This neglects the real-time risk and stochastic nature of the system [54]. One approach to advance this area is the use of probabilistic techniques [55, 56]. The others that address uncertainty are stochastic optimization, robust optimization and chance-constrained optimization [57]. [53] introduces this concept by considering several predefined states and zones for the system (health, marginal and in risk) and it assigns probabilities to each state from a combination of components outages. These states are defined in order to meet the operation limits [58]. However, the actual real-time health conditions are not considered. With the emergence of smart grid and ability to obtain real-time health condition data, the techniques should be updated to integrate such information. Figure 2.1 displays a sample system where health condition information is available from the main components.

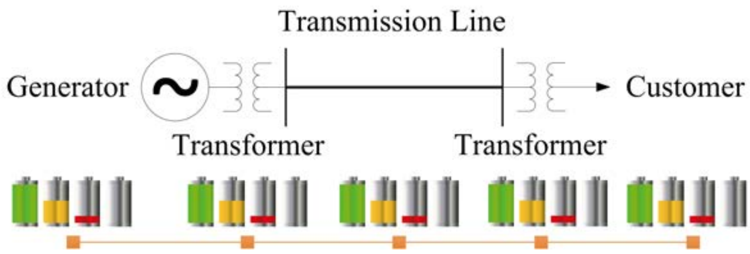


Figure 2.1: A power system with sensors installed at components

[59] considers the smart grid definition where components are being monitored. Based on the collected information, a Markov model is built for each component where the states of each component are calculated based on the probability values. The failure of smart monitoring devices are also similarly modeled where although in a probabilistic manner, consideration of health condition information shows its importance through comparisons of several reliability indexes such as system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), customer average

interruption duration index (CAIDI) and energy not served (ENS).

Risk in power system studies is generally evaluated from two perspectives of adequacy and security. [60–64] use historical condition (failure) data of generation units in their analyses. [60] considers full and partial outage of generation units where wind power is also considered. It defines the risk as the number of incidents when the generation does not meet the demand. [61] delivers an economic dispatch model where the risk is associated with a cost factor caused by outages of generators and other factors. [62] considers an optimal dispatch problem and defines risk as a penalty term issued whenever the balance between generation and demand is not met. The outages of generators are modeled as random increased values in the demand. [63] develops a model for power system reserve capacity planning where risk is defined as a combination of loss of load expectation (LOLE) and two reliability and economic factors. [64] integrates risk into unit commitment study. It defines several operating states for the generators and two up and down states for the photovoltaic generators with various probabilities for each state. [65] considers the problem of calculation of optimal spinning reserve where forced outage rate (FOR) of generation units is implemented. Conditional-value-at-risk (CVaR) is also considered as an index for risk. The risk in [66] considers two penalty terms of ENS and reserve not served (RNS) in the objective function. The generators outages are modeled by increased values in the demand.

[67] assumes that the risk is imposed due to uncertainty in the wind power. It considers two ways to handle this risk. In the first way, it creates an objective function of expected energy not supplied (EENS) and in the second way, it considers that the uncertainty in the wind power is handled by adding additional reserve. [68] introduces a two-stage stochastic unit commitment model where risk in form of loss of load probability (LOLP) is considered to maintain the balance between total cost and reliability of the system. [69] considers risk as overload, low-voltage, over-voltage and power violation caused by wind power uncertainty. [70] considers risk as wind curtailment, loss of load and transmission lines overflow. The risks are considered to be caused by the uncertainty in the wind power forecasts and are addressed through a probabilistic approach. [71] defines LOLP as probability level of operation risk and expected demand not supplied (EDNS) as severity level of operation risk. [72] defines a risk index as a combination of impact of load shedding and voltage violation to study risk evaluation of cascading contingencies. *N-k* contingency for transmission lines is also selected randomly. [73] considers a security-constrained optimal power flow problem and introduces risk as a constraint. The risk is defined as probability of occurrence of a contingency multiplied by its severity index where outages of transmission lines are considered as contingencies. This multiplication should always be less than a predefined maximum risk level. [74] uses the risk index to estimate the occurrence of a cascading blackout. The cascading failures are modeled by randomly selecting outages of transmission lines. The risk index is calculated by multiplying the load shedding amount by the probability of occurrence of that particular random outage. A voltage risk is defined in [75] to coordinate the preventive and corrective controls. The risk is considered as multiplication of the probability of an outage event by its severity, in this

case, loss of voltage instability. The loss of voltage instability is also defined as LOLE multiplied by service interruption cost plus additional damages and blackout costs. The risk index is calculated for normal and post-contingency operating conditions. [76] defines a regret function to demonstrate risk where it relates to load curtailment by considering worst event and scenario criterion. All these studies address risk without considering maintenance scheduling and neglect their mutual connection.

[77] considers a generation maintenance scheduling (GMS) problem where a surplus generation capacity index is used to check the supply adequacy and random transmission line outages are also included to make the system security analysis more reasonable. For instance, in the generation adequacy index, a 7% capacity margin is simply assumed for the independent system operator (ISO). However, the approach to obtain and evaluate such a number is neglected. In a similar way, a 70% congestion rate is assumed for the transmission lines capacity adequacy. [78] proposes a sample formulation for generation and transmission maintenance scheduling. It considers a limit for EENS where the method to obtain such a limit and its impact on the operation and sensitivity are disregarded. It also mentioned that an optimal maintenance scheduling method should be proposed to obtain the balance between the overhaul and opportunity costs. [79] proposes a maintenance scheduling problem with multi-objectives. Minimization of total operation cost, sum of squares of reserve (SSR) and LOLE are considered as objectives where during each maintenance outage, EENS is also calculated for further analysis of risk. These works study the system risk after performing maintenance scheduling and ignore the impact of change in the condition of the generators over the planning horizon. The generators are considered either fully available or in failed state which in the operation and planning, hides the impact of sudden change and evolution in the condition. [80] performs a maintenance scheduling problem for the generation units through ant lion optimizer where spinning reserve is included and the problem tries to minimize an objective function of SSR. Integration of real-time condition of the components as well as their individual imposed risk and mutual connections are not studied.

On the other hand, [81] considers random failures in generators as well as deterioration of generators through a Markov model in a maintenance scheduling problem. The model solely considers three deteriorating stages. The model is applied to one generating unit and expansion to a power system with multiple generation units and transmission lines are considered as future work. [82] proposes an analytical approach to prioritize components for maintenance activities based on their historical failure statistics without considering real-time condition monitoring information of the components. [83] considers a system to have an information state and a hardening state at each time. From historical data, a Markov model is created for a sample transformer and the transition probabilities are calculated. Then, based on the evolution of the deterioration calculated from the Markov model, certain maintenance and hardening decisions are taken. It is mentioned that the future work will consider a multicomponent system with dynamic weather conditions. [84] defines a Markov model and transition probability matrix (TPM) for a hydro turbine, a generator and a transformer from historical data.

It adds a deterministic forecast of electricity prices to account for the cost incurred due to downtime during the maintenance actions. Similar to previous works, optimal maintenance scheduling based on condition in a multicomponent system is considered as future work.

[85, 86] present a framework to apply reliability-centered maintenance (RCM) framework to distribution systems to identify critical components. To add risk in GMS problem, [87] considers congestion costs and takes into account random failures in transmission. A load-shedding cost function is also defined to incorporate the security risk in the operation. The impact of reliability requirement on the operation is considered as future work. [88] proposes a tool based on genetic algorithm which has capability of carrying out maintenance scheduling with several different objectives and provides visualization of the results as well. LOLE is considered as the reliability risk measure. Both of the two previous studies neglect the impact of the real-time condition evolution of components on the operation and the optimum maintenance solution. [89] uses condition monitoring data of circuit breakers and by defining performance indexes, it analyzes the maintenance schedules for the breaker. It defines four main condition stages of healthy, minor, major and failure for the component. [90] demonstrates a diagnostic tool which displays the health of generators based on the recorded condition data. Although multiple components are considered and compared, the impact of their connection and mutual interactions are disregarded.

[91] derives a framework to carry out cost-benefit analysis on circuit breakers through condition monitoring data and EENS is used as the risk measure. Four deterioration stages of health, minor, major and failure are defined for the circuit breakers. The approach should be extended where it considers multiple generation units and their condition and imposed risks. [92] derives reliability model for three thermal power plant types with multiple components. Obtaining optimum maintenance strategies and schedules of generators with transmission lines are considered as future works. [93] calculates LOLP and EENS for a system by considering random and deterioration failure rates. The results show the importance of including the impact of maintenance and average condition information. [94] calculates reliability indexes of SAIFI, SAIDI and CAIDI for a distribution system where the impact of preventive and corrective maintenance on the failure rate of the components are modeled. The connection among the components and the operation cost are not considered. [95] proposes a framework for maintenance of wood poles. Condition information from poles are also considered and assist in measuring component and system risk.

[96] considers constant inspection intervals and optimizes maintenance by creating a dynamic risk threshold which is defined as the product of time-dependent down time cost and a scale factor. Development of condition based maintenance policies for multicomponent systems and determination of optimal risk threshold are considered as future studies. [97, 98] define a dynamic cost function to translate the changes in the condition of the generators into remaining life distribution. At first, it obtains condition monitoring information and it calculates the remaining life distribution. Next, a maintenance scheduling is carried out. Then, it freezes the problem, obtains

new information, recalculates the remaining life distribution and a new maintenance scheduling is performed. During this freeze period, if a generator condition index exceeds a threshold, it undergoes a corrective maintenance action. In an update, they add unit-commitment and dispatch costs as well. The results demonstrate the importance of integration of condition monitoring information. However, the real-time evolution of the risk imposed on the system and the impact of strategic maintenance scheduling of the generators are not studied.

[99] analyzes the impact of emissions on reliability indexes such as LOLP and EDNS without considering maintenance scheduling and health condition information. [100] models several cost functions that affect maintenance scheduling such as failures and interruptions and concludes that solely considering one cost function in the deregulated power market environment can deviate the results from an optimal maintenance schedule. [101] defines an outage model in order to demonstrate the impact of operating conditions on maintenance decisions. In a two-stage problem, maintenance scheduling is carried out where the available wind power is unknown in the first stage and in the second stage, the available wind power in known and a load shedding cost is considered. Also, the load-shedding and reserve costs are fixed and assumed to be 100 times and 10% of the average generation cost at any moment, respectively. The results show that adding even fixed forced outages can improve the O&M scheduling where obtaining load-shedding and reserve cost factors can be further studied. [102] proposes a probabilistic framework for risk assessment in power systems where several threats, vulnerabilities and contingencies are defined and modeled. Loss of load (LOL) is also calculated as a risk measure (in MW). [103] proposes a real-time probabilistic reliability assessment where risk is defined as product of a contingency, failure in clearing the contingency and the impact of the interruption to customers. [104] carries out a critical component identification study where random failures and weather conditions are taken into account. A criticality index is calculated for all the transmission lines based on ENS. However, a maintenance scheduling, its impact on the operation and its relation to the risk are neglected [102–104]. [105] proposes a model for preventive and corrective maintenance scheduling where maintenance degree and efficiency are two parameters. [106, 107] propose the maintenance management and risk reduction (MMRR) method by defining two condition and risk indicators that integrate the condition monitoring information from components into the operation.

Table 2.2: Summary of reviewed literature on power system condition monitoring and risk

References		Maintenance	Historical Condition Data	Real-time Condition Data	Component Risk	System Risk
[67–76]						✓
[60–66]			✓			✓
[77–80]		✓				✓
[81–84]		✓	✓			
[85–88]		✓	✓			✓
[89, 90]		✓	✓	✓	✓	
[91–95]		✓	✓		✓	✓
[96–98]		✓	✓	✓		
[99]					✓	✓
[100, 101]		✓	✓		✓	
[102]			✓		✓	✓
[103]			✓	✓		✓
[104]			✓	✓	✓	✓
[105]	Chapter 4	✓	✓		✓	
[106, 107]		✓	✓	✓	✓	✓

2.4. Preventive Maintenance Scheduling in Electric Power System Generation

The topics chosen in this area are maintenance, historical and real-time condition data, exogenous and endogenous electricity price, uncertainty in load, distributed energy resource (DER) and price, RES (wind and solar) and transmission lines. Each of these topics are selected after the thorough review of many studies where ignoring any of these topics shows a great deal of influence on the outcomes in the O&M field. For instance, considering historical condition data of components in an average form is a traditional approach where consideration of real-time changes and their evolution has been recently gaining attention. Consideration of endogenous electricity prices in the calculations are also becoming popular as the computational power and the optimization techniques have been significantly improved in recent years. Due to the increase in integration of RES in the operation of electric power systems, their uncertainty plays an important role where variations bring about risks that should be studied. With this regard, Table 2.3 shows the key points that have been chosen as references for reviewing the literature. The gap is to improve the PM scheduling through the aforementioned topics. Hence, analysis of impact of these points on improving O&M from system level is the addressed scientific gap in chapter 5. They address how the operation of the system can be affected from profit and cost perspectives.

[108] proposes a model through fuzzy evolutionary programming for maintenance scheduling where it considers uncertainty of several parameters. [109] solves the maintenance scheduling problem by combining fuzzy knowledge based system and genetic algorithm where the objective function is sum of operation, maintenance and penalty costs. [110] develops a model where the maintenance outage window is chosen based on the operation hours of the generation units where stochasticity in neglected. [111] considers a model where maintenance and demand side management are coordinated and the results show that shiftable loads have the potential to improve economy and reliability of the system. [112] proposes a clonal selection algorithm for the maintenance scheduling problem and compares it with the results based on evolutionary programming algorithm where the proposed algorithm presents better results. [113] proposes a procedure to assess the level of impact of generation units on spinning reserve where the assessment is performed after solving a PM scheduling problem. The proposed method increases the O&M costs and reduces the total system costs. [114] compares mathematical approach assisted differential evolution and mathematical approach assisted particle swarm optimization techniques and concludes that the former outperforms the latter technique in large scale problems in GMS. [115] performs maintenance scheduling by considering equivalent operating hours where the objective function is to minimize the fuel and start-up costs. The results show that average reserve rates can be improved by 1.7% while total generation cost does not have a significant increase. These techniques ignored the impact of change in health condition of the generators in the operation.

[116] proposes a GMS model where generation company (GENCO) considers its financial risks and the electricity prices are forecasted. Consideration of transmission lines outages causes overload where it can be reduced by redispatching or changing the maintenance schedules. Either way, it increases the operation cost. [117] proposes a model to find the Nash-Cournot equilibrium for GENCOs profit-maximization problem and concludes that uncertainties of generation units availability and fuel costs have great impact on GENCOs expected profit. [118] proposes a conflict assessment framework to characterize the relation between an ISO and GENCOs. While GENCOs try to maximize their profit, ISO tries to minimize LOLP index and a sensitivity analysis is performed on several parameters. The results show that FORs and maintenance constraints affect the results differently. For instance, low load factors as well as large FORs and high peak load values can cause high conflicts among market participants. [119] considers aging momentum of thermal generation units in terms of their failure rates and evaluates the impact of PM on these values. [120] proposes a maintenance scheduling model where it optimizes the maintenance tasks for several components (e.g. transformer, circuit breaker, switches, cable) in a power system. It considers a multi-objective optimization problem where minimization of cost and unreliability indexes are solved by non-dominated sorting genetic algorithm.

[121] develops a GMS problem where the gas network operator is considered along with the electric network operator. Through an iterative process, GENCOs try to maximize their profit. Their maintenance schedules are evaluated by the ISO on reliability basis and a penalty/incentive signal is issued. [122] proposes a method through hybrid improved binary particle swarm technique where it demonstrates the improvement in performance and convergence characteristics on similar approaches such as genetic algorithm. [123] considers a maintenance scheduling problem where ISO and GENCOs solve the problem with their own objectives and then reach an agreement by solving the problem iteratively. The profit of GENCOs are calculated as multiplication of forecasted (known) market clearing prices into their output power minus the operation costs. The objective of ISO is to maximize the reserve capacity. [124] develops a GMS model where a coordination procedure is developed between the ISO and GENCOs based on a reliability signal. The stochasticity and sensitivity analyses are proposed for future studies. [125] proposes a multi-objective GMS problem where GENCOs profit, system reliability and operation cost are the three objectives. One of the conclusions is that the profit of the cheapest GENCO does not have any conflict with the total operation cost.

[126] proposes an equilibrium problem with equilibrium constraints for maintenance scheduling of generation units. Analysis of stochasticity, FORs and strategic behavior of generation units are mentioned as future works. [127] proposes a unit commitment model for multi-regional electricity markets and [128] develops a model to find Nash equilibrium (NE) in the operation of a power system in a pool-based electricity market through a bi-level optimization model where maintenance scheduling is not considered. [129] firstly calculates the costs due to downtime of the components through a mixed-integer programming model. Next, it defines several condition states for the

components and their evolutions through a Markov decision process. The objective is to minimize the total operation cost considering various condition states for the components and the type of maintenance actions. Renewable sources and electricity prices are neglected. [130] evaluates the impact of demand response through PM scheduling of generation units. The objective function is a minimization that includes fuel, maintenance, reserve, demand response and emissions costs. [131] considers a transmission-constrained GMS problem where demand response is integrated. The objective function is maximization of social welfare which is the difference between the customer gross surplus and generation cost. Similarly, [132] integrates demand response in a PM scheduling and solves it in a multi-objective framework where lexicographic approach is applied. Condition monitoring information, uncertainty and RES are not considered.

[133] proposes a hybrid particle swarm optimization based on genetic algorithm and shuffled frog leaping algorithm to solve long-term GMS problem. [134] proposes a long-term energy-mix optimization model where it links the planning with the short-term requirements such as primary and secondary services. These two studies do not consider transmission lines and the electricity prices are given. [135] decouples short- and medium-term optimization problem into three separate optimization problems where impact of covariates are taken into account. However, uncertainty and RES are disregarded. [136] proposes a weighted objective function for maintenance scheduling where it includes cost and service related terms. Random and targeted failures are analyzed on nodes and links. [137] proposes an integrated generation and transmission maintenance scheduling model. Benders decomposition method is applied to divide the problem into master and sub-problems. Sub-problems verify the feasibility of solution of the master problem and the N-1 criterion. An additional relaxation technique is introduced to improve the computation performance of the model. [138] proposes a coordination mechanism between ISO and GENCOs in a maintenance scheduling problem. GENCOs submit their plans and ISO verifies them based on a reliability perspective. If the plans are in line, they are accepted, otherwise, ISO proposes new plans where the plans are based on achieving the reliability perspective that ISO considers. Health condition information of components, uncertainty and RES are neglected.

[139] integrates several constraints from the coal and natural gas systems into the GMS in the electric power system where the objective function is minimization of operation costs. [140] proposes a game-theory based RCM scheduling problem where the criticality of the generation units is assessed by the risk they impose to the system if they fail. These two studies do not consider RES and uncertainties. [141] proposes a fuzzy game-theoretic framework for GMS where the objective of GENCOs is to maximize their profit. [142] proposes a GMS problem where the objective function is minimization of production and maintenance costs as well as peak regulation pressure penalty. [143] proposes a two-stage generation scheduling for hydrothermal power plants where the uncertainty in the water inflows are considered. The evolution of health condition information of the equipment and their impacts on the operation are not considered.

[144] proposes two models based on regression and unit commitment to assess the impact of wind penetration on the electricity prices. [145] proposes an optimal scheduling problem with thermal, wind, solar and battery systems. The objective function is minimization of operation cost as well as a mean adjustment cost to account for costs due to the intermittent nature of RES. These two studies also neglect the health condition of the equipment and do not address maintenance scheduling. [146] proposes a GMS problem where a coordination process is developed to link the centralized and decentralized plannings. [147] proposes a GMS model for an islanded microgrid with solar, wind and battery systems. It evaluates the operation of the system from two perspectives of centralized and decentralized and compares the profit of the microgrid in both perspectives. [148] proposes two centralized and decentralized GMS models for a power system with wind power source where detailed information of the wind farm are considered. For instance, the impact of wake effect, various transfer vessels and working shifts are studied.

Table 2.3: Summary of reviewed literature on generation maintenance optimization

References		Maintenance	Historical Condition Data	Real-time Condition Data	Exogenous Electricity Price	Endogenous Electricity Price	Uncertainty (Load/DER/Price)	Renewable Sources (Wind/Solar)	Transmission
[108]		✓					✓		✓
[109–115]		✓							
[116]		✓			✓		✓		
[117]			✓		✓		✓		
[118]		✓	✓		✓				
[119, 120]		✓	✓						
[121]		✓	✓		✓		✓		✓
[122]		✓	✓				✓		
[123–125]		✓			✓				
[126]		✓				✓			✓
[127, 128]						✓	✓	✓	✓
[129]		✓	✓						✓
[130–132]		✓			✓				✓
[133]		✓	✓		✓				
[134]					✓		✓	✓	
[135]		✓	✓	✓	✓				✓
[136–138]		✓							✓
[139, 140]		✓	✓		✓				✓
[141]		✓			✓		✓		
[142]		✓						✓	
[143]									✓
[144]					✓			✓	
[145]							✓	✓	✓
[146]	Chapter 5	✓				✓	✓	✓	✓
[147]	Chapter 5	✓		✓		✓		✓	✓
[148]	Chapter 5	✓	✓	✓		✓	✓	✓	✓

3 Data-driven Methodologies for Operation and Maintenance of Assets

The state-of-the-art review in chapter 2 revealed a major scientific gap in the literature that raises the question of "how the health condition data from components can help improve operation of the system?". This chapter presents four data-driven methodologies for performance evaluation and maintenance management through four different and generic frameworks in order to address the discovered gap in the component level including past, current and future horizons. In order to improve the state-of-the-art, each framework delivers a model for a specific perspective and horizon. An anomaly model is derived to detect the abnormalities and under-performance during the operation along with carrying out a root-cause analysis on the past operation. A Markov model analyzes the past operation and provides insight on the previous operation and maintenance (O&M) decisions and possibilities for the improvement of maintenance strategies through a mid-term operation analysis for future horizon. A stress model proposes an idea to estimate the impact of maintenance actions on the performance for maintenance evaluation. Finally, a health condition model provides a parametric formulation where it can be used to overcome difficulties such as scalability and adaptability of component models in large scale projects through past and current performance analyses.

Each of these four frameworks are developed through several steps. Some of the steps are common in all of the frameworks and methodologies as shown in Figure 3.1. The first common step is data analysis (DA). The second common step is creating an normal behavior model (NBM) and the third common step is generating a deviation signal (DS).

The DA step includes collecting and processing the collected raw data. Several filters can be applied during DA step to clear the data (e.g. remove outliers). A model for predicting normal behavior of the component is created in the NBM step. The NBMs in this dissertation are mainly developed through artificial intelligence techniques. In the NBM step, various configurations are tested for the models with the cleared data from the DA step in order to obtain a suitable NBM. The DS step includes creating a signal which displays the difference between the actual observed operation and the prediction of the model. This can be achieved through different ways. The way selected in this dissertation is the simple differentiation between the outcomes of the NBMs and the actual measurements. Then, depending on how such results are used, various methodologies can be further derived. In this dissertation, four methodologies are developed which each of them tries to address a different, yet related, aspect in the O&M field with new contributions. The main contribution of this chapter is providing data-driven methodologies for using the collected operation data from component level in improving the O&M field for past, current and future horizons.

The first methodology carries out a root-cause analysis (RCA). The link between the final RCA step and the DS step is an anomaly detection (AD) step. The AD constitutes applying a static threshold to the DS extracted from the NBM step. The static threshold is obtained through several trials and errors on the actual measurement data. It should be mentioned that such threshold is very dependent on the performance of the NBM and the data used. After applying the threshold to the DS, principal component analysis (PCA) technique is applied to the anomaly data points in order to assist in detecting the root of the anomaly. Due to the statistics nature of the utilized techniques, additional investigations (by experts) are required to verify and confirm the findings of the framework in this methodology.

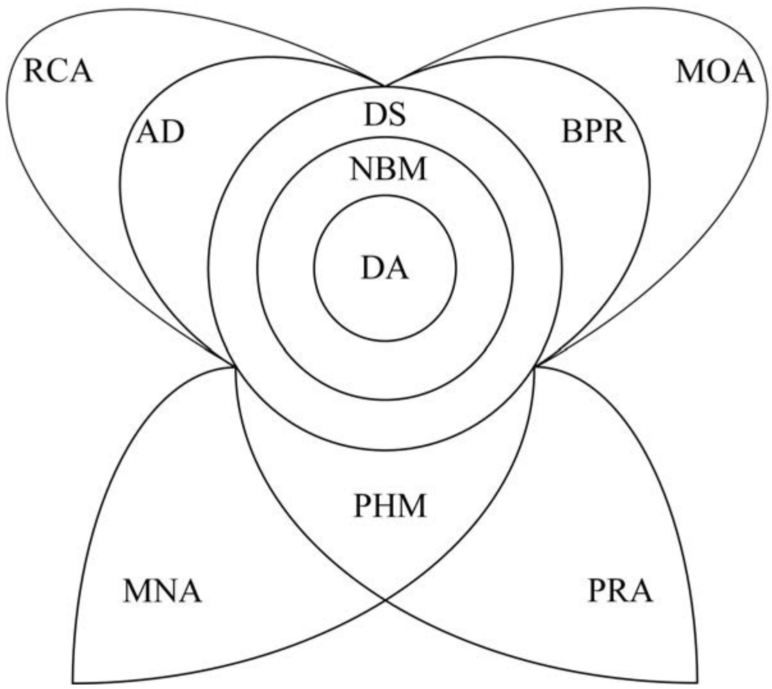


Figure 3.1: Overall diagram of steps for methodologies in Chapter 3

The second methodology carries out a mid-term operation analysis (MOA). The link between the final MOA step and the DS step is a behavior pattern recognition (BPR) step. The objective of BPR step is to detect and extract different patterns that exist in the DS. The DS can be divided into predefined classes based on the the observed pattern and specific thresholds can be used. Then, by finding the physical meanings of each of these patterns and their connection with the actual measurements, they can assist to further investigate any of these patterns and check how to prevent the component to enter into the negative patterns (i.e. abnormalities and failures). Connecting the observed behavior with each pattern through probabilistic approach can provide a mid-term operation analysis for the asset owner. This indeed assists in maintenance scheduling and improving the overall operation of the asset.

The third methodology carries out a maintenance analysis (MNA) and the last methodology carries out a performance analysis (PRA). These two methodologies have another common step between the DS step and their final outcomes. Both of MNA and PRA steps project the deviation from DS step onto a proportional hazards model (PHM) form. MNA considers maintenance action data and combines the outcomes of DS step and NBM with PHM. This way, MNA can provide details on the efficiency of the maintenance actions to some degree, compare maintenance actions, compare the environment where the assets are located and provide insight and recommendations on the applied maintenance strategies. On the other hand, PRA uses the combination of DS, NBM and PHM in another way and provides a health condition NBM which has a parametric form. Such a parametric model integrates more detailed data from the asset by considering data obtained from various sub-assemblies. The parametric model has the capability of addressing scalability issues, providing better understanding of physical operational conditions and being embedded as a measure for asset performance in maintenance optimization models.

The frameworks developed in each methodology are further analyzed through case studies where the focus has been put on wind turbine (WT)s. Since each framework has a different perspective, a detailed analysis of the surveyed studies in line with each work is provided in the Introduction section of each case study where the general state-of-the-art point of view is presented in Table 2.1.

3.1. RCA Methodology

The RCA methodology aims at assisting the asset owner and the operator to improve the O&M activities by analyzing the past and current operation. One of the resultant advantages of this approach is decreasing the maintenance down-time. Since this approach is able to point out the component that is responsible for the abnormality in the system, the maintenance crew will not need to search the entire system to find the faulty component; rather, they can directly hover over the defective part and perform the maintenance [148]. The other connected advantage is increasing the availability of the system and hence, bringing about higher savings and efficiency. This study is presented by the author in [27, 28].

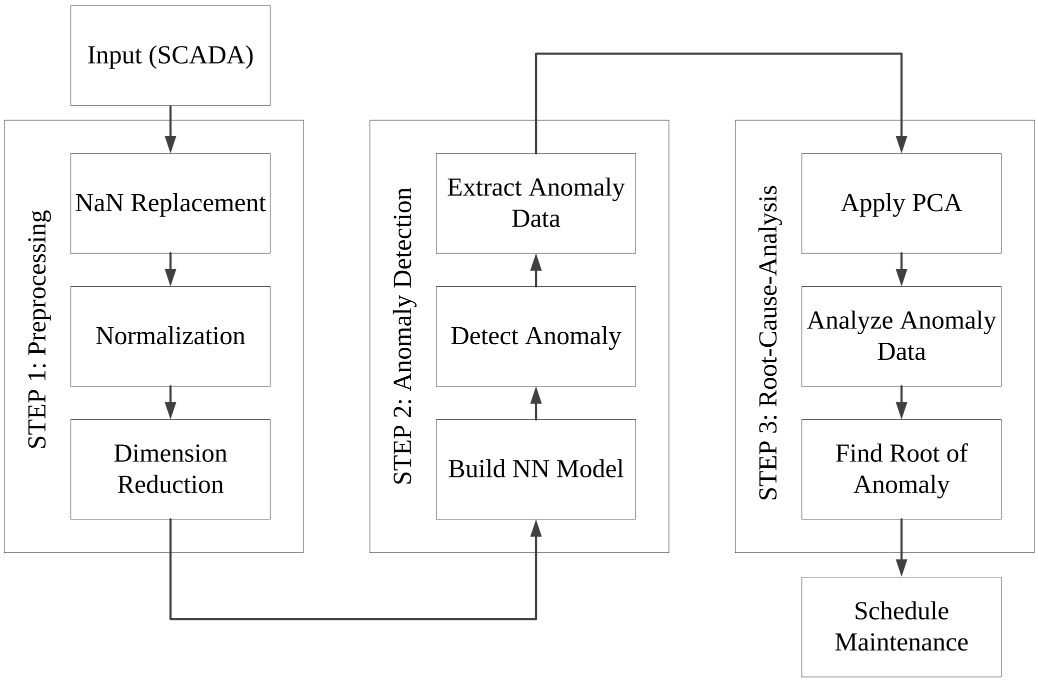


Figure 3.2: The proposed PAAD framework

3.1.1. PAAD Algorithm

The RCA methodology presents a generic data-driven performance analysis and anomaly detection (PAAD) framework, Figure 3.2. Primarily, faulty input data, in this dissertation represented as not-a-number (NaN), are cleared by applying different filters where details and examples are mentioned in section 3.1.2.2.1. Next, an NBM is obtained through data-driven modeling for the component. Then, abnormal behaviors are extracted and root-cause analysis is carried out on the extracted anomaly data points.

3.1.1.1. Step1: Preprocessing

Recorded measurements from sensors installed on components create a large raw data set. Normally, these data are not in a format to be directly used for any purpose. Analyses of the large recorded data sets can be complex, time-consuming, inefficient and in cases, impossible due to limitations of computational power. For these reasons, several techniques such as clustering, scatter plot, confidence intervals and Pearson correlation (PC) [149] are used. Since statistical techniques lack physical knowledge, consideration of cause-and-effect relationships will improve the analysis. Before applying the PC technique, the variables can be scaled. The following provides a positive-based normalization:

$$x_i = \frac{\varphi[x_i - Min(x)]}{Max(x) - Min(x)} \tag{3.1}$$

where $x = \{x_1, x_2, ..., x_n\}$ is a variable, φ is the desired maximum limit for the normalization range, n is the number of measurement data points and Max and Min represent maximum and minimum values of x, respectively. It should be noted that (3.1) sets the minimum limit to zero.

The information provided by PC technique only show whether two variables are linearly related. Although this is limited, it can present elementary information which at the preliminary stage of the analysis is advantageous. The types of information that PC technique offers are as follows [150]:

- Sign of the coefficient: while '+' sign in the output coefficient means a linearly positive relationship among the two variables, '-' sign means a linearly negative relationship. '0' shows that there is no linear relationship.
- Magnitude of the coefficient: while values in the range of [0.1, 0.3] mean small correlation between the variables, values in the range of [0.3, 0.5] mean medium correlation level exists. Values larger than 0.5 show that there is a significant correlation.

$$pc_{x,y} = \frac{\sum_{i=1}^{n}(x_i - x')(y_i - y')}{\sqrt{\sum_{i=1}^{n}(x_i - x')^2}\sqrt{\sum_{i=1}^{n}(y_i - y')^2}} \tag{3.2}$$

where $X = \{x_1, x_2, ..., x_n\}$ and $Y = \{y_1, y_2, ..., y_n\}$ are the two vectors to be compared, x' and y' are mean values of their corresponding vectors and n is the number of observations.

3.1.1.2. Step2: Anomaly Detection

In order to analyze the performance of the component, an NBM is created to simulate the operation of the component. By comparing the outcome of the NBM and the monitored behavior, an anomaly could be detected. The details of this process is provided in the following.

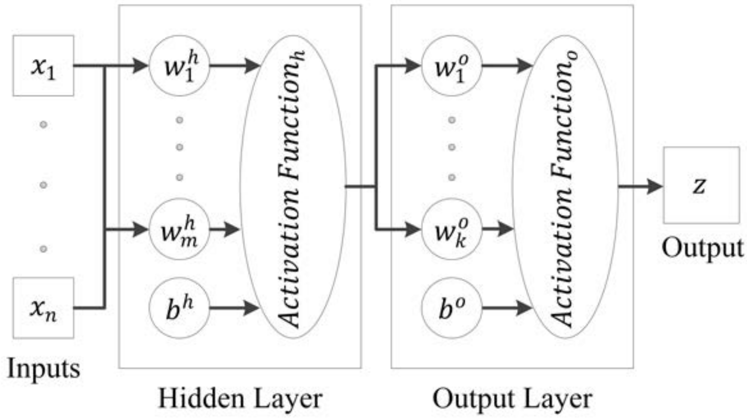


Figure 3.3: Multilayer perceptron feed-forward neural network structure

3.1.1.2.1. Neural Networks In this case study, neural network (NN) technique (multilayer perceptron feed-forward type, Figure 3.3), due to its great flexibility in addressing nonlinear complex systems, is used to build the NBM for the component. The input variables of the NN are real-time measurements from sensors installed on the component and the target variable can be decided based on the objective of the model.

The first phase in building the NN model is to find the optimum configuration for the NN. To find the best configuration for the NN, various possible combinations should be tested. Different performance evaluation methods can be used in the training of the NN and in this study these four performance measures are applied: mean absolute error (MAE) (3.3), mean squared error (MSE) (3.4), sum absolute error (SAE) (3.5) and sum squared error (SSE) (3.6).

$$MAE = \frac{1}{k}\sum_{j=1}^{k} \mid z_i - z_i' \mid \tag{3.3}$$

$$MSE = \frac{1}{k}\sum_{j=1}^{k} (z_j - z_j')^2 \tag{3.4}$$

$$SAE = \sum_{j=1}^{k} \mid z_j - z_j' \mid \tag{3.5}$$

$$SSE = \sum_{j=1}^{k} (z_j - z_j')^2 \tag{3.6}$$

where z_j and z_j' are NN output and target values and k is the number of data points.

As shown in Figure 3.3, structure of the NN used in this study constitutes one hidden layer and one output layer where each has a different activation function. Additional studies can further analyze various structures and assess their performance.

$$ActivationFunction_1 = f_1(w_i^h x_i + b^h) \tag{3.7}$$

$$ActivationFunction_2 = f_2(w_i^o v_i^h + b^o) \tag{3.8}$$

where w_i^h is weight of a neurons in hidden layer, b^h is the bias value of hidden layer, w_i^o is weight of a neurons in output layer, b^h is the bias value of output layer and v_i is output of hidden layer to output layer.

The first activation function (f_1) calculates outputs of the hidden layer based on Sigmoid function with Hyperbolic Tangent form as shown in (3.9) [151]:

$$f_1(w_i^h x_i + b^h) = \frac{2}{1 + e^{-2(w_i^h x_i + b^h)}} - 1 \tag{3.9}$$

and the second activation function (f_2) estimates outcome of the output layer based on a linear function as shown in (3.10):

$$f_2(w_i^o v_i^h + b^o) = w_i^o v_i^h + b^o \tag{3.10}$$

A powerful supervised learning algorithm, scaled conjugate gradient is used to train the NN [152]. Based on the chosen performance measure, the objective of the algorithm is to minimize the function by tuning biases and weights of the NN. Therefore, the NBM based on NNs will provide an expected performance of the component.

3.1.1.2.2. Deviation Signal The deviation variable (DS) is defined as:

$$DS = \mid PredictedValue - MeasuredValue \mid \tag{3.11}$$

Deviations from the predicted performance by the NBM could represent anomalies. The anomalies may be due to the inaccuracy of the model, developing failures, random failures or transient abnormal behaviors. While positive differences between predicted and measured values can account for an under-performance of the component, a negative difference could also hold information such as abnormality in measurement devices. Due to nonlinearity and complexity of the NNs, some false predictions are likely. Therefore, a filter can be applied that considers that among three consecutive data points, the value of the second data point should not exceed four times the average of the first and the third data point. In other words, two of them must be outside the resultant dynamic confidence band to be considered as false deviations. This type of filter is common in control quality works [153].

In order for the DS to be sensitive to the changes in input parameters at each NN, a 95% confidence interval is applied to the resultant DS. 95% confidence interval here can be assumed as a distribution of the deviation points where 95% of these points are inside the confidence interval. This means that after the prediction is performed with the NN model and the primary DS is calculated, only the remaining 5% deviation points (that are outside this 95% confidence band) are considered in the DS. Confidence interval simply trims the signal and intensifies the impacts of changes in the trend. The impact of applying this confidence interval was also observed during preparation of the model where using the DS without considering confidence interval did not provide useful information on the evolution of changes in the input data. This is due to the fact that many of the deviation data points have small values, and when many of them are accumulated, this reduces the accuracy of the model by increasing the difficulty in finding the patterns in the input data [153].

Due to differences in NNs and components, deviations need to be interpreted for individual components. These deviations carry information about performance of component and since various actions are performed towards them (e.g. maintenance), it can be assumed that they can be useful to analyze these actions and take advantage of data for future operating years. In this regard, a detailed analysis of deviations can also be performed.

3.1.1.3. Step3: Root Cause Analysis

In multivariate statistical analysis, PCA is one of the most important techniques to deal with correlated data. PCA transforms these correlated data into uncorrelated linear data by defining a new system of coordinates. These new resultant variables are called principal components and they aim to capture highest levels of change and variability in the data; consequently, first principal component bears the highest impact in the data [150, 154].

After the anomalies are detected in the system, the data are sent to be further analyzed by PCA. PCA can primarily say how many of the input variables are sufficient to model the system without losing any characteristic. The inputs of PCA are the extracted data points that were considered to be anomalies by the NN model in the previous step. It should be mentioned that if the number of data points is too little, the results may not be accurate. This can be verified through several trials and experience.

At first, PCA calculates the covariance matrix for the data. For an n dimensional data, the covariance matrix is as shown in (3.12) where $cov(x,y)$ is the covariance between x and y calculated as (3.13) with n data points.

$$[C]_{n\times n} = [cov(x,y)] \tag{3.12}$$

$$cov(x,y) = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - X')(Y_i - Y') \tag{3.13}$$

Then, PCA extracts the eigenvectors and eigenvalues of the covariance matrix. Afterwards, principal component is defined as the eigenvector that has the largest eigenvalue. A feature vector, a matrix of vectors, is then created from these calculated eigenvectors. One could consider only those vectors that correspond to highest eigenvalues, or all vectors in case one would like to maintain complete data. By multiplying the feature vector into the transposed of original data, final PCA outcomes in terms of new principal components (eigenvectors) are obtained [155]. As outputs of PCA, coefficients of the principal components, original data in the new coordinate system, variance of the newly defined principal components and information on the percentage of these variances are generally in literature referred to as “components coefficients”, “component score”, “latent” and “explained”, respectively.

3.1.2. Case Study: Wind Turbine Anomaly Detection

While the scientific gap in the literature has been identified in section 2.2 and Table 2.1, detailed analysis of one approach to fill that gap is reviewed here. The focus is on improving the O&M field in component level for past and current operation by analyzing the collected data.

3.1.2.1. Introduction

Environment friendly and cost effectiveness are two of the factors that have driven societies towards vast utilization of wind energy by large investment and deployment of WTs and wind farms in the past few decades. With being able to effectively operate and produce power for up to 25 years [156], some of the early installed WTs are approaching their end of life. This aging matter is bringing up more frequent incidents (failures, malfunctions etc.) and longer unavailability which raise the alarm that a more developed monitoring system is required to address these issues.

Condition monitoring system (CMS) on modern WTs use the data from supervisory control and data acquisition (SCADA) systems where they record the data of WTs from different sensors installed on them. An accurate CMS does not necessarily require large numbers of sensors (hence a costlier system), rather a system that provides the owner of the asset with enough information to avoid anomalies and failures with an acceptable accuracy [157, 158]. Moreover, including operational conditions in the analysis can help improve the maintenance management [159].

Recently, there have been several studies that benefit from SCADA data by developing CMSs for WTs. [21] investigated the processing of the SCADA data and raised some concerns on the analysis of these data as they had large variations and this makes it difficult to detect incipient failures. There have also been a few research works where they review applied techniques on condition monitoring and fault diagnosis of WTs [158, 160–165]. Ultimately, all these works suggest that the need for developing an algorithm that can manage a broad area is yet to be achieved. Furthermore, most of the approaches and techniques applied are focused on a particular sub-assembly (e.g. generator, pitch system) in the WT. There have been several research works focusing on reliability and maintenance of WTs considering them as a whole or in sub-assemblies [166–173]. Some studies focus particularly on pitch systems in the WTs [174–178].

The techniques must be able to model normal behavior of the component in order to detect anomalies. In reality, this often requires modeling nonlinear relationships among several variables (internal and external) that characterize the behavior of an industrial component. NN is one of the techniques widely used in the analysis of WTs mainly due to its flexibility and adaptability to various conditions, and it offers the possibility of modeling these nonlinear relationships. Its applications range from behavior prediction to classification and fault diagnosis and have been applied to different sub-assemblies in WTs [39, 44, 179, 180], gearboxes [181–183], bearings [184, 185] and generators [186]. Adaptive neuro fuzzy inference system was applied to find malfunctions in WTs [187, 188]. Since the results are the outcomes of pure statistics without interference of human knowledge and information, an expert manually implements a number of rules to narrow down the possible origin of the failure. [189] presents an improved fuzzy-synthetic assessment method and applies it to generator of a WT.

There are several areas to improve in order to obtain a thorough CMS. The areas include sensors and data acquisition [190], data processing [191], behavior and performance modeling [38], abnormality and anomaly extraction and evaluation, diagnosis and prognosis, and interactive and integrated procedures. Since they cover a wide area, each individual work can focus on specific parts. This example provides a link between system layer and component layer which makes it an overall condition monitoring technique for WTs.

3.1.2.2. Step1: Preprocessing

The measurements are recorded for each parameter at frequencies less than 10 minutes; however, one average number for these values is provided as the final value, over the 10-minute period. This case study comprises recorded data of 62 signals from SCADA system of a WT. The data consist of measurements for the period of approximately 22 months, divided into WindMSP1 and WindMSP2 data sets. WindMSP1 has the data for the WT during its normal operation. WindMSP2 has the data for the WT during its normal and abnormal operation, hence a bigger data set.

3.1.2.2.1. NaNs Replacement NaN values are caused by errors in reading the measurements from sensors and writing the measurement data into a digital file. Since dismissing the measurements can have significant impacts in modeling and analysis, the NaNs are replaced. Available values before and after the NaN point are located and the NaN value is replaced with an average value of these two available values. In this way, if an abnormality happened for some period of time, the resultant variation can be reflected in the data by the difference between the values that are measured before and after that abnormality time.

3.1.2.2.2. Dimensionality Reduction Table 3.1 presents a complete list of recorded signals by the SCADA system in this case study. Since some parameters do not change based on the active power output of wind turbine (AP) or their change does not cause any specific variation to the AP, there will be a reduction in the number of parameters for modeling. It should also be noted that the “cause and effect” relationship should be taken into account. The seven primarily chosen parameters are AP, pitch angle (PA), rotor speed (RS), ambient temperature (AT), gearbox temperature (GT), temperature of oil in gearbox (TOG) and wind speed (WS). These parameters are selected solely from experience.

Table 3.1: List of recorded signals by the SCADA system

#	Parameter (unit)	#	Parameter (unit)
1	Year	32	Ground RFC 1 Version
2	Month	33	Ground RFC 2 Version
3	Day	34	Ground RFC 3 Version
4	Hour	35	Ground ILC Version
5	Minute	36	Ground RFC Version
6	Second	37	Hydraulic Group pressure (bar)
7	Wind direction	38	Hydraulic Group temp. (°C)
8	Ambient temp. (°C)	39	Hydraulic valve output voltage
9	Ice detection temp. (°C)	40	Gearbox temp. (°C)
10	Wind speed (m/s)	41	Gearbox oil temp. (°C)
11	Elect. generator ring temp. (°C)	42	Year ProdPower
12	Elect. generator LA bearing temp. (°C)	43	Day ProdPower
13	Elect. generator LOA bearing temp. (°C)	44	Hour ProdPower
14	Power factor set-point	45	Month ProdPower
15	Elect. generator alarm temp. (°C)	46	Producible power (W)
16	Generated active power (kW)	47	Total ProdPower 1
17	Generated total power (kW)	48	Network frequency
18	Elect. generator stator power (kW)	49	Network power
19	Generated reactive power (kVAR)	50	Network reactive power
20	Elect. generator rotor power (kW)	51	Network voltage (V)
21	Elect. generator winding 1 temp. (°C)	52	Pitch angle (deg)
22	Elect. generator winding 2 temp. (°C)	53	Rotor iced possibility
23	Elect. generator winding 3 temp. (°C)	54	Rotor speed (rpm)
24	Elect. generator speed top (rpm)	55	Stopped by tool
25	Mechanical over speed (rpm)	56	Ambient temp top (°C)
26	Nacelle position	57	Elect. transformer max temp. (°C)
27	Yaw brake pressure	58	Elect. transformer 1 temp. (°C)
28	Nacelle temp. (°C)	59	Elect. transformer 2 temp. (°C)
29	Tower height	60	Elect. transformer 3 temp. (°C)
30	Elect. generator speed ground (rpm)	61	High speed detection
31	Ground version	62	Wind turbine state

One technique is scatter plot of parameters. The idea is simply to look at the plots and see if some particular relationship (linear or nonlinear) can be observed. If no pattern seems to exist, it would be advisable to dismiss that parameter. Figure 3.4 displays the relationship between the primarily selected parameters and the AP. Table 3.2 displays the PC between a few variables and AP. WS variable shows the highest linear relationship to AP. As displayed, nacelle temperature (NT) does not show any linear relation.

3.1.2.2.3. Normalization After the NaNs are substituted and parameters in building the model are selected, the data are scaled and normalized through (3.1). Normalization converts original data into a newly defined range. This indeed matters when

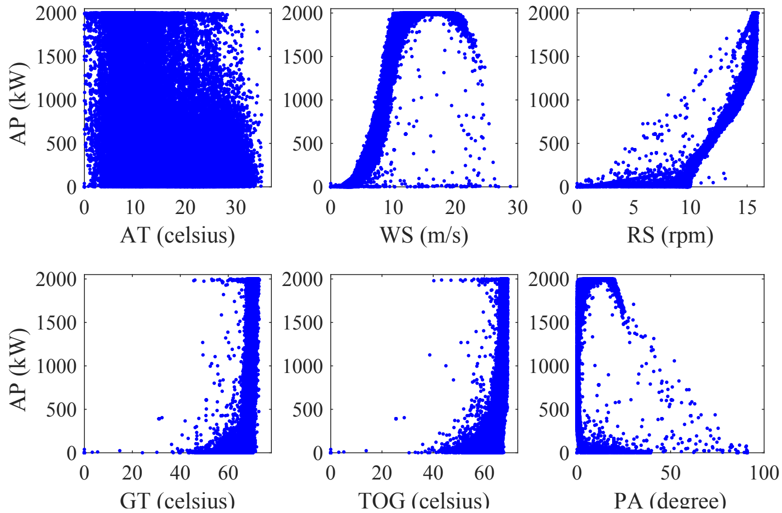


Figure 3.4: Mutual behavior of seven parameters in WindMSP1

Table 3.2: Results of Pearson correlation analysis for WindMSP1

Parameter	AP
Ambient temperature	- 0.416
Nacelle temperature	- 0.081
Pitch angle	- 0.207
Gearbox temperature	+ 0.363
Temperature of oil in gearbox	+ 0.392
Rotor speed	+ 0.728
Wind speed	+ 0.876

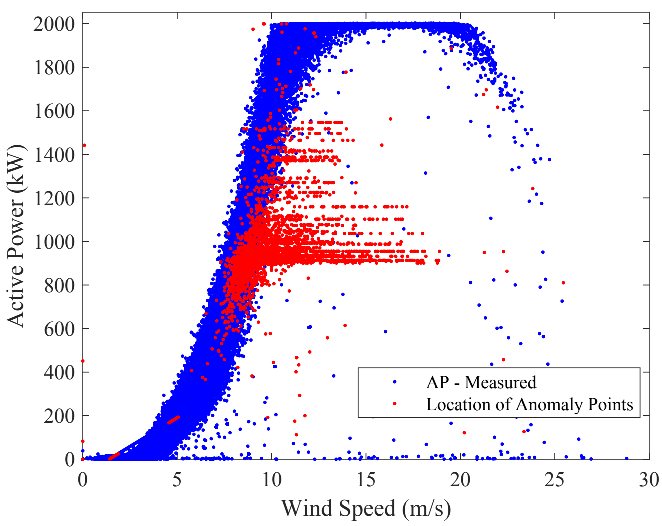


Figure 3.5: Detected anomaly points in WindMSP2

industry would like to maintain privacy of the data of its assets. The normalization range for each parameter is: AP:[0,2000], PA:[0,90], RS:[0,16], AT:[0,35], GT:[0,80], TOG:[0, 70] and WS:[0,30]. The unit of each parameter is [kW], [degree], [rpm], [°C], [°C], [°C] and [°C], respectively.

3.1.2.3. Step2: Anomaly Detection

Analysis of the performance of the monitored WT is carried out through its power-curve. For this purpose, an NBM is created where the inputs of the model are real-time inputs of the WT (e.g. WS, AT) and information about sub-assemblies (e.g. GT, TOG). The target input parameter for the NN model is the observed AP and the output of the NN model is the predicted AP.

3.1.2.3.1. Building NN Inputs of the NN are PA, RS, AT, GT, TOG and WS, and AP is the target input. Testing various configurations has resulted in creation of 60 different NNs, Table 3.3. Two layers, one hidden layer and one output layer, are selected for the NN. It should be mentioned that the data in training, validation and testing are divided randomly and training ratio of 70%, validation ratio of 15% and test ratio of 15% have been applied. The details on creating the NNs are explained in section 3.1.1.2.1.

3.1.2.3.2. NN Training Outcomes Table 3.3 shows the training results of the NNs. The PA parameter exhibits low level of accuracy when it is used as a single input, with the highest level of accuracy at 74%. This is due to the fact that the NN tries to familiarize the model with all various available behaviors in the data and large range of variations in PA makes such task very challenging. After changing other parameters, considering PA as a single input, the maximum achieved improvement in the accuracy was 7% (74%-67%), thus, it is preferable to use more than one parameter to account for relation among parameters as well.

From a performance point of view, NN49 obtained the lowest value with MAE method (38), NN58 obtained the lowest value with MSE method (2763), NN59 obtained the lowest value with SAE method (2914994) and NN60 obtained the lowest value with SSE method (202990237). Considering iterations, NN39 achieved the lowest iteration number of 6 while NN11 has the highest iteration number of 952. Interestingly, none of these two NNs has the lowest error in performance. On the time duration of the operation, while NN39 has the lowest running time (00:01), NN59 has the largest time (02:49). It can be seen that MAE and SAE resulted in high number of iterations and large running times more frequently than other performance measures. From the accuracy perspective, NN60 outperform all other models. After considering all the discussed points, NN60 is chosen as the optimum NN.

Table 3.3: Various tested neural networks for building the model using WindMSP1

Input					Output						
								Accuracy (%)			
NN	Input	Target Output	Hidden Layer	Performance Evaluation Method	Performance	Iteration	Duration (MM:SS)	Training	Validation	Test	All
1	PA	AP	10	MAE	226	212	00:11	67.728	67.813	65.358	67.391
2				MSE	199696	92	00:06	71.290	73.254	70.705	71.491
3				SAE	20515095	370	00:18	69.837	71.592	71.168	70.301
4				SSE	18524265462	56	00:10	71.401	72.023	71.819	71.559
5			20	MAE	214	435	01:04	70.128	70.527	69.936	70.161
6				MSE	191101	65	00:06	72.989	72.301	73.407	72.947
7				SAE	19921847	195	00:12	70.639	71.097	71.128	70.782
8				SSE	17729273653	55	00:05	72.964	73.193	73.035	73.007
9			50	MAE	209	692	02:01	70.825	70.098	69.998	70.595
10				MSE	186981	89	00:12	73.915	72.862	73.112	73.636
11				SAE	18365149	952	02:35	72.017	71.675	72.297	72.007
12				SSE	17345756035	46	00:07	73.423	74.382	74.311	73.701
13	TOG	AP	10	MAE	216	414	00:20	85.383	84.810	85.192	85.270
14				MSE	108156	73	00:13	85.650	85.801	86.126	85.745
15				SAE	19860487	68	00:09	85.529	85.490	85.203	85.472
16				SSE	10046781727	21	00:03	85.867	85.881	85.080	85.753
17			20	MAE	203	273	00:17	86.596	86.589	86.198	86.536
18				MSE	97885	78	00:13	87.143	87.047	87.606	87.199
19				SAE	18284890	111	00:24	87.066	87.066	87.126	87.075
20				SSE	9049578417	156	00:29	87.331	87.009	87.243	87.271
21			50	MAE	198	550	01:50	86.573	86.822	86.347	86.576
22				MSE	100630	18	00:04	86.875	86.652	86.738	86.820
23				SAE	18243110	207	00:52	86.929	86.592	86.493	86.814
24				SSE	9065135049	65	00:27	87.305	86.737	87.481	87.248
25	WS	AP	10	MAE	69	74	00:14	94.292	94.269	95.011	94.395
26				MSE	44137	127	00:14	94.337	94.499	94.873	94.443
27				SAE	6382392	7	00:01	94.387	93.841	94.969	94.395
28				SSE	4099235357	16	00:02	94.465	94.309	94.500	94.447
29			20	MAE	69	207	00:44	94.283	94.978	94.434	94.408
30				MSE	44156	59	00:10	94.520	94.185	94.323	94.440
31				SAE	6365863	369	01:01	94.376	94.229	94.728	94.406
32				SSE	4100660843	11	00:02	94.630	93.638	94.385	94.446
33			50	MAE	69	189	01:02	94.375	94.314	94.640	94.404
34				MSE	44270	126	00:23	94.428	94.656	94.176	94.425
35				SAE	6374251	11	00:05	94.315	94.788	94.433	94.404
36				SSE	4103518408	22	00:04	94.617	93.807	94.251	94.441
37	WS + PA	AP	10	MAE	50	58	00:09	99.109	99.079	99.079	99.100
38				MSE	7230	120	00:07	99.123	99.047	99.118	99.111
39				SAE	4604124	6	00:01	99.101	99.085	99.107	99.100
40				SSE	638644505	79	00:05	99.155	99.167	99.146	99.155
41			20	MAE	49	499	00:40	98.970	99.084	98.894	98.976
42				MSE	5764	313	00:20	99.287	99.296	99.310	99.292
43				SAE	4094790	34	00:05	99.302	99.258	99.273	99.291
44				SSE	534570291	18	00:03	99.302	99.252	99.288	99.293
45			50	MAE	76	347	01:29	96.439	96.500	96.449	96.449
46				MSE	5757	232	01:17	99.289	99.309	99.296	99.293
47				SAE	4071580	77	00:19	99.306	99.258	99.258	99.291
48				SSE	533523088	21	00:06	99.293	99.339	99.259	99.295
49	WS + PA + TOG + RS + AT + GT	AP	10	MAE	38	862	01:40	99.487	99.495	99.467	99.485
50				MSE	2885	164	00:10	99.647	99.636	99.652	99.646
51				SAE	3356199	55	00:07	99.645	99.642	99.646	99.645
52				SSE	254290172	79	00:11	99.664	99.674	99.660	99.665
53			20	MAE	40	498	00:38	99.443	99.428	99.483	99.447
54				MSE	3517	81	00:11	99.574	99.572	99.538	99.569
55				SAE	3556626	103	00:27	99.568	99.539	99.545	99.561
56				SSE	258631853	64	00:17	99.662	99.649	99.656	99.659
57			50	MAE	47	463	02:18	99.194	99.229	99.187	99.198
58				MSE	2763	164	00:40	99.661	99.660	99.666	99.662
59				SAE	2914994	784	02:49	99.717	99.721	99.712	99.717
60				SSE	202990237	43	00:17	99.733	99.732	99.730	99.732

3.1.2.3.3. Verification of NN Outcomes WindMSP2 data set is used to verify the accuracy of the model in anomaly operating times. Figure 3.5 plots anomaly data points detected by the NN60 after applying a threshold in the model for WindMSP2. It can be seen while the WS is at range [10:20], the AP does not behave optimally and produces power below the expected value [1000:1500]. In this work, the threshold was obtained through several trials and errors as well as cross-validating the input data with the outcomes. The threshold level was defined as 200 units which means only those points with higher values showed significant impact and therefore were stored. This threshold is applied on the difference between the predicted and measurement data, on the DS variable. Figure 3.5 verifies that the level of the defined threshold is acceptable as it detects anomaly points with high accuracy. In addition, it is expected that the threshold level for each WT (and each failure mode) to be different.

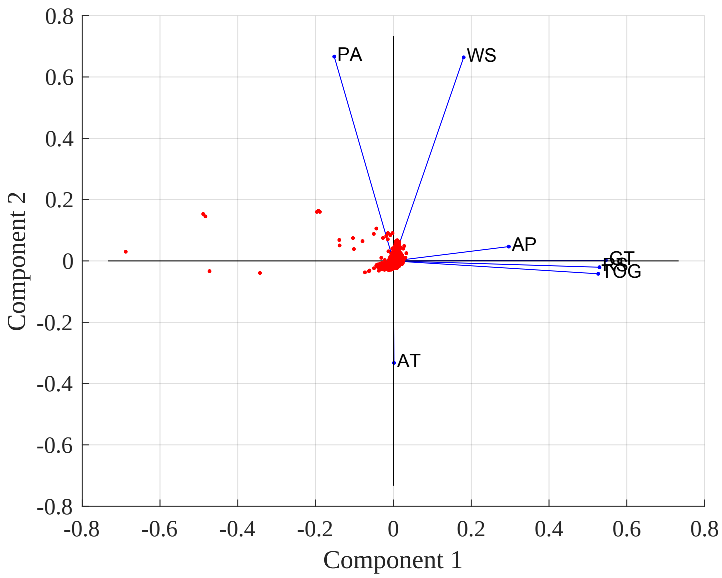


Figure 3.6: Anomaly data points analyzed by PCA from WindMSP2

3.1.2.4. Step3: Root Cause Analysis

The RCA analysis is carried out by applying PCA to the DS resulting from WindMSP2 and comparing it with the normal behavior observed by using WindMSP1. The final outcome is obtained by combining the results from statistics and experts knowledge and experience.

3.1.2.4.1. Principal Component Analysis It should be remembered that after the dataset WindMSP2 is analyzed, a new behavior, which origins from an abnormality, is observed. This abnormal behavior is the consequence of irregular performance of one (or more) of the input variables. As the first principal component in the PCA contains the highest variance in the data, by comparing these outputs with the outputs resulting from WindMSP1, the defective sub-assembly with abnormal behavior can be uncovered.

3.1.2.4.2. Principal Component Analysis Outcomes Table 3.4 displays PCA results for the anomaly data points extracted by the NN model from WindMSP2. As it can be seen, PCA has created seven principal components. The most important observation from Table 3.4 is the behavior of the anomaly data points which shows that the first principal component covers 41% of the variances in the anomaly data. Thus, this principal component could be the major reason for the anomalies.

Figure 3.6 visualizes the variables in a plot for 3000 anomaly data points extracted by the NN in WindMSP2. The plot is drawn from the “Coefficients” and “Scores” parameters that are calculated for each of the variables and their corresponding principal components [192]. They were scaled to the maximum Score value and maximum Coefficient

Table 3.4: Results of PCA analysis for anomaly points by NN in WINDMSP2

	Latent	Explained
Principal component 1	2.873	41.041
Principal component 2	1.720	24.568
Principal component 3	1.060	15.141
Principal component 4	0.878	12.545
Principal component 5	0.367	5.236
Principal component 6	0.056	0.802
Principal component 7	0.047	0.666

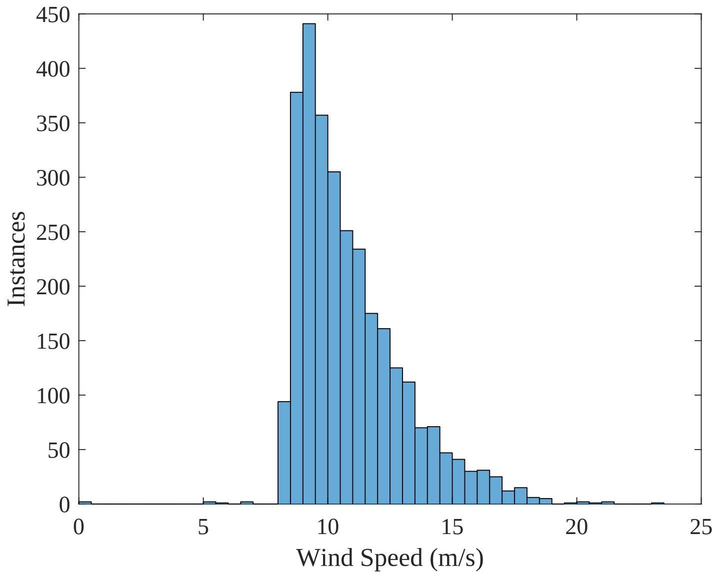


Figure 3.7: WS for anomaly flagged data points in WindMSP2

length. For example, the largest coefficients in the second principal component (Component2) correspond to the PA and WS variables; and for the first principal component (Component1), PA has the lowest score in the negative direction. GT, TOG, RS and AP variables are closely grouped together because they show a coherent behavior which is a significant observation. AT also obtains the lowest value by the second principal component (Component2).

Knowing that principal components 1 and 2 together account for more than 65% of the variance in the data (Table 3.4), the reference for analyzing the results should be based on these two principal components. From statistical perspective, after analyzing WindMSP2, the final conclusion is that WS, PA and AT are the three variables causing irregularity in the performance of the WT.

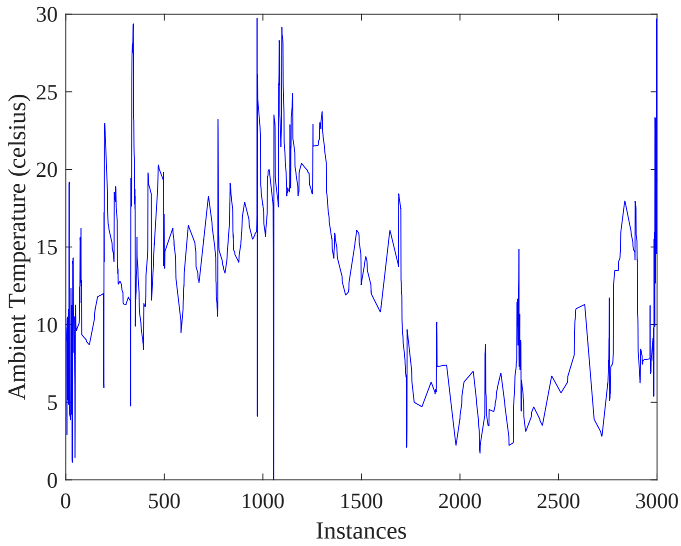


Figure 3.8: AT for anomaly flagged data points in WindMSP2

3.1.2.5. Results

NN accurately detected anomaly data points in WindMSP2 and statistical results concluded that PA, WS and AT are the main factors for the observed abnormality. Figure 3.7 displays the histogram of the WS values during the anomaly time. It is evident that the anomalies occurred when the WS had a normal profile with average WS of about 10 (m/s). Similarly, the AT behavior during this time is plotted in Figure 3.8 which shows a normal behavior as well (when compared with the rest of the period). It should also be remembered that these data points are not sequential. As a conclusion, WS and AT can be disregarded as the causes of detected anomalies. The next variable flagged by PCA is PA. To verify this as the final conclusion, further investigation is carried out.

Figure 3.7 shows that the anomalies happened when the WS varied mainly between the values of 9 and 16. Figure 3.9 displays the performance of the WT for the normal data (WindMSP1) and anomaly data in (WindMSP2) over the WS range of 9 and 16. One point to mention here is that Figure 3.9 demonstrates how the model accurately detected the anomaly points. The AD part has managed to correctly discover an "under-performance" situation in the WT which is very beneficial for the asset owner and the maintenance management. From here, they can decide on a preventive maintenance (PM) action prior to an actual failure which brings about a significant impact for the WT.

To review the analysis so far, Figure 3.9 shows for WS above 11 (m/s), the expected AP should be higher than the recorded AP and the anomaly has been detected accurately. Then, PCA suggested that the reason for this under-performance is probably related to WS, AT and PA. Analyzing the data of WS and AT confirmed these two parameters could not be the cause of the observed situation.

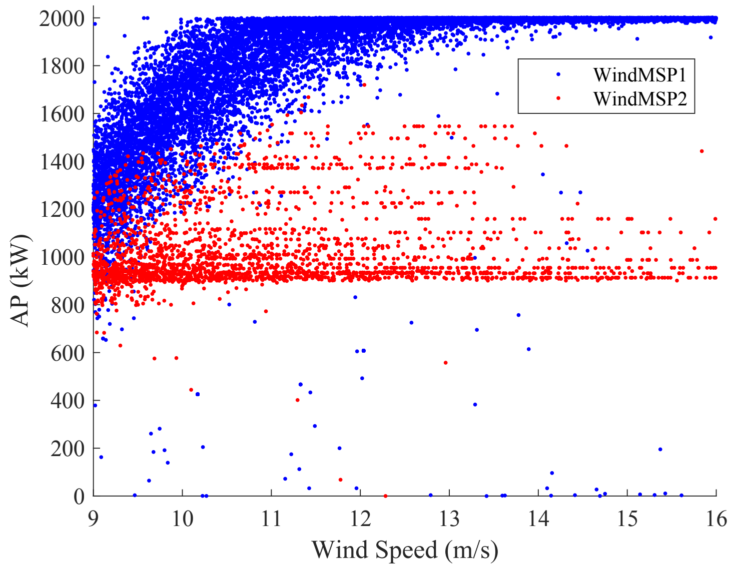


Figure 3.9: Power-curve for a particular WS range

Pitch system in the WT operates through a controller. This controller fits the angle of the pitch to the wind conditions based on the orientation of the WT. Therefore, in analysis of PA variable, it must be remembered that not only the PA is considered, other components in the pitch system (e.g. controller) are also accounted for. This is an extremely important point to be taken into account. Considering that the PA parameter can physically be origin of the detected anomaly and PCA analysis has also flagged PA as the major parameter, behavior of the PA during normal operation and abnormality (in both data sets) is compared in Figure 3.10.

The abnormality shown in Figures 3.9 and 3.10 can be interpreted as follows: although the WS is in normal condition and follows the expected behavior, the measured AP is not following the correct path (many PA points with 86 and 90 degrees). Considering the structure of the pitch system, the only remained diagnosis is that a component inside the pitch system (e.g. controller) is causing these abnormalities (e.g. reading/sending incorrect signals). This is one of the points in designing a control algorithm in active pitch control as well [193]. Final practical verification of the result is indeed achieved after discussing the results with the WT owner and the owner claimed this abnormal behavior was due to the testing of new controllers in the pitch system which is in conformance with the result of the proposed PAAD framework.

3.1.2.6. Case Study Conclusion

This case study follows the proposed RCA methodology for performance analysis and abnormality detection. The framework uses the data obtained from SCADA system of a WT and is divided into three steps: preprocessing of the raw input data, AD and root-

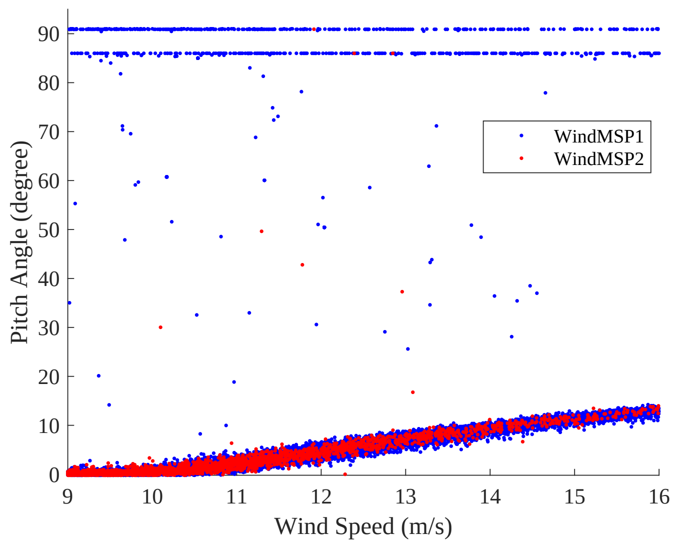


Figure 3.10: PA versus WS

cause analysis. In the first part of the framework, raw input data from SCADA system are processed and the dimensionality of the data is reduced. An NN model is built in the second step. Detailed phases in building the NN are described by evaluating several important factors. The created NN model detects anomalies through monitoring the performance of the WT from its power-curve and extracts the detected anomaly data points. In the final step, PCA technique analyzes the data in order to discover the origin of the anomalies by exploring the information carried through the data. To verify the model, real data have been examined and the steps to apply and use the framework are explained in detail. The results show that the framework is capable of very accurately evaluating the performance of a WT and can also assist in discovering the root of anomalies.

3.1.3. RCA Methodology Conclusion

In this section, a methodology for performing root-cause analysis is proposed. The defined PAAD framework is a data-driven modeling approach where uses operation data to analyze performance of a component. The framework can be applied to any industrial component where enough operation data is available. Although too little data can affect the outcome of the framework, the required amount of data to apply this framework can differ among components based on dynamic of the operation. By considering the maintenance time as the time required to detect an abnormal behavior and locate the faulty part and perform the maintenance, the benefits of applying this framework are reductions in maintenance time and cost, and increase in availability and in return profit of the component.

3.2. MOA Methodology

The MOA methodology aims at improving the medium-term O&M planning of an asset. One of the advantages of this methodology is obtaining new knowledge on the previous behavior of the asset where improvements in the operation can be suggested. These improvements can be in form of PM schedules through monitoring the performance of the asset from the recorded operation data. Moreover, this methodology delivers a benchmark for comparing multiple assets in terms of efficiency in their performance and maintenance strategies. This study is presented by the author in [38].

3.2.1. PAME Framework

The performance and maintenance evaluation (PAME) framework proposed for MOA methodology consists of three main parts, Figure 3.11:

1) Create an NBM for the component in order to detect deviations from the normal operation.
2) Further analyses of these deviation data points through unsupervised learning techniques such as self-organizing maps (SOM) [194]. SOM identifies patterns in the behavior of deviations (DS). The outcome of the second step is a number of clusters (patterns) observed in the operation of the component.
3) Finally, to represent the relation among clusters and provide an insight into mid-term performance and maintenance evaluation, a Markov model can be developed. The memoryless property in the Markov models says that transition from one state to another depends solely on the state that the transition starts from. In particular, systems with slow rates of change among states can benefit from this property. The Markov chain (MC) can be supplemented by new indexes to provide assistance for decision making process in the management of the asset.

3.2.1.1. Performance Modeling

To model normal behavior of a component, a NN model can be created where PC technique can be used to find the right number of parameters for the model. Next, the performance modeling can be carried out through DS variable as explained in section 3.1.1.2. Please note that these NNs are system level models where they forecast the overall performance of the component through the observed input parameters.

3.2.1.2. Behavior Pattern Recognition through Self-Organizing Maps

Information carried in the resultant deviations (DS) from 3.2.1.1 lack detailed interpretations. Therefore, to assess the deviation data, an unsupervised clustering technique,

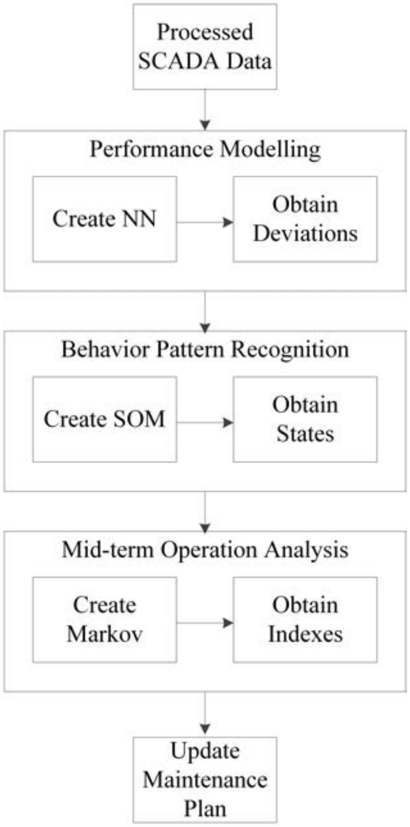


Figure 3.11: The proposed PAME framework

SOM, can be used [195]. SOM detects patterns in the DS and extracts the knowledge. Since deviations hold information on performance of the component, SOM outcomes represent past behavior and performance of the component including the applied maintenance.

In order to further analyze behavior of the component and be able to assert predictions, clusters created through SOM (named "States") are transferred to an MC model. These clusters will feature different operating modes exerted from the DS. Equation (3.14) displays t calculated data points of the X deviation sequence and (3.15) shows n states where each S_i is an observed deviation clustered into state i through SOM.

$$X = \{x_1, x_2, ..., x_t\} \tag{3.14}$$

$$S = \{S_1, S_2, ..., S_n\} \tag{3.15}$$

3.2.1.3. Mid-term Operation Analysis through Markov

In this part, a discrete-time MC model with finite state space is used to characterize the performance through the extracted DS. MC has the ability to feature a preview of future operation in case that the system continues the operation without any significant change; hence, it provides an insight on both past and future operating conditions. From the observed states and their sequence, transition probability matrix (TPM) and initial state probability (ISP) of each state are calculated for the component. TPM and ISP are demonstrated respectively as:

$$TPM = [p_{ij}]_{n\times n} \tag{3.16}$$
$$ISP = [q_1, q_2, ..., q_n]_{1\times n} \tag{3.17}$$

where p_{ij}=$P(S_j|S_i)$ and q_i=$P(S_i)$. TPM presents the probability of moving from one state to another whereas ISP represents probability of being at each state in the beginning.

Since MC is a theoretical model defined as memoryless, it indicates that current state only depends on the previous state, regardless of the transition path among the previously observed states and it is shown as following:

$$P(S_n \mid S_{n-1}, S_{n-2}, ..., S_1) = P(S_n \mid S_{n-1}) \tag{3.18}$$

One point which should be acknowledged here is that this methodology can also contribute to the developments in the SCADA alarm systems that are currently used. For instance, [196] mentions that on average in measurement time, 10 alarms are triggered in a wind farm and more than 70% of them need inspection and cannot be cleared remotely. Thus, setting the alarm threshold makes great difference in the number of alarms and their potential importance. Inadequate alarms can bring high risk of neglecting anomalies where too frequent alarms become perplexing and could increase maintenance cost inaccurately. In this methodology, a brief comment on the alarm systems is mentioned and the potential consequence and root of various alarm thresholds are stated. Although objective of this methodology is not on the alarm systems, it does provide some information and insight on the difficulties faced in this regard and more research would need to be carried out to obtain distinct outcomes.

[197] defines an abnormal level index to suggest a limit on the values of the parameters with AD perspective. In this framework, two similar anomaly index (AI) are proposed based on the developed Markov model. AI1 is considered to expose minor abnormal behavior, e.g. under-performance and AI2 is assumed to indicate major abnormal behavior, e.g. a failure. These two indexes correspond to two different levels of security in the operation of the component and such distinction is proposed to motivate prioritization in actions as it can be of assistance in decision making process. In order to calculate the values of indexes, they need to be mathematically formulated. To this purpose, as an example of a Markov model with four states, AI2 can be mathematically represented as:

$$P(x_3 = S_4, x_2 = S_1, x_1 = S_1) \tag{3.19}$$

Equation (3.19) denotes probability of being at *State1* at *time1*, staying at *State1* at *time2* and then transiting to *State4* at *time3*. This can be expanded to a general case, where the system has N states. For a time series, a state transition path like $(S_n^t, S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1)$ is defined as an anomaly symbol in this case study where k is a data point. For each S_i^k, the superscript k represents the time series and the subscript i indicates the state that the system resides in. The method to calculate this probability and the proof of it are as follows:

From *conditional probabilities* we have:

$$\begin{aligned}&P(S_n^t, S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) = \\ &P(S_n^t \mid S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) \times P(S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1)\end{aligned} \tag{3.20}$$

The path to reach one state by starting from a different state and passing through another state (multi-order MC) can be rewritten as:

$$\begin{aligned}&P(S_n^t, S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) = \\ &P(S_n^t \mid S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) \times \\ &P(S_{n-1}^{t-1} \mid S_{n-2}^{t-2}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) \times ... \times P(S_3^3 \mid S_2^2, S_1^1) \times P(S_2^2 \mid S_1^1) \times P(S_1^1)\end{aligned} \tag{3.21}$$

Since MC has *Memoryless* property, (3.18), then, in this case:

$$P(S_n^t \mid S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) = P(S_n^t \mid S_{n-1}^{t-1}) \tag{3.22}$$

Hence, (3.21) can be rewritten as:

$$\begin{aligned}&P(S_n^t, S_{n-1}^{t-1}, ..., S_i^k, ..., S_3^3, S_2^2, S_1^1) = \\ &P(S_n^t \mid S_{n-1}^{t-1}) \times P(S_{n-1}^{t-1} \mid S_{n-2}^{t-2}) \times ... \times P(S_3^3 \mid S_2^2) \times P(S_2^2 \mid S_1^1) \times P(S_1^1)\end{aligned} \tag{3.23}$$

In which $P(S_n^t|S_{n-1}^{t-1})$ equals to the transition probability between the two states and $P(S_1^1)$ can be calculated from the distribution of the states. Therefore, for AI2 it renders to:

$$P(x_3 = S_4, x_2 = S_1, x_1 = S_1) = P(S_4^3 \mid S_1^2) \times P(S_1^2 \mid S_1^1) \times P(S_1^1) \tag{3.24}$$

Similarly, mathematical representation of AI1 becomes:

$$P(x_2 = S_4, x_1 = S_3) = P(S_4^2 \mid S_3^1) \times P(S_3^1) \tag{3.25}$$

3.2.2. Case Study: Wind Turbine Markov Model

While the scientific gap in the literature has been identified in section 2.2 and Table 2.1, detailed analysis of one of the approaches to fill that gap is reviewed here. The focus is on improving the O&M field in component level for past and future operation by analyzing the collected data.

3.2.2.1. Introduction

A wind farm project is capital-intensive where up to 80% of total cost of the project covers constructions, WTs and connection to the electric network. The majority of the other 20% of the costs are due to O&M [198]. Therefore, keeping WTs to work at a relatively high efficiency and formulating optimal maintenance schedules are the main interests of shareholders, especially in an offshore wind farm (OWF). Reducing O&M costs results from two main parts, improvement in the performance, and improvement in the maintenance. Moreover, efficient maintenance strategies bring about high availability. In order to reach such efficient planning, one would primarily require an assessment of the current maintenance schemes and their influence on the performance. After that, the schemes can be improved by the knowledge exerted from analysis of the current status. These can be achieved by taking advantage of the large volumes of data stored through operation of WTs where integration of such information would be an important advancement.

Many efforts have been done to tackle the issue by developing a failure prediction model and assigning possible consequences to various failure modes; these indeed carry a large degree of uncertainty as well as numerous simplifications due to high complexity in modeling [199–202]. Furthermore, they require significant amount of thorough high quality historical data which currently are not yet available [203, 204].

[205–208] have performed studies to help the operators obtain an understanding of the performance and maintenance status in component level. However, they are parts of a larger goal in order to achieve an overall framework in this regard. The reliability centered asset management (RCAM) method proposes a ten-step approach to connect maintenance with cost and reliability through statistical measures of failure and maintenance strategies [166]. This method was proved to be an efficient solution to enhance reliability, availability, and profitability of wind power plants [209, 210]. When trying to apply RCAM to wind farms to reduce the O&M costs, especially offshore, new blocks could be added in order to account for recent technological advancements in the system. This work can be considered as a tool embedded in RCAM framework, which aims at evaluating WT current performance and maintenance from a system level perspective.

To develop the framework proposed in this case study, historical SCADA data, artificial intelligence techniques and stochastic theory are combined to make the approach theoretically well-grounded and applicable in practice. WT SCADA data are used as they carry comprehensive information for internal factors such as AP and gearbox bearing temperature, and external factors such as WS and AT. Due to such advantages, numerous studies have adopted SCADA data to investigate behavior and health condition of various components in WTs [211, 212]. In this work, after filtering out invalid data, several parameters such as WS, AT, GT, PA and RS are selected for normal behavior modeling [213].

As mentioned before, NN is a widely used technique to build nonlinear models [214, 215]. During recent years, deviations from the normal behavior are often used in failure and AD in WT reliability analysis. In this case study, NN is used to create an NBM of a WT and obtain the DS. [157] uses the deviation of AP to assess the performance of a WT. [153] uses the deviation of GT as a risk indicator which can have impacts on health conditions. In this case study, to capture the patterns in the deviations, an unsupervised learning technique, SOM, is employed for clustering the deviations data. SOM is a variant of artificial NNs designed for data clustering [194]. [216] constructs a SOM to classify the predicted WS.

In WT reliability analysis, Markov model is widely used due to its memoryless property. If it is assumed that the anomaly (or degradation) in the WT follows a discrete path which any state can be determined from its previous state, such consideration will provide opportunity to apply a Markov model. [217] models WT component reliability with discrete Markov Chains. Additionally, in this case study, two indexes are created to evaluate performance and maintenance efficiency of the WTs.

3.2.2.2. Preprocessing

The proposed PAME framework has been applied for 9 WTs using SCADA data. The data of WT1-WT4 and WT5-WT9 are for 2-year and 5-year periods, respectively. The configurations of the models are detailed in this section. Due to the way that the SCADA data are stored, often there is a need to preprocess data and eliminate spurious data points. In this case study, several filters have been applied. The details of the filters are explained in section 3.1.2.2. The WS parameter in all 9 WTs is normalized between [0, 25] (m/s) and AP in [0, 2000] (kW). Other parameters ranges and their corresponding normalization ranges and units are: RS [0, 20] (rpm), AT [0, 45] (°C), GT [0, 90] (°C) and PA [0, 35] (Degree).

3.2.2.3. Neural Networks

After several trials and tests, 50 neurons are considered for the hidden layer as this number reached a balance between accuracy and the computational time. The training function is scaled conjugate gradient backpropagation [215]. The training of each NN model takes about an hour for each WT. Moreover, SSE measure, (3.6), is chosen as performance function and the maximum number of epochs is set to 5000 iterations. In the end, the models are also checked to avoid overfitting issue in NNs. The accuracy of all of the 9 NNs is about 99% which means they can predict the normal behavior of WTs with the accuracy of 99%, Figure 3.12.

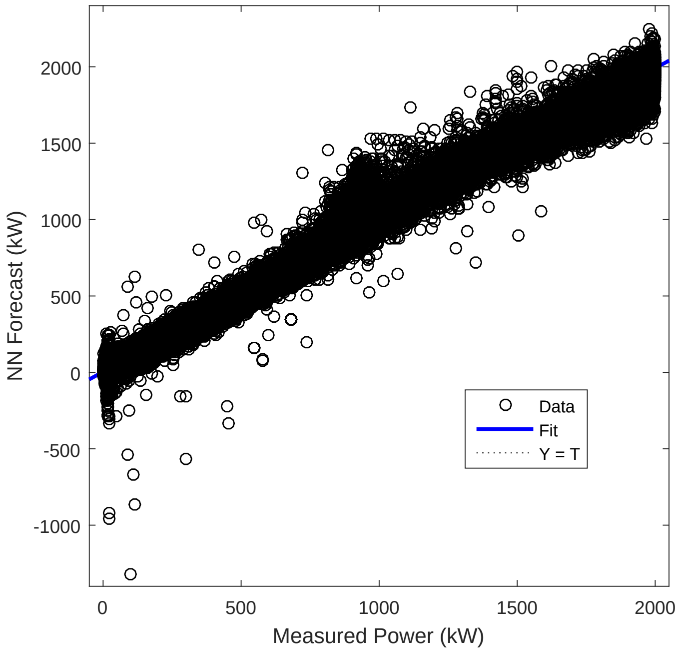


Figure 3.12: Performance of NN for WT1

3.2.2.4. Self-Organizing Maps

The SOM considered here has 24 neurons with the dimension of 4×6 which was trained with MSE, (3.4), as its performance function. As an example, Figure 3.13 illustrates SOM for WT1 with 24 neurons where their relations are presented through colors. Neurons with the same (or similar) spectrum color belong to the same cluster and the number of distinct colors can be chosen as the number of clusters. For instance, Cluster1: neuron 1, Cluster2: neurons 2, 5, Cluster3: neurons 9, 10 and Cluster4: neurons 3, 4, 6-8, 11-24. In another representation, Figure 3.14 displays weights of these 24 neurons. The deviation (DS) data are therefore divided into four main states. The corresponding states and their ranges are as follows:

- State1 : Deviation level low = [0,200]
- State2 : Deviation level medium = [200,300]
- State3 : Deviation level high = [300,500]
- State4 : Deviation level very high = [500,1000]

To make this classification more clear, physical meaning of each state should be verified. Based on [53], which it provides definitions to each operating state of components in the power system (e.g. in a power plant), four states are named by the deviation levels for each WT. Range of these states can be seen in Figure 3.15. In more details, Figure 3.16 plots the histogram of the deviation data. The total number of recorded deviations for WT1 is 91208 data points.

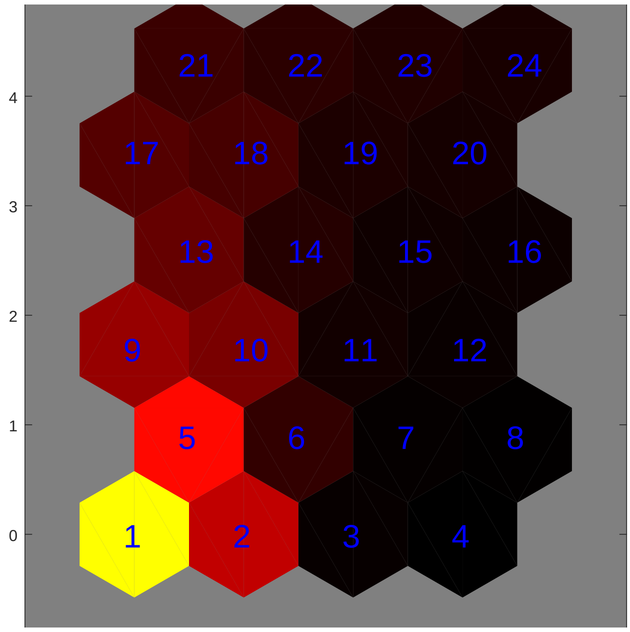


Figure 3.13: SOM for WT1 with neurons positions

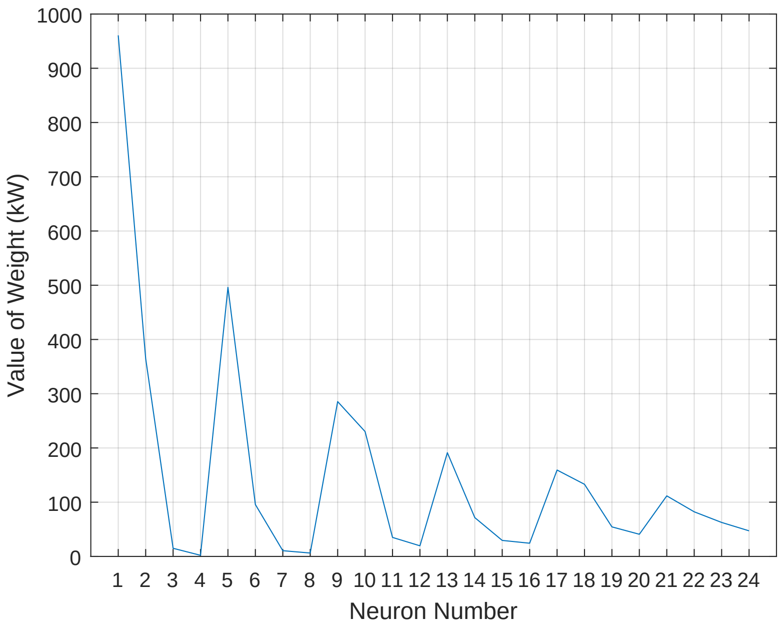


Figure 3.14: Weights of 24 neurons used in SOM for WT1

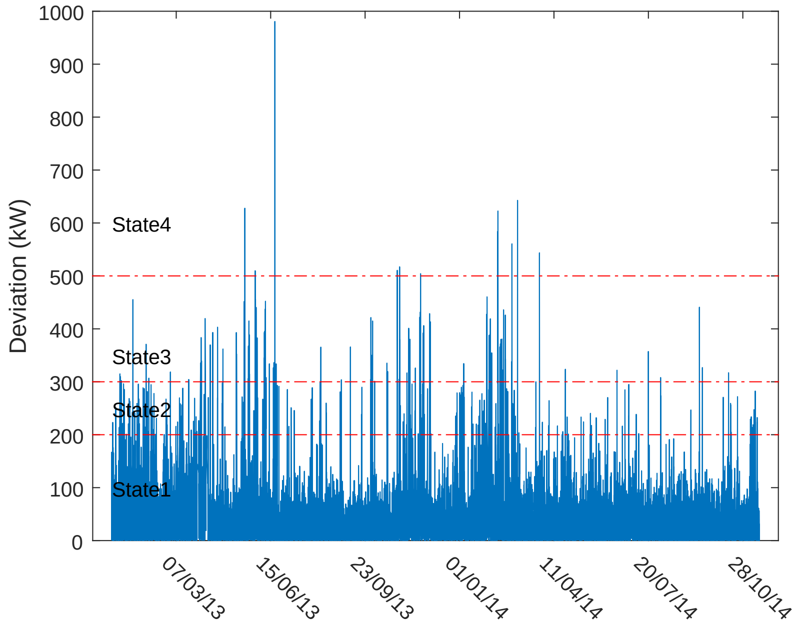


Figure 3.15: DS and states for WT1

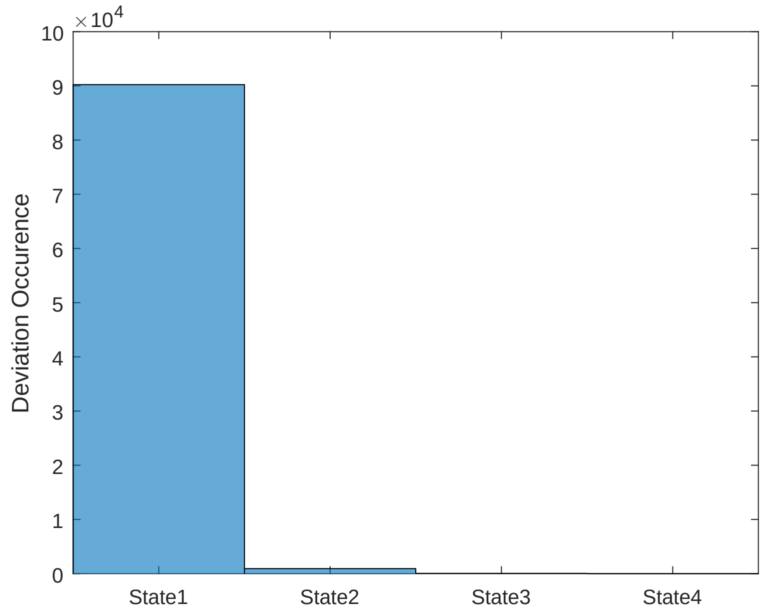


Figure 3.16: Histogram of DS for WT1

After states are carefully created for the WT, accuracy of the states can be verified through the classified data and investigating the input data parameters. For this purpose, several samples are drawn from each state and more detailed analysis is performed to find the probable physical causes. From the samples, it was observed that deviation points in *State4* can be accounted for a probable anomaly with highest probability than other states. For instance, none of the samples chosen from *State1* and *State2* showed any physical issue while very few from *State3* and almost all of *State4* showed an anomaly with meaningful physical root.

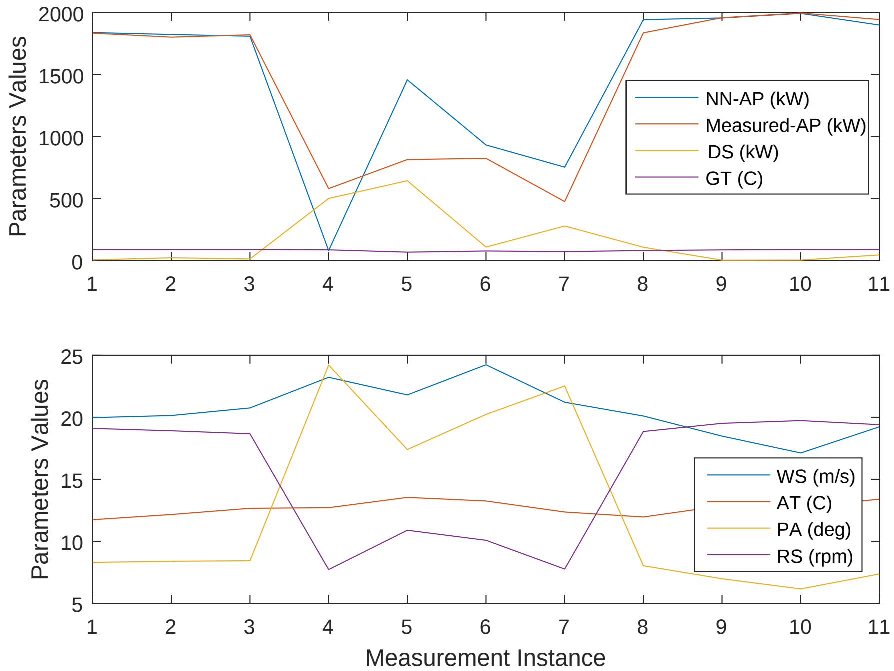


Figure 3.17: Sample deviation data points from State4 in WT1

Figure 3.17 exhibits sample data selected from *State4* for about two hours of operation (11 consecutive data points) where NN-AP is the NN forecast for AP and Measured-AP is the recorded AP through sensors. It can be seen that WS has almost a constant and high value where it reaches 24 (m/s) during this period while AP drops significantly. It is observed that changes in WS close to cut-out speed causes the PA to behave abnormally. A normal behavior from pitch system in this situation for this WT should follow small gradual changes so that maximum energy is extracted from wind and smooth power is produced. Indeed, one might assume such behavior was set to avoid damage to the WT; however, this behavior, pitch operating sensitively, was observed only a few times which refutes the assumption. This behavior has resulted in loss of production by about 60% at the occurring instance. Thus, the model and the DS represented an accurate performance towards an anomaly. After the NN models are created and their accuracy is verified for all WTs, it is time to extract knowledge about their mid-term performance as explained in the next step.

3.2.2.5. Markov Model

Each observed deviation is at first categorized in its respective deviation level and then labeled with its corresponding state (*State1*-*State4*) as defined in the previous section. Then, the transition rates among these new labeled states, or the frequency that the WT goes from one state to another state, is calculated as TPM of the WT where Table 3.5 displays this result for WT1. As it can be seen, each row sums to 1 which means the WT is at any of these finite 4 states at each observation time. TPM provides the probability of being in one state or transiting from one state to another at any moment.

Table 3.5: TPM calculated for WT1

	S1	S2	S3	S4
S1	0.99400	0.00497	0.00101	0.00002
S2	0.62901	0.27755	0.09066	0.00279
S3	0.33865	0.27092	0.36255	0.02789
S4	0.35714	0.14286	0.28571	0.21429

In another illustration, Figure 3.18 displays the Markov model for WT1 where the numbers represent transition probabilities among the defined states. Considering the result of previous part that most of *State4* observations accounted for an abnormality, the distribution of transfers to *State4* from other states can be seen in Figure 3.18 where transitions from *State3* have the highest number. This means that most of the observations in *State4* are developed from *State3*. Therefore, focusing the attention on the system whenever it reaches *State3* could be one way to avoid an upcoming abnormality. Similarly, eight different MC models were created for the other eight WTs.

In WT1, malfunctioning of pitch system was the major contributor to the WT entering *State4*. This requires an inspection on the pitch system. From the information extracted from the MC model, Figure 3.19 proposes that the issue with the pitch system may occur about every twenty days on average where it suggests a maintenance window for a scheduled maintenance action. It should be reminded that the amount of power lost due to the observed problem is at minimum 500 kW at each operating moment where considering a large scale wind farm, such behavior can not only cause lost profit, it could also create stability issues for the grid [218].

So far, a detailed study on 9 WTs is performed to analyze their performance and find out their probable thresholds towards anomalies. From the analysis of the results, two assumptions were made. Assumption1 considers that a minor abnormality in the behavior and performance of a WT occurs when it changes its state from *State3* to *State4* in one transition. Assumption2 presumes that a major abnormality happens whenever WT follows a distinct path. This path is defined as changing state from *State1* to *State4* by staying in *State1* for two consecutive time steps and then a direct transition to *State4*.

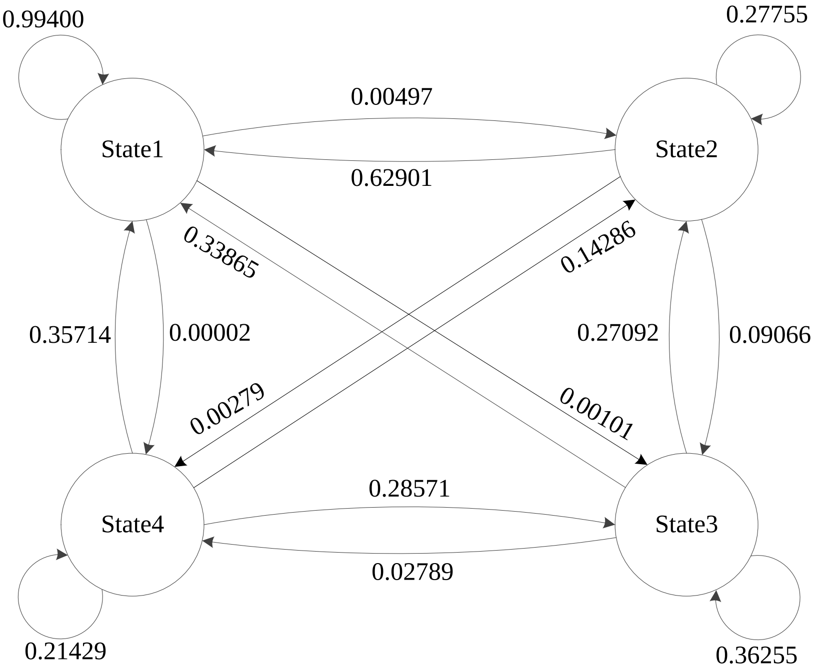


Figure 3.18: Markov Model for WT1 and transition probabilities

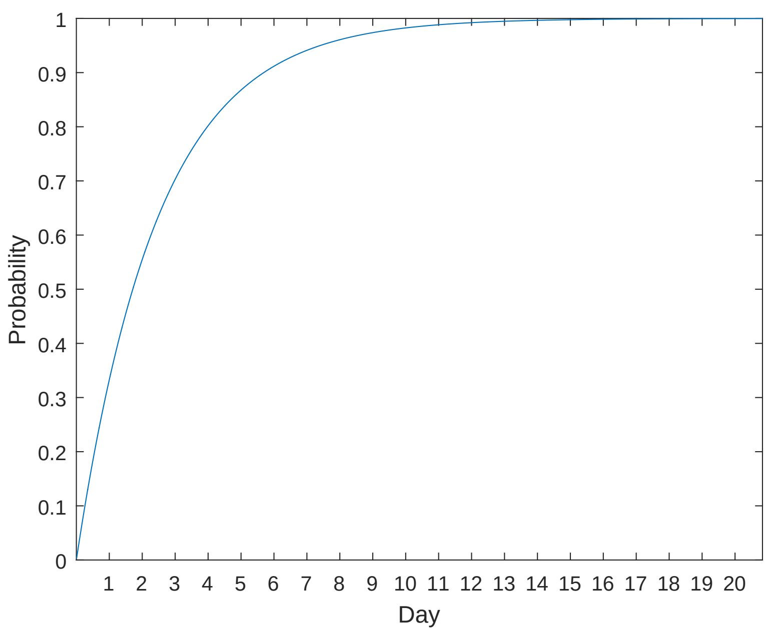


Figure 3.19: Transition to *State4* directly from *State1* and *State2* in WT1

These two indexes correspond to two different levels of security in the operation of WT and such distinction is proposed to motivate prioritization in actions as they can be of assistance in the decision making process. While Table 3.6 shows the ISP calculated for WT1 from the DS, Table 3.7 displays the computed anomaly indexes.

Table 3.6: ISP calculated for all WTs

	P(S_1^1)	P(S_2^1)	P(S_3^1)	P(S_4^1)
WT1	0.9892	0.0079	0.0028	0.00015
WT2	0.9510	0.0382	0.0079	0.00290
WT3	0.9494	0.0449	0.0052	0.00048
WT4	0.9870	0.0120	0.0008	0.00021
WT5	0.9900	0.0079	0.0019	0.00018
WT6	0.9699	0.0282	0.0018	0.00005
WT7	0.9557	0.0400	0.0037	0.00056
WT8	0.9943	0.0038	0.0015	0.00045
WT9	0.9860	0.0122	0.0014	0.00037

Table 3.7: Values of defined anomaly indexes

	AI1	AI2
State Transition	S3-S4	S1-S1-S4
WT1	0.00008	0.00002
WT2	0.00071	0.00042
WT3	0.00010	0.00006
WT4	0.00002	0.00007
WT5	0.00005	0.00006
WT6	0.00002	0.00001
WT7	0.00012	0.00016
WT8	0.00004	0.00006
WT9	0.00004	0.00010

3.2.2.6. Results

Table 3.7 presents the results of AI1 and AI2 for the 9 WTs in this case study. These numbers, although averaged, are dependent on the study period and it should be reminded that the period of SCADA data for WT1-WT4 are approximately for two years where for WT5-WT9 are about five years. Moreover, WT1-WT4 belong to a different wind farm than WT5-WT9 and they also use a different technology. These are some of the points that need to be considered if a comparison among WTs of different wind farms is to be carried out.

Comparing the WTs from AI2 perspective, it can be seen that among WT1-WT4, WT2 holds a significantly larger risk of a minor anomaly where between WT5-WT9, WT7 stands front. From AI1 point of view, the same two WTs stand out. A conclusion here then can be drawn where these two WTs, WT2 and WT7, are operating in a harsher condition than other WTs. Considering these numbers carry information regarding the maintenance actions as well. It can be concluded that these two WTs need additional inspections and probably a significant change in their current maintenance strategies. This is important information for an asset management team to take into account.

Another interpretation on status of WTs can be inferred by comparing the values of two indexes for each WT individually. For instance, if the value of AI1 is greater than the value of AI2, the WT is operating with higher risk of having a major anomaly, e.g. failure, than to endure a minor anomaly, e.g. under-performance. This knowledge expresses the necessity of a detailed analysis on any WT in such condition as such an event should be avoided. As an example, if it is assumed that the current PM strategy for WT7 is a planned maintenance at every six months, the results suggest that this period needs to be reduced and after several months, such study can be repeated. Another point that can be of assistance in this section would be the maintenance cost.

To advance the analysis in more detail, alarm and maintenance data of WT5-WT9 for the period of study are considered where no maintenance information for WT1-WT4 are available. Table IV displays this information for WT5-WT9. Until this moment, no information is available on how many of the actions corresponded to minor or major anomalies and downtimes which can be focus of a future work. Although WT7 has the highest number of alarms and PM actions, WT5 suffered the longest alarms and WT7 had longest PM actions. It can be observed that the highest number of alarms corresponds with the highest number of PM actions and longest PM times.

In order to present a view on efficiency of PM actions, production loss profit (PLP) has been defined for each WT based on the PM duration. Although not all maintenance actions require complete shutdown of the WT, for simplicity, it is assumed that the WT was offline during PM. Moreover, it should be mentioned that no information are provided about the number and duration of corrective maintenance actions for the study period. PLP (€) is calculated by multiplication of the average power produced by the WT (MW) during the study period and the total PM time (hr.) and an average electricity price of 21 (€/MWh) (from Nord Pool during 2015 [219]). Although WT5 has less number of PMs, its PLP is higher than WT9. Another observation from Table 3.7 is through comparing indexes of WT5 and WT9 and it can be exerted that WT9 needs more maintenance where PM numbers at Table 3.8 support this finding. Then, even though the number of PMs in WT9 is higher, the PLP is less. Thus, it could conclude that efficiency of PM in WT9 has been better than WT5.

By considering information in Tables 3.7 and 3.8, WT6 has the least number of alarms and PM actions; this is in accordance with the values of the indexes developed in this case study for this WT. Another observation is that higher values for the indexes correspond with higher number of alarm and maintenance actions and longer maintenance times.

Table 3.8: Several maintenance information on WT5-WT9

	# Alarms	Alarms Dur. (hr.)	PM	PM Dur. (hr.)	PLP (€)
WT5	450	1006	8	23.38	$23.38 \times 0.79 \times 21 = 388$
WT6	292	622	7	15.11	$15.11 \times 0.65 \times 21 = 206$
WT7	471	765	13	49.09	$49.09 \times 0.65 \times 21 = 670$
WT8	319	722	13	40.25	$40.25 \times 0.69 \times 21 = 583$
WT9	341	669	9	22.63	$22.63 \times 0.66 \times 21 = 314$

Thus, actions that reduce values of these indexes will result in lower maintenance actions and shorter maintenance times which is the objective of any asset management team.

3.2.2.7. Case Study Conclusion

Efficient performance and effective maintenance schedules of WTs are main aims of wind farm owners and operators. In this case study, MOA methodology is applied to several WTs through the developed framework. Parameters are selected from WT SCADA system, and NNs are used for normal behavior modeling and calculation of deviations. To capture the pattern in the DS, SOM is applied. The clustered outcomes are the basis for the time-discrete Markov model created for mid-term O&M assessment. Based on the transition matrix and anomaly events, two indexes are defined and mathematically formulated in order to provide insight in the decision making process. After applying this framework to 9 WTs, the indexes are calculated and compared, the results of which prove effectiveness of the developed framework in evaluating the current operating condition and maintenance strategies. As a result, recommendations are made on how the PM schemes could be improved in order to increase performance and availability while reducing costs.

3.2.3. MOA Methodology Conclusion

The MOA methodology proposes a system level framework for mid-term operation analysis of industrial components. It takes the advantage of large amount of operational data that are collected during the operation of an asset. PAME framework assists in evaluating the operation from performance and maintenance aspects. By extracting patterns from the monitored behavior, a Markov model is derived. Depending on the number of observed states, the number of states for the discrete Markov chain model can differ. While traditional strategies deal with O&M analysis of industrial assets by generally considering average values, this framework provides a great benchmark for comparing these strategies by integrating collected operational data.

3.3. MNA Methodology

To perform a maintenance evaluation study on a component, the MNA methodology is proposed. This methodology uses large amount of operational data, extracts the information from the data and combines the information with the maintenance data. The integration of these two data sets (maintenance and operation) assists the asset owner to evaluate the maintenance strategies of the assets and provides suggestions on improving the applied strategies. A summary of the steps is displayed in Figure 3.20. This study is published by the author in [39].

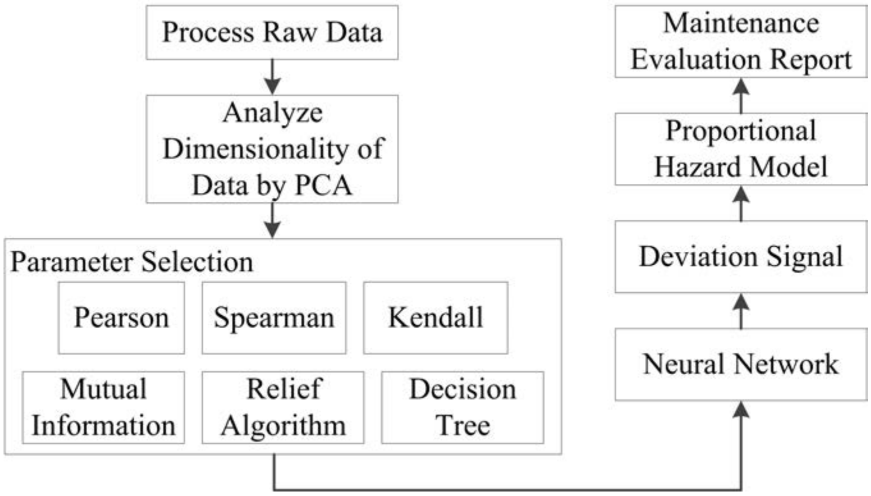


Figure 3.20: Flowchart of the maintenance evaluation framework

3.3.1. Stress Model

In the MNA methodology, two approaches are combined to provide an insight on the analysis of maintenance strategies. The first approach uses the concepts developed in the previous methodologies (RCA, MOA), and the other one develops a stress model where it depends on evolution of the loading on a component over a period of time. Thus, at first, the knowledge embedded in the operation data is extracted and an NBM is developed for the component. Next, this information is used in developing a stress model that addresses the overall loading of the component. Then, the model is combined with maintenance data through PHM technique to investigate the propagation of the stress along the time and operation in the component.

3.3.1.1. Preprocessing

After applying several filters for clearing the data (e.g. outliers, NaNs), the parameters are normalized, (3.1). The details of the filters are previously explained in section 3.1.2.2.

3.3.1.2. Principal Component Analysis

The details of PCA and how to use it are already explained in section 3.1.1.3.

3.3.1.3. Parameter Selection

After PCA showing that dimension of the original data can be reduced, sifting through a number of parameter selection techniques assists in ranking the parameters in order of importance with regard to the target parameter. The aim is to select these important parameters in constructing an NBM. There are various types of relations among the variables and different techniques can be used in order to evaluate each type of relation. Towards this goal, the techniques are opted in a way to assess and distinguish monotonicity, linearity, nonlinearity, known and unknown distribution types for relationships among variables. It should be noted that variables, predictors, features or attributes are interchangeably used in the literature in this area.

3.3.1.3.1. Pearson Correlation The PC obtained from (3.2) shows how two variables are linearly correlated. The details on PC are already explained in section 3.1.1.1.

3.3.1.3.2. Spearman Measure Spearman measure (SP) compares two variables on the basis of finding out whether these two are monotonically correlated, (3.26), [220].

$$\rho(x,y) = \frac{n^2(n-1) - 6\sum_{i=1}^{n}(x_i - y_i)^2}{n^2(n-1)} \tag{3.26}$$

3.3.1.3.3. Kendall Measure Kendall measure (KL) tries to find whether two variables have any dependencies, (3.27). While positive value of sign function mean a positive relationship, a negative sign indicates the opposite. Complete negative relationship (-1) and complete positive relationship (+1) are the range of Kendall τ rank correlation coefficient. Moreover, KL does not make any assumption on the distribution of the variables [221, 222].

$$\tau(x,y) = \frac{2\sum\sum_{i<j} sgn[(x_i - x_j)(y_i - y_j)]}{n(n-1)} \tag{3.27}$$

where *sgn* is the sign function.

3.3.1.3.4. Mutual Information Average amount of information in variable x which is transferred through variable y is expressed as mutual information (MI), (3.28), [223].

$$I(x,y) = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} P_{x,y}(i,j) log\left(\frac{P_{x,y}(i,j)}{P_x(i)P_y(j)}\right) \tag{3.28}$$

where P_x and P_y are marginal probability distribution functions of x and y, respectively, and $P_{x,y}$ is their corresponding joint probability distribution function.

In order to find the MI among the variables through the above equation, at first, P_x, P_y and $P_{x,y}$ should be calculated. To obtain these values, histogramming is selected as the density estimation technique. In histograms, the number of bins plays an important role. In order to find the optimum number of bins for the underlying histograms, Freedman-Diaconis rule is used through (3.29), [224].

$$\chi_x = \frac{Max(x) - Min(x)}{2[\zeta(75) - \zeta(25)]n^{-\frac{1}{3}}} \tag{3.29}$$

where χ is the optimum number of bins, ζ is the quantile for variable x and Max, Min represent maximum and minimum values of x, respectively.

After the optimum number of bins is calculated, marginal and joint probability distributions can be estimated. It should be noted that in computing MI, both x and y should have the same number of bins for their corresponding histograms.

3.3.1.3.5. Regressional ReliefF Algorithm Relief algorithm has been commonly used as feature (variable) selection in preprocessing step in modeling where the connection of the features are evaluated towards a target variable [225, 226]. The extended version of Relief algorithm, ReliefF, shows tolerance towards noise and is unbiased with the dependence among features in a multi-class problem [227]. When the target variable is numeric, the rank and relationship among features can be estimated through regressional ReliefF (RReliefF) algorithm [228].

RReliefF algorithm uses k-nearest neighbor (kNN) technique in the process of ranking the features. In this case study, kNN is set to perform an exhaustive search to find "k" nearest neighbors of the query data where the distance between the query data and all other data is measured through "city block" distance, (3.30). Next, these distances are used in assigning weight values to each feature to sort them in order of importance. Interested readers can refer to [229] for further information on kNN.

$$d_{p,q} = \sum_{j=1}^{m} \mid x_{p,j} - x_{q,j} \mid, \tag{3.30}$$

where $d_{p,g}$ is the distance between features p and q at any instance.

3.3.1.3.6. Decision Tree In machine learning, decision tree (DT) is considered as a technique under supervised learning category where DTs forecast a response value for a given set of input variables. The tree is built by creating split decisions resulting from an objective function in which the aim generally is to maximize the reduction in MSE measure between the response and target variable. In other words, at each node, the input variable that causes the largest decrease in MSE by splitting is the right candidate and will make the branch, (3.31). The prediction is performed by starting from the root node to the leaf node where the leaf node holds the value of predicted response. The stopping criteria for split at any node is based on the decrease in MSE [230].

$$MSE_{p,k} = \frac{1}{n}\sum_{i=1}^{n}(z_i - z'_k)^2 \quad \forall p, \tag{3.31}$$

where z_i is the predicted response at instance i, z'_k is the target variable at node k and p is the input variable.

After the tree is constructed, variable ranking is performed for the tree. The ranks are calculated for all best splits (final decisions) and all branch nodes. Each split causes some reduction in MSE. The importance of each variable is calculated as aggregate of this reduction, divided by the total number of branch nodes.

3.3.1.4. Neural Networks

Following the steps in section 3.3.1.3, a reduced number of variables are selected as the most important variables which show the highest impact on the target variable. These variables are then used in generating an NBM for the component through NN where the aim of the model is to predict the target variable. The details on NNs are provided in section 3.1.1.2.1.

3.3.1.5. Deviation Signal

In practice, output of the NN model, predicted target variable, may not always follow the actual production. For instance, whenever there is an anomaly, there can be a noticeable difference between the two values. Since the model uses averaged weights, and duration of anomalies is often few cycles, the NN can be trained so as to be able to predict normal operation efficiently. To this purpose, the DS variable is created as explained in section 3.1.1.2.2.

On the other hand, the developed DS is created for every measurement instance and carries information about the asset. The three areas of health condition, maintenance actions and degradation process have different characteristics. The health condition worsens with time and PM actions are supposed to slow down this rate. Regarding the degradation processes, while a natural degradation process cannot be avoided, an accelerated degradation process can be detected and treated. The accelerated degradation can be caused by internal and external factors and result in failure, if it remains unattended. Therefore, a new model should be able to address and adopt the real-time health condition variations, real-time and cumulative degradation processes and the impact of maintenance on the component. The advancement in this regard would be the ability of conveying impact of these connected areas and articulating their individual influence. Therefore, in order to account for instantaneous and long-term gradual condition degradation of the component through the DS, a mathematical formulation in forms of PHM is adopted.

3.3.1.6. Proportional Hazard Model

Mathematical form of PHM is of interest as it can incorporate both average and real-time changes in the condition of a component. General form of a PHM is shown in (3.32).

$$S(t,X_i) = S_0(t)C(X_i,\beta_i), \tag{3.32}$$

where $S(t,X_i)$ is the stress condition of the component at time t and for input variables of S_i; $S_0(t)$ is the baseline function and $C(X_i,\beta_i)$ is the covariate function. β_i values are also coefficients of each covariate i.

While the baseline is considered to carry the average gradual change in the condition of the component, the covariate function conveys the real-time changes in input variables. The baseline function is represented by a Weibull distribution, (3.33), and the covariate function has an Exponential form, (3.34).

$$S_0(t) = \frac{\gamma}{\eta}\left(\frac{t}{\eta}\right)^{(\gamma-1)} \tag{3.33}$$

$$C(X_i,\beta_i) = e^{\sum_i \beta_i X_i} \tag{3.34}$$

The developed stress condition model for the component requires estimations of parameters γ,η,β_i. These parameters are related to the health condition of the component. Towards this goal, the parameters of baseline and covariates function are calculated individually.

In order to account for overall health condition degradation, parameters of the baseline function can be estimated through a nonlinear regression technique, Levenberg-Marquardt nonlinear least squares algorithm [231]. The baseline is regressed against cumulative form of the developed DS. On the other hand, since the covariates function should exhibit real-time changes, it is regressed against real-time target variable (output performance) of the component. This way, whenever for instance one input variable is zero, the stress of the component is also zero (as there is no loading) and thus the condition should only degrade by its natural way. When the parameters of both baseline and covariates functions are estimated, the complete form of stress condition function of the component is constructed.

So far, two models have been developed: NN, and stress condition where the former represents real-time performance and the latter is the real-time stress condition of component. When combined, these two models can reveal valuable information about past and present performance and health condition, and provide recommendations on future O&M planning.

3.3.2. Case Study: Wind Turbine Stress Model

3.3.2.1. Introduction

While wind industry rapidly continues growing, the established fleets of wind farms enter a new phase in their life cycle. Maintenance actions play a key role in this phase in which WTs should be maintained at their maximum operative condition. Achieving this goal requires detailed and sound knowledge of maintenance schemes. Maintenance in this regard can be divided into two main categories: proactive and reactive. Proactive maintenance targets preventive and predictive actions which are performed regularly or based on condition. Reactive maintenance is carried out after failure events. Since the direct influences of different proactive maintenance strategies on sub-assemblies and wind farms are not yet clear, obtaining such information requires extensive research studies. Thus, there is a need to link the performance and condition of the WT with proactive maintenance strategies based on the considerate available datasets.

Reactive and time-based maintenance are the two common maintenance strategies which are being applied to WTs. Since critical components can cause significant cost at failure events (e.g. maintenance cost and profit loss), run-to-failure maintenance policy, in which the WT operator waits until a failure occurs and then carries out the maintenance, is of the least importance to wind farm operators. This shifts the attention towards proactive maintenance [232–234]. Indeed, advancements in condition monitoring and DA techniques can greatly improve those strategies [185, 190, 235].

Preventive and predictive maintenance will vary according to the application objective. For instance, if reliability and security have higher importance than economic aspect, one could increase the number of preventive actions. The reliability-centered maintenance (RCM) is the most common approach used in power systems which performs such tasks by identifying the most susceptible components to failure [236]. [237] applies RCM to two WTs and finds that frequency and quality of maintenance can greatly influence the health condition and performance of the WT. On the other hand, the most requested strategy is the one that balances reliability, security and economical aspects. For this aim, proactive maintenance scheduling becomes an optimization problem that should take real-time health condition of components into account. This resulted in RCAM framework [166] and general asset management model [238]. To achieve the goal, [239] applies maintenance optimization to an OWF in order to find the most suitable maintenance window by considering constraints such as weather; and [240] applies life cycle cost analysis to WTs and concludes that a CMS with 80% efficiency can increase the profit by 1.5%. This is an example which shows the potential of the large collected datasets in improving maintenance planning.

Although there are numerous studies on condition monitoring, failure and AD [241], and performance evaluation of WTs, little attention has been directed to verify the efficiency of the previously applied proactive maintenance plans. [159] points out that an efficient maintenance strategy should include operational conditions. [38] proposes the PAME framework which use MC to assess overall performance of the WT and provides recommendations on maintenance planning. Recent literature study reviews on condition monitoring of WTs and maintenance of OWFs highlight the great potential of an accurate proactive maintenance policy [242, 243]. [244] underlines the importance of data collection and emphasizes that the need for such studies on the premature component failures in WTs, with highest numbers in gearbox, is of great importance in the field. [245] compares one offshore and two onshore wind farms and concludes that there is need for improvement and integration of information extracted from SCADA system into proactive maintenance planning. [246] tries to improve the maintenance scheduling by studying a 13-year old wind farm based on lean techniques and modularization and concludes that although lean and modularization can improve performance and decrease maintenance time, the offshore wind industry is still in its immature phase and requires studies on more systematic maintenance planning. Indeed, since proactive maintenance plans are modified frequently, this adds to the complexity of the problem.

This case study proposes an approach to improve proactive maintenance planning by enabling evaluation and assessment of previously applied maintenance strategies through analysis of the large SCADA datasets in WTs. It is necessary here to mention that the goal of the proposed approach is to analyze the overall performance of the WT and aim for knowledge extraction towards the maintenance management area. To this end, at first step, the data are checked to see whether the high dimensional collected data can be represented in lower dimensions. For this goal, PCA is used. Next, in order to choose the most influential parameters, the relationships of all parameters against one target parameter are assessed. This has been performed by six statistical techniques, namely PC, SP and KL measures, MI, RReliefF and DT. After choosing the right number of parameters, NN approach is applied to build an NBM for the WT. Through this NBM, a DS is extracted which holds knowledge and information about the stress condition and health of the WT. Subsequently, from the developed DS, a stress model for the WT, in the form of a PHM, is constructed. Finally, the stress and NBMs are supplied with maintenance data to provide a review on the goodness of the previously applied maintenance strategies and propose suggestions for future maintenance planning.

3.3.2.2. Preprocessing

The data are collected from SCADA system of a WT over a period of 5 years in 10-minute frequencies and consist of 17 parameters. These parameters and their corresponding units are: WS [m/s], NT [°C], GT [°C], TOG [°C], AT [°C], hydraulic

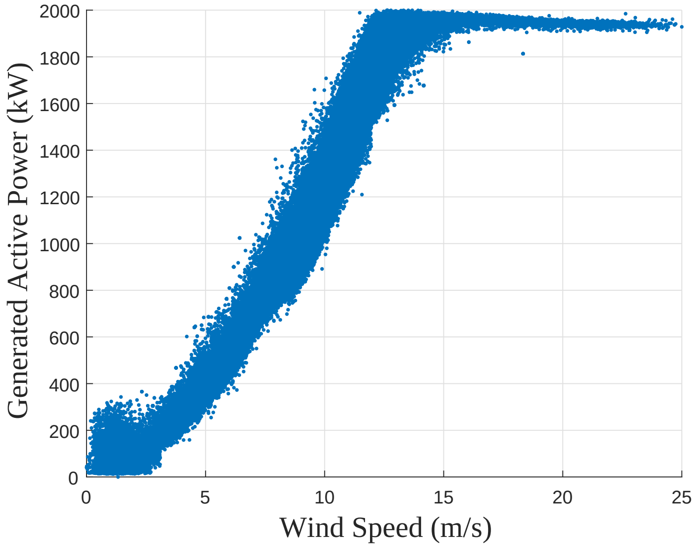


Figure 3.21: Power-curve of WT after preprocessing

group temperature (HGT) [°C], lower bearing temperature (BLAT) [°C], upper bearing temperature (BLOAT)) [°C], generator winding temperature (GWT) [°C], hydraulic group pressure (HGP) [bar], RS [rpm], voltage of converter (GCV) [volt], generator frequency (GF) [Hz], rotor active power (RAP) [kW], generated active power of WT (AP) [kW], reactive power (QP) [kvar] and PA [deg]. Please notice that no vibration data are available for the considered WT. The parameters have been correspondingly normalized through (3.1) in [0, 25], [0, 50], [0, 90], [0, 80], [0, 45], [0, 60], [0, 100], [0, 1500], [0, 140], [0, 210], [0, 20], [0, 750], [0, 50.5], [0, 60], [0, 2000], [0, 60] and [0, 35] ranges.

At first, the raw data are filtered through the power-curve to remove spurious data points. Then, NaN and faulty data from readings of sensors are substituted by the average of previous and next available values. This procedure reduces the number of data entries for the 17 considered parameters to a matrix of size $[262280 \times 17]$. Input raw data are filtered and the power-curve of the WT from the processed data is illustrated in Figure 3.21. The details on the filters are previously explained in section 3.1.2.2.

Figure 3.22 is displayed from the results of PCA. As it can be seen, PCA suggests that in order to reduce dimensionality of this dataset, the dataset can be approximately represented by the first seven principal components. These components account for more than 90% of the variations in the dataset. It can also be seen that principal components 3 to 7 contribute at similar levels. In addition, projection of original data onto the principal components as well as the contribution of each original variable is displayed in Figure 3.23 where variables of WS, RS and AP are magnified. It should be mentioned that due to the large amount of data and limitation of computational memory, Figure 3.23 only includes the first 1000 data points.

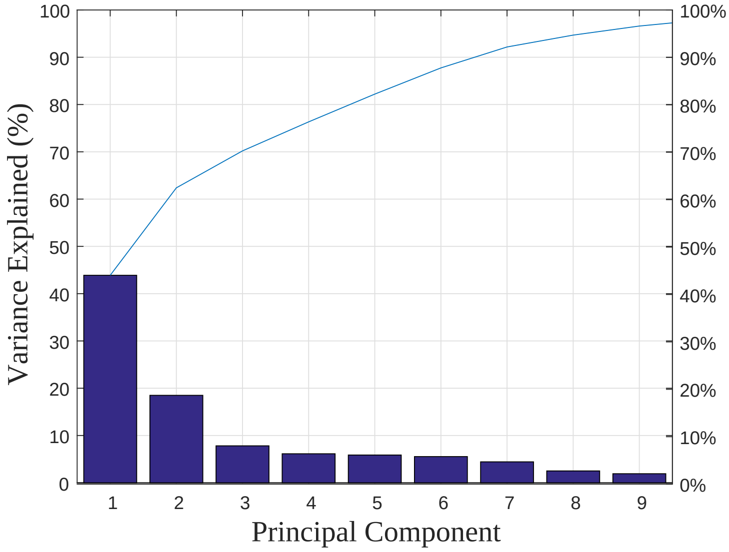


Figure 3.22: Outcome of PCA for dimensionality reduction

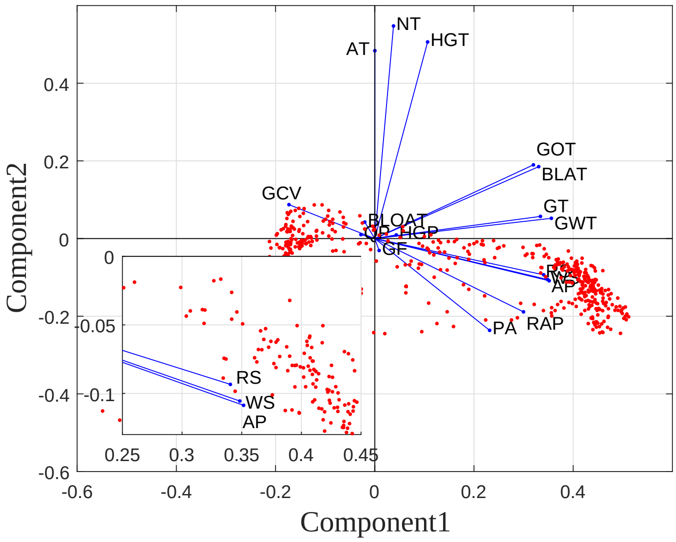


Figure 3.23: Projection of original data onto principal components 1 and 2

3.3.2.3. Parameter Selection

In section 3.3.1.3, six techniques are proposed and their results are displayed in Table 3.9. As it is shown, all techniques produced similar outcomes. WS and RS have ranked among the top four by all techniques. It should be reminded that the 17^{th} variable is the AP and since it is the target variable in normal behavior modeling, these results show the relation of other 16 variables towards the AP. Moreover, from Figure 3.23, three variables of AT, NT and HGT seem to show a similar pattern along the 2^{nd} principal component, hence, one of these three variables is also chosen as a representative. The final parameters for NN modeling are: WS, RS, GWT, PA and AT.

3.3.2.4. NN Modeling

In this case study, the NBM is built through a two-layer perceptron feed-forward neural network. The hidden layer has its activation function in form of Sigmoid function with Hyperbolic Tangent (3.9) and the output layer has its activation function in form of a linear function (3.10). The total number of data points used in creating the NN model is 262280. While training function of the NN model is scaled conjugate gradient backpropagation, the performance function is SSE. The hidden layer has 50 neurons. The maximum iterations limit is set to 5000. The input data in divided into three shares for training, validation and test. In this regard, 70% of the input data is assigned to the training set, 15% is assigned to the validation set and the remaining 15% is assigned to the testing set. Moreover, to avoid over-fitting issue with the NN model, performance of the training, validation and test datasets are compared and after multiple trials, the NN model with the best performance is selected.

Table 3.9: Results of parameter selection

Rank	PC	SP	KL	MI	RReliefF	DT
1	WS	RS	RS	RAP	RAP	RAP
2	RS	WS	WS	RS	RS	WS
3	GWT	GT	GT	WS	GF	RS
4	GT	GWT	GWT	PA	WS	PA
5	RAP	TOG	TOG	GT	QP	QP
6	BLAT	BLAT	BLAT	GWT	GCV	GT
7	TOG	RAP	RAP	TOG	GWT	AT
8	PA	QP	HGP	BLAT	HGP	GWT
9	HGP	PA	QP	NT	BLOAT	BLOAT
10	HGT	HGP	HGT	AT	PA	NT
11	GF	HGT	GF	GCV	BLAT	HGP
12	QP	GF	BLOAT	HGT	AT	TOG
13	BLOAT	NT	AT	QP	TOG	GF
14	NT	BLOAT	PA	BLOAT	HGT	BLAT
15	AT	AT	NT	GF	GT	GCV
16	GCV	GCV	GCV	HGP	NT	HGT

3.3.2.5. PHM Modeling

In order to estimate γ and η, at first, a cumulative version of the developed DS is created. Next, the baseline function is regressed towards the cumulative DS through the previously mentioned nonlinear regression technique. The β parameters in covariates

Table 3.10: Results of parameter estimation

Variable	Estimate
WS	0.0146
RS	0.0110
GT	-0.0048
PA	0.0098
AT	0.0015
η	734
γ	2

function should follow the real-time changes and show the condition of the system based on the loading and stress levels, thus, the nonlinear regression is performed by regressing the covariates function towards cumulative version of AP. Note that the selected parameters, WS, RS, GWT, PA and AT are used here. The outcomes of these two processes are summarized in Table 3.10. As it can be seen, AT has the smallest coefficient which confirms the findings in 3.3.1.3 and Table 3.9. In addition, the obtained p-values in both of the processes and all parameters are zero which show the significance of the parameters.

3.3.2.6. Results

The developed stress condition model for the WT is shown in (3.35) and plotted in Figure 3.24. As one observation, it can be seen that increase in the stress condition function on dates "24/12/07", "27/01/09" and "15/08/09" is rather significant compared with the complete period. Such observations in real-time can assist the operator in identifying stressful operation times which require further attention as they could result in failures.

$$S(AT, WS, RS, PA, GWT, t, \eta, \gamma) = \\ (\frac{2}{734})(\frac{t}{734})\ e^{0.0015AT}\ e^{0.0146WS} e^{0.0110RS}\ e^{0.0098PA}\ e^{-0.0048GWT} \tag{3.35}$$

For the WT considered in this case study, 34 maintenance actions ($M1 - M34$) are registered over the 5-year study period. Figure 3.25 shows the evolution of cumulative DS derived from NN model along time and by each maintenance action. Figure 3.26 shows the aggregated increase in stress condition based on maintenance actions through the developed model. The number of maintenance actions for years 2005, 2006, 2007, 2008 and 2009 correspondingly are 1 ($M1$), 9 ($M2 - M10$), 8 ($M11 - 18$), 11 ($M19 - M29$) and 5 ($M30 - M34$).

Although year 2008 has the highest number of maintenance actions (11), the DS and the stress inferred from the stress condition model do not show significant difference with other years. Therefore, one could assume that the maintenance strategy adopted for 2008 was not the most efficient strategy.

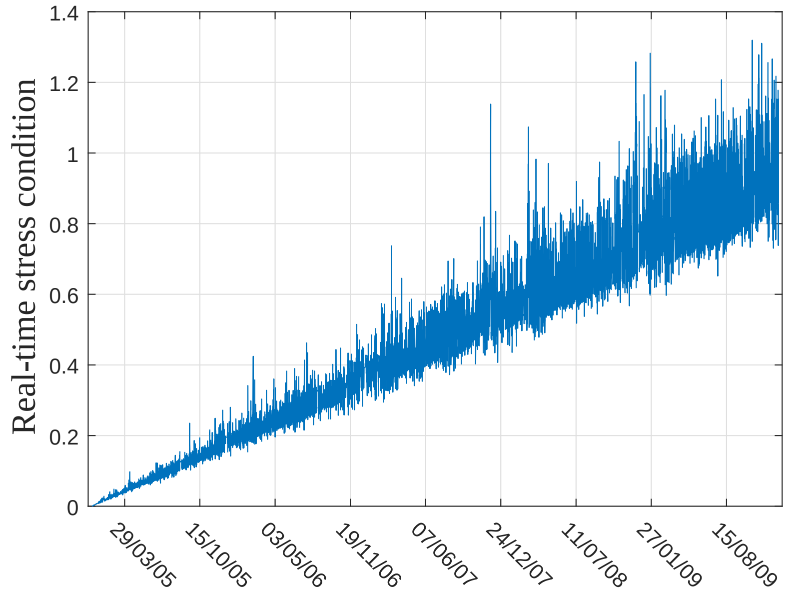


Figure 3.24: Stress condition evolution along the time

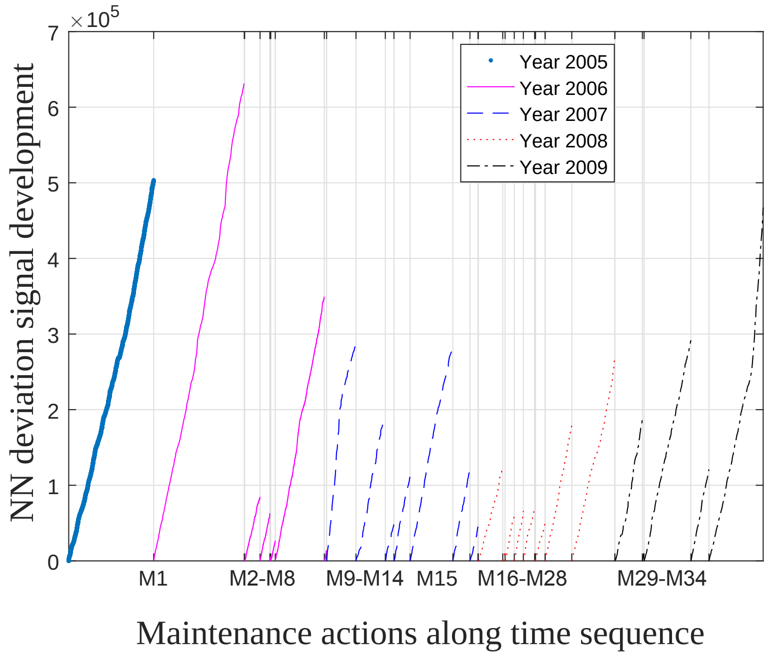


Figure 3.25: Maintenance along with DS evolution

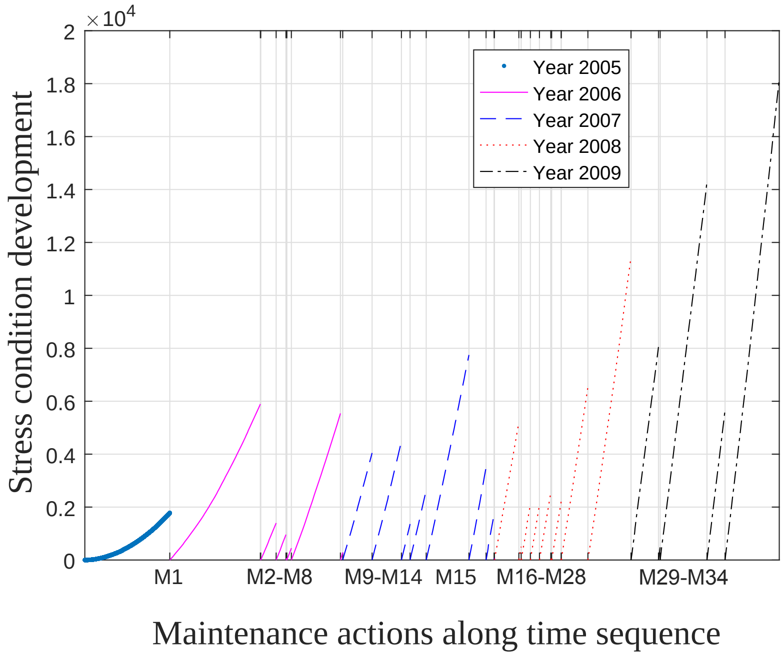


Figure 3.26: Maintenance along with stress condition evolution

Figures 3.24, 3.25 and 3.26 are in the same scale in horizontal axis so that the maintenance times can also be compared with real-time stress condition. As an example, the time dates mentioned previously which suffered higher stress values in Figure 3.24, also registered higher numbers of maintenance actions, Figures 3.25 and 3.26. Thus, one conclusion here is that out of ordinary behaviors, observed through the developed stress condition model, correspond with frequent maintenance actions. Therefore, using Figure 3.24 as a monitoring medium can be of great help for the WT operator. In addition, such a model is a parametric model which has advantage over complex models like NNs where the coefficients of the variables are not easily accessible.

Figures 3.25 and 3.26 together provide knowledge and information where one cannot simply extract from either of them individually. For instance, the increase in DS from $M1$ up until $M2$ in Figure 3.25 is more than increase in DS from $M8$ until $M9$; however, the time window is shorter. Solely from this figure, it is not possible to draw a conclusion about such observation. By considering the same period in Figure 3.26, it shows that even the loading and stress of the WT was higher. Therefore, it could be concluded that these two periods faced similar conditions. On the other hand, one could interpret that $M2$ and $M9$ were very low quality maintenance actions since their following maintenance occurrences ($M3$ and $M10$) happened quickly. Indeed, another reason for a short maintenance time window could be external factors which are not included in this case study as the required data are not available.

$M11$ and $M15$ have almost the same level of accumulated deviation when the maintenance was performed (Figure 3.25); however, the stress observed through stress condition model is less for $M11$. The maintenance time window for $M11$ is also shorter. Hence, one could conclude that the DS alone is not an accurate measure for degradation signal. However, a combination of these two models could provide a measure for real-time degradation modeling which is of great interest among researchers and operators.

One interesting observation is that whenever both of the models operate for a long time without any interruption by maintenance and increase more than the average of the year, the number and frequency of the following maintenance actions increase. Considering the cost of each action, one recommendation for the operator would be to balance the maintenance actions and update their maintenance policy in order to avoid such incidents. A dynamic maintenance threshold can be very beneficial in such decision making situations.

3.3.2.7. Case Study Conclusion

In this case study, MNA methodology is applied to WTs through the developed framework. In the parameter selection part of the study, six techniques of PC, SP and KL, MI, RReliefF algorithm and DT are applied in order to rank the input variables based on their importance. Next, an NBM is created based on NNs. Subsequently, a DS is developed from the results of the NN model in which it carries health condition information of the WT. Then, a stress condition model based on PHM is built. The approach is supplemented with maintenance data over a 5-year study period. The results demonstrate applicability of the approach and the challenges of applying this methodology to WTs.

3.3.3. MNA Methodology Conclusion

The MNA methodology proposes a hybrid framework based on NNs and PHM where the former assists in real-time performance evaluation and the latter helps in real-time stress condition assessment. A combination of the outcomes of the two models offer the possibility to evaluate the asset management policies adopted by the asset operator and offers recommendations to improve the maintenance strategies.

3.4. PRA Methodology

This methodology proposes a model to evaluate performance of a component through its sub-assemblies by developing a parametric form. The parametric form overcomes some of the disadvantages of non-parametric forms (e.g. scalability) and provides better insight through its variables. The model is responsible for measuring real-time and overall performance of a component and if the developed signal continues to deviate from the expected normal performance, it issues warning and demands particular attention. Hence, the practice of the model can also be classified as preventive acts required to maintain a satisfactory performance. This study is published by the author in [44].

3.4.1. Health Condition Model

This approach proposes to create a parametric health condition monitoring model (as an NBM) which observes the real-time and overall health condition of a component through its sub-assemblies and raises an alert flag whenever the component condition drifts away from the expected normal condition. To this aim, at first, a NN model is constructed for each considered feature. Next, a signal which is sensitive to changes in health condition of each feature is extracted as the DS. Then, this signal is used in creating a parametric model which has a PHM-based form for each of the features. These created models with PHM forms are combined based on the performance of the NN and PHM-based models to develop the final additive parametric health condition model of the component. The final model is used in real-time and overall health condition monitoring of the component which provides assistance to the operator and asset management team in order to improve the O&M scheduling.

There are three main motivations for the proposed health condition model:

- requirement of a parametric model,
- need for an easily scalable and adaptable model, and
- a model capable of demonstrating the connection between a component and its sub-assemblies.

As for the first and second motivations, a parametric model has easy access to the coefficients of the parameters where in non-parametric models, it is very perplexing [247]. Therefore, the capability of such model would be its adaptability to be used for other components without needing to collect a significant amount of data from various sub-assemblies over a long period of time [242]. For instance, if the number of components in a system is large (assuming all components are similar), the complexity of the work increases as every component requires a model. The proposed parametric model in this case study can be used in reducing the complexity of the works that the operator and asset management team perform. This is due to the reason that a model constructed for one component could be applied to other similar components in the system by simply modifying some of the parameters in the parametric model. This is one of the main drawbacks of complex NN models as the parameters are not easily accessible and do not hold clear physical meanings [248]. As for the third motivation, the health condition model developed in this case study combines a component and system level monitoring schemes where each parameter would relate to a specific feature and the main model would be able to detect anomalies in both sub-assemblies and the overall system. Therefore, the model developed in this case study also provides a link between component and system levels. In the end, the model also has the potential to be used in degradation and remaining useful life estimation.

3.4.1.1. NN Modeling

In this methodology, an NBM is created for each of the sub-assemblies in the asset. NNs have shown their advantages in being able to construct NBMs for complex assets due to their structure and flexibility. Details on NNs, their structure and parameters are previously explained in section 3.1.1.2.1.

3.4.1.2. Deviation Signal

At the end of each NN modeling step for the selection sub-assemblies, the variable deviation (DS) is calculated as explained in section 3.1.1.2.2, (3.11). If the data used in the NN modeling do not carry information about any significant anomaly during the operation of the asset, the accumulated DS can be assumed to represent the change in normal health condition along the monitored time. This cumulative DS is calculated as sum of all single deviation points during the observation period.

3.4.1.3. Deviation Signal Representation through PHM

The common conception of the PHMs is the study of failure. However, the developed health condition model in this case study solely has the mathematical form of the PHMs. In this study, the baseline shows pattern of the change in overall health condition (mean cumulative deviation) along the time and is extracted from the developed DS as one of the main ideas and contributions of this study. The covariates are assumed to deliver the impact of various monitored variables in real-time. In this study, the following PHM form has been adopted:

$$HC(t, X_i) = H_0(t)C(X_i, \beta_i) \tag{3.36}$$

where t is time, X_i is the value of covariate i, β_i is coefficient of covariate i, $H_0(t)$ is baseline health condition function (BHF), $C(X_i, \beta_i)$ is covariates function (CF) and $HC(t, X_i)$ is considered as real-time health condition function (HC) for features.

3.4.1.3.1. Baseline Health Condition Function By assuming the natural health condition degradation (aging) as an accumulative function over time, a component will suffer an increasing value of stress due to overwork, incipient failures and natural aging. Moreover, the maintenance can impact the condition of a component. Thus, it is assumed that the BHF represents the long-term pattern of the behavior of a feature. This means that the BHF carries hidden information (unknown patterns in behavior of a feature) about the average performance along the life-time. Regardless of values of covariates, the BHF is dependent on the time (and the accumulated impacts of various working conditions). The BHF can take different forms and in this case study, it is assigned to have the form of Weibull distribution as following:

$$H_0(t) = \frac{\gamma}{\eta}\left(\frac{t}{\eta}\right)^{(\gamma-1)} \tag{3.37}$$

3.4.1.3.2. Covariates Function Covariates vary continuously and directly or indirectly impact performance of the component and system. As an example, when value of one covariate is high, the component can be producing at its nominal output. This situation causes the component to endure higher levels of stress (than the situations when the value of the covariate is low or zero). Indeed, high stress value does not necessarily mean an anomaly, however, it could expedite and pave the path towards facing an anomaly. In this case study, the CF resides in an Exponential form as following:

$$C(X_i, \beta_i) = e^{\sum_i \beta_i X_i} \tag{3.38}$$

After the HC has been defined, in order to estimate the parameters (γ, η, β_i), information on health condition should be provided. As a health condition related indicator, the cumulative form of the developed DS (calculated from the NNs) is utilized. Same definition of the DS has been used in other research studies with similar objectives [153, 249].

To find the parameters of the HC, a nonlinear regression technique is used where the HC is regressed with the accumulative DS. The applied technique uses Levenberg-Marquardt nonlinear least squares algorithm [231] and through an iterative process, provides estimates for the parameters. Additional to estimations of the parameters, the p-values are provided for each parameter. The p-values show the influence and significance of the estimated parameters on the regressed variables (i.e. accumulative DS, or accumulative health condition degradation). Moreover, accuracy of the HCs is represented by root mean squared error (RMSE) as another outcome of the nonlinear regression analysis:

$$RMSE = \sqrt{\frac{1}{k}\sum_{l=1}^{k}(y_l - y'_l)^2} \tag{3.39}$$

where y_l and y'_l are respectively known and calculated values in the nonlinear regression technique over k considered data points.

3.4.1.4. Additive Health Condition Function

After the HC models are created for each feature, they are evaluated individually. An additive health condition function (HCWT) is proposed that represents a global view of the health condition of the component and takes the following form:

$$HCWT = \sum_{i} \alpha_i HC_i \tag{3.40}$$

where α_i is weight parameter of HC_i. In order to generalize the approach, two constraints are considered for these weights:

$$0 \leq \alpha_i \leq 1 \tag{3.41}$$
$$\sum_{i} \alpha_i = 1 \tag{3.42}$$

Estimation of weights (α_i) is performed by considering accuracy of the NN and HC models. To consider the weights through accuracy of the models, four steps are taken.

1. At the first step, the accuracy of the NN models are assessed as:

$$\Lambda_i = \frac{(o_i - \overline{o_i})(o'_i - \overline{o'_i})}{(n-1)\Psi(o_i - \overline{o_i})\Psi(o_i - \overline{o'_i})} \tag{3.43}$$
$$r_{NN_i} = 1 - \Lambda_i \tag{3.44}$$

   where Ψ is the standard deviation, Λ is the accuracy of the NN approach and r is the error.

2. In the second step, r values are calculated for the HC models as:

$$r_{HC_i} = RMSE_{HC_i} \tag{3.45}$$

3. The third step aggregates r values that are calculated for both the NN and HC models for each feature:

$$r_i = r_{NN_i} + r_{HC_i} \tag{3.46}$$

4. And in the last step, the weights are scaled as:

$$\alpha_i = \frac{r_i}{\sum_k^N r_k} \tag{3.47}$$

where N is the number of covariates (features).

3.4.1.5. Dynamic Threshold

In this regard, a dynamic threshold (Φ) is developed where the health condition values above the Φ correspond with the deviated behavior or health condition from the expected normal condition. It should be noted that a single value above the dynamic threshold does not necessarily mean that there is a failure or a major anomaly. Single random deviations above the dynamic threshold can have two main reasons: transient turbulence or the model error. Moreover, various failure modes can have different forms. Therefore, a general failure or major anomaly form can be considered as when the output is above the dynamic threshold for a particular amount of time (depending on the failure/anomaly mode) and the deviation does not revert back to normal [153, 250, 251]. The Φ is developed through the same technique mentioned in 3.4.1.3.2, the nonlinear regression.

To derive the form of the Φ function, two main considerations are taken into account:

1. The threshold should follow the average pattern that the additive model exhibits during the normal operation
2. The threshold should change with time.

Therefore, at first, a function should be defined where it can take the average form of the defined additive model (average form is considered different from a PHM form). Thus, based on experiences of the authors [252] and several regression trials of the HCWT (the additive model obtained in previous step), a two-part Exponential function (Γ) shows an acceptable fitting performance:

$$\Gamma(t) = d_1 e^{d_2 t} + d_3 e^{d_4 t} \tag{3.48}$$

where d_j values are estimated by regressing Γ to the additive model.

Afterwards, the difference between the additive model and Γ function is calculated as ($|HCWT(t) - \Gamma(t)|$). Then, the confidence interval, Θ, is defined as the value of 99% confidence interval obtained for the $|HCWT(t) - \Gamma(t)|$ signal. To enable the threshold to change along time while maintaining its form and including possibility of selecting flexible Θ values (e.g. for future studies, operational security based reasons, different sensitivity criteria), a new term is added to the Γ function. Lastly, the Φ is defined as the following function:

$$\Phi(t) = d_1 e^{d_2 t} + d_3 e^{d_4 t} + \frac{\Theta t}{N_T} \tag{3.49}$$

where N_T is the length of the study period in measurement frequency (number of measurements).

3.4.2. Case Study: Wind Turbine Additive Model

3.4.2.1. Introduction

There are currently several challenges in WT condition monitoring where some of them are discussed here. The first challenge is that due to various techniques in condition monitoring and separation of models for sub-assemblies (one model for gearbox, one model for bearing etc.), the wind industry receive many (false) alarms which make the supervision of the operation very complex. The second challenge is that currently there is one model for each WT and in large wind farms, handling all the models becomes very difficult. Therefore, scalability of CMSs in large wind farms is a hurdle. The third challenge is that to set limits for alarms, data for each WT should be monitored and stored for several months. This makes the process costly and for the beginning months, there is no standard for the parameters of the model. Thus, there is a need for significant improvement in the current CMSs [242].

A modern WT is a complex system. It shows dynamic nonlinear behaviors due to various sub-assemblies, e.g. pitch system, and is subject to random turbulences (e.g. wind) [253]. These nonlinearities make modeling of such systems extremely difficult. Clear and distinct representation of a WT can simplify its management which cannot be easily achieved through complex nonparametric models when they are difficult to obtain or sufficient measurable knowledge do not exist for their formulation. Hence, parametric models on health condition monitoring are of significant importance for reasons such as easy implementation, few input data, low complexity, easier interpretation of results, clear relationship among covariates and easy clarification on physical meanings of changes [190, 254].

Currently, there is no system level parametric model for WTs which considers the behavior of component level sub-assemblies and addresses real-time health condition monitoring, AD and overall performance evaluation. [255] develops a parametric model on condition monitoring of a sub-assembly of a WT (generator temperature) where the impacts of time, degradation, failure prediction and AD are proposed as future studies. The developed parametric model uses regression technique in order to find a polynomial form for predicting generator temperature. The input parameters of the model are generator power and another variable which is created by combining generator cooling temperature, NT and AT. [256] presents a parametric model for control of a single sub-assembly, and by taking advantage of its parametric form, the model is used to optimize the total energy production [257]. The future work is mentioned to be further development of the model and make it applicable to a real WT with varying atmospheric conditions.

Several research studies that use parametric models in this field mainly attempt to represent power-curve of a WT [258–260], where even a ninth degree polynomial was considered [261]. However, the majority of the parametric models developed for WTs in literature focus on degradation, reliability and failure detection. In this regard, PHMs have been used through failure data [262–265] or simulation [266]. PHMs have a general form with two main parts, baseline and covariates and they have been numerously applied in failure analysis [267, 268].

Although most demanded, more research should be done on parametric models regarding health condition monitoring that are able to accurately simulate the condition of a WT while maintaining the balance between simplicity and meaningfulness [180, 269, 270]. This has driven researchers and industry towards complex, time-consuming and hardly interpretable models in machine learning such as NN, gaussian processes and gaussian mixture models [29, 271, 272]. [273–276] propose generalized models for WTs through NNs and fuzzy metrics in order to perform AD. The procedure shows significant dependence on high quality and large collection of datasets besides the difficulties in defining an accurate threshold technique. Moreover, as one of the drawbacks, they concluded performance of a model built for one WT and tested on other WTs varies greatly depending on the data used in training of the model.

Apart from the uncertainties in the input data, there are a handful of parameters used in constructing a NN which any modification in those could result in an inaccurate model. Some of the issues related to NN based models which largely affect the accuracy of the NNs are as follows: number of (hidden) layers, number of neurons, number of input parameters, training cycles, initial values, optimization algorithms, overfitting, stopping criteria, measures of goodness of fit, need for high quality and large datasets with and without anomaly and the difficulty in finding physical meaning and interpretations of results due to being non-parametric. There is yet no straight-forward procedure in finding the right configuration and combination of these parameters in constructing a NN. Moreover, after some time or even a significant event (e.g. a failure), a new dataset would be required to create a new NN [185]. Meanwhile, several research studies compare the parametric and non-parametric models which only focus on modeling the power-curve [261, 277, 278].

Besides the previously mentioned concerns with non-parametric models, the need for parametric models of WT shows its importance when a study about optimization or performance and maintenance evaluation is demanded [38, 179, 239, 279]. For instance, when using a non-parametric model, optimization of performance of a WT (from power generation point of view) would require evolutionary algorithms where they add to the uncertainty and complexity of the work (let alone not having an optimal solution) [280]. A parametric model which is able to show health condition, degradation or reliability of the WT with regard to its various sub-assemblies would answer significant questions on performance monitoring and planning objectives [240]. Inspired by the discussed issues, this study tries to lay the path and formulate a parametric model for WTs which represents the health condition of WTs in real-time and includes input parameters such as NT, AP and WS.

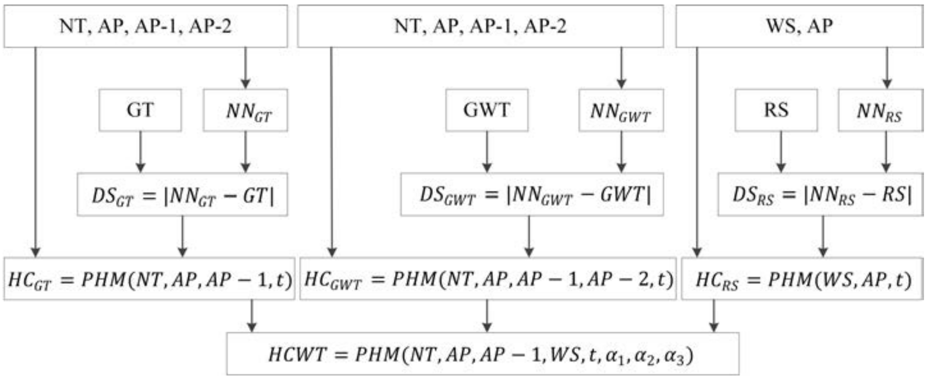


Figure 3.27: Summary of steps in developing the HCWT model

3.4.2.2. Preprocessing

The dataset used in the proposed model is from a WT that suffered neither any failure nor major anomaly over a period of one year. To prepare this data for the analysis, spurious data points should be filtered out. For this purpose, several filters are applied where the details are previously explained in section 3.1.2.2. The AP has been scaled in [0,2000] (kW), WS in [0,25] (m/s), GT in [0,90] (°C), NT in [0,45] (°C), GWT in [0,150] (°C) and RS in [0,35] (rpm). The inputs are also checked in order to verify that the observed values follow the distribution of the typical values for each variable. This prevents the model to obtain an output using unknown input values which partially assists in reducing the error of the model.

3.4.2.3. Normal Behavior Evaluation

The procedure applied in building the proposed model is represented in Figure 3.27 where the notations are explained in detail through the following sections. The procedure involves modeling three features, RS, GT and GWT which are selected based on modeling experience of WTs, and on practice as they account for normally long downtimes in WTs [158, 281].

3.4.2.4. NN Models for Features

This step creates the NN models in order to simulate the normal behavior of GT, GWT and RS. A multilayer perceptron feed-forward with the structure of one hidden layer with 50 neurons and one output layer is the configuration of the NN for the three NN models. The inputs of NN_{GT} and NN_{GWT} are the NT, AP, AP-1 and AP-2 with the corresponding target variables of GT and GWT. The AP-1 and AP-2 are active power measured at the two previous consecutive time stamps. The reason to include these two covariates is to investigate the impact of some past behavior in the operation of the current moment.

Inputs of the NN_{RS} are the WS and AP with RS as the target variable. About one year of data (37000 measurement points) that are averaged over 10-minute intervals were divided randomly by 70%, 15% and 15% for training, test and validation processes, respectively. The "random" sampling technique is chosen as it makes each sampled data equally probable. That is in every 100 samples, 70 are chosen for training, 15 for testing and 15 for validation. Indeed, this is the outcome of the many tests performed by the authors on the data in this case.

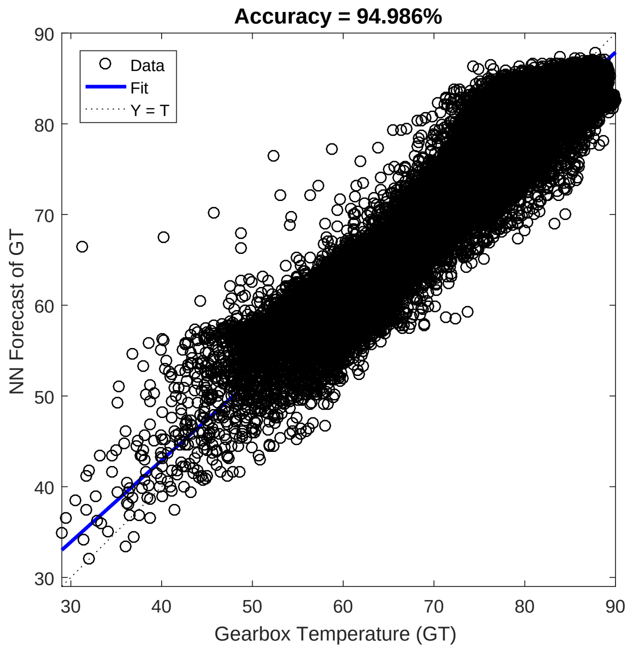


Figure 3.28: NN regression overall accuracy for NN_{GT}

The overall accuracy of the NN_{GT}, NN_{GWT} and NN_{RS} correspondingly are 94.98%, 96.15% and 99.83% where Table 3.11 shows the r values for the constructed NNs. These values are obtained after several trials. The trials are carried out in order to avoid some of the obstacles in dealing with the NNs, such as the over-fitting issue. Therefore, after each test, the model is accepted only if the differences between the performance in the "training", "test" and "validation" datasets are less than 0.1%. Hence, only one graph which represents the overall set is displayed, Figure 3.28, as the three graphs (training, testing and validation) are the same with 0.1% accuracy. Otherwise, the models should be updated until they pass this constraint. Once again, this experience is obtained by performing many tests and checking the outcomes of the model. After passing this constraint, the error values of the three datasets are averaged to give the overall error values for each NN model. Moreover, if some sub-assembly is replaced or there has been a significant modification in the component, a new NN model should be trained.

3.4.2.5. Features Demonstration through PHM

Table 3.12 summarizes the inputs and outcomes of the nonlinear regression analysis for all PHM-based models. Once again note that the nonlinear regression of each PHM-based model is performed towards its corresponding accumulated DS that was calculated in the previous step. It should be mentioned here that the errors on the model at this step could be the results of erroneous operation in the previous step. For instance, if the performance of the NN models in the previous step are not satisfactory (e.g. due to lack of data, over-fitting), it will directly affect the process in this step. As a result, one parameter that is in fact not significant may come out as an important parameter which will thoroughly influence the model.

In Table 3.12, it can be observed that the *p*-value for the coefficient of AP-2 in the HC_{GT} is larger than 0.05, meaning that this parameter can be neglected in constructing the HC_{GT}. Similarly, AP-2 and AP-1 are disregarded in the HC_{GWT}. One finding here thus becomes that in normal operation of GT and GWT, AP-2 does not show any significant influence and hence can be neglected in creating NN models in future studies.

Table 3.11: r values calculated for NNs and HCs of features

$r_{NN_{GT}}$	$r_{NN_{GWT}}$	$r_{NN_{RS}}$	$r_{HC_{GT}}$	$r_{HC_{GWT}}$	$r_{HC_{RS}}$
0.05016	0.03852	0.00171	0.0281	0.0291	0.0305

Table 3.12: Coefficients of HC_{GT}, HC_{GWT} and HC_{RS} models

	HC_{GT}		HC_{GWT}		HC_{RS}	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
AP-2	-1.4353e-06	0.6997	-7.4907e-08	0.9759	-	-
AP-1	6.9809e-06	0.0077	-1.5448e-06	0.3785	-	-
AP	-5.9272e-06	0.0236	-4.3616e-06	0.0129	-1.4981e-05	0
NT	-0.008126	0	-0.0009	0	-	-
WS	-	-	-	-	0.0029	0
η	136.88	0	117.95	0	261.65	0
γ	1.7892	0	1.7289	0	1.9965	0

Several interesting observations can be made from Figure 3.29 which shows the developed HC models. First, there are moments that all three features are affected simultaneously, either by an increase or a decrease, and they do not necessarily share the same type of behavior at those moments. For instance, while two of the features increase (HC_{GT} and HC_{RS}), the other one (HC_{GWT}) decreases. Another noteworthy finding through multiple data investigations is that the HC_{RS} tends to show larger changes at the end of a stressful period (high loading) while the HC_{GT} and HC_{GWT} display smaller impacts. At the beginning of such a change, the HC_{GT} and HC_{GWT} show some variations and their behaviors alter. These various behaviors with different magnitudes can be observed in

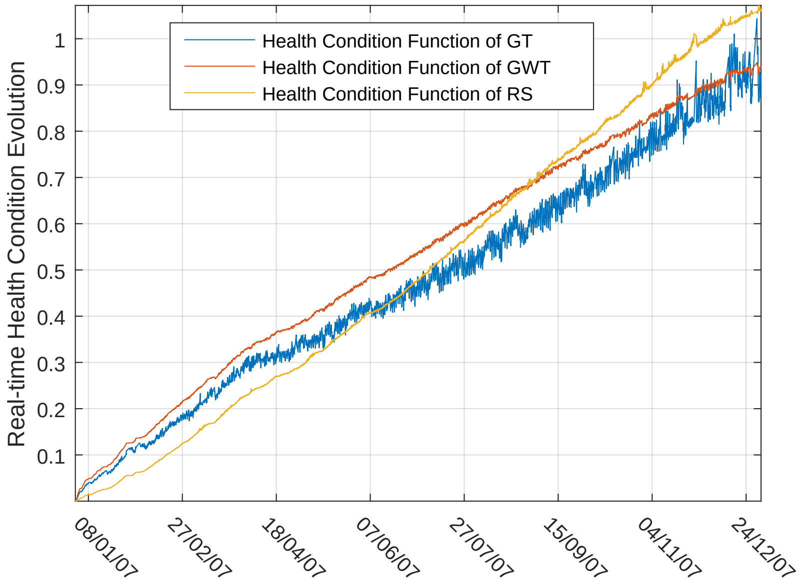


Figure 3.29: Developed health condition models for GT, GWT and RS

Figure 3.29. As a conclusion, this could be interpreted as if a model that is solely based on RS may not be able to accurately magnify a developing stressful situation. It can also be seen that even though at some moments all three are affected by some change in condition, the degrees of their reactions are not the same.

Another point inferred from the graph shows that there are various times that only one HC model is influenced while others maintain their condition. This simply means that only one of the features is suffering from an increased stress in the operation. Indeed, in order to analyze such a behavior, one would need to take into account other factors (e.g. external factors).

It can also be seen that the HC_{GT} and HC_{GWT} start off on a very similar path until "18/04/07" where the level of the health condition of the HC_{GT} changed its development slope. This could be assumed as an impact of a maintenance action on gearbox. Indeed, further investigation would be required to verify this assumption.

An observation assumed to be related to maintenance from Figure 3.29 is when the HC_{RS} crosses the HC_{GWT}. The HC_{RS} started lower than the HC_{GWT} and after about nine months, it reached the HC_{GWT} level. One could assume that degradation rate of the rotor has increased and more attention would be needed to focus on the rotor. Since these three HC models show both common and distinct behaviors at moments, it is then preferable to obtain one model where the behaviors are transferred. An additive model is one solution where the weights and parameters can be calculated and thus are known.

3.4.2.6. Overall Wind Turbine Model

In order to find appropriate values for α_i where the utmost knowledge (on the health condition) from the features and their corresponding individual HC models is transferred, the accuracy of both NN and HC models were considered. Table 3.11 displays the r measure values calculated through (3.44)-(3.47) and Table 3.13 shows the estimated weights of the additive model.

Table 3.13: Weight values α_i of additive model

α_1	α_2	α_3
0.44	0.38	0.18

The resulting form of the developed HCWT model for the WT over the study period of one year is shown below:

$$\begin{aligned}
&HCWT(NT, AP, AP-1, WS, t, \alpha_1, \alpha_2, \alpha_3) = \\
&HC_{GT} + HC_{GWT} + HC_{RS} = \\
&1.2 \times 10^{-4}\, t^{0.8}\, e^{7\times 10^{-6} AP_{-1}}\, e^{-6\times 10^{-6} AP}\, e^{-0.008 NT} + \\
&1.7 \times 10^{-4}\, t^{0.7}\, e^{-4\times 10^{-6} AP}\, e^{-0.0009 NT} + \\
&5.4 \times 10^{-6}\, t\, e^{-2\times 10^{-5} AP}\, e^{0.003 WS}
\end{aligned} \tag{3.50}$$

3.4.2.7. Applying Dynamic Threshold

The developed HCWT model so far may not be suitable for being applied in operation directly. One of the reasons is that the accuracy of the NN and HC models used in the process may not be 100%. Moreover, the HCWT is trying to model a very complex and nonlinear system. This can cause the model to act inaccurately in normal/faulty conditions. Thus, the errors of the model should be managed. In order to address these erroneous operations, a margin can be considered on the output of the HCWT model so that it filters, as much as possible, the mistakes of the model in detecting the significant changes in the behavior during the operation of the WT.

Through the procedure mentioned in 3.4.1.5, the calculated d_j values are: $d_1 = 0.4$, $d_2 = 3 \times 10^{-5}$, $d_3 = -0.3$ and $d_4 = -9 \times 10^{-5}$. After calculating the Θ, the Φ function is shown as:

$$\Phi(t) = 0.4\, e^{3\times 10^{-5} t} - 0.3\, e^{-9\times 10^{-5} t} + \frac{0.0245\, t}{37000} \tag{3.51}$$

where 0.0245 is the value of the Θ and N_T is 37000.

It should be reminded that the developed dynamic threshold here is specific to this WT and simply applying it to other WTs could produce different results. Moreover, although applying this threshold assists in filtering abnormal patterns, it is not a generic approach and there is a probability that it may not filter abnormal behaviors.

3.4.2.8. Results and Discussion

Figure 3.30 displays the developed WT health condition model and the corresponding Φ. Figure 3.31 shows the cumulative health condition evolution after applying the Φ. Several confidence interval degrees were tested for the Θ and the 99% confidence interval showed the best results in sense that it accurately corresponds with the actual changes in the input data.

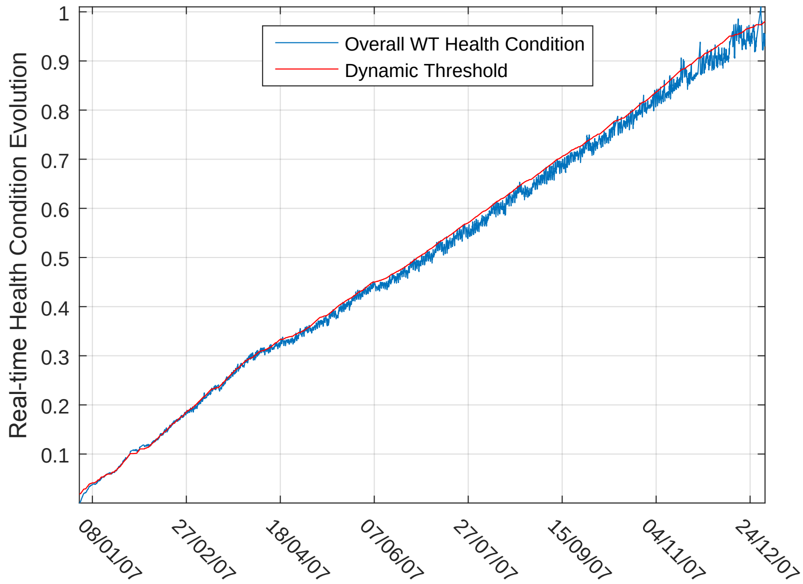


Figure 3.30: Overall WT health condition model and Φ function

It should be reminded that the case study using the proposed HCWT model is prepared with input data without any major anomaly. As an example, there is a sudden jump between "15/09/07" and "04/11/07" as seen in Figure 3.31. Assessing this behavior from the input data shows that in a period of time with low WS, there is a sudden increase in the WS for one time stamp and is followed by a low WS period. This sudden jump increases stress of the WT (due to loading) and the model clearly exposes this situation. As another example, when the time is approaching "24/12/07", there is a rather sharp elevation in the developed cumulative health condition signal. Making an enquiry about this change through the input data reveals that in a low WS period, for two consecutive time stamps, WS increases from 6 to 8 (m/s). This change resulted in power increase in the output of the WT, from 50 to 280 (kW). After these two moments pass, the WS starts to decrease gradually and the AP reduces slowly as well. Several other verifications were also made and all resulted in accurate detection of such changes. In case major anomaly data are also available, this study can be further progressed to find the thresholds for failures and failure modes by updating 3.4.2.7.

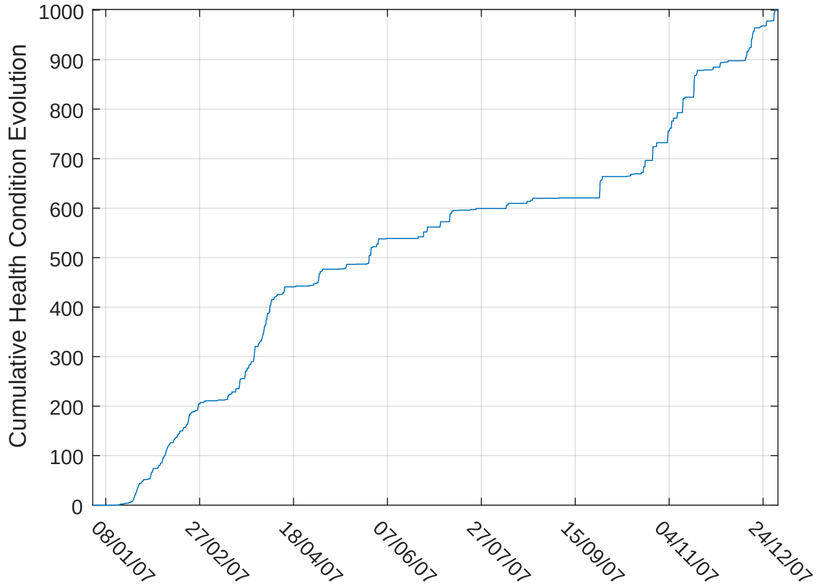


Figure 3.31: Cumulative health condition evolution developed after applying Φ

Due to the lack of access to actual failure or major anomaly data, five artificial major anomaly incidents (unknown anomaly mode) have been created in order to demonstrate the ability and potential benefit of the proposed model. The difference in the behavior of these five incidents with normal operation is that these five events last for at least one hour while others fluctuate below and above the dynamic threshold (e.g. turbulence). Events correspondingly lasted for 300, 400, 350, 60 and 200 minutes. To create these five events, it is assumed that the AP and NT suddenly decrease significantly, however, the WT continues its operation. For instance, the AP reduces from above 1500 to 50 (kW) and NT falls down from above 40 to 10 (°C.)

These five events are considered to demonstrate sensitivity of the proposed model under two perspectives: a) a sudden change in the health condition of the WT, and b) the gradual impact of multiple incidents of such events on the health condition of the WT along the time. It should also be mentioned that different failure or anomaly modes may exhibit different behaviors and thus, the dynamic threshold proposed in this case study can be further analyzed to become inclusive of various failure and anomaly modes. For example, if an anomaly mode displays a reduction behavior in the developed model, the dynamic threshold can be advanced in order to include a lower bound as well. Such propositions can be progressed in future studies.

Figure 3.32 displays the sampled artificial major anomaly events where the fifth major anomaly is magnified. As it can be seen, the developed parametric health condition model distinguishes such anomalies. This shows the effectiveness of the model and the threshold in the condition monitoring field. The parametric form of the model simplifies the condition monitoring assessments which is an important achievement.

In order to analyze the accumulated impact of the five major anomaly events, Figure 3.33 illustrates the moments when they occurred and their influence on the cumulative

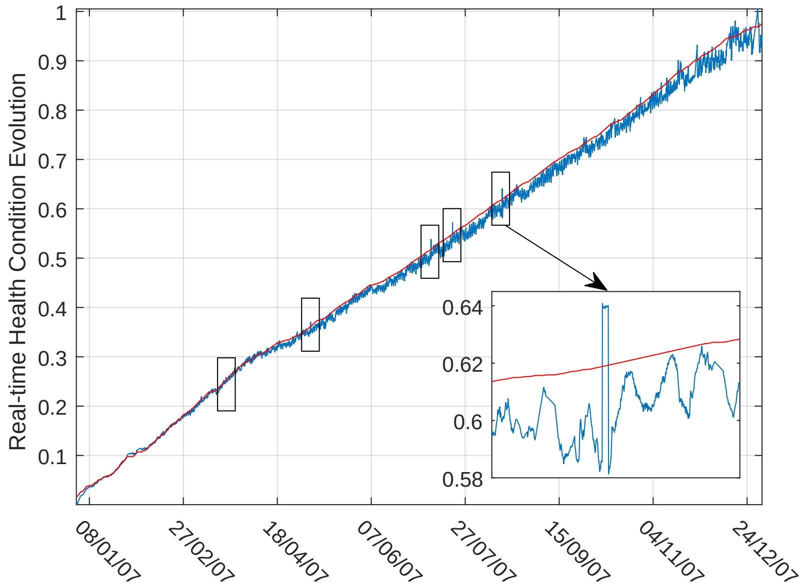


Figure 3.32: WT health condition in presence of major anomaly events

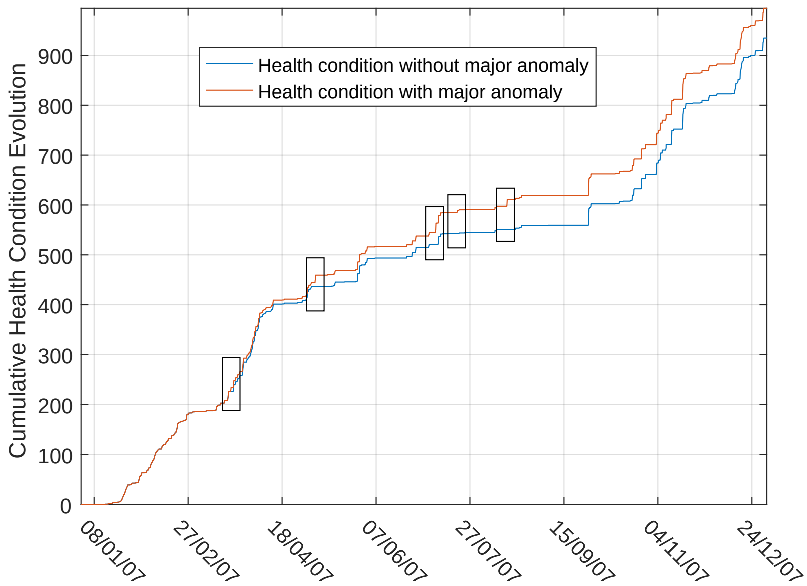


Figure 3.33: Cumulative health condition in presence of major anomaly events

health condition signal. The overall effect of these five major anomaly events on the health condition of the WT at the end of the study period is 60 units. The individual effect of each event on the health condition respectively is 8, 15, 19, 4 and 14 units. The maximum value that the cumulative health condition has reached over the study period for this WT without any major anomaly is 935 units while with the supplemented artificial major anomalies it reached 995 units. This outcome demonstrates capability of the proposed parametric health condition model in evaluating impacts of some major anomalies on the WT. These results can be used by the operator and the asset management team to improve performance of the WT and administer maintenance schedules.

Moreover, one can set a threshold limit for both individual events and the yearly overall evolution of the health condition so that whenever the threshold is reached, an operative action is carried out. For instance, the operator can consider a limit for the effects of individual events. This means that whenever the cumulative health condition exhibits an increase in the values larger than a specific value (e.g. 15), the WT should be observed carefully as a failure may occur. In this case, this results that the third major anomaly event should be particularly monitored in real-time. In another example, the asset management team can set a limit for the overall yearly cumulative health condition so that whenever the threshold is reached, an overhaul could be carried out. For the understudy WT, this number can be 950 where surpassing it endangers the WT.

In order to further demonstrate the scalability and adaptability features of the proposed approach, two health condition models have been developed for two new WTs (WT_2, WT_3) which are located at the same wind farm as the previous WT (WT_1). The three health condition models for WT_1, WT_2 and WT_3 can be seen in (3.50), (3.52) and (3.53), respectively. By observing these three equations, a set of average parameters can be extracted and a generalized WT health condition model can be developed for the wind farm. This is one of the significant advantages and novelties of the proposed approach which overcomes some of the previously mentioned challenges in the field [242, 247, 254, 276]. Such an analysis can be expanded to all wind farms which could solve the obstacle in the lack of data in the beginning months of operation of the wind farms. It should be mentioned that the procedure applied to all three WTs is the same. For instance, the structure of the NNs for all the three WTs (i.e. the number of layers, the number of neurons in each layer, the types of activation functions and the performance measure etc.) are the same.

Figure 3.34 displays the health condition of the three WTs for about seven months since the data for the entire study period is not available for the WT_3. As it can be seen, the health condition of the WT_3 is developing faster than the other two WTs. This observation is of great importance for the operator and asset management team and it suggests that the WT_3 requires an additional attention, for instance, there can be a thorough inspection or change of maintenance strategy. On the other hand, the WT_1 and WT_2 exhibit a parallel behavior in the development of their health condition and since WT_2 follows a higher level, WT_2 may require maintenance before WT_1. Figure 3.34 shows that the WT_1 has the best health condition among these three WTs in the wind farm.

$$
\begin{aligned}
&HCWT(NT, AP, AP-1, WS, t, \alpha_1, \alpha_2, \alpha_3) = \\
&HC_{GT} + HC_{GWT} + HC_{RS} = \\
&36 \times 10^{-4}\, t^{0.5}\, e^{-2\times10^{-5}AP_{-1}}\, e^{0.006NT} + \\
&0.4 \times 10^{-4}\, t^{0.8}\, e^{6\times10^{-6}AP_{-1}}\, e^{-3\times10^{-6}AP}\, e^{-0.002NT} + \\
&2.6 \times 10^{-6}\, t\, e^{-1\times10^{-5}AP}\, e^{0.002WS}
\end{aligned}
\tag{3.52}
$$

$$
\begin{aligned}
&HCWT(NT, AP, AP-1, WS, t, \alpha_1, \alpha_2, \alpha_3) = \\
&HC_{GT} + HC_{GWT} + HC_{RS} = \\
&75 \times 10^{-6}\, t^{0.6}\, e^{-6\times10^{-6}AP_{-1}}\, e^{0.0007NT} + \\
&6.5 \times 10^{-6}\, t\, e^{-1\times10^{-5}AP}\, e^{-0.003NT} + \\
&8.4 \times 10^{-4}\, t^{0.6}\, e^{-3\times10^{-5}AP}\, e^{-0.007WS}
\end{aligned}
\tag{3.53}
$$

To summarize and discuss capabilities of the proposed parametric model, the developed parametric health condition model can be of interest from different aspects where it addresses some of the current challenges reviewed and listed in a recent literature study [242]. It should be reminded that a method of health condition modeling is proposed in this case study and a very important strength of the developed model is its parametric form. In addition, all the analyses are performed through monitoring the normal behavior where it has the potential to compensate for lack of failure data in the field.

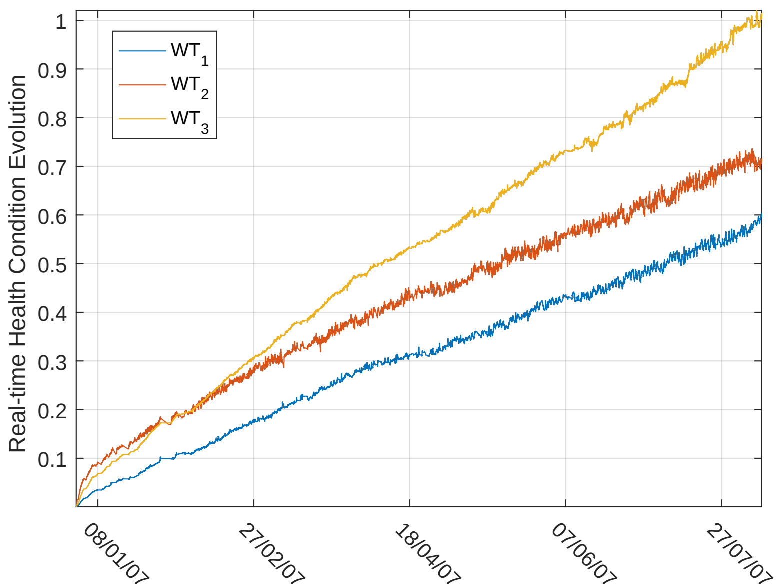


Figure 3.34: Cumulative health condition evolution of three WTs

3.4.2.9. Case Study Conclusion

This case study applied the PRA methodology in WTs. The health condition model considers that a WT can be partially represented through three main features: RS, GT and GWT. By utilizing NNs, an NBM is built and a DS is extracted as the difference between the simulated behavior and actual measurement. This signal is then applied through a parametric model, in mathematical form of PHM, to create a health condition function for each considered feature. Next, an additive model is proposed to represent the WT as a system which can be used for condition monitoring and AD. Afterwards, a dynamic threshold is defined for the health condition model and tested where it detects condition change in the behavior of the WT. The model is verified through analyzing the actual and artificial data.

3.4.3. PRA Methodology Conclusion

The PRA methodology presents steps in order to develop a parametric health condition model for industrial components. The health condition model considers a number of sub-assemblies in the component to represent the overall performance and condition of the component. The outcome of the model provides real-time and overall health condition monitoring which directly assists in AD. The model has simple formulation with small number of parameters. The ongoing work aims at finding similar patterns in parameters of the models for components in the same (and different) systems. The developed health condition model opens a window to several other areas (e.g. maintenance optimization) where a parametric model is of significant advantage.

3.5. Chapter Conclusion

In section 2.2, several studies in the literature were reviewed where the focus was on AD and performance assessment in an industrial component. The results of the comparison concluded that there is lack of knowledge in these areas and more research should be carried out. After thorough review of the details, the author found four main deficiencies withing the discovered gap. Therefore, four frameworks were develop to address the gap from four different, yet connected, perspectives. These four methodologies are shown in Figure 3.1. The basis of all these four methodologies is data-driven modeling which has recently emerged due to the availability of large amounts of operational data for industrial components.

The RCA methodology, in section 3.1, proposes a framework to obtain the root of an anomaly in an industrial component by applying several statistical techniques. The MOA methodology, in section 3.2, proposes a framework for the study of mid-term operation of an industrial component. The MNA methodology, in section 3.3, proposes a framework to evaluate the maintenance strategies of an industrial component by developing a maintenance benchmark model. Finally, the PRA methodology, in section 3.4, proposes a framework to assess the performance of an industrial component with respect to its sub-assembly parts through a parametric model. Each of these frameworks address one of the perspectives in the discovered gap in the literature. All these models together deliver the first objective of this dissertation, as mentioned in section 1.2.

4 Impact of Condition Monitoring in Operation

This chapter presents a study that is performed to demonstrate the advantages that integration of real-time health condition information from industrial components can bring about in operation of a system. The information are collected from the models developed in the previous chapter. Based on the models, new indicators are defined. Then, the indicators are implemented in the operation where the impact of the collected health condition information from components on the system can be investigated. This study is published by the author in [107].

4.1. MMRR Approach

4.1.1. Introduction

Chapter 3 presented four frameworks for analysis of operation and maintenance (O&M) in component level where the data are collected from the operation of industrial components thanks to the increase in the number of installation of sensors on the components. The developed models demonstrated several advantages to improve the operation of the component through the modeling of the data.

While the models in chapter 3 focused on one industrial component without being linked to the system, this chapter tries to implement those component models into the operation of a system. Embedding these component level models in the operation of a system enables the system operators to monitor the operation of the system while accounting for component level changes obtained from health condition data collected from components. Performing the assessment of influence of component level information in system level analysis is the second objective of this dissertation. For this purpose, maintenance management and risk reduction (MMRR) approach is proposed. This chapter is considered in continuation of the mentioned studies with the objective of integrating the extracted knowledge from the historical and current information and applying it in maintenance management.

4.1.2. Condition Indicator

Condition indicator (CI) can be estimated based on different algorithms and sources of information as demonstrated in chapter 3 [235, 282–284]. For instance, [38, 39, 44] consider collected operation data from several sensors in wind turbine (WT)s. They extract knowledge and information such as under-performance of the WTs from the operation data and develop models for anomaly detection (AD), performance and maintenance assessment.

To translate the possibility of failure of a component, due to changes in the condition or health, from categorical states (e.g. good, bad) to numerical values (e.g. 0.75, 0), a unit-less indicator, CI, is defined. After the status of the component is obtained (through the previously mentioned algorithms), the next step, which is integration of these information into operation, is developed and illustrated. As an example, Table 4.1 shows how CI can be evaluated in numerical values from categorical states. It should be noted that the "very bad" state does not mean a failure, rather a condition level when the operator would need to take an action in order to prevent a failure as soon as possible.

Table 4.1: CI conversion from categorical values

State	CI
very good	0.00
good	0.25
medium	0.50
bad	0.75
very bad	1.00

In order to observe the impact that the knowledge of CI can have in the new context of smart systems, which is still far from better considerations of its possible estimations, CI has been used as the well-known classical function of unreliability ($F(t)$) in the reliability literature. Better estimations of CI are possible as mentioned in [157]. CI can take the value of 0 when the probability of failure based on condition of the component is the lowest, and 1, when the probability of failure based on condition of the component is the highest. Since unreliability is related to the condition of the asset and it changes along time (increase or decrease) due to different reasons (e.g. aging, repair), the health condition of component is considered as a function of time ($CI(t)$). As an example in a WT, [39, 44] consider CI based on time and additional factors such as gearbox temperature (GT) and wind speed (WS). The main parameters that drive this evolution are "aging" and "maintenance". It is assumed that good maintenance actions influence the condition of assets positively and thus, CI is affected due to maintenance.

In general, investments in maintenance try to improve performance and gain profit by reducing the failure probability of an asset. In this chapter, a maintenance model is defined and several types of influences that maintenance actions can have over CI are considered. CI will include the effect of both unreliability behavior and the applied maintenance along time. As an example, when the component is operating, its CI increases and when the maintenance is carried out, it is supposed that CI decreases to a certain level. The CI will start to increase again after the maintenance is over. This model assumes a finite number of values for CI (five in this example), and each value has a label attached to it, as illustrated in Figure 4.1. Since there is no complete standard for acceptable risk exposure, it is assumed that the threshold, as to when maintenance actions should be performed, is obtained from experience and through opinions of experts which is based on the observed condition of the component at any time.

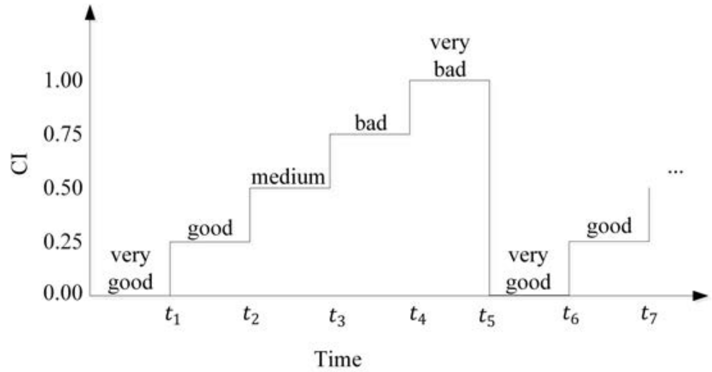


Figure 4.1: Evolution of CI along time

In Figure 4.1, the height of each stair is considered to be 0.25. The considered model is stair-wise where more complex models can also be adopted. The stairs have equal width and for each component, the width is calculated from the mean-time-between-failure (MTBF) value of that component divided by the number of defined states. It should be mentioned that when the real-time health condition information are available, the width and height of the stairs can turn into random numbers. While this approach provides the general idea and in depth study of integration of these indicators by applying to a rather large test system, other studies have suggested the importance of development of such indicators for small specific cases [147, 148]. According to the applied maintenance times and the observed time-to-failure (from historical data), it is possible to establish an acceptable risk level threshold which is compatible with the maintenance and failure times. The proposed CI demonstrates such flexibility in this model.

4.1.3. Risk Indicator

After the CI has been developed for all the considered components in the system and integrated into the model, to represent the impact of these indicators on the system level, risk indicator (RI) is defined for the components and the overall system. The RI of the component is considered as the amount of component specific output that will be lost, if the component goes out of operation. The RI of the system is an accumulated value of risk of components imposed by the conditions of the components in operation. In addition, by setting a limit for the RI on both components and the system, the operators can run the system with different perspectives. The operator can opt for a highly secure operation at particular times by selecting only components with small RI values, or in case security does not have priority, select components with larger RI values.

Deploying the MMRR approach very much depends on the system. Therefore, to demonstrate the applicability of this approach, along with the overall scope of this dissertation, the power system field has been selected. Following the thorough literate review performed in section 2.3, through the following case study, MMRR approach tailored for unit commitment and economic dispatch problem has been developed.

4.2. Case Study: Unit Commitment and Economic Dispatch with Condition Indicators

This case study demonstrates application of the proposed MMRR approach through an example in power system operation field. It designs the defined CI and RI in this context and links them from component level to system level analysis. It then further analyzes the improvements by comparing the traditional and the updated approach.

4.2.1. Nomenclature

b_g	Gross to net power coefficient for generator g
$q_{h,i,g}$	Total net power dispatched by generator g at hour h at bus i as variable
$u_{h,g}$	Binary variable indicating if generator g produces power at hour h
q_g^{min}	Minimum gross power capacity of generator g that must be produced
q_g^{max}	Maximum gross power capacity of generator g that can be produced
ru_g	Upward ramp rate of generator g
rd_g	Downward ramp rate of generator g
N_h	Number of hours
N_g	Number of generators
$y_{h,g}$	Startup decision for generator g at hour h as a binary variable
$z_{h,g}$	Shutdown decision of generator g at hour h as a variable
α_g	Variable fuel consumption coefficient for generator g
β_g	Fixed fuel consumption coefficient for generator g
oc_g	Fixed O&M cost for generator g
o_g	Variable cost of O&M of generator g
f_g	Price of fuel used by generator g
γ_g	Fuel consumption of generator g at startup
σ_g	Fuel consumption of generator g at shutdown
P_{ik}	Active power between bus i and bus k
X_{ik}	Inductance of transmission line between bus i and bus k

θ_i	Voltage angle as bus i
S_B	Base power
$pf_{h,i,k}$	Active power flow at hour h from bus i to bus k as a variable
$d_{h,i}$	Demand at bus i at hour h
N_j	Number of transmission lines
N_i	Number of buses
$CI_{h,g}$	Condition of generator g at hour h
$RI_{h,g}$	Behavior risk of generator g at hour h
$Threshold_g$	Conditional limit of generator g

4.2.2. Introduction

One of the variables affecting the operation of the power system is maintenance of the generators. preventive maintenance (PM) of generators is conventionally based on periodic actions, regardless of the current condition of the components. The conventional plans are commonly based on Weibull or Exponential distribution functions. One of the disadvantages of using such functions is their dependence on the availability of historical information and their disconnection from the evolution of health condition of the component. Lack of such connection causes the decisions to deviate from an actual case in practice. This is an important aspect which needs to be investigated since a scheduled maintenance could be delayed, or advanced, according to the current health condition of the component and its impact on the performance of the system. In this regard, recent changes in the power system through installation of numerous monitoring devices in the grid and emergence of smart grid can provide assistance in creating this connection [285].

In order to illustrate the impact of health condition information on maintenance and performance of the power system, this case study is focused on three areas of: condition monitoring, economic dispatch, and maintenance and risk. The objective is to find out how the available information on health condition of the components can be linked to maintenance and risk, and accordingly assess the influence of this information on the performance of the power system. Among all these data however, currently there is no direct link between the information about condition of components and performance of the system. The literature review here is focused on studies that address generation maintenance scheduling (GMS).

4.2.2.1. Condition Monitoring

The installation of smart meters and intelligent electronic devices in an electric power system with the possibility of real-time communications, gives the system operators ability to monitor their performance and expedite the decision-making process [285]. To make this bridge from component level to operation and planning level, there is a need for an indicator which represents the health information of the component.

[286] presents a literature review on concepts and functions of condition monitoring and popular monitoring methods, as well as several research projects on transformers, generators and induction motors. [287] performs a study on the impacts and resilience of the power system towards extreme external factors (e.g. natural disasters). [288–291] introduce and apply techniques that are used for behavior analysis and monitoring of generators with different sizes and types, including small WTs. [292] provides an overview on current standards for smart grids regarding monitoring, protection and control applications and highlights the challenges related to integration, implementation, flexibility and compatibility. [293] gives a critical overview on intelligent system monitoring. Although these studies show that the current condition monitoring system (CMS)s are capable of extracting and delivering information on the health condition of the components, their connection and impact on the network is not considered directly in the operation.

4.2.2.2. Economic Dispatch

Unit commitment is defined as which generators should produce power in the planned horizon [294]; and economic dispatch is considered as optimum economical generation planning for the system based on a set of constraints (e.g. limitations of capacity of generators and transmission networks) [295]. Various techniques have been used for solving economic dispatch problems [296]. [297, 298] review traditional approaches whereas [299, 300] review more recent techniques in power system optimization. [301] proposes a stochastic model for economic dispatch. A unit commitment problem is primarily solved where the units are considered to be fully available. However, this assumption is simplified as condition of the units is considered healthy and fixed at all times. [302] evaluates unit commitment risk due to variations in the wind power. [303] evaluates a system through an economic dispatch model where uncertainty for wind, solar and load are considered and impact of uncertainty is shown. However, no uncertainty on the generators or their availability and condition is assumed. The current hourly network constraint unit commitment (HNCUC) process in operation of power systems receives the down-times of assets (e.g. generator, transformer, and transmission line) and based on that, it plans the operation. There are two main concerns in this regard: firstly, there is no factor that provides the impact and influence of such decision for both the system operator and the asset owner; secondly, there is no index as feedback for the asset owners so that they can evaluate the efficiency of their maintenance management policy. Therefore, by integrating health condition information of the components and implementing them in the dispatch problem, an economically efficient operation can be achieved which can overcome the conventional maintenance planning.

4.2.2.3. Maintenance and Risk

Since the maintenance actions influence the condition of a component, the link between the collected condition information and maintenance should also be used in dispatch models. After a maintenance action is carried out, the degree of the maintenance action significantly affects the system operator and asset owners [304]. For instance, the answers to the questions "Can the system tolerate if component x continues to operate for another y hours in condition z?" or "What happens if the maintenance of component x in condition z is postponed for y hours?" are of great importance for both system operators and asset owners. There are numerous studies on the topic of maintenance which cover various aspects; from the impact of preventive and corrective maintenance actions on the components and systems [305, 306], to the impact of maintenance degrees (e.g. as-good-as-new (AGAN), as-bad-as-old (ABAO) and imperfect maintenance (IM)) [307–309].

Research on maintenance continues in optimization area in finding the best maintenance outage window for thermal units, transmission lines and transformers [119, 310]. In addition, many studies have tried to connect maintenance and reliability [311, 312]. Furthermore, introduction of smart grid has guided some researchers to propose the idea of smart maintenance [313]. [314] proposes a severity risk indicator which acts as an indicator of severity of an event and measures the change in reliability of the system after each event. This indicator specifies the performance of the bulk power system, however, the impacts on the distribution system are not included and weights used in this indicator are based on industry judgment. An upgrade to this indicator is presented in another study [315] which concentrates more on loss of service to distribution customers; however, load lost due to distribution resources is not taken into account in the new enhanced indicator. Review of more studies are provided in section 2.3 and Table 2.2.

In this case study, MMRR approach is proposed that allows both system operators and asset owners to account for condition changes in the components, and assesses the impacts of their maintenance decisions. At first, from the current status of the component, a CI is developed. Next, the impact of different maintenance strategies on the CI is evaluated. Then, the updated CI is integrated into the HNCUC, and operation and planning is carried out. Later, an RI is defined to analyze both the operation performance and the proposed maintenance plans. Therefore, the MMRR approach assists system operators to analyze the overall condition and security of the system in order to avoid blackouts resulting from bad conditions in components of the system and simultaneously, it helps asset owners to assess the efficiency of their maintenance management by considering its impact on the system. Additionally, studies in this area generally solve the operation and planning problem using two separate tracks, economical- and risk-based. This case study on the other hand, considers both of these aspects simultaneously. Therefore, the main contribution is integration of condition and risk indicators to address economical and risk oriented concerns concurrently. The results bring about outcomes in form of monetary savings and improved security where had not been accounted for due to the lack of the mentioned connections between health condition information and power system operation.

4.2.3. MMRR-based Model

The complete algorithm for the proposed MMRR approach with focus on power system operation is displayed in Figure 4.2 where the contribution of this approach is illustrated in dash-line boxes.

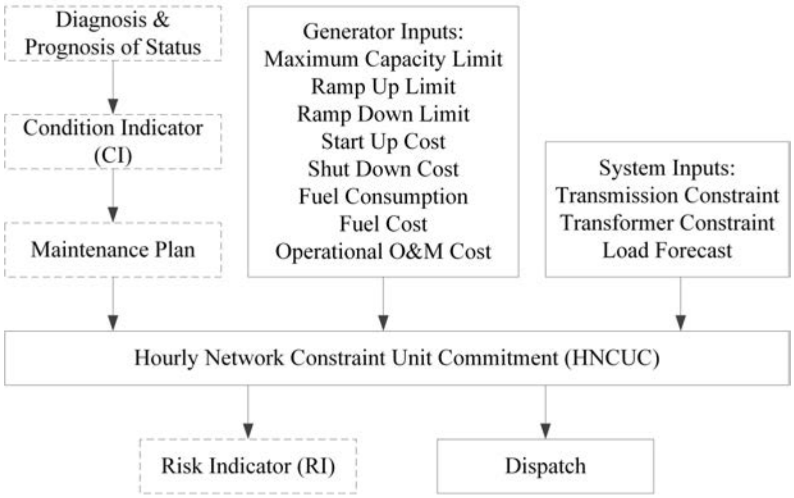


Figure 4.2: The proposed MMRR approach

Since the components under study in this case are generators, MTBF values are shown in Table 4.3 and are obtained from IEEE-RTS [316, 317]. For instance, if MTBF of a component is 3000 hours ($t_5 = 3000h$), the width of the stairs for that component is 600 hours ($3000/5 = 600h$). Based on Figure 4.1, when the component has been in the "very bad" condition for its defined time with CI value of 1.0, a maintenance action is performed (in which the maintenance time is also accounted for). After the maintenance is over, the component has a new condition (e.g. the "very good" condition in AGAN maintenance strategy) and this process repeats. It should be noted that since the maintenance action is assumed to be performed on the degraded condition states, the sensitivity analysis is considered to address the issue of impact of various "maintenance times" and "maintenance types" as parameters of the model.

In this case, the unit of RI for all the generators is in mega-watt. At first, an hourly individual RI is obtained for all generators from multiplication of their hourly CI by the hourly dispatched power of the generator (e.g. $RI_{G5} = CI_{G5} \times q_{G5}$). Then, the RI of the system is calculated as the summation of these values for all generators at each hour. As an example, if a generator with the "very bad" condition (CI = 1) is producing 100MW, its RI is $1 \times 100 = 100$MW. This means that the risk imposed by this particular generator at this moment is 100MW. It should be reminded that currently there is no such an indicator in the state-of-the-art algorithms in this area; the health condition of the generators is neglected and their availability is considered to be 100% during the whole operation.

4.2.3.1. HNCUC Formulation

An optimization model is considered for an HNCUC problem integrating the newly defined indicators. The general concepts of the model applied here are based on the economic dispatch formulation defined in another study [318]. The main contribution of this case study is the addition and implementation of CI and RI in the formulation in order to study the impact of the newly available health condition information in the power system.

4.2.3.1.1. Equations, Constraints and CI Implementation Minimum and maximum net capacities of each power plant are defined respectively as shown below:

$$q_{h,i,g} \geq u_{h,g} b_g q_g^{min} \tag{4.1}$$
$$q_{h,i,g} \leq u_{h,g} b_g q_g^{max} \tag{4.2}$$

$q_{h,i,g}$ is the total net power dispatched by generator g at hour h at bus i as a variable, $u_{h,g}$ is the binary variable to indicate whether generator g is producing power at hour h, b_g is the gross to net power coefficient for generator g, q_g^{min} is the minimum gross power capacity of generator g that must be produced and q_g^{max} is the maximum gross power capacity of generator g that can be produced.

Ramp-up and Ramp-down of thermal generators are also included in the model and they are designed respectively as follows:

$$q_{h,i,g} - q_{h-1,i,g} \leq ru_g \tag{4.3}$$
$$q_{h-1,i,g} - q_{h,i,g} \leq rd_g \tag{4.4}$$

ru_g and rd_g are the upward ramp rate and the downward ramp rate of generator g, respectively.

Start-up and shut-down actions should follow the logic that if a unit is already connected, it cannot be re-connected:

$$u_{h,g} = u_{h-1,g}(h > 1) + y_{h,g} - z_{h,g} \tag{4.5}$$

$y_{h,g}$ is the startup decision for generator g at hour h as a binary variable and $z_{h,g}$ is the shutdown decision of generator g at hour h as a variable.

Costs associated with generation units are divided into three types: production, start-up and shut-down costs. The production costs are as well divided to fuel, and O&M costs where fuel costs for wind and hydro generators are considered to be zero. For thermal generation units, fuel costs are generally expressed as a quadratic function of the output power:

$$c_g = \beta_g + \alpha_g \frac{q_g}{b_g} + \delta_g \frac{q_g^2}{b_g} \tag{4.6}$$

c_g is the cost function, δ_g is the heat coefficient and q_g in this equation is the gross power measured at the generator output terminal. α_g is variable fuel consumption coefficient for generator g and β_g is fixed fuel consumption coefficient for generator g. To simplify the model, cost functions of the generators are assumed to have a shape where they can be considered linear and thus the quadratic part is omitted. Similarly, O&M costs are considered to be linearly dependent on the gross output power as well as having a constant term where $O\&M_c$ represents O&M costs.

$$O\&M_c = oc_g + o_g \frac{q_{h,i,g}}{b_g} \tag{4.7}$$

oc_g and o_g are the fixed and variable costs of O&M of generator g, respectively.

In consideration of power flows between different nodes in the system, an optimal power flow problem needs to be solved to determine producible active power and the voltage of each generator at each node. Solving this optimal power flow produces nonlinear terms. By assuming that voltages of all nodes are almost the same, the inductive parts become significantly greater than the resistive parts and the difference in voltage angles becomes very small. Then, the problem is transformed into a linear relation as formulated below:

$$P_{ik} = S_B \frac{\theta_i - \theta_k}{X_{ik}} \tag{4.8}$$

P_{ik} is the active power between bus i and bus k, S_B is the base power, θ_i is the voltage angle as bus i and X_{ik} is the inductance of transmission line between bus i and bus k.

Equation (4.8) shows that by using voltage angles of nodes as variables in the problem, the power flow between nodes can be controlled. Finally, the demand balance formulation presented in (4.9) forces the generation to meet the demand at each hour and each node in the system.

$$\sum_{g=1}^{N_g} q_{h,i,g} - \sum_{k=1}^{N_k} pf_{h,i,k} + \sum_{k=1}^{N_k} pf_{h,k,i} = d_{h,i} \tag{4.9}$$

$pf_{h,i,k}$ is the active power flow at hour h from bus i to bus k as a variable and $d_{h,i}$ is the demand at bus i at hour h.

The formulation presented so far for the HNCUC model tries to perform the hourly dispatch with the objective of keeping the operational costs at minimum level. However, it does not include the risk associated with the health condition of the generators. This means that the system will not be able to benefit from distinguishing among generators with different health conditions. As the contribution of the MMRR approach, new indicators are defined which take into account the condition and state of each of the generators in operation. The CI is represented in the formulation with an additional parameter called “Threshold”. The threshold parameter is the actual threshold considered for the condition of the generator that is not allowed for the operation. As mentioned earlier, the threshold in this case study is decided based on opinions of expert and condition of the generator. For instance, when the threshold state of “very bad” with corresponding CI value of “1.0” is defined, whenever the condition of the generator reaches the “very bad” condition (or CI=1.0), the generator is automatically excluded from the operation and is scheduled for maintenance. This equation is formulated in an IF-conditional case as shown below:

$$If \quad CI_{h,g} \geq Threshold_g \Rightarrow \text{“}perform \;\; maintenance\text{”} \tag{4.10}$$

$CI_{h,g}$ is the condition of generator g at hour h, and $Threshold_g$ is the conditional limit of generator g during the operation.

In order to exhibit the various threshold levels in the model that alternative opinions of experts could bring about, a sensitivity analysis is carried out. The sensitivity analysis aims at displaying the impact of parameters of the model, which also include the maintenance threshold. In addition, along with the sensitivity analysis, a scenario is defined based on the current maintenance practice, Scenario1, which is then compared with the rest of the scenarios to demonstrate the benefits that the proposed approach offers.

The model is flexible in a way that the threshold can be defined as a function of time and condition. For simplicity, the threshold in this case study is considered to be solely dependent on condition. If the system operator decides to take more risk, it can set the level of the threshold to high (e.g. the “very bad” condition); and in contrast, if the system operator needs to have a highly reliable operation, it can put the level of the threshold at lower levels (e.g. the “bad” condition). Threshold value can take categorical or numerical values. Once again, it should be mentioned that CI can be calculated (or forecasted) as explained in the previous section or taken directly from intelligent electronic devices installed in the generators and thus is known prior to each operation and planning period (or obtained in real-time).

4.2.3.1.2. Objective Function and RI Implementation Finally, the objective function for the new cost-risk HNCUC model is formulated as follows:

$$\sum_{h=1}^{N_h}\sum_{i=1}^{N_i}\sum_{g=1}^{N_g}[f_g\alpha_g\frac{q_{h,i,g}}{b_g} + f_g u_{h,g}\beta_g + f_g\gamma_g y_{h,g} + f_g\sigma_g z_{h,g} + oc_g + o_g\frac{q_{h,i,g}}{b_g}] \tag{4.11}$$

where the objective is to minimize this general term which is subject to costs and risks. f_g is the price of fuel used by generator g, γ_g is the fuel consumption of generator g at startup and σ_g is the fuel consumption of generator g at shutdown.

The term $f_g\alpha_g q_{h,i,g}/b_g$ denotes the linearized operation cost of each generator; $f_g u_{h,g}\beta_g$, $f_g\gamma_g y_{h,g}$ and $f_g\sigma_g z_{h,g}$ take into account commitment status, start-up and shut-down costs, respectively. Then, for each generator and at each hour, the RI is defined as follows:

$$RI_{h,g} = CI_{h,g} \times q_{h,i,g} \tag{4.12}$$

where $RI_{h,g}$ is the risk of generator g at hour h imposed due to its observed condition.

Once again, it should be commented that the RI can be defined in other forms (e.g. squared) based on the objective and perspective of the work. In this case study, RI is defined through a linear relation.

4.2.3.2. Test System

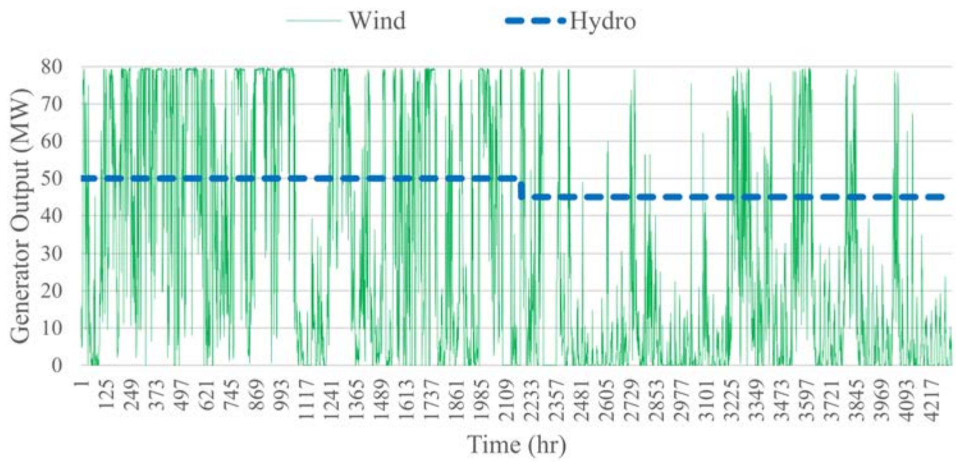


Figure 4.3: Forecast profile of renewable sources as input

To verify the model presented in this case study, the model is applied to IEEE-RTS [316, 317] with some modifications in order to consider generators based on renewable energy. One modification is addition of two wind farms, each with the capacity of 80 MW, which makes the total number of generators in the system to 34 with a generation capacity of 3656 MW. Figure 4.3 shows the profile of the wind farms and redefined hydro generators used in this model for the period of 6-month (4320 hrs.).

Peak load in this system is considered to be 2850 MW. These two wind farms are added to bus9 and bus19 in IEEE-RTS. For the purpose of this study, the considered optimization period is about 6 months (4320 hrs.) with hourly load profile. A short summary of the data of the generation units is provided in Table 4.3. The model is then coded in general algebraic modeling system (GAMS) software [319] as the optimization tool and solved using the mixed-integer linear programming (MILP) technique with CPLEX solver [320].

4.2.4. Test Scenarios

To analyze the model and test it for different situations, several scenarios have been defined in order to show:

Table 4.3: Summary of generation units information (FS = fossil steam; CT = combustion turbine; NS = nuclear steam)

Generator	Type	Fuel	Incremental term of fuel consumption [Mbtu/MWh]	Fixed term of fuel consumption [Mbtu/hr]	Fuel consumption during start-up [Mbtu]	Fuel consumption during shut-down [Mbtu]	Upward ramp [MW/hr]	Downward ramp [MW/hr]	Maximum gross power [MW]	Minimum gross power [MW]	Gross to net power conversion factor	Cost of fuel consumed [$/MBtu]	Fixed O&M Cost [$/MW/yr]	Variable O&M Cost [$/MWh]	MTBF [hr]
G1	FS	#6 Oil	10.20	69	53	5.3	10	10	12	2	0.94	2.3	10000	0.9	3000
G2	FS	#6 Oil	10.20	69	53	5.3	10	10	12	2	0.94	2.3	10000	0.9	3000
G3	FS	#6 Oil	10.20	69	53	5.3	10	10	12	2	0.94	2.3	10000	0.9	3000
G4	FS	#6 Oil	10.20	69	53	5.3	10	10	12	2	0.94	2.3	10000	0.9	3000
G5	FS	#6 Oil	10.20	69	53	5.3	10	10	12	2	0.94	2.3	10000	0.9	3000
G6	CT	#2 Oil	12.67	40	5	0.5	15	15	20	5	0.94	3	300	5	500
G7	CT	#2 Oil	12.67	40	5	0.5	15	15	20	5	0.94	3	300	5	500
G8	CT	#2 Oil	12.67	40	5	0.5	15	15	20	5	0.94	3	300	5	500
G9	CT	#2 Oil	12.67	40	5	0.5	15	15	20	5	0.94	3	300	5	500
G10	FS	Coal	10.08	85	596	59.6	60	60	76	10	0.94	1.2	10000	0.9	2000
G11	FS	Coal	10.08	85	596	59.6	60	60	76	10	0.94	1.2	10000	0.9	2000
G12	FS	Coal	10.08	85	596	59.6	60	60	76	10	0.94	1.2	10000	0.9	2000
G13	FS	Coal	10.08	85	596	59.6	60	60	76	10	0.94	1.2	10000	0.9	2000
G14	FS	#6 Oil	7.77	125	408	40.8	70	70	100	20	0.94	2.3	850	0.8	1250
G15	FS	#6 Oil	7.77	125	408	40.8	70	70	100	20	0.94	2.3	850	0.8	1250
G16	FS	#6 Oil	7.77	125	408	40.8	70	70	100	20	0.94	2.3	850	0.8	1250
G17	FS	Coal	7.62	179	607	60.7	100	100	155	30	0.94	1.2	700	0.8	1000
G18	FS	Coal	7.62	179	607	60.7	100	100	155	30	0.94	1.2	700	0.8	1000
G19	FS	Coal	7.62	179	607	60.7	100	100	155	30	0.94	1.2	700	0.8	1000
G20	FS	Coal	7.62	179	607	60.7	100	100	155	30	0.94	1.2	700	0.8	1000
G21	FS	#6 Oil	8.67	133	609	60.9	150	150	197	40	0.94	2.3	500	0.7	1000
G22	FS	#6 Oil	8.67	133	609	60.9	150	150	197	40	0.94	2.3	500	0.7	1000
G23	FS	#6 Oil	8.67	133	609	60.9	150	150	197	40	0.94	2.3	500	0.7	1000
G24	FS	Coal	7.32	335	3192	319.2	250	250	350	50	0.94	1.2	450	0.7	1250
G25	NS	LWR	8.92	360	3500	350	300	300	400	60	0.95	0.6	500	0.3	1250
G26	NS	LWR	8.92	360	3500	350	300	300	400	60	0.95	0.6	500	0.3	1250
G27	Wind	Wind	0.00	0	0	0	80	80	80	0	1	0	100	0	3600
G28	Wind	Wind	0.00	0	0	0	80	80	80	0	1	0	100	0	3600
G29	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000
G30	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000
G31	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000
G32	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000
G33	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000
G34	Hydro	Hydro	0.00	0	0	0	50	50	50	0	1	0	100	0	2000

- impact of maintenance strategy and degree of applied maintenance actions
- consequence of different maintenance plans based on participation of generators
- effect of simplifications made on cumulative distribution function of failure rate
- influence when generators start the operation with different ages, health or failure levels
- effectivity and comparison of applied maintenance actions
- sensitivity of parameters of the model

Table 4.4 presents a summary of the applied scenarios. Two reference scenarios are defined from different perspectives that follow the current practice and they are compared with additionally defined scenarios to demonstrate the capability and benefits of the proposed approach. From the unit commitment and economic dispatch perspective, Scenario1 is the reference scenario which is based on the classical and current common economic dispatch problem models where the health condition information of the generators (the new indicators) is not considered. Since it does not include the risk term, all generators are considered to have a predefined, below threshold and stable condition during the whole operating period which later shows the simplification degree of such scenario. It should be noted here that this general assumption is far from the reality because the condition of generators varies with time. The new indicators are introduced in the formulation from Scenario2 onwards. From the maintenance management perspective, Scenario2 is the reference scenario which is based on current maintenance practices and assumes that the PM times of a generator are known and determined prior to the operation (e.g. every 1250 hrs.). It is also assumed that the generator operates as long as it can without enduring a failure, and after each maintenance action the component has the condition of AGAN.

Table 4.4: Summary of scenarios

	Generators under Maintenance	Initial Condition	Condition before Maintenance	Condition after Maintenance	Maintenance Type	Maintenance Time (hr)
Scenario1	-	-	-	-	-	-
Scenario2	G25	very good	very bad	very good	AGAN	24
Scenario3	G25	very good	bad	very good	AGAN	24
Scenario4	G25	very good	very bad	good	IM	24
Scenario5	G25	very good	bad	good	IM	24
Scenario6	G18,G25	very good	very bad	very good	AGAN	24
Scenario7	G17,G18,G19	very good	very bad	very good	AGAN	24
Scenario8	G1,G6,G10,G17,G25,G27	very good	very bad	very good	AGAN	24
Scenario9	G1,G6,G10,G17,G25,G27	medium	very bad	very good	AGAN	24
Scenario10	G1,G6,G10,G17,G25,G27	very good	very bad	very good	AGAN	48

Scenarios 2-5 also exhibit a sensitivity analysis. In Scenario2, the health condition of Generator25 (G25) is assumed to be monitored and implemented through CI based on the preplanned maintenance schedules in current practice; hence, only G25 undergoes maintenance. G25 is considered to start the operation in the "very good" condition and health. Whenever the condition changes its state to "very bad" the maintenance action starts and lasts for the defined maintenance time (which is 24 hours in Scenario2). After the maintenance action is over, G25 reaches the "very good" condition again, in other words, the maintenance type is AGAN. The reason for choosing G25 with 400 MW capacity is that it ranks second in production in Scenario1 by supplying about 18% of the total demand (G26 ranks first by producing about 21% of the total generation). While Scenario2 and Scenario3 have AGAN maintenance types, Scenario4 and Scenario5 have IM types. These scenarios are defined to show the impact of different maintenance levels and degrees on the operation expenses.

In Scenario6, G18 with the capacity of 155 MW is also added to the generators undergoing maintenance. Production participation of G18 in Scenario1 is 4.33% of the total demand. In Scenario7, it is assumed that G17, G18 and G19 undergo maintenance concurrently. These three generators together produce 11.12% of the total demand in Scenario1.

Scenario8, Scenario9 and Scenario10 are defined in order to show the impact of using this tool on all six groups of generators from the impact of starting the operation with a medium health level and a different maintenance time. Specifically, Scenario9 is important as it holds a very realistic case. In practice, when a power system is installed, not all generators start at the same age and new generators are added as the time passes (e.g. based on the load growth). Therefore, analysis of Scenario9 provides several interesting and new insights in the power system operation and planning.

4.2.5. Results

Different scenarios are defined to analyze various aspects of the proposed methodology. To order the evaluation process, the analysis starts by comparing scenarios from cost-risk perspective as the considered sensitivity analysis. Next, it considers the parameters "maintenance type", "maintenance number", "condition before maintenance", "initial condition" and change in the "O&M cost". In the end, an influence of change in "maintenance time" in Scenario10 is also considered.

4.2.5.1. Impact of Overall Cost-Risk

A summary of the results from operation cost and risk point of view is presented in Table 4.5 where hourly operation cost and risk for Scenario4 are plotted in Figure 4.4. A change in RI is due to a change in the overall condition of the generation fleet. With a cost-oriented objective function, cheaper generators have priority where this can sacrifice security for economic advantages. Through such figures, the system operator can analyze the security of its cost-oriented planning and if required, make modifications. For instance, the RI is very high at hour 3700. If an important event is occurring at that time, the operator may need to change its operation plan (by choosing healthier generators) to reduce this risk.

Table 4.5: Brief comparison of scenarios

	Average Operation Cost per Hour ($/hr)	Maximum Operation Cost per Hour ($/hr)	Average Operation Risk per Hour (MW/hr)	Maximum Operation Risk per Hour (MW/hr)	Minimum Operation Risk per Hour (MW/hr)	Number of Maintenance Actions
Scenario1	2421797	2432511	-	-	-	0
Scenario2	2421854	2437235	797	2288	0	4
Scenario3	2421854	2435085	762	2288	0	5
Scenario4	2421855	2436049	832	2288	0	5
Scenario5	2421876	2437762	800	2288	0	7
Scenario6	2421857	2437235	789	2249	0	5+4 (9)
Scenario7	2421816	2434940	782	2172	0	5+5+5 (15)
Scenario8	2421847	2437235	785	2195	0	1+10+2+5+4+1 (23)
Scenario9	2421835	2432882	807	1954	89	2+10+3+5+4+1 (25)
Scenario10	2421865	2434112	789	2154	0	1+9+2+5+4+1 (22)

As it can be observed in Table 4.5, while the average operation cost and risk remain almost the same in all scenarios, the maximum values tend to differ. Although this may seem that the changes do not make significant impact on the system, this offers a great insight to the critical and extreme cases. It can also be seen that having the highest operation costs (average and maximum) cannot mean a more secure system, which is an important remark.

Analysis of Scenario6 and Scenario7 can help to understand prioritization of maintenance for generating agents in the system with the goal of achieving an optimum

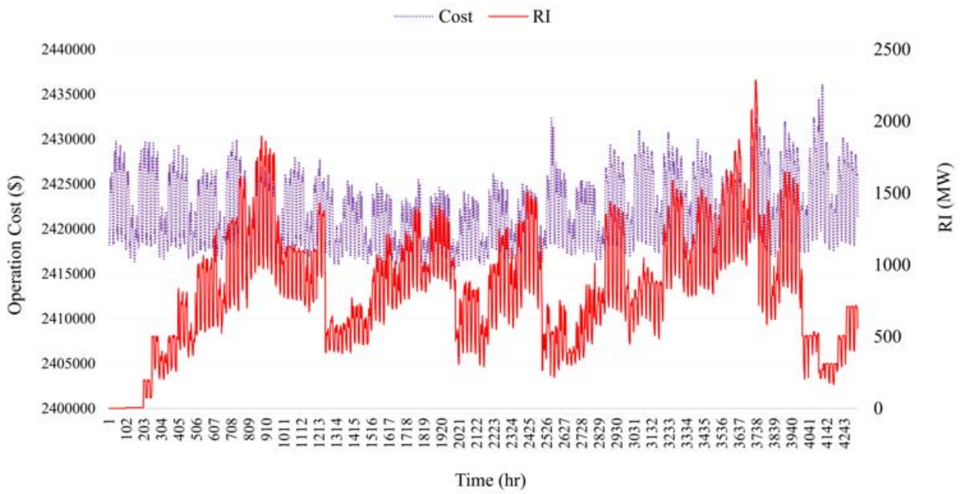


Figure 4.4: Operational cost-risk for Scenario4

cost-risk oriented operation. Sum of production share of G18 and G25 in Scenario1 is 22.34% whereas this value for G17, G18 and G19 is 11.12%. As it can be seen in Table 4.5, Scenario7 has higher number of maintenance actions (15). However, this not only results in lower average and maximum risk, it also decreases average and maximum operation costs.

4.2.5.2. Impact of Maintenance Type & Maintenance Number

Scenarios 2-5 vary in maintenance type (Table 4.4) and this has not caused any reduction in the maximum risk levels, Table 4.5. Another interesting observation from the comparison of these four scenarios is how the number of maintenance actions influence operational expenses. For instance, Scenario2 and Scenario5 with the lowest (4) and the highest (7) number of maintenance actions on G25 respectively, both resulted as expensive scenarios. So far, this matches the general conception of having an optimum number of maintenance actions for an optimum operation cost. In the next step, it is investigated whether this common assumption can hold from the risk point of view as well. By having a look at average risk column in Table 4.5, it can be seen that although Scenario2 and Scenario5 have the highest operation costs (among these four scenarios), they do not have the lowest risk levels, and in fact, Scenario3 ranks the best option between them. The outcome for the system operator from this part (bearing in mind all the parameters such as the projected load profile) is to aim for Scenario3; and the next best option is Scenario4. These steps will result in an optimum cost-risk operation.

It can be observed that increasing the number of maintenance actions (which can be achieved by lowering the maintenance condition threshold level) although may bring down the risk, it directly affects the operation cost by increasing it, Table 4.5. An important observation during this analysis is that if postponing maintenance of some generators are determined individually and they coincide, this will increase both the operation cost and the risk level of the system. Indeed, the system operator would like to avoid such situations. This is obtained by testing scenarios similar to 2 and 3.

4.2.5.3. Impact of Condition Before & After Maintenance

Assuming a "very good" condition for the generator after each maintenance action is a simplified situation as it neglects various possibilities such as human factor and cumulative aging (Scenarios 2 and 4). Scenario5 resonates greatly with an actual case. It denotes that the model is more sensitive when the maintenance should be carried out (Scenario2), and the condition of the generator after maintenance is more rational (Scenario3). This shows that the sensitivity of these two parameters, when applied simultaneously, can better represent the risk that the system endures due to the health condition changes. The number of required maintenance actions are also closer to reality (7 versus 4), Table 4.5. In conclusion, the average operation cost is more sensitive towards the "maintenance type" parameter. Average operation risk is more sensitive towards the traditional mean-time-to-failure (MTTF) parameter which shows that integration of such indicators can have great impact on the operation risk in the system.

Figure 4.5 analyzes Scenario5 to show the sensitivity of the model towards the mean-time-between-maintenance (MTBM) variations. These changes correspond to the impact of change in CI and maintenance of G25 on the overall network. The longer the generators remain in states with lower CI values, the better it will be for the system operation security. Therefore, one could set the maintenance threshold in CI in a way that the generator always remains in the "very good" state. However, considering costs of maintenance actions, the asset owner should seek for a balance point between the maintenance cost and the gained profit.

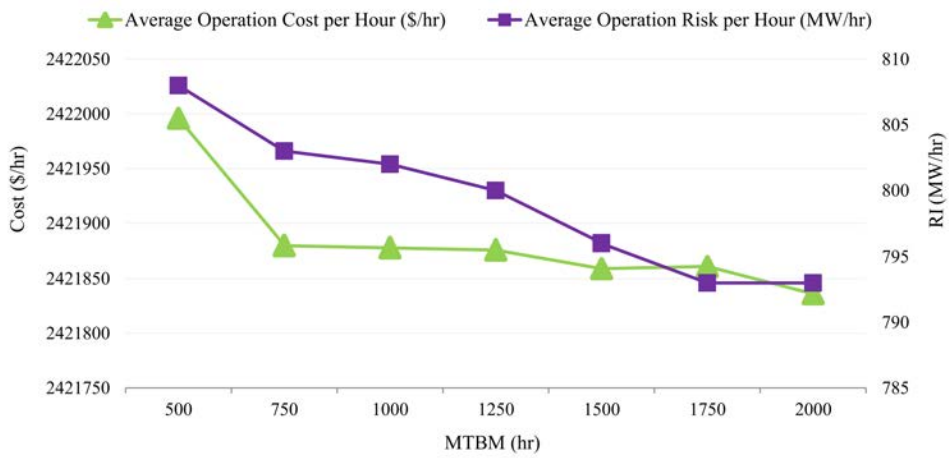


Figure 4.5: Sensitivity analysis of the model on maintenance-time parameter

4.2.5.4. Impact of Initial Condition

Although participating generators in Scenario8, Scenario9 and Scenario10 are the same, the biggest change in production happens in Scenario10. Despite having high average cost and risk, Scenario9 has much lower maximum cost and risk values (Table 4.5). This means that Scenario9 distributes high risk values in the operation horizon while in the other two scenarios, high risk values are accumulated. This is due to the fact that different generators enter the system with different conditions and it is precisely what happens in practice. Therefore, it is even more accurate in the analysis if the conditions of the generators are considered close to reality. This realistic feature is made possible through the main contribution presented in this study.

4.2.5.5. Impact of O&M Cost Change

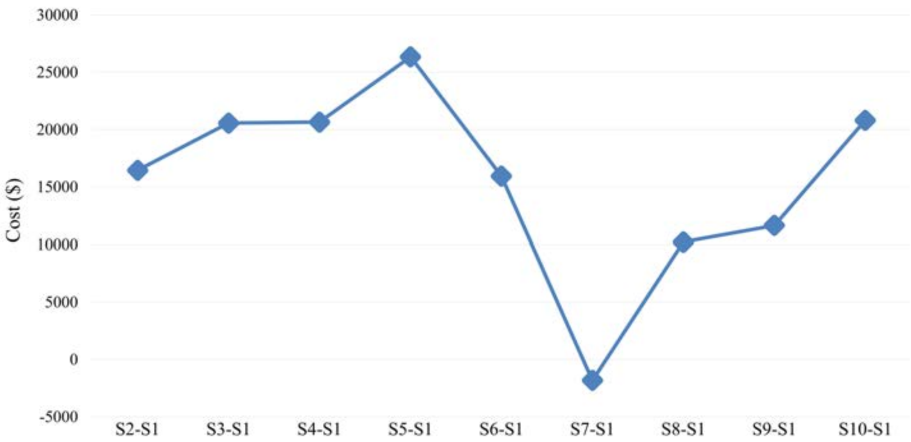


Figure 4.6: Change in O&M costs with respect to Scenario1

Another detailed analysis is performed from the O&M costs perspective based on (4.7), Figure 4.6. It shows the amount that the O&M costs have changed with respect to Scenario1. As it can be seen, the largest sum of changes in the O&M costs, \$26349, occurs in Scenario5. The reason for this high cost is that the maintenance type in Scenario5 for G25 is IM, from the "bad" condition to the "good" condition (Table 4.4). This has resulted in distributing the power, that was previously produced by G25, among other generators with costlier O&M parameters. It should be noted that this incremented cost has a direct influence on the operation cost. This change results in an increase of 79 \$/hr (2421876-2421797=79, Table 4.5) in average operation cost.

One more interesting observation is the reduction in the O&M costs in Scenario7 when compared with Scenario1. This means that by actually having the proposed maintenance plan defined in Scenario7, the O&M costs decrease when compared with Scenario1 where the CI is not included. The reason for having less O&M costs in

Scenario7 is the fact that generators with expensive O&M parameters go under maintenance and the compensated power is distributed among cheaper generators. In details, the production share of G17, G18 and G19 in Scenario7 decreases by -0.09%, -0.11% and -0.08% respectively. These reductions have resulted in an increase of 19 \$/hr in average operation cost (2421816-2421797 = 19, Table 4.5). The outcome for the system operator from this analysis is that it shows how some simple changes in maintenance plans of a particular generator can impact the operation cost, let alone the imposed risk.

4.2.6. Case Study Conclusion

This case study demonstrates an example for the proposed MMRR approach in operation of power systems. Currently, in "unit commitment and economic dispatch", and "maintenance management" problems, evolution of health condition of the generators is disregarded. This results in simplifications in the operation and planning. However, due to the recent advancements in the CMSs, the power system is transiting towards smart grid with significant improvement potentials. Therefore, the contribution of this approach is to introduce two indexes to take the health condition of the generators into account and show the potential benefits for the system operator and the asset owner in terms of operation cost and risk. In particular, the results indicate that having a very high (average and maximum) operation costs does not bring about a very highly secured operation for the system. Furthermore, various maintenance types may result in the different operation costs, however, the maximum exposure of the system to risk may be the same under different maintenance types. Moreover, maintenance type has strong impact on average operation cost while MTTF affects average operation risk greatly. Finally, considering various initial conditions for the generators displayed higher risk and operation costs which is the result of integration of condition indicators and mean the studies without considering such information may provide underestimated values for the cost and risk.

4.3. Chapter Conclusion

This chapter proposes the MMRR approach. It builds up on the information and models developed in the component level (through chapter 3). Implementing those models into the system level operation means integrating the information obtained from health condition of components and analyze their impacts on the system. A condition indicator and a risk indicator are introduced to grasp the impact of the new information. Apart from external factors, these indicators are also influenced by maintenance policies and thus, carry information about maintenance management as well. When these two indicators are not considered in the operation, the operation is generally performed with the objective of having the least operation cost, regardless of evolution of condition of components. This means that at any time, there could be a failure which can greatly endanger the operation of the system. This approach bridges the mentioned gap and leads to the following two outcomes: the asset owner will be able to increase the utilization time of its assets which brings more profit, and the system operator will be able to manage the system with reduced risk of failure and higher security. Moreover, the MMRR approach provides a list of prioritized actions for both the system operator and the asset owner (instead of one single action), and they can choose the suitable action based on the current situation considering the external constraints and factors.

5 Power Generation Maintenance Optimization in Deregulated Power System

After a detailed literature review in section 2.1, several scientific gaps were found in the literature. In particular, the state-of-the-art algorithms in preventive maintenance (PM) scheduling in power generation system lack the link between the maintenance and deregulated power system with several various considerations. For instance, traditionally, studies that consider condition of components in the maintenance planning solely use historical average failure data and disregard the collected operation information.

On the other hand, several various parameters were observed to have significant impact on the operation and maintenance (O&M) planning. However, due to complexity of formulating a PM problem (from mathematical modeling and computational solving), the models neglect parameters such as uncertainty in demand and intermittent renewable energy sources (RES). Moreover, with the deregulation of the electric power system, the direct connection between maintenance decisions and the electricity market bring about great influence on the operations. Therefore, this chapter presents three studies that are performed to propose new approaches in generation maintenance scheduling (GMS) in electric power systems to address the mentioned gaps in Table 2.3. This delivers the third objective of this dissertation as stated in section 1.2.

The first study develops a game theoretic PM scheduling model where uncertainty for demand and RES are considered. The model compares state-of-the-art algorithms in regulated and deregulated power systems. Additionally, it derives two new rescheduling signals to address the conflicting operation between the centralized and decentralized operating states. Following the main path from the first study, the second study proposes a formulation for strategic O&M planning for an offshore wind farm (OWF) in a deregulated power system. The model builds on the previous approaches by considering different transportations vessels and uncertainty in environmental parameters. Similar to the second study, the third study proposes a model to address strategic PM scheduling in a microgrid (MG) where small scale RES as well as storage units are modeled. Moreover, the second and third studies borrow from chapters 3 and 4 and integrate the component level developed condition models into the PM models in a deregulated power system where the impact of such integration on maintenance operation and planing is further analyzed.

The primary purpose of these three studies is to bring the traditional PM scheduling problem up to date with recent advances in systems by connecting market to maintenance planning, and by integrating the health condition information from component level into the system level operation.

5.1. Game Theoretic Generation Maintenance Optimization

The first study here develops a state-of-the-art PM scheduling model for generation units in power systems. It accounts for various parameters and investigates their impacts. Mainly, it derives models for two main perspectives in dealing with maintenance scheduling: centralized and decentralized. Each of these perspectives have different operation methods. While centralized means the maintenance scheduling is performed by one entity for all the agents in the system, decentralized means that all agents have the possibility in choosing their maintenance schedules. Additionally, to maintain a balance between these two perspectives, new signals are developed that account for cost and risk in the operation of the system. This study is published by the author in [146].

5.1.1. Nomenclature

Indexes:	
t	Index for time period
h	Index for hour
g	Index for generation unit
p	Index for generation company (GENCO)
i, j	Index for bus
s	Index for stochastic scenario
w_p	Index for strategy of GENCO p
k	Index for iteration of sending rescheduling signal
Sets:	
$\Upsilon(i)$	Generators connected to bus i
$\Theta(i)$	Buses connected to bus i
$\Xi(p)$	Generators owned by GENCO p
Parameters:	
N_t	Number of time periods
N_g	Number of generators
N_p	Number of GENCOs
N_i	Number of buses
N_s	Number of stochastic scenarios
α_g	Incremental term of fuel consumption (MBTU/MW) of generator g
f_g	Cost of fuel (\$/MBTU) of generator g
o_g	Fixed operation cost (\$/h) for generator g
β_g	Variable operation cost (\$/MW) of generator g
$Q_{t,g}$	Maximum power (MW) of generator g at time t
$\overline{Q}_g$	Upward ramp (MW/h) of generator g
$\underline{Q}_g$	Downward ramp (MW/h) of generator g
$X_{i,j}$	Inductance (Ω) of line between buses i and j

$F_{i,j}$	Capacity (MW) of line between buses i and j
$D_{t,i,s}$	Demand (MW) at time t, bus i and scenario s
ρ_s	Probability of stochastic demand scenario s
z_0	Initial maintenance plans
T_g	Maintenance action duration (h) for generator g
C_g	Maintenance action cost (K$/h) for generator g
Z	Maximum simultaneous maintenance actions
$t'_{k,g}$	Last hour that generator g was under maintenance in iteration k
Ψ_{ENS}	Energy not served (ENS) penalty ($)
Ψ_{OC}	Operation cost (OC) penalty ($)
$\mho_{ENS}$	ENS incentive ($)
$\mho_{OC}$	OC incentive ($)
v_{ENS}	Weighting factor of ENS penalty/incentive ($/MW)
v_{OC}	Weighting factor of OC penalty/incentive ($/MW)
ENS_{CM}	ENS obtained in cost-minimization GMS
$ENS_{NE,k}$	ENS obtained for Nash equilibrium (NE) solution in iteration k
M_1, M_2	Sufficiently large number
Variables:	
$q_{t,g,s}$	Power generation (MW) of unit g at time t and scenario s
$\theta_{t,i,s}$	Voltage angle (rad) at bus i, time t and scenario s
$z_{t,g}$	Binary variable of maintenance status of unit g at time t
W	NE strategy vector
Π_p	Profit ($) of GENCO p
$b_{1_{k,g}}, b_{2_{k,g}}$	Binary variables used in rescheduling signal
a_k	Binary variable used in rescheduling signal
c	Binary variable in issuing rescheduling signal
w_p^*	Strategy of GENCO p in NE
$\mu_{t,i,s}$	Electricity price at time t, bus i and scenario s
$\lambda'_{t,g,s}$	Auxiliary variable for linearization
$\lambda_{1_{t,i,s}}$	Lagrange multiplier of demand balance
$\lambda_{2_{t,g,s}}$	Lagrange multiplier of upward ramp
$\lambda_{3_{t,g,s}}$	Lagrange multiplier of downward ramp
$\lambda_{4_{t,i,j,s}}$	Lagrange multiplier of power-flow
$\lambda_{5_{t,g,s}}$	Lagrange multiplier of maximum capacity limit
$\lambda_{6_{t,g,s}}$	Lagrange multiplier of capacity positivity

5.1.2. Introduction

As the demand increases, the supply requires to maintain a high level of operational performance in order to meet the demand considering cost, reliability and profit for all actors. Ensuring this, the maintenance actions of generators need to be coordinated and managed.

In the maintenance field, there are two main maintenance categories: corrective and preventive. While corrective maintenance denotes remedial actions performed after a failure in order to restore the operation back to its previous operating state, PM refers to actions carried out to maintain operability of an asset at an acceptable level. Towards such a goal, GMS problem in power systems alludes to arranging a plan for generation units to undergo PM actions in order to decrease their probability of failure. In addition, generation and maintenance scheduling is commonly performed for short-, medium- and long-term horizons ranging from hours to years [321, 322].

In a vertically integrated (regulated) power system, there is generally one stakeholder that acts as a system operator and decides on the maintenance decisions for GENCOs. In this type of power system, the objective is to minimize the (social and operational) costs within acceptable reliability limits [323].

In a liberalized (deregulated) power system, there are two main stakeholders with different interests. An independent system operator (ISO) is responsible for operating the power system by setting regulations on social welfare and reliability of the system. On the other hand, GENCOs seek to maximize their profit and they generally consider cost and profit aspects. Therefore, organizing such a plan in a liberalized power system is a difficult and complex conundrum with conflicting objectives for ISO and GENCOs.

To account for various objectives, optimization techniques have gained popularity by addressing multiple criteria in GMS in power systems. One important aspect here is to link these various points. Optimization techniques have the flexibility to allow for coordination of different objectives which in turn assist to fulfill the requirements of different actors in the system [324]. Hence, GMS in a liberalized power system will be beneficial to all the players by including all three aspects of cost, reliability and profit.

In a regulated power system, solving a GMS problem with the objective of minimizing the costs results in a perfectly competitive market scenario, which is commonly used as a benchmark as in this case study. However, by emergence of competition through electricity market in a deregulated power system, game theoretic approaches are gaining attention. For instance, in order to find an equilibrium point in profit for all the GENCOs participating in the market, and to avoid exercise of market power by some actors, obtaining a NE point strategy would be beneficial.

Where specific studies in accordance with this case study are represented in the following paragraphs, a thorough review on the research performed on maintenance scheduling can be found in [323, 325–329]. [325] provides explanations of the terminologies and the maintenance scheduling problem. The survey is carried out with the view of checking the objective functions, deterministic or stochastic analyses and optimization techniques. The approaches are cost- and reliability-oriented. While the cost-oriented approaches are computationally infeasible, the reliability-oriented approaches are too simplistic.

[326] evaluates the main characteristics of the maintenance scheduling problem from objectives and constraints point of view. It is suggested that a combination of economic and reliability aspects would probably interest the system most, the method should be

able to provide optimal or near-to-optimal solution and a link between the operational researchers and the power system planners would bring more benefit for all.

[327] addresses the transition from regulated to deregulated power systems. This means that the maintenance scheduling which traditionally was performed by a power system operator, is no longer centrally controlled and it endangers the reliability criterion of the system. Therefore, the traditional approaches are not ideal for the new environment and should be updated. [328] reviews the techniques applied in solving maintenance scheduling including heuristics and mathematical techniques. It mentions that where heuristics may not lead to optimal solution for complex systems, mathematical techniques could fail due to time-limits. It is also mentioned that a multi-stage approach can assist as it breaks down the main problem into several sub-problems.

[323, 329] deliver a thorough review on the maintenance scheduling field from various perspectives. For instance, the studies with objectives of cost, reliability and their combination in a power system with regulated structure are reviewed. Next, the problems in the deregulated structure that consider uncertainty are studied. After going through different techniques applied in solving the maintenance scheduling problem, it is concluded that considering solely cost or reliability objectives are not suitable for the new deregulated structure. Hence, they propose approaches that are based on maximization of profit of GENCOs while coordinating the decisions of different agents; this in turn results into a game theoretic problem. They raise several aspects that still require to be looked into, such as, load uncertainty, coordination between GENCOs and the ISO and integration of RES with their stochastic nature. The literature review in this case study covers state-of-the-art studies in three areas of: 1) bi-level programming, 2) coordination process and 3) game-theory that are related to GMS.

5.1.2.1. Bi-level programming in GMS

Due to the inherent structure of maintenance scheduling problems, many authors have used multi-level approaches to tackle this issue [125, 330, 331]. Mainly in a two-level GMS problem, the upper-level schedules maintenance where the lower-level manages other considered criteria. While objective of the upper-level ranges from profit maximization to risk reduction [332–335], objective of the lower-level normally includes social welfare maximization or operation cost minimization [126, 336–338]. However, due to the complexity of the problem, many simplifications are considered, e.g. disregarding transmission constraints, assuming given electricity prices, and neglecting stochasticity of demand and RES. This case study on the other hand, includes these aspects and assesses their impacts. In addition, in order to represent the impact of variability of RES, the capacity of the generators constraint and ramping rates which are generally considered in economic dispatch problems are also included [339]. In this regard several case studies are defined and analyzed in section 5.1.4; *Case*1 is considered as the benchmark model, *Case*2 is the model that considers the profit of the GENCOs, renewable wind power is considered in *Case*4 and *Case*8, and demand stochasticity is considered in *Case*9. Please notice that the ramp rates of generators and transmission constraints are used in all of the cases.

5.1.2.2. Coordination in Profit-maximization GMS

While the objective of GENCOs in this GMS is to maximize their profit, the system reliability and economic degrees should be maintained at acceptable levels. This necessitates a coordination procedure in order to attain an optimal solution which satisfies both of these objectives. In [330] and [340], at first, problem of GENCOs for finding maintenance schedules is solved, then, through an iterative process, a rescheduling signal is issued. The signal promotes alternative decisions for GENCOs so that system requirements are met. Various forms of reliability and economic signals are assessed in [330, 335, 341] and [125, 340, 342, 343]. However, GMS can also benefit from a comparative study of these signals. In this case study, two rescheduling signals are defined and issued to the GENCOs. While reliability requirement limit of the system is based on ENS, economic limit is based on OC. ENS and OC signals ensure that result of the profit-maximization GMS is in the given reliability and operation cost limits, respectively. In this case study, these reliability and economic limits are obtained from the defined cost-minimization GMS. Moreover, incorporation of these two signals into one signal is proposed and compared with either of them, individually. In this regard, *Case*5 considers solely the ENS-based rescheduling signal, *Case*6 considers solely the OC-based rescheduling signal and *Case*7 integrates both of these rescheduling signals into the model.

5.1.2.3. GMS representation in Market Equilibrium

In a deregulated power system where each GENCO aims to maximize its profit, the resulting GMS is the NE of the simultaneous-move game which is played by the GENCOs considering all of their strategies [344]. To this goal, researchers adopt game theory for GMS [124, 345, 346]. For instance, [345, 346] perform studies where the market-clearing price is forecasted from the marginal price of each generation unit, demand stochasticity and RES are neglected, and rescheduling signal is not considered. [124] considers a reliability rescheduling signal through penalty and incentive where market clearing price is predicted from the marginal price of generators. Demand stochasticity and integration of RES are also disregarded and an upper limit is set by ISO on the number of iterations in order to find the solution. Moreover, the study of impact of considering portfolios, e.g. GENCOs with multiple generation units, is also neglected. Portfolio analysis provides insight into evaluating the strategic cooperation of generation units. In this regard, different portfolio cases are defined and studied. While *Case*1 and *Case*2 have the same type of portfolio (each generator is one GENCO), the other cases have different portfolio types. For instance, *Case*3 has the portfolio type 2 which means generators 1, 4 and 5 form the GENCO1 and the generators 2 and 3 form the GENCO2.

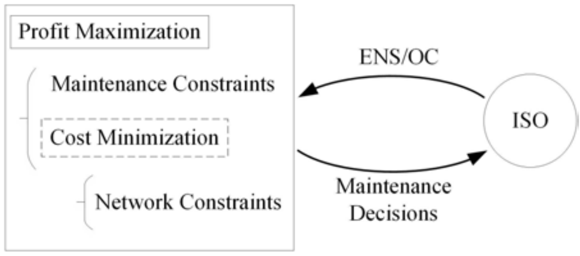


Figure 5.1: Overall diagram from the relationships among the decision variables

This case study investigates strategic behavior of GENCOs in a GMS problem. Two bi-level formulations for GMS problem are provided as cost-minimization and profit-maximization GMS. Where the aim of cost-minimization GMS is minimizing operation cost of the system without accounting for profit of GENCOs, the goal of profit-maximization GMS is to maximize profit of GENCOs satisfying at the same time the reliability targets imposed by the ISO. These defined bi-level problems are transformed into a mixed-integer linear programming (MILP) through Karush–Kuhn–Tucker (KKT) conditions. In case ISO considers reliability and economic limits in the system, impact of these two types of limits are further analyzed by incorporating them into the model through a rescheduling signal. In addition, variations in RES as well as demand stochasticity are also introduced and their impacts are explored. Since NE is obtained as the final solution of the GMS problem among the GENCOs, their strategic behavior where each GENCO individually attempts to maximize their profit is exemplified. The overall diagram of the relation among the GENCOs and ISO is displayed in Figure 5.1.

5.1.3. Problem Formulation

5.1.3.1. Cost-minimization GMS

Cost-minimization GMS is considered as a maintenance scheduling problem where one entity, i.e. ISO, decides about both maintenance scheduling and operation of the system. Both of these tasks are carried out by the objective of minimizing the operation cost of the system. Formulation of cost-minimization GMS through a bi-level optimization problem (BLP) is represented as follows:

$$\min_{z} \sum_{t,g} \left\{ \sum_{s} \left[\rho_s (f_g \alpha_g q_{t,g,s} + \beta_g q_{t,g,s} + o_g) \right] + C_g z_{t,g} \right\} \tag{5.1a}$$

$$\sum_{t} z_{t,g} - T_g = 0 \qquad \forall g \tag{5.1b}$$

$$\sum_{g} z_{t,g} - Z \leq 0 \qquad \forall t \tag{5.1c}$$

$$z_{t,g} = 0 \qquad \forall t > N_t, g \tag{5.1d}$$

$$z_{t+1,g} - z_{t,g} - z_{t+T_g,g} \leq 0 \qquad \forall t < N_t, g \tag{5.1e}$$

$$\min_{q,\theta} \sum_{t,g,s} \Big[\rho_s(f_g\alpha_g q_{t,g,s} + \beta_g q_{t,g,s} + o_g)\Big] \tag{5.1f}$$

$$-\sum_{g\in\Upsilon(i)} q_{t,g,s} + \sum_{j\in\Theta(i)} \frac{(\theta_{t,i,s} - \theta_{t,j,s})}{X_{i,j}} + D_{t,i,s} = 0 : \lambda_{1_{t,i,s}} \qquad \forall t, i, s \tag{5.1g}$$

$$q_{t+1,g,s} - q_{t,g,s} - \overline{Q}_g \leq 0 : \lambda_{2_{t,g,s}} \qquad \forall t < N_t, g, s \tag{5.1h}$$

$$q_{t,g,s} - q_{t+1,g,s} - \underline{Q}_g \leq 0 : \lambda_{3_{t,g,s}} \qquad \forall t < N_t, g, s \tag{5.1i}$$

$$\frac{(\theta_{t,i,s} - \theta_{t,j,s})}{X_{i,j}} - F_{i,j} \leq 0 : \lambda_{4_{t,i,j,s}} \qquad \forall t, i, j \mid j \in \Theta(i), s \tag{5.1j}$$

$$q_{t,g,s} - (1 - z_{t,g})Q_{t,g} \leq 0 : \lambda_{5_{t,g,s}} \qquad \forall t, g, s \tag{5.1k}$$

$$-q_{t,g,s} \leq 0 : \lambda_{6_{t,g,s}} \qquad \forall t, g, s \tag{5.1l}$$

The upper-level, (5.1a)-(5.1e), schedules maintenance while minimizing the total O&M costs of the system and the lower-level, (5.1f)-(5.1l), finds the optimal dispatch of the system given the maintenance schedules found in the upper-level.

First term in (5.1a) is the fuel costs of generation units, second term is regarding variable operational costs, the third term is regarding fixed operation cost and the last term is about costs of maintenance actions where $q_{t,g,s}$ results from lower-level are constant in upper-level. While (5.1b) declares the duration of maintenance actions for each generator, (5.1c) limits the maximum number of generators that can be under maintenance simultaneously. Constraint (5.1e) links the maintenance start time with its corresponding duration time while (5.1d) maintains the values of $z_{t,g}$ within the predefined limits in (5.1e) in the time period of the problem.

Objective function of the lower-level, (5.1f), is the same as the objective function of the upper-level minus the maintenance cost. Note that $z_{t,g}$ is constrained in the lower-level. Equation (5.1g) is the power balance equation at each bus (node). While (5.1h) and (5.1i) define the upward and downward ramping limits of each generator, (5.1j) confirms that the flows in the transmission lines remain in the capacity limit. Finally, (5.1k) and (5.1l) apply the upper and lower limits of the produced power in each of the generation units.

In the BLP of (5.1), the commitment status of the units are considered in two main categories, "unavailable" and "available". Units are unavailable ($z_{t,g} = 1$) whenever they undergo maintenance by enforcing equation (5.1k) and the cost $C_g z_{t,g}$ is incurred [339]. On the other hand, the available units ($z_{t,g} = 0$) are divided into "in production" and "idle". Whenever a unit is in production ($q_{t,g,s} > 0$), it endures the costs $f_g\alpha_g q_{t,g,s} + \beta_g q_{t,g,s}$ and all units have an idle constant cost of o_g over the study horizon for being available, regardless of their operational status.

Moreover, the upper- and lower-level objective functions of this BLP are collinear and have a *Pareto Optimal* solution [347]. This results in transformation of the derived BLP into a single-level optimization problem (SLP) as in (5.2):

$$\min_{z,q,\theta} \sum_{t,g} \left\{ \sum_{s} \left[\rho_s (f_g \alpha_g q_{t,g,s} + \beta_g q_{t,g,s} + o_g) \right] + C_g z_{t,g} \right\} \tag{5.2a}$$

$$(5.1b) - (5.1e),\ (5.1g) - (5.1l) \tag{5.2b}$$

The above SLP is considered as the benchmark and it assumes that ISO solves GMS with the objective of minimizing operation and maintenance costs. Note that this SLP is a MILP and can be solved by available commercial software.

5.1.3.2. Profit-maximization GMS

In profit-maximization GMS, GENCOs decide about maintenance scheduling with the objective of maximizing their profit while ISO dispatches the system and minimizes the operation cost. These two objectives contradict each other and the resulting BLP cannot be simply merged as an SLP (as in section 5.1.3.1) and requires additional attention.

5.1.3.2.1. GMS for each GENCO In profit-maximization GMS, each GENCO at the upper-level problem aims to maximize its profit while ISO seeks minimizing the operational costs at the lower-level. These two objectives oppose each other as correspondingly one increases electricity prices whereas the other one decreases them. In this case study, profit of each GENCO is defined as subtracting cost of power production and maintenance of generators from revenue obtained by selling power, i.e. multiplication of price and power. GMS of each GENCO is formulated as follows:

$$\max_{z} \sum_{t,g \in \Xi(p)} \left\{ \sum_{s} \left[\rho_s (\mu_{t,i,s} q_{t,g,s} - f_g \alpha_g q_{t,g,s} - \beta_g q_{t,g,s} - o_g) \right] - z_{t,g} C_g \right\} \tag{5.3a}$$

$$\mu_{t,i,s} = \frac{1}{\rho_s} \lambda_{1_{\substack{t,i,s \\ i \leftarrow g}}} \qquad \forall t,i,s \tag{5.3b}$$

$$z_{t,g} = z_0 \qquad \forall t,g \notin \Xi(p) \tag{5.3c}$$

$$(5.1b) - (5.1e) \tag{5.3d}$$

$$\min_{q,\theta} \sum_{t,g,s} \left[\rho_s (f_g \alpha_g q_{t,g,s} + \beta_g q_{t,g,s} + o_g) \right] \tag{5.3e}$$

$$(5.1g) - (5.1l) \tag{5.3f}$$

where $\mu_{t,i,s}$ is the locational marginal price at time t, bus i and stochastic scenario s, and obtained through (5.3b) using the Lagrange multiplier (dual variable, $\lambda_{1_{t,i,s}}$) of the power balance equation in (5.1g). The symbol "$i \leftarrow g$" indicates the bus i in which generator unit g is located. At each iteration, the decisions of other GENCOs are considered as fixed, (5.3c).

5.1.3.2.2. Karush–Kuhn–Tucker Conditions To handle the developed conflicting BLP, KKT approach is applied and BLP transforms into an SLP. In order to do this, KKT conditions are derived from the lower-level problem of (5.1f)-(5.1l): stationarity (gradient of Lagrangian with respect to lower-level variables), complementary slackness, primal constraints (original inequalities) and dual constraints [348]. Forming the Lagrangian function ($\mathscr{L}$) provides:

$$\begin{aligned}
\mathscr{L}(q,\theta,\lambda) &= \sum_{t,g,s}\Big[\rho_s(f_g\alpha_g q_{t,g,s}+\beta_g q_{t,g,s}+o_g)\Big]+\sum_{t,i,s}\lambda_{1_{t,i,s}}\Bigg[\sum_{g\in\Upsilon(i)}-q_{t,g,s}\\
&+\sum_{j\in\Theta(i)}\frac{(\theta_{t,i,s}-\theta_{t,j,s})}{X_{i,j}}+D_{t,i,s}\Bigg]+\sum_{t<N_t,g,s}\lambda_{2_{t,g,s}}\Big[q_{t+1,g,s}-q_{t,g,s}-\overline{Q}_g\Big]\\
&+\sum_{t<N_t,g,s}\lambda_{3_{t,g,s}}\Big[q_{t,g,s}-q_{t+1,g,s}-\underline{Q}_g\Big]+\sum_{t,i,j\in\Theta(i),s}\lambda_{4_{t,i,j,s}}\Bigg[\frac{(\theta_{t,i,s}-\theta_{t,j,s})}{X_{i,j}}-F_{i,j}\Bigg]\\
&+\sum_{t,g,s}\lambda_{5_{t,g,s}}\Big[q_{t,g,s}-(1-z_{t,g})Q_{t,g}\Big]+\sum_{t,g,s}\lambda_{6_{t,g,s}}(-q_{t,g,s})
\end{aligned}\tag{5.4}$$

Stationarity conditions are written as follows:

$$\frac{\partial\mathscr{L}(q,\theta,\lambda)}{\partial q}=\rho_s(f_g\alpha_g+\beta_g)-\lambda_{1_{t,i,s}\atop i\leftarrow g}-\lambda_{2_{t,g,s}}+\lambda_{3_{t,g,s}}+\lambda_{5_{t,g,s}}-\lambda_{6_{t,g,s}}=0 \qquad \forall t=1,g,s \tag{5.5}$$

$$\frac{\partial\mathscr{L}(q,\theta,\lambda)}{\partial q}=\rho_s(f_g\alpha_g+\beta_g)-\lambda_{1_{t,i,s}\atop i\leftarrow g}+\lambda_{2_{t-1,g,s}}-\lambda_{2_{t,g,s}}-\lambda_{3_{t-1,g,s}}+\lambda_{3_{t,g,s}}+\lambda_{5_{t,g,s}}-\lambda_{6_{t,g,s}}=0 \qquad \forall t\in(1,N_t),g,s \tag{5.6}$$

$$\frac{\partial\mathscr{L}(q,\theta,\lambda)}{\partial q}=\rho_s(f_g\alpha_g+\beta_g)-\lambda_{1_{t,i,s}\atop i\leftarrow g}+\lambda_{2_{t-1,g,s}}-\lambda_{3_{t-1,g,s}}+\lambda_{5_{t,g,s}}-\lambda_{6_{t,g,s}}=0 \qquad \forall t=N_t,g,s \tag{5.7}$$

$$\frac{\partial\mathscr{L}(q,\theta,\lambda)}{\partial \theta}=\sum_{j\in\Theta(i)}\frac{(\lambda_{1_{t,i,s}}-\lambda_{1_{t,j,s}})}{X_{i,j}}+\sum_{j\in\Theta(i)}\frac{(\lambda_{4_{t,i,j,s}}-\lambda_{4_{t,j,i,s}})}{X_{i,j}}=0 \qquad \forall t,i,s \tag{5.8}$$

And from complementarity conditions:

$$\lambda_{2_{t,g,s}}\Big(q_{t+1,g,s}-q_{t,g,s}-\overline{Q}_g\Big)=0 \qquad \forall t<N_t,g,s \tag{5.9}$$

$$\lambda_{3_{t,g,s}}\Big(q_{t,g,s}-q_{t+1,g,s}-\underline{Q}_g\Big)=0 \qquad \forall t<N_t,g,s \tag{5.10}$$

$$\lambda_{4_{t,i,j,s}}\left(\frac{(\theta_{t,i,s}-\theta_{t,j,s})}{X_{i,j}}-F_{i,j}\right)=0 \qquad \forall t,i,j\in\Theta(i),s \tag{5.11}$$

$$\lambda_{5_{t,g,s}}\Big(q_{t,g,s}-(1-z_{t,g})Q_{t,g}\Big)=0 \qquad \forall t,g,s \tag{5.12}$$

$$\lambda_{6_{t,g,s}}(-q_{t,g,s})=0 \qquad \forall t,g,s \tag{5.13}$$

The complementarity conditions (5.9)-(5.13) include nonlinearities. One way to linearize these nonlinearities is by defining new additional binary variables through disjunctive constraints [349]. Since one of the goals of this case study is to obtain an NE solution for the GMS problem, these new binary variables extremely complicate the problem and a solution may not be reachable. Since the lower-level problem, (5.1f)-(5.1l), is convex, as the unit commitment decisions (start-up and shut-down) are not considered and $z_{t,g,s}$ in (5.1k) acts as a parameter, these complementarity conditions are substituted by strong duality equation as follows:

$$\begin{aligned}
&\sum_{t,g,s}\Big[\rho_s(f_g\alpha_g q_{t,g,s}+\beta_g q_{t,g,s}+o_g)\Big]=\sum_{t,g,s}\rho_s o_g+\sum_{t,i,s}\lambda_{1_{t,i,s}}D_{t,i,s}\\
&-\sum_{t,i,j\in\Theta(i),s}\lambda_{4_{t,i,j,s}}F_{i,j}-\sum_{t<N_t,g,s}\Big[\lambda_{2_{t,g,s}}\overline{Q}_g+\lambda_{3_{t,g,s}}\underline{Q}_g\Big]\\
&-\sum_{t,g,s}\lambda_{5_{t,g,s}}(1-z_{t,g})Q_{t,g}
\end{aligned} \tag{5.14}$$

Now, the BLP has been converted into an SLP in the following form:

$$\max_{z,q,\theta}\ \sum_{t,g\in\Xi(p)}\left\{\sum_s\Big[\rho_s(\mu_{t,i,s}q_{t,g,s}-f_g\alpha_g q_{t,g,s}-\beta_g q_{t,g,s}-o_g)\Big]-z_{t,g}C_g\right\} \tag{5.15a}$$

$$(5.1b)-(5.1e),(5.1g)-(5.1l),(5.3b),(5.3c),(5.5)-(5.8),(5.14) \tag{5.15b}$$

The obtained SLP has two nonlinear terms which can be linearized. One nonlinearity is in the last term of the strong duality (5.14), $\lambda_{5_{t,g,s}}(1-z_{t,g})$ and the other one is in the objective function in (5.15a), $\lambda_{1_{t,i,s}}q_{t,g,s}$, which comes from (5.3b). In order to linearize $\lambda_{5_{t,g,s}}(1-z_{t,g})$, at first, this term is substituted by a new variable as [350]:

$$\lambda'_{t,g,s}=\lambda_{5_{t,g,s}}(1-z_{t,g}) \tag{5.16}$$

Afterwards, three following constraints need to be added to (5.15) as the equivalent of the nonlinear term in order to ensure correct transformation:

$$\lambda'_{t,g,s}\le(1-z_{t,g})M_1 \qquad \forall t,g,s \tag{5.17}$$

$$\lambda_{5_{t,g,s}}-\lambda'_{t,g,s}\le\Big(1-(1-z_{t,g})\Big)M_1 \qquad \forall t,g,s \tag{5.18}$$

$$\lambda_{5_{t,g,s}}-\lambda'_{t,g,s}\ge-\Big(1-(1-z_{t,g})\Big)M_1 \qquad \forall t,g,s \tag{5.19}$$

where M_1 is a large positive constant ("bigM") [349].

To linearize $\lambda_{1_{t,i,s}} q_{t,g,s}$, at first, stationarity conditions (5.5)-(5.7) are multiplied by $q_{t,g,s}$ and are summed for each portfolio:

$$\sum_{t,g\in\Xi(p),s}\Big[\rho_s(\frac{1}{\rho_s}\underset{i\leftarrow g}{\lambda_{1_{t,i,s}}} q_{t,g,s} - f_g\alpha_g q_{t,g,s} - \beta_g q_{t,g,s})\Big] = \sum_{g\in\Xi(p),s}\Big[-q_{1,g,s}\lambda_{2_{1,g,s}} + q_{1,g,s}\lambda_{3_{1,g,s}} + q_{1,g,s}\lambda_{5_{1,g,s}} - q_{1,g,s}\lambda_{6_{1,g,s}} + \sum_{t\in(1,N_t)}\Big(q_{t,g,s}\lambda_{2_{t-1,g,s}} - q_{t,g,s}\lambda_{2_{t,g,s}} + q_{t,g,s}\lambda_{3_{t,g,s}} - q_{t,g,s}\lambda_{3_{t-1,g,s}} + q_{t,g,s}\lambda_{5_{t,g,s}} - q_{t,g,s}\lambda_{6_{t,g,s}}\Big) + q_{N_t,g,s}\lambda_{2_{N_t-1,g,s}} - q_{N_t,g,s}\lambda_{3_{N_t-1,g,s}} + q_{N_t,g,s}\lambda_{5_{N_t,g,s}} - q_{N_t,g,s}\lambda_{6_{N_t,g,s}}\Big] \tag{5.20}$$

It should be noted here that in order to create the terms required for the linearization, (5.20) is divided into three time periods of $t=1$, $t\in(1,N_t)$ and $t=N_t$. Moreover, after the multiplication, the terms $\rho_s(f_g\alpha_g+\beta_g)-\lambda_{1_{t,i,s}}$ in (5.5)-(5.7) are moved to the other side of the equality and then factored by ρ_s. Next, through complementarity slackness conditions (5.9) and (5.10) (re-written in similar three time periods), and substituting (5.3b), (5.12), (5.13) and (5.16) into (5.20), the right-hand side renders in:

$$\sum_{t,g\in\Xi(p),s}\Big[\rho_s(\mu_{t,i,s} q_{t,g,s} - f_g\alpha_g q_{t,g,s} - \beta_g q_{t,g,s})\Big] = \sum_{t<N_t,g\in\Xi(p),s}\Big(\lambda_{2_{t,g,s}}\overline{Q}_g + \lambda_{3_{t,g,s}}\underline{Q}_g\Big) + \sum_{t,g\in\Xi(p),s}\lambda'_{t,g,s}Q_{t,g} \tag{5.21}$$

which forms the linear equivalent of the nonlinear terms in objective function (5.15a).

Using (5.21), (5.15) transforms into the final linearized SLP with portfolio of GENCOs and stochastic terms:

$$\max_{z,q,\theta} \sum_{t<N_t,g\in\Xi(p),s}\Big[\rho_s(\lambda_{2_{t,g,s}}\overline{Q}_g + \lambda_{3_{t,g,s}}\underline{Q}_g)\Big] + \sum_{t,g\in\Xi(p)}\Big[\sum_s \rho_s(\lambda'_{t,g,s}Q_{t,g} - o_g) - z_{t,g}C_g\Big] \tag{5.22a}$$

$$\mu_{t,i,s} = \frac{1}{\rho_s}\underset{i\leftarrow g}{\lambda_{1_{t,i,s}}} \qquad \forall t,i,s \tag{5.22b}$$

$$z_{t,g} = z_0 \qquad \forall t,g\notin\Xi(p) \tag{5.22c}$$

$$\sum_t z_{t,g} - T_g = 0 \qquad \forall g \tag{5.22d}$$

$$\sum_g z_{t,g} - Z \le 0 \qquad \forall t \tag{5.22e}$$

$$z_{t,g} = 0 \qquad \forall t > N_t, g \tag{5.22f}$$

$$z_{t+1,g} - z_{t,g} - z_{t+T_g,g} \le 0 \qquad \forall t < N_t, g \tag{5.22g}$$

$$- \sum_{g\in\Upsilon(i)} q_{t,g,s} + \sum_{j\in\Theta(i)} \frac{(\theta_{t,i,s}-\theta_{t,j,s})}{X_{i,j}} + D_{t,i,s} = 0 : \lambda_{1_{t,i,s}} \quad \forall t,i,s \tag{5.22h}$$

$$q_{t+1,g,s} - q_{t,g,s} - \overline{Q}_g \le 0 : \lambda_{2_{t,g,s}} \quad \forall t < N_t, g, s \tag{5.22i}$$

$$q_{t,g,s} - q_{t+1,g,s} - \underline{Q}_g \le 0 : \lambda_{3_{t,g,s}} \quad \forall t < N_t, g, s \tag{5.22j}$$

$$\frac{(\theta_{t,i,s}-\theta_{t,j,s})}{X_{i,j}} - F_{i,j} \le 0 : \lambda_{4_{t,i,j,s}} \quad \forall t,i,j \mid j\in\Theta(i), s \tag{5.22k}$$

$$q_{t,g,s} - (1-z_{t,g})Q_{t,g} \le 0 : \lambda_{5_{t,g,s}} \quad \forall t,g,s \tag{5.22l}$$

$$- q_{t,g,s} \le 0 : \lambda_{6_{t,g,s}} \quad \forall t,g,s \tag{5.22m}$$

$$\rho_s(f_g\alpha_g+\beta_g) - \lambda_{\substack{1_{t,i,s}\\ i\leftarrow g}} - \lambda_{2_{t,g,s}} + \lambda_{3_{t,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0 \quad \forall t=1,g,s \tag{5.22n}$$

$$\rho_s(f_g\alpha_g+\beta_g) - \lambda_{\substack{1_{t,i,s}\\ i\leftarrow g}} + \lambda_{2_{t-1,g,s}} - \lambda_{2_{t,g,s}} - \lambda_{3_{t-1,g,s}} + \lambda_{3_{t,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0 \quad \forall t\in(1,N_t), g, s \tag{5.22o}$$

$$\rho_s(f_g\alpha_g+\beta_g) - \lambda_{\substack{1_{t,i,s}\\ i\leftarrow g}} + \lambda_{2_{t-1,g,s}} - \lambda_{3_{t-1,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0 \quad \forall t=N_t, g, s \tag{5.22p}$$

$$\sum_{j\in\Theta(i)} \frac{(\lambda_{1_{t,i,s}}-\lambda_{1_{t,j,s}})}{X_{i,j}} + \sum_{j\in\Theta(i)} \frac{(\lambda_{4_{t,i,j,s}}-\lambda_{4_{t,j,i,s}})}{X_{i,j}} = 0 \quad \forall t,i,s \tag{5.22q}$$

$$\begin{aligned}\sum_{t,g,s}\Big[\rho_s(f_g\alpha_g q_{t,g,s}+o_g+\beta_g q_{t,g,s})\Big] &= \sum_{t,g,s}\rho_s o_g + \sum_{t,i,s}\lambda_{1_{t,i,s}}D_{t,i,s}\\ &- \sum_{t<N_t,g,s}\Big[\lambda_{2_{t,g,s}}\overline{Q}_g + \lambda_{3_{t,g,s}}\underline{Q}_g\Big] - \sum_{t,i,j\in\Theta(i),s}\lambda_{4_{t,i,j,s}}F_{i,j}\\ &- \sum_{t,g,s}\lambda_{5_{t,g,s}}(1-z_{t,g})Q_{t,g}\end{aligned} \tag{5.22r}$$

$$\lambda'_{t,g,s} \le (1-z_{t,g})M_1 \quad \forall t,g,s \tag{5.22s}$$

$$\lambda_{5_{t,g,s}} - \lambda'_{t,g,s} \le \Big(1-(1-z_{t,g})\Big)M_1 \quad \forall t,g,s \tag{5.22t}$$

$$\lambda_{5_{t,g,s}} - \lambda'_{t,g,s} \ge -\Big(1-(1-z_{t,g})\Big)M_1 \quad \forall t,g,s \tag{5.22u}$$

The above problem is a MILP which can be solved with available commercial software.

5.1.3.2.3. Nash Equilibrium Each GENCO seeks maximizing its profit individually by abiding with the constraints imposed by regulatory bodies. Such situation constructs a multiple-leaders single-follower game [351]. While the follower in this game is ISO, GENCOs are the leaders which are assumed to compete non-cooperatively. The players are considered to have complete information which means they know the strategy space of one another in the game.

In this regard, NE solution concept is defined as a set of strategies of GENCOs where no GENCO is able to increase its profit by individually deviating from that strategy.

Hence, decisions of all GENCOs are in an NE. In this context, strategies of GENCOs are their maintenance decisions. To formulate this equilibrium point, NE strategy vector W is defined as (5.23). In order to obtain such condition, the solution needs to result in:

$$W = \{w_1^*, w_2^*, ..., w_{N_p}^*\} \tag{5.23}$$

$$\Pi_p(w_p^* \mid w_{-p}^*) \geq \Pi_p(w_p \mid w_{-p}^*) \qquad \forall p, w_p \tag{5.24}$$

where Π_p is profit of GENCO p as objective function in (5.22).

NE is mathematically obtained by iteratively solving (5.22) for each GENCO until a point where no GENCO tries to change its strategy which conceptually is the result of simultaneous play of the game. In this problem, there is possibility that multiple Nash equilibria points exist. In this case study, the first NE found is considered. To find the other Nash equilibria, if there are any, the solution can be repeated by removing the already found NE and start from a different initial point.

5.1.3.3. Rescheduling Signal

The derived SLP in (5.2), cost-minimization GMS, solves GMS from perspective of ISO with the objective of minimizing operation and maintenance costs. The OC and ENS outcomes of this GMS are the reference for regulatory decisions of ISO. In this case study, multiplication of a weighting factor into the ENS and OC obtained from cost-minimization GMS are considered as regulatory limits of ISO in profit-maximization GMS. The OC and ENS outcomes of the profit-maximization GMS may violate these regulatory limits and when they are violated, a rescheduling signal, consisting of two terms of penalty and incentive, is issued to each GENCO in order to motivate them to modify their decisions. In this case study, two types of penalty and incentive (based on OC and ENS) for rescheduling signals are defined. While penalty- and incentive-type1 contemplate the limit for ENS ($\Psi_{ENS}, \mho_{ENS}$), penalty- and incentive-type2 consider the limit for OC ($\Psi_{OC}, \mho_{OC}$). It should be noted that these signals are calculated at the end of each obtained NE and thus, act as a parameter in the next iteration. The formulation for penalty-type1 is as follows:

$$\Psi_{ENS,k} = \frac{v_{ENS}}{N_g}(ENS_{NE,k-1} - ENS_{CM}) \qquad \forall k > 1 \tag{5.25}$$

where $ENS_{NE,k-1}$ is the resultant ENS of the NE in previous iteration for the profit-maximization GMS, ENS_{CM} is the resultant ENS for the cost-minimization GMS, and v_{ENS} is the weighting factor of reliability penalty signal estimated for each network configuration. The same formulation can be derived for $\Psi_{OC}, \mho_{ENS}$ and $\mho_{OC}$.

A binary variable c is defined where 0 and 1 correspondingly mean receiving incentive or penalty. To obtain the value of c for each GENCO at every iteration, additional constraints and terms are required as follows:

$$1 - z_{t,g} = b1_{k,g} \qquad \forall t = t'_{k,g}, g, k \tag{5.26}$$

$$1 - z_{t,g} = b2_{k,g} \qquad \forall t = t'_{k,g} - T_g + 1, g, k \tag{5.27}$$

$$a_k - 1 \leq \sum_{g \in \Xi(p)} [b1_{k,g} + b2_{k,g}] M_2 \qquad \forall k \tag{5.28}$$

$$a_k - 1 \geq - \sum_{g \in \Xi(p)} [b1_{k,g} + b2_{k,g}] M_2 \qquad \forall k \tag{5.29}$$

$$c \geq a_k \qquad \forall k \tag{5.30}$$

where $t'_{k,g}$ is the last hour the generator g was under maintenance in iteration k, and M_2 is a sufficiently enough large number ("bigM").

If the reliability or economic limits are violated at iteration k, a rescheduling signal is created and (5.26)-(5.30) prepare the penalty or incentive in the current iteration based on the recorded maintenance decisions in previous iterations. For instance, if the signals are violated and the maintenance decision in iteration k is the same as a maintenance decision in any of the past iterations, c becomes 1 and a penalty is issued. In case the signals are violated and the maintenance decision in iteration k is not the same as any maintenance decisions in the past iterations, c becomes 0 and an incentive is issued. The goal here is to encourage GENCOs to bring the ENS and OC lower than the limits by changing their maintenance schedules in order to satisfy the ISO requirements.

In this regard, at each iteration k, constraint (5.26) reminds the times of previous iterations when the maintenance of generator g finished; in other words, the last time periods where $z_{t,g}$ was equal to 1. Similarly, constraint (5.27) reminds the first time when the $z_{t,g}$ was equal to 1, i.e. the maintenance started. Then at iteration k, if generator g decides to choose the same maintenance decision as any of the previous iterations, this would result in the same start and end maintenance times. Such behavior by the generator triggers binary variables of b_1 and b_2 to become 0. Constraints (5.28) and (5.29) ensure that the binary variable a_k turns 1 whenever a generator repeats its maintenance decision. In such cases, constraint (5.30) enforces the binary variable c to order the penalty signal. If b_1 and b_2 are 1 for each iteration, the constrains on a_k, (5.28) and (5.29), are relaxed causing a_k to be 0. Consequently, c becomes 0 where it offers incentive to GENCOs in order to motivate them to choose a new maintenance schedule. In order to summarize the profit-maximization model, the steps are illustrated in Figure 5.2.

Finally, the complete SLP formulation of profit-maximization GMS of GENCOs with penalty and incentive is as follows:

$$\begin{aligned} \max_{z,q,\theta} \sum_{t<N_t, g \in \Xi(p), s} & \left[\rho_s (\lambda_{2_{t,g,s}} \overline{Q}_g + \lambda_{3_{t,g,s}} \underline{Q}_g) \right] \\ & + \sum_{t, g \in \Xi(p)} \left[\sum_s \rho_s (\lambda'_{t,g,s} Q_{t,g} - o_g) - z_{t,g} C_g - c \, \Psi_{ENS} + (1-c) \, \mho_{ENS} \right] \end{aligned} \tag{5.31a}$$

$$\mu_{t,i,s} = \frac{1}{\rho_s} \lambda_{1_{\substack{t,i,s\\ i \leftarrow g}}} \qquad \forall t,i,s \tag{5.31b}$$

$$z_{t,g} = z_0 \qquad \forall t, g \notin \Xi(p) \tag{5.31c}$$

$$\sum_t z_{t,g} - T_g = 0 \qquad \forall g \tag{5.31d}$$

$$\sum_g z_{t,g} - Z \leq 0 \qquad \forall t \tag{5.31e}$$

$$z_{t,g} = 0 \qquad \forall t > N_t, g \tag{5.31f}$$

$$z_{t+1,g} - z_{t,g} - z_{t+T_g,g} \leq 0 \qquad \forall t < N_t, g \tag{5.31g}$$

$$-\sum_{g \in \Upsilon(i)} q_{t,g,s} + \sum_{j \in \Theta(i)} \frac{(\theta_{t,i,s} - \theta_{t,j,s})}{X_{i,j}} + D_{t,i,s} = 0 : \lambda_{1_{t,i,s}} \quad \forall t,i,s \tag{5.31h}$$

$$q_{t+1,g,s} - q_{t,g,s} - \overline{Q}_g \leq 0 : \lambda_{2_{t,g,s}} \qquad \forall t < N_t, g, s \tag{5.31i}$$

$$q_{t,g,s} - q_{t+1,g,s} - \underline{Q}_g \leq 0 : \lambda_{3_{t,g,s}} \qquad \forall t < N_t, g, s \tag{5.31j}$$

$$\frac{(\theta_{t,i,s} - \theta_{t,j,s})}{X_{i,j}} - F_{i,j} \leq 0 : \lambda_{4_{t,i,j,s}} \qquad \forall t, i, j \mid j \in \Theta(i), s \tag{5.31k}$$

$$q_{t,g,s} - (1 - z_{t,g}) Q_{t,g} \leq 0 : \lambda_{5_{t,g,s}} \qquad \forall t, g, s \tag{5.31l}$$

$$-q_{t,g,s} \leq 0 : \lambda_{6_{t,g,s}} \qquad \forall t, g, s \tag{5.31m}$$

$$\rho_s (f_g \alpha_g + \beta_g) - \lambda_{1_{\substack{t,i,s\\ i \leftarrow g}}} - \lambda_{2_{t,g,s}} + \lambda_{3_{t,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0 \qquad \forall t = 1, g, s \tag{5.31n}$$

$$\rho_s (f_g \alpha_g + \beta_g) - \lambda_{1_{\substack{t,i,s\\ i \leftarrow g}}} + \lambda_{2_{t-1,g,s}} - \lambda_{2_{t,g,s}} - \lambda_{3_{t-1,g,s}} + \lambda_{3_{t,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0$$

$$\forall t \in (1, N_t), g, s \tag{5.31o}$$

$$\rho_s (f_g \alpha_g + \beta_g) - \lambda_{1_{\substack{t,i,s\\ i \leftarrow g}}} + \lambda_{2_{t-1,g,s}} - \lambda_{3_{t-1,g,s}} + \lambda_{5_{t,g,s}} - \lambda_{6_{t,g,s}} = 0 \quad \forall t = N_t, g, s \tag{5.31p}$$

$$\sum_{j \in \Theta(i)} \frac{(\lambda_{1_{t,i,s}} - \lambda_{1_{t,j,s}})}{X_{i,j}} + \sum_{j \in \Theta(i)} \frac{(\lambda_{4_{t,i,j,s}} - \lambda_{4_{t,j,i,s}})}{X_{i,j}} = 0 \qquad \forall t, i, s \tag{5.31q}$$

$$\begin{aligned}
\sum_{t,g,s} \Big[\rho_s (f_g \alpha_g q_{t,g,s} + o_g + \beta_g q_{t,g,s}) \Big] &= \sum_{t,g,s} \rho_s o_g + \sum_{t,i,s} \lambda_{1_{t,i,s}} D_{t,i,s} \\
&- \sum_{t < N_t, g, s} \Big[\lambda_{2_{t,g,s}} \overline{Q}_g + \lambda_{3_{t,g,s}} \underline{Q}_g \Big] - \sum_{t,i,j \in \Theta(i), s} \lambda_{4_{t,i,j,s}} F_{i,j} \\
&- \sum_{t,g,s} \lambda_{5_{t,g,s}} (1 - z_{t,g}) Q_{t,g}
\end{aligned} \tag{5.31r}$$

$$\lambda'_{t,g,s} \leq (1 - z_{t,g}) M_1 \qquad \forall t, g, s \tag{5.31s}$$

$$\lambda_{5_{t,g,s}} - \lambda'_{t,g,s} \leq \Big(1 - (1 - z_{t,g})\Big) M_1 \qquad \forall t, g, s \tag{5.31t}$$

$$\lambda_{5_{t,g,s}} - \lambda'_{t,g,s} \geq -\Big(1 - (1 - z_{t,g})\Big) M_1 \qquad \forall t, g, s \tag{5.31u}$$

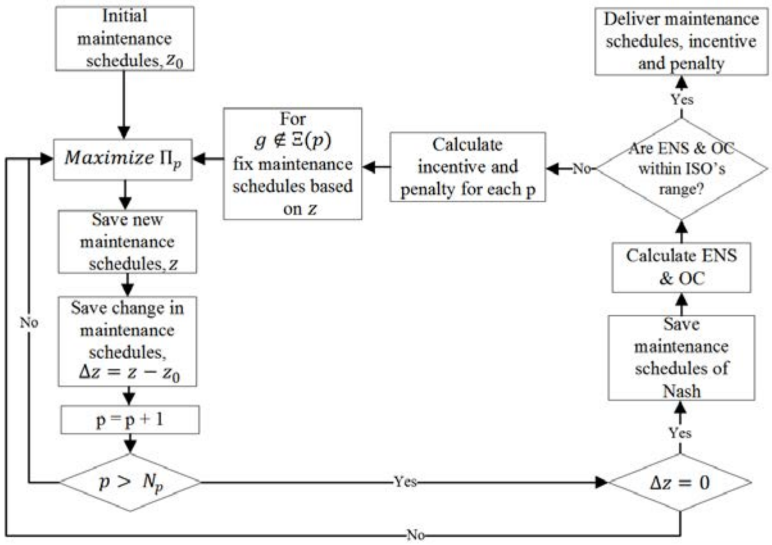


Figure 5.2: Summarized flowchart of the proposed profit-maximization GMS model

$$1 - z_{t,g} = b_{1_{k,g}} \qquad \forall t = t'_{k,g}, g, k \tag{5.31v}$$
$$1 - z_{t,g} = b_{2_{k,g}} \qquad \forall t = t'_{k,g} - T_g + 1, g, k \tag{5.31w}$$
$$a_k - 1 \leq \sum_{g \in \Xi(p)} [b_{1_{k,g}} + b_{2_{k,g}}] M_2 \qquad \forall k \tag{5.31x}$$
$$a_k - 1 \geq - \sum_{g \in \Xi(p)} [b_{1_{k,g}} + b_{2_{k,g}}] M_2 \qquad \forall k \tag{5.31y}$$
$$c \geq a_k \qquad \forall k \tag{5.31z}$$

where (5.31) can be similarly written for OC.

The original contributions of the proposed model with respect to previous approaches are summarized as following: the prices are considered endogenous to the model as compared to the previous studies where the prices are predicated and given. In addition, transmission constraints, ramp rates of generation units, stochasticity of demand and variability in RES are accounted for. Moreover, to introduce limits of regulations from perspective of system into the model, two new signals are formulated. The first signal addresses the reliability perspective (ENS) and the second signal attends to the economic (social cost) perspective (OC). Based on these two signals, two incentive and penalty terms are created and issued to the GENCOs in case their results cause violations of the reliability and economic limitations. Finally, to find the outcome for the GENCOs that satisfy both of the imposed restrictions by the ISO and deliver an optimum profit solution for all, a game theoretic NE solution is obtained.

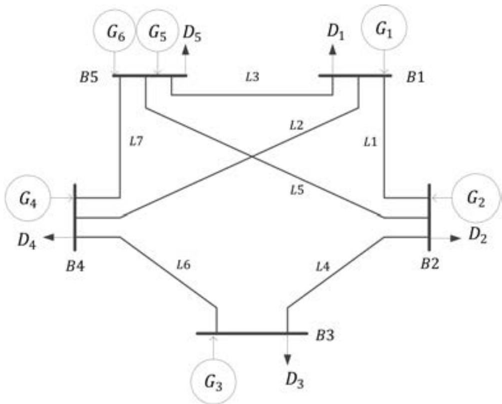


Figure 5.3: The utilized 5-bus test system

5.1.4. Case Study

5.1.4.1. Test System

The models (5.2), (5.22) and (5.31) are coded in GAMS v24.4.6 [319] and solved using CPLEX v12.6.2 [320] on a machine running with 16 GB of RAM and four Intel i7 2.60 GHz processors. A 5-bus network (Figure 5.3) is defined to demonstrate applicability of the developed GMS model. Buses can be considered as electrical nodes in the electric transmission system, that the incoming and outgoing flows of power should be in balance at any moment, and are denoted by letter B. Generators that produce the electric power in the system are represented by the letter G and are connected to the buses. The generators have constraints such as maximum producible power and upward/downward ramp rates. Similar to the generators, one bulk of demand is considered at each bus and is symbolized by the letter D. Finally, the transmission lines that connect the buses together are indicated by the letter L and have transmission capacity constraints. Details of the generators are provided in Table 5.2. The inductance of transmission lines $L1, L2, L3, L4, L5, L6$ and $L7$ are correspondingly $0.100, 0.280, 0.200, 0.075, 0.300, 0.095$ and 0.200. The capacities of all lines are set to 60 MW. In addition, maximum number of generators that can undergo maintenance simultaneously is set to 3, $Z = 3$, and required number of maintenance actions for all generators is assumed to be 1 over the time period of study, N_t. Although the adopted time unit is hour, the model is generic and can be expanded to the desired time horizon in hourly basis.

5.1.4.2. Cases

In this case study, nine main cases ($C1 - C9$) are designed to address multiple criteria that were mentioned in section 5.1.2 and identified as scientific gaps in this field. Thus, these nine cases focus on strategic maintenance scheduling of generation units under portfolio operations, addition of demand stochasticity and variations of RES, and change in the behavior of the GENCOs when faced with the rescheduling signals received from ISO.

Table 5.2: Operational and maintenance information of generators

Generator	$Q_{t,g}$	$\overline{Q}_g$,$\underline{Q}_g$	α_g	f_g	o_g	β_g	T_g	C_g
G1	85	75	0.1	1	100	1	1	10
G2	85	75	0.3	3	300	3	2	15
G3	85	75	0.5	5	500	5	3	20
G4	85	75	0.7	7	700	7	4	25
G5	85	75	0.9	9	900	9	5	30
G6	80[a]	80	0	0	100	9	3	10

[a] Set based on Figure (5.5)

Table 5.3: Defined case studies

	Type	Portfolio	Rescheduling Signal	Wind	Model
C1	Cost-Min[a]	1	-	-	(5.2)
C2	Prof-Max[b]	1	-	-	(5.22)
C3	Prof-Max	2	-	-	(5.22)
C4	Prof-Max	3	-	✓	(5.22)
C5	Prof-Max	2	ENS	-	(5.31)
C6	Prof-Max	2	OC	-	(5.31)
C7	Prof-Max	2	ENS & OC	-	(5.31)
C8	Prof-Max	4	-	✓	(5.22)
C9	Prof-Max	2	-	-	(5.22)

[a] Cost-Minimization
[b] Profit-Maximization

Table 5.4: Defined portfolios

	Portfolio1	Portfolio2	Portfolio3	Portfolio4
GENCO1	G1	G1, G4, G5	G1, G4, G5	G1, G4, G5
GENCO2	G2	G2, G3	G2, G3	G2, G3, G6
GENCO3	G3	-	G6	-
GENCO4	G4	-	-	-
GENCO5	G5	-	-	-

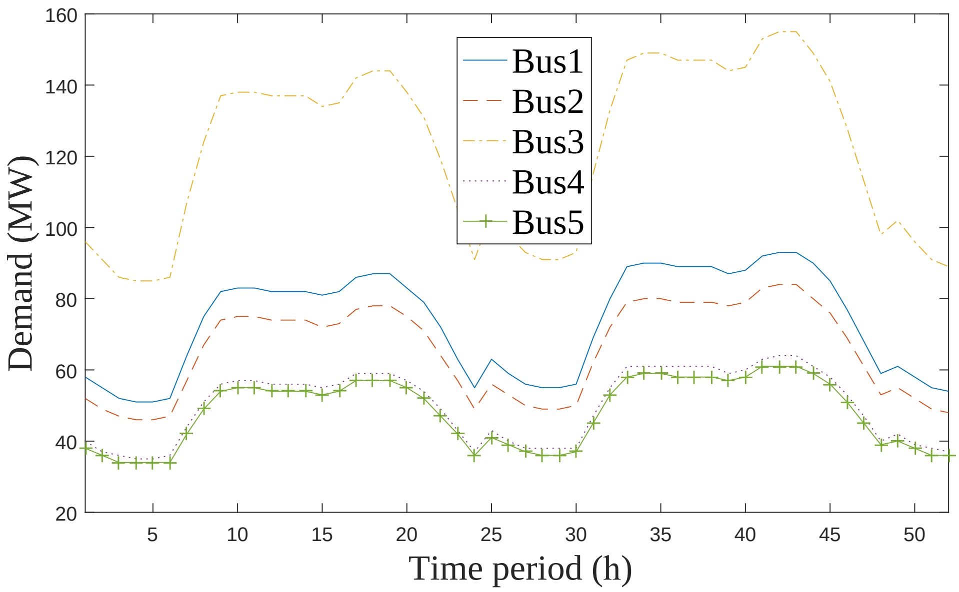


Figure 5.4: Load profile in the test system

Table 5.3 and Table 5.4 show a summary of case studies and the considered portfolios for each case. The distribution of the demand at each bus in the test system during the 52 time periods is illustrated in Figure 5.4.

5.1.4.2.1. Case1 $C1$ is considered as benchmark and the current state-of-the-art algorithm which is created within the cost-minimization framework. In this case all the decisions are made by one entity, ISO.

5.1.4.2.2. Case2 $C2$ is the new proposed formulation where the objective is that all GENCOs try to maximize their profit without considering the newly defined rescheduling signals. Both of these cases apply Portfolio1 which considers that each GENCO has one generation unit, Table 5.4.

5.1.4.2.3. Case3 $C3$ uses the same profit-maximization formulation as in $C2$. $C3$ adds the portfolio weight in the approach and provides insight into the analysis of strategic combined operation of the generation units.

5.1.4.2.4. Case4 $C4$ introduces the wind power integration (G6 with wind-scenario1) for the first time and it considers that the wind farm is entering the market as an independent player, GENCO3, Table 5.4. Such a case provides the possibility to analyze how much decisions of a single renewable player can affect the outcomes of other players.

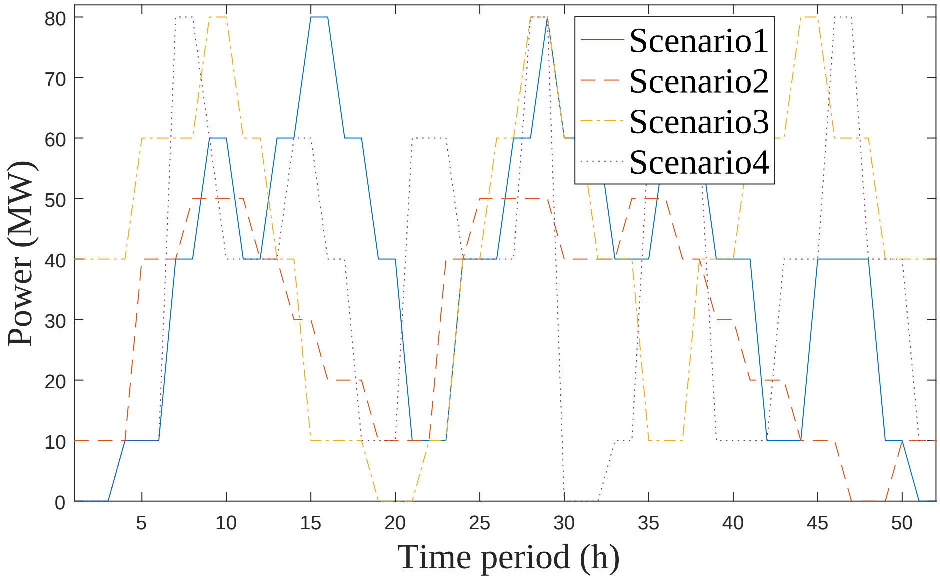


Figure 5.5: Wind profiles for the test system

5.1.4.2.5. Case5 *C*5 considers that a reliability criterion imposes a limit and the rescheduling signal (penalty/incentive) is issued based on whether this reliability limit is violated.

5.1.4.2.6. Case6 *C*6 performs the same analysis as in *C*5 while the reliability signal is substituted by an economic signal.

5.1.4.2.7. Case7 *C*7 incorporates both reliability and economic limits and a rescheduling signal is issued if either of these two limitations are violated. The limits for rescheduling signal, on whether it should be issued, are set to 1.32 and 7.6 times of OC and ENS of cost-minimization GMS, respectively, and are adopted by the ISO based on the prioritized preferences. The values of v_{ENS} and v_{OC} are correspondingly considered to be 1000 and 0.8 for the test system as they produce large enough penalty/incentive terms in the process.

5.1.4.2.8. Case8 In *C*8, impact of variations in wind power is included by defining four distinct wind scenarios as displayed in Figure 5.5. Wind-scenario1 (*C*8.1) is assumed to show a normal behavior (without sudden extreme changes in wind) and mean available power of 38 MW at each time period. Wind-scenario2 (*C*8.2) and Wind-scenario3 (*C*8.3) have the lowest and highest average available wind power of 29 and 43 MW, respectively. Finally, Wind-scenario4 (*C*8.4), despite having an average available wind power of 36 MW, exhibits some extreme behaviors such as falling from maximum to zero.

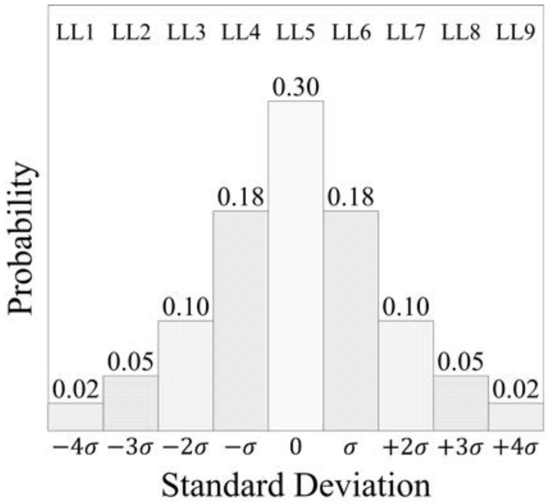


Figure 5.6: Stochasticity defined for demand

5.1.4.2.9. Case9 Demand stochasticity is considered only in $C9$ and variations range from -4 to +4 standard deviations through nine load levels. The probability of each load level is illustrated as in Figure 5.6.

5.1.5. Results

Table 5.5 presents outcomes of all cases in terms of OC, ENS and average electricity price over time period of the study. It should be reminded that the solutions are affected by the initialization and therefore one initial point has been considered in all cases, (5.3c). The problem can be scaled up; however, existence of a NE cannot be guaranteed for any case. The maximum number of iterations in order to reach an answer in the cases was 30. The numbers of iterations are dependent on the coefficients of the network as well as the considered level of reliability and economic limitations.

One observation from Table 5.5 is the distinct difference between $C1$ and $C2$ - $C9$. This shows that strategic behavior of GENCOs affects the outcomes significantly, thus, any analysis based on $C1$ would hold rather large simplifying assumption. Analogously, comparing $C1$ with the rest of the cases through Figure 5.7, it can be seen that GENCO1 schedules the maintenance for its expensive generators (G4 and G5) simultaneously in order to increase the electricity prices. In such situations, the cheap generator of GENCO1 (G1) will produce at maximum capacity and largely increase the profit of GENCO1. Figure 5.8 shows the overall load, prices and maintenance schedules at the market equilibrium point for $C2$. In this case, the Nash solution is obtained where all generators act as an individual company, Portfolio1, Table 5.4.

By comparing $C3$ with $C5$ - $C7$, it can be seen how the network would benefit by incorporating penalty and incentive signals. Since in $C3$ there is neither penalty nor incentive for GENCOs discrediting economic and reliability limitations, results are

Table 5.5: Short summary of cases

Cases	OC (M$)	ENS (MW)	Avg. Price ($/MWh)
C1	3.375	173	25
C2	3.557	372	29
C3	4.489	1390	27
C4	4.150	992	21
C5	4.424	1319	26
C6	4.401	1294	26
C7	4.415	1309	26
C8.1	4.154	996	21
C8.2	4.264	1113	22
C8.3	4.039	869	22
C8.4	4.274	1126	23
C9	4.529	1433	23

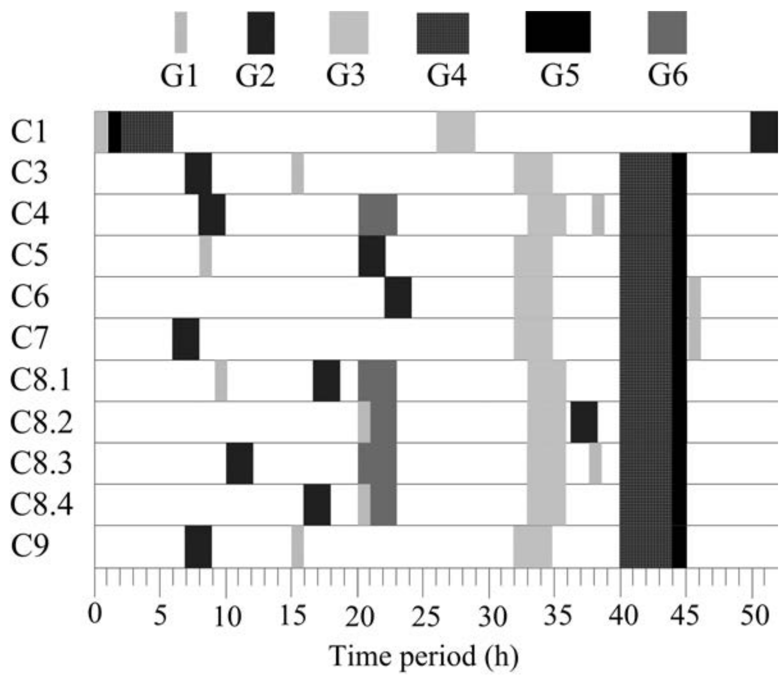


Figure 5.7: Maintenance schedules for $C1, C3-C9$

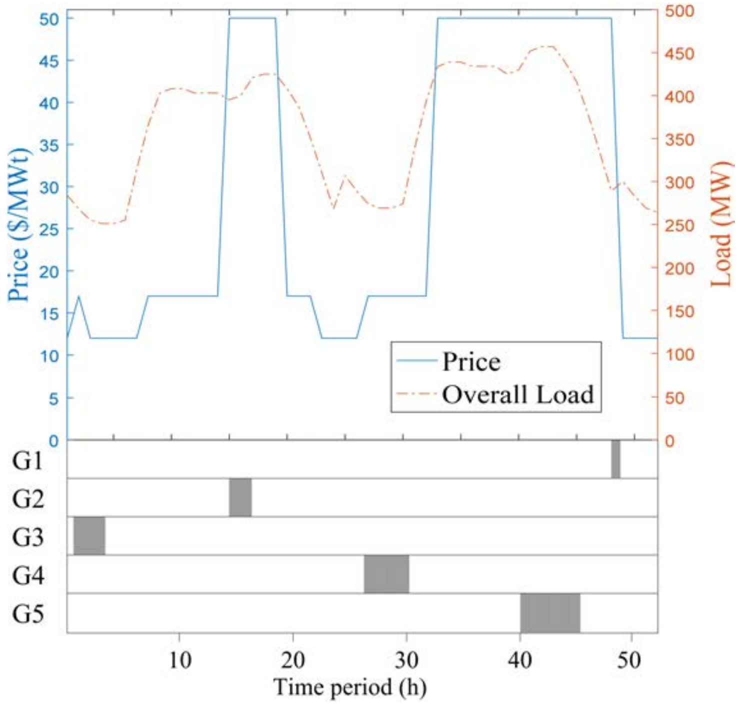


Figure 5.8: Electricity prices and maintenance schedules for *C*2

completely in favor of them with high OC and ENS. In addition, comparison of *C*2 and *C*3 shows OC and ENS increase significantly when the generators join each other (Portfolio1 versus Portfolio2).

A comparison of *C*5 and *C*6 shows that when a rescheduling signal is issued solely based on violation of reliability limit, this results in higher OC and ENS than when the signal is issued solely based on the economic limit. This exhibits that in this test system, a signal based on the economic limit outperforms the one based on the reliability limit in having lower ENS and OC. *C*7 demonstrates a case where ISO requires both the economic and reliability limits explicitly. As seen in Table 5.5, *C*7 results in lower ENS and OC values than *C*5. In case the priorities of economic and reliability limits vary, one could modify the weights accordingly.

Integration of RES (*C*8.1 - *C*8.4) has shown to affect the network by driving ENS, OC and prices down, Figure 5.9. The wind power in this system accounts for 16% of the installed capacity, *G*6 in Table 5.2. To analyze possible impacts of wind in the network, four wind scenarios are defined and tested. Average, low and high availability of wind are considered through scenario1, scenario2 and scenario3 correspondingly and are evaluated through *C*8.1, *C*8.2 and *C*8.3, respectively. Table 4.4 indicates that the average and high wind power affect average prices less than ENS and OC. From Figure 5.7, it can be seen that maintenance actions of expensive generators are scheduled at the same time and all on the time periods with the highest demand levels.

*C*4 investigates a case where a new renewable generator (*G*6 with wind-scenario1) enters

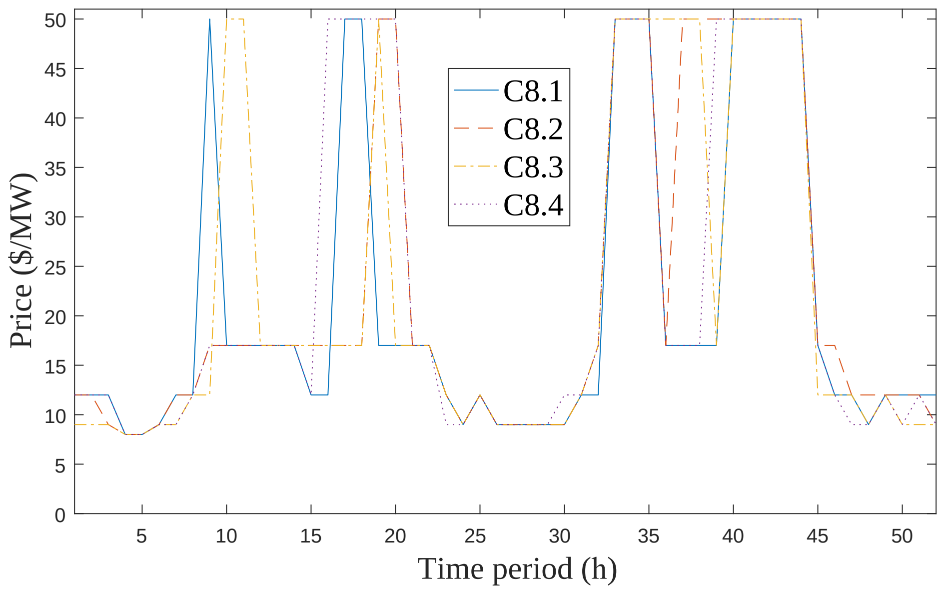


Figure 5.9: Electricity prices for the case 8

the market as an individual company in comparison with when it joins one of the GENCOs, GENCO2 as in $C8.1$. Interestingly, the results of $C8.1$ show that both GENCOs 1 and 2 gain more profit if $G6$ is acquired by GENCO2. The profit of GENCO1 increases by 0.6% and the profit of GENCO2 increases by 29%.

Furthermore, following extreme changes in the wind power, scenario4, two main observations are made. One is a sudden large increase in availability of wind power, scenario4 in Figure 5.5 and at time $t = 6$, which has resulted in no reduction in prices. The other one is a sharp reduction at time $t = 30$ in wind power. This decrease made same reflection on the prices. It should be noted that at both of these times, $t = 6$ and $t = 30$, the demand level is very similar and has low levels. In addition, comparison between $C8.1$ and $C8.4$ displays that sudden extreme behaviors of wind affect average price of the system, ENS and OC even more than a normal low wind availability.

Table 5.6 displays the profit of GENCOs. At first, it can be seen that in the final schedules of maintenance, GENCOs find solutions where none of them receives any penalty. Since the incentives are for satisfying the constraints set by ISO, they are taken from the social welfare to achieve these ENS and OC targets. In $C5$ where the rescheduling signal is issued from violation of reliability limit, both GENCOs gain more profit than when the rescheduling signal is issued from violation of economic limit. $C6$ and $C7$ result in the same profit since the economic limit plays the key role by setting more strict restrictions on maintenance decisions. An important remark is to note the difference in the leading GENCO through cases embedded with wind RES. When availability of wind is average and high, $C8.1$ and $C8.3$ respectively, GENCO2 earns more profit while, when the availability of wind is low, $C8.2$, GENCO1 secures more profit. This is a noteworthy outcome which demonstrates how the change in availability of wind can switch the position of prominent GENCOs. Note that there is no rescheduling signal (penalty or incentive) in $C4$.

All the considered nine case studies were solved in less than 10 minutes with C9 requiring the highest computational time. Since the proposed model includes disjunctive constraints in the form of "bigM", it requires high computational power and proper adjustment of the "bigM" [352, 353]. Several difficulties may rise when larger test systems are considered. Some of these difficulties are:

- A large scale problem will take very long time to solve, if possible at all, with current configurations.
- In a large scale model, it will also be extremely difficult, if possible at all, to assess strategic behaviors of players as the number of decisions variables influencing one another increases significantly. Thus, the proposed model is suitable in order to gain insight on the strategic operations and learn about the outcomes.
- An NE solution does not exist for every system.

On these points, three main proposals can be applied here:

- Use of snapshots
- Use of dimensionality reduction techniques
- Use of decomposition techniques

These three methods of solving large scale problems are gaining attention as the systems are becoming more integrated. Due to diffusion of smart grids, the number of variables in the system increases significantly and it becomes impossible to account for all of them in the analysis. For instance, in the first proposal, this case study benefits from a very simplified version of utilizing four snapshots of different profiles of wind power. Each profile can be formed in order to assess one aspect of a real situation. There are several research works in similar fields which are applying snapshots in their calculations [354, 355]. Similarly, there are studies trying to address large scale systems through different reduction techniques which build a smaller equivalent of a large scale system (e.g. less number of generators, shorter time horizon) [356, 357]. Finally, application of decomposition techniques (e.g. Benders decomposition [358, 359]) could be applied here which may require additional simplifications. Therefore, future studies can further analyze the model through the mentioned points to overcome such obstacles and evaluate their outcomes.

5.1.6. Case Study Conclusion

This case study derives formulation for solving GMS of non-cooperative GENCOs through game theory. The problem is addressed by developing a BLP and transforming it into an SLP using KKT optimality conditions. Afterwards, two rescheduling signals are defined to coordinate the conflicting situation between GENCOs and ISO. These

Table 5.6: Profit and incentive of each GENCO for all cases (M$)

	GENCO1		GENCO2		GENCO3
	Profit	Incentive	Profit	Incentive	Profit
C3	3.323	-	2.495	-	-
C4	1.482	-	1.245	-	0.367
C5	3.099	0.249	2.339	0.246	-
C6	2.858	0.179	2.263	0.179	-
C7	2.858	0.444	2.263	0.444	-
C8.1	1.491	-	1.602	-	-
C8.2	1.932	-	1.859	-	-
C8.3	2.078	-	2.146	-	-
C8.4	2.162	-	1.956	-	-
C9	3.061	-	2.318	-	-

signals favor in two different aspects of ENS and OC limits required by the system operator. Therefore, a combination of these signals is also presented to propose a trade-off among them. Moreover, wind variations as well as demand stochasticity are considered. Multiple case studies have been defined in order to address the improvements of the proposed model over the current available approaches in the field of GMS. These cases include RES integration degree, locational marginal prices and strategic portfolio behavior as well as the aforementioned reliability and economic considerations. The results indicate that strategic behavior of GENCOs significantly affects the outcomes such as prices, OC and ENS. Additionally, the results show that if solely one of the signals of OC or ENS are considered, the system could still be further away from its optimum operation point. Moreover, portfolio analysis displayed that a wind power plant joining one of the two portfolios can increase profit of all, rather than entering the market independently. Finally, the analysis of different wind scenarios shows how change in the availability of wind power can switch the prominent GENCOs in profit.

5.2. Strategic Offshore Wind Farm Maintenance Optimization

The second study proposes a model to analyze strategic maintenance scheduling problem for an OWF. Similar to the first study, the strategic maintenance scheduling of offshore wind farm (SMSOWF) model compares this problem from centralized and decentralized perspectives while accounting for various uncertainties. It also investigates impact of the market operations on the maintenance scheduling considering different transportation mediums for the OWF. This study is published by the author in [148].

5.2.1. Nomenclature

Indexes:

i, j	Index for bus
h	Index for hour
k	Index for wind turbine
g	Index for generation unit
s	Index for stochastic scenario
r	Index for maintenance round (number)

Sets:

$\Theta(i)$	Buses connected to bus i
$\Upsilon(i)$	Generators connected to bus i

Parameters:

α_g	Incremental term of fuel consumption (MBTU/MW) of generator g
f_g	Cost of fuel (\$/MBTU) of generator g
o_g	Variable operation cost (\$/MW) of generator g
$\overline{Q}_{h,g}$	Maximum capacity (MW) of generator $g \neq OWF$ at time h
$\overline{Q}'_{h,g,k,s}$	Maximum available wind power (MW) of wind turbine k at time h and scenario s in $g = OWF$
$X_{i,j}$	Inductance (Ω) of line between buses i and j
$F_{i,j}$	Capacity (MW) of line between buses i and j
$D_{h,i}$	Demand (MW) at hour h and bus i
T_k	Maintenance action duration for each wind turbine k at OWF
T''_g	Maintenance action duration for $g \neq OWF$
C	Maintenance action cost (\$)
Z	Maximum simultaneous maintenance actions
τ	Night time parameter
m_b	Cost factor for vessel b
$w_{h,s}$	Wave height prediction (m) at hour h and scenario s
L_b	Wave height limit (m) for vessel b
$T'_{k,b}$	Transportation time (h) for vessel b between wind turbine k and shore
h'	Maximum time limit for maintenance from alarm signal of condition

	monitoring system
k'	Wind turbine that has received an alarm signal
N_h	Number of time periods
N_g	Number of generators
N_i	Number of buses
N_s	Number of stochastic scenarios
N_r	Number of maintenance rounds
M_1, M_2, M_3	Sufficiently large numbers
Variables:	
$q_{h,g,s}$	Power generation (MW) of unit g at hour h and scenario s
$\theta_{h,i,s}$	Voltage angle (rad) in node i at hour h and scenario s
$z_{h,k,b,r}$	Binary variable of maintenance status of wind turbine (WT) k at hour h with vessel b on maintenance action r
$u_{h,k,b,r}$	Binary variable of utilization status of vessel b for WT k at hour h on maintenance action r
$y_{h,g,r}$	Binary variable of maintenance status of generator g (except OWF) at hour h on maintenance action r
$\mu_{h,i,s}$	Electricity price at hour h, bus i and scenario s
$\lambda_{1_{h,i,s}}$	Lagrange multiplier of demand balance
$\lambda_{2_{h,i,j,s}}$	Lagrange multiplier of power-flow
$\lambda_{3_{h,g,s}}$	Lagrange multiplier of maximum capacity limit for $g \neq OWF$
$\lambda_{4_{h,g,b,s}}$	Lagrange multiplier of maximum capacity limit for $g = OWF$
$\lambda_{5_{h,g,s}}$	Lagrange multiplier of capacity positivity
$\lambda'_{h,g,k,b,s}$	Variable used for linearization in strong duality
$\lambda''_{h,g,s,s}$	Variable used for linearization in strong duality

5.2.2. Introduction

Environmental concerns accompanied by exhaustion of fossil fuels have the interest for integration of RES. Among various types of RES, wind energy in the form of wind farm has evolved rapidly and is replacing conventional energy sources in several power systems. The estimates for offshore wind show large and rapid growth where offshore is expected to produce about 10% of the global installed capacity by 2020 [360] from the first OWF at Vindeby, Denmark in 1991. O&M costs of an OWF are high and O&M costs can reach up to 30% of the total cost [361, 362] where they have reached up to 23% in some European OWFs [171]. Moreover, if the farm is located at remote offshore areas, its availability can reduce down to 70% as the vessel accessibility decreases [363]. In addition, as future OWFs will be further away from the coast (e.g. 200 km), arranging the transportation vessel to the farm becomes very important as it could take more than 10 hours to reach a site [171, 364, 365].

The downtime due to maintenance can cause loss in the profit. Especially, in the deregulated power system where the electricity prices vary constantly, finding the optimum maintenance window is a difficult task. There are several models focused on PM scheduling of components in a WT through failure rate and age modeling [38, 366–368]. Apart from the uncertainty in input data, the uncertainty in failure rate, age or degradation models and the corresponding threshold values are the most important parameters that influence the performance of such models [39, 190, 369]. PM scheduling of OWFs can be divided into two categories of passive and active based on their relation with the market. Passive maintenance scheduling denotes that the schedules of maintenance are obtained with the objective of minimizing the operation cost of the power system without considering opportunities of making profit whereas active maintenance scheduling stands for maintenance decision making with the objective of maximizing the profit resulting from consideration of varying electricity prices. Furthermore, with the developments in the condition monitoring system (CMS)s in the wind industry and the requirement for quick reactions towards alarm and failure signals, in deregulated power systems, active maintenance scheduling carries more importance and holds greater interests for the wind farm operators.

[370] presents currently applied maintenance logistics organization for OWFs and concludes that operational maintenance should try to better adapt to the dynamic of the issues. [371] analyzes simulation models and suggests that future studies should try to cover optimization perspectives. Several models with focus on O&M strategies are reviewed in [372]. [373–375] investigate the impact of meteorological parameters on availability and maintenance planning where for instance, significant changes in production loss and availability are observed and addition of alternative access methods, e.g. a helicopter, is suggested for future studies. [210, 239] perform cost-based optimizations by considering different transport vessels, seasonal environment and component changes in order to find the optimum PM schedules and the number of permanent maintenance teams. In addition, a sensitivity analysis is carried out which deduces that the electricity price is one of the major parameters affecting the outcomes. Moreover, [376, 377] mention that there is also a need for improving the way the condition monitoring features are being currently exploited as the transportation costs and scheduling the transport mediums include majority of the costs [378]. Furthermore, [379] performs a sensitivity analysis in order to find out the most important parameters affecting O&M. It concludes that repair duration and labor working shift length are two of the most significant variables influencing the cost; maintenance resource availability and failure rates of components are the other two impacting availability.

There are several studies addressing active PM scheduling of wind farms in a network comprised of multiple types of power plants [106, 380–382]. [380] performs maintenance scheduling where particular wind power plant related matters (e.g. varying wind) are neglected. [106] solves the maintenance scheduling while neglecting the strategic behavior of OWF operator. [381] performs a maintenance scheduling by maximizing the reliability of a power system with wind generation where two wind particular constraints of wind variations and weather conditions are used. [382] reviews maintenance scheduling studies in the electricity industry and provides several propositions such as modifying the models based on the regulated and deregulated systems, addressing price volatility, tailoring the objectives which enhances strategic behavioral analysis in this area and addition of specific constraints for different types of power plants. For instance, currently when a power system comprised of multiple power plant types is considered, maintenance schedules of wind power plants (regardless of their constraints) are handled similar to other power plants with one single maintenance schedule for the whole farm. This includes many simplifications that distances it from an actual case. For example, the impact of wake effect or vessel availability are ignored. Indeed, this assumption is not realistic as each WT can have a different maintenance time. Therefore, there is lack of a study which performs active maintenance scheduling with being detailed on wind farms and WTs in a deregulated power system.

From the number of challenges and undeveloped areas that have been mentioned, this case study proposes a PM scheduling model for WTs of an OWF in a deregulated power system through a BLP. In the lower-level problem, an economic dispatch is performed with the objective of minimizing the operation cost (maximizing social welfare) of the system. The constraints of the lower-level problem are capacity of transmission lines, maximum available power through wind in the OWF and other power plants, and the demand balance equation. In the upper-level problem, maintenance scheduling of all WTs in the OWF is carried out. Multiple constraints such as duration of each PM action, the time required for each type of transfer vessel to reach the farm and return to the coast, the wave height limit for the vessels, the working shift limits, the wake effect and priority for some WTs are considered. The objective of the upper-level is to maximize the profit of the OWF which is produced by multiplication of the electricity price into the produced power deducted by O&M costs. The wake effect influencing the wind farm is added through the lower-level. Finally, the priority feature allows inclusion of condition monitoring signals into the maintenance scheduling. This BLP is reformulated in an SLP through KKT conditions.

5.2.3. Problem Formulation

Two maintenance scheduling models are proposed in this section. The first model, passive maintenance scheduling, aims to find the maintenance time windows as well as their corresponding transport vessels by minimizing the operation cost of the power system where the OWF maintenance related costs are also considered. In this model, the decisions are made by an ISO. The active maintenance scheduling model tries to solve this decision making problem through a profit-maximization perspective.

5.2.3.1. Cost-minimization Maintenance Scheduling

For cost-minimization maintenance scheduling model, an SLP is defined as following:

$$\min_{q,u,y,z,\theta} \sum_{h,g=OWF} \Big[\sum_s \rho_s (f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}) + \sum_{k,b,r} (u_{h,k,b,r} m_b + z_{h,k,b,r}) C\Big] + \sum_{h,g \neq OWF} \Big[\sum_s \rho_s (f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}) + \sum_r y_{h,g,r} C\Big] \tag{5.32a}$$

$$\sum_h y_{h,g,r} - T''_g = 0 \qquad \forall g \neq OWF, r \tag{5.32b}$$

$$\sum_{g \neq OWF} y_{h,g,r} - 1 \leq 0 \qquad \forall h, r \tag{5.32c}$$

$$y_{h+1,g,r} - y_{h,g,r} - y_{h+T''_g,g,r} \leq 0 \qquad \forall h, g \neq OWF, r \tag{5.32d}$$

$$\sum_{h,b} z_{h,k,b,r} - T_k = 0 \qquad \forall k, r \tag{5.32e}$$

$$\sum_{k,b} z_{h,k,b,r} - 1 \leq 0 \qquad \forall h, r \tag{5.32f}$$

$$\sum_r z_{h,k,b,r} - 1 \leq 0 \qquad \forall h, k, b \tag{5.32g}$$

$$\sum_{k,b} u_{h,k,b,r} - 1 \leq 0 \qquad \forall h, r \tag{5.32h}$$

$$\sum_r u_{h,k,b,r} - 1 \leq 0 \qquad \forall h, k, b \tag{5.32i}$$

$$z_{h+1,k,b,r} - z_{h,k,b,r} - z_{h+T_k,k,b,r} \leq 0 \qquad \forall h, k, b, r \tag{5.32j}$$

$$z_{h,k,b,r} = 0 \qquad \forall h < T'_{k,b}, k, b, r \tag{5.32k}$$

$$z_{h,k,b,r} = 0 \qquad \forall h > N_h - T'_{k,b}, k, b, r \tag{5.32l}$$

$$z_{h,k,b,r} \leq u_{h,k,b,r} \qquad \forall h, k, b, r \tag{5.32m}$$

$$z_{h,k,b,r} \leq u_{h-T'_{k,b},k,b,r} \qquad \forall h > T'_{k,b}, k, b, r \tag{5.32n}$$

$$z_{h,k,b,r} \leq u_{h+T'_{k,b},k,b,r} \qquad \forall h < N_h - T'_{k,b}, k, b, r \tag{5.32o}$$

$$u_{h+1,k,b,r} - u_{h,k,b,r} - u_{h+T_k+2T'_{k,b},k,b,r} \leq 0 \qquad \forall h, k, b, r \tag{5.32p}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_1, r \tag{5.32q}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_2, r \tag{5.32r}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_3, r \tag{5.32s}$$

$$\sum_{h,b} u_{h,k,b,r} - 6 \leq 0 \qquad \forall k, r \tag{5.32t}$$

$$z_{h,k,b,r} = 0 \qquad \forall h \in \tau, k, b, r \tag{5.32u}$$

$$z_{h,k,b,r} = 0 \qquad \forall h > h', k = k', b, r \tag{5.32v}$$
$$w_{h,s} + (u_{h,k,b,r} - 1)M_1 \leq L_b \qquad \forall h, k, b, s, r \tag{5.32w}$$
$$-\sum_{g \in \Upsilon(i)} q_{h,g,s} + \sum_{j \in \Theta(i)} \frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} + D_{h,i} = 0 \quad \forall h, i, s \tag{5.32x}$$
$$\frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} - F_{i,j} \leq 0 \qquad \forall h, i, j \mid j \in \Theta(i), s \tag{5.32y}$$
$$q_{h,g,s} - (1 - y_{h,g,r})\overline{Q}_g \leq 0 \qquad \forall h, g \neq OWF, s, r \tag{5.32z}$$
$$q_{h,g,s} - \sum_k \left[(1 - z_{h,k,b,r})\overline{Q}'_{h,g,k,s}\right] \leq 0 \qquad \forall h, g = OWF, b, s, r \tag{5.32aa}$$
$$-q_{h,g,s} \leq 0 \qquad \forall h, g, s \tag{5.32ab}$$

The objective function (5.32a) accounts for the operation cost of the system as well as the maintenance action and vessel transportation costs. Constraint (5.32b) enforces all the generators (except the OWF) to have their necessary required maintenance time. While (5.32c) limits the maintenance action to only one generator at each hour, (5.32d) defines the continuous maintenance operation. Constraint (5.32e) ensures that all WTs undergo maintenance for the required predefined maintenance time T_k. Constraints (5.32f) and (5.32h) make sure that for each hour, at most one maintenance action and one vessel are utilized, respectively. Constraints (5.32g) and (5.32i) help to distinguish among various maintenance actions. While constraint (5.32j) guarantees a continuous maintenance action, constraints (5.32k) and (5.32l) provide enough time for the vessels to reach wind farm from the coast and return back, respectively.

A primary link between maintenance action and vessel operation is provided through (5.32m) where $u_{h,k,g,r}$ is triggered to become 1 whenever $z_{h,k,b,r}$ is 1. Next, whenever $z_{h,k,b,r}$ is 1, constraints (5.32n) and (5.32o) correspondingly cause $u_{h,k,b,r}$ to be 1, based on transportation time of the vessel. In other words, they consider the required time for the vessel to reach the wind farm and come back from the wind farm, respectively. Subsequently, (5.32p) secures a continuous operation of the vessel transportation. Constraints (5.32q)-(5.32t) force the various vessel types to follow their predefined transportation time and do not exceed the overall specified time by limiting the operation of the vessels through each WT. It is assumed that the vessel remains at site of the WT during the maintenance time. It is also considered that the maintenance schedules are required to be performed only during specific time shifts through (5.32u).

Constraint (5.32v) delivers the possibility of linking the model with a CMS and combining the information in the decision making process. For instance, if the information from the CMS expresses that a particular WT (k') will need maintenance shortly (in the next h' hours), these commands are implemented in the model through constraint (5.32v). Even if a sudden change occurs in the middle of the time horizon, by fixing the already made decisions for other WTs, the model can run again solely for that particular WT. Moreover, each vessel has a wave height limit. Whenever the wave height is higher than the limit, the vessel cannot be used. Constraint (5.32w) applies this limitation. It should be mentioned that no limitation for the usage of the helicopter is considered.

Demand is supplied at each node in the system through (5.32x) and the transmission capacity constraints are considered through (5.32y). Each generator has a maximum capacity and the maximum capacity of the wind farm is sum of all available power that can be produced by each WT. The produced power of the generators should be less than these constraints and also positive, (5.32z)-(5.32ab).

5.2.3.2. Profit-maximization Maintenance Scheduling

For profit-maximization maintenance scheduling model, a BLP is derived as following:

$$\max_{u,y,z} \sum_{h,g=OWF} \Big[\sum_s \rho_s(\mu_{h,i,s}q_{h,g,s} - f_g\alpha_g q_{h,g,s} - o_g q_{h,g,s}) - \sum_{k,b,r}(u_{h,k,b,r}m_b + z_{h,k,b,r})C\Big] - \sum_{h,g\neq OWF}\Big[\sum_s \rho_s(f_g\alpha_g q_{h,g,s} + o_g q_{h,g,s}) + \sum_r y_{h,g,r}C\Big] \quad (5.33a)$$

$$\mu_{h,i,s} = \frac{1}{\rho_s}\lambda_{1_{h,i,s}} \qquad \forall h,i,s \quad (5.33b)$$

$$\sum_h y_{h,g,r} - T''_g = 0 \qquad \forall g \neq OWF, r \quad (5.33c)$$

$$\sum_{g\neq OWF} y_{h,g,r} - 1 \leq 0 \qquad \forall h,r \quad (5.33d)$$

$$y_{h+1,g,r} - y_{h,g,r} - y_{h+T''_g,g,r} \leq 0 \qquad \forall h,g,r \quad (5.33e)$$

$$\sum_{h,b} z_{h,k,b,r} - T_k = 0 \qquad \forall k,r \quad (5.33f)$$

$$\sum_{k,b} z_{h,k,b,r} - 1 \leq 0 \qquad \forall h,r \quad (5.33g)$$

$$\sum_{r} z_{h,k,b,r} - 1 \leq 0 \qquad \forall h,k,b \quad (5.33h)$$

$$\sum_{k,b} u_{h,k,b,r} - 1 \leq 0 \qquad \forall h,r \quad (5.33i)$$

$$\sum_{r} u_{h,k,b,r} - 1 \leq 0 \qquad \forall h,k,b \quad (5.33j)$$

$$z_{h+1,k,b,r} - z_{h,k,b,r} - z_{h+T_k,k,b,r} \leq 0 \qquad \forall h,k,b,r \quad (5.33k)$$

$$z_{h,k,b,r} = 0 \qquad \forall h < T'_{k,b}, k,b,r \quad (5.33l)$$

$$z_{h,k,b,r} = 0 \qquad \forall h > N_h - T'_{k,b}, k,b,r \quad (5.33m)$$

$$z_{h,k,b,r} \leq u_{h,k,b,r} \qquad \forall h,k,b,r \quad (5.33n)$$

$$z_{h,k,b,r} \leq u_{h-T'_{k,b},k,b,r} \qquad \forall h > T'_{k,b}, k,b,r \quad (5.33o)$$

$$z_{h,k,b,r} \leq u_{h+T'_{k,b},k,b,r} \qquad \forall h < N_h - T'_{k,b}, k,b,r \quad (5.33p)$$

$$u_{h+1,k,b,r} - u_{h,k,b,r} - u_{h+T_k+2T'_{k,b},k,b,r} \leq 0 \qquad \forall h,k,b,r \quad (5.33q)$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_1, r \quad (5.33r)$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_2, r \tag{5.33s}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_3, r \tag{5.33t}$$

$$\sum_{h,b} u_{h,k,b,r} - 6 \leq 0 \qquad \forall k, r \tag{5.33u}$$

$$z_{h,k,b,r} = 0 \qquad \forall h \in \tau, k, b, r \tag{5.33v}$$

$$z_{h,k,b,r} = 0 \qquad \forall h > h', k = k', b, r \tag{5.33w}$$

$$w_{h,s} + (u_{h,k,b,r} - 1)M_1 \leq L_b \qquad \forall h, k, b, s, r \tag{5.33x}$$

$$\min_{q,\theta} \sum_{h,g,s} \rho_s \left[f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s} \right] \tag{5.33y}$$

$$-\sum_{g \in \Upsilon(i)} q_{h,g,s} + \sum_{j \in \Theta(i)} \frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} + D_{h,i} = 0 : \lambda_{1_{h,i,s}} \quad \forall h, i, s \tag{5.33z}$$

$$\frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} - F_{i,j} \leq 0 : \lambda_{2_{h,i,j,s}} \qquad \forall h, i, j \mid j \in \Theta(i), s \tag{5.33aa}$$

$$q_{h,g,s} - (1 - y_{h,g,r})\overline{Q}_g \leq 0 : \lambda_{3_{h,g,s}} \qquad \forall h, g \neq OWF, s, r \tag{5.33ab}$$

$$q_{h,g,s} - \sum_{k} \left[(1 - z_{h,k,b,r})\overline{Q}'_{h,g,k,s} \right] \leq 0 : \lambda_{4_{h,g,b,s}} \ \forall h, g = OWF, b, s, r \tag{5.33ac}$$

$$-q_{h,g,s} \leq 0 : \lambda_{5_{h,g,s}} \qquad \forall h, g, s \tag{5.33ad}$$

The upper-level problem, (5.33a)-(5.33x), schedules the vessels and maintenance actions for each WT with the objective of maximizing profit of the OWF. The lower-level problem, (5.33y)-(5.33ad), performs an economic dispatch in the system with the objective of minimizing operation costs.

The objective function (5.33a) is profit of the wind farm minus the maintenance actions and operation costs of other generating units. The terms related to other generating units are included here as they significantly reduce the required computing power and facilitate reaching an optimum solution. Please notice that the drawback of this inclusion of variables is that it transforms the problem into a cooperative maintenance scheduling. This cooperative matter has been evaluated in one of the case studies. Indeed, if more computing power is available, one can further study the proposed SMSOWF model by solely focusing on the non-cooperative perspective. The first term, $\mu_{h,i,s}q_{h,g,s}$, is the revenue which comes from multiplication of the electricity price (locational marginal price, $\mu_{h,i,s}$) into the production of the wind farm, $q_{h,g,s}$. Please note that $\mu_{h,i,s}$ is obtained through the dual variable of the demand balance, $\lambda_{1_{h,i,s}}$, in (5.33z). The second and third terms, $f_g\alpha_g q_{h,g,s}$ and $o_g q_{h,g,s}$, account for operation costs. The fourth and fifth terms, $(u_{h,k,b,r}m_b + z_{h,k,b,r})C$, build the costs regarding the maintenance actions and transportation of the vessel. The last terms, $q_{h,g,s} + o_g q_{h,g,s} + y_{h,g,r}C$, consider the O&M costs of generating units except the wind farm. Objective function of the lower-level problem, (5.33y), consists of costs related to the operation cost of the system where a minimization would result in the least operation cost. λ values are the Lagrange multipliers of their corresponding constraints in the lower-level problem. It should be noted that in the profit-maximization model where the profit of the OWF is maximized, the scheduling of all power plants are included. Such consideration offers evaluation of strategic operations. Moreover, a comparison between *CaseIII* (where the maintenance schedule of all power plants, except the OWF, is decided by the ISO) and other cases (where such consideration is relaxed) delivers insight into different perspectives in the O&M planning.

5.2.3.3. Karush–Kuhn–Tucker Conditions

The profit-maximization model formulated in (5.33) is a bi-level problem. It should be noted that since the unit commitment decisions (start-up and shut-down) are not directly considered, the lower-level problem, (5.33y)-(5.33ad), is convex. Therefore, the BLP can be transformed into an SLP through KKT conditions. The KKT conditions include stationarity (gradient of Lagrangian function ($\mathscr{L}$) with respect to lower-level variables), complementary slackness, primal (original inequalities) and dual constraints [348]. These should be derived from the lower-level problem. The following shows the Lagrangian function:

$$
\begin{aligned}
\mathscr{L}(q,\theta,\lambda) &= \sum_{h,g,s} \rho_s \left[f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s} \right] + \sum_{h,i,s} \lambda_{1_{h,i,s}} \Bigg[\sum_{g \in \Upsilon(i)} -q_{h,g,s} \\
&+ \sum_{j \in \Theta(i)} \frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} + D_{h,i} \Bigg] + \sum_{h,i,j \in \Theta(i),s} \lambda_{2_{h,i,j,s}} \left[\frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} - F_{i,j} \right] \\
&+ \sum_{h,g \neq OWF,s,r} \lambda_{3_{h,g,s}} \left[q_{h,g,s} - (1 - y_{h,g,r}) \overline{Q}_g \right] + \sum_{h,g=OWF,b,s,r} \lambda_{4_{h,g,b,s}} \Bigg[q_{h,g,s} \\
&- \sum_{k} \left[(1 - z_{h,k,b,r}) \overline{Q}'_{h,g,k,s} \right] \Bigg] + \sum_{h,g,s} \lambda_{5_{h,g,s}} (-q_{h,g,s})
\end{aligned} \tag{5.34}
$$

From stationarity conditions:

$$
\rho_s (f_g \alpha_g + o_g) - \lambda_{1_{\substack{h,i,s \\ i \leftarrow g}}} + \lambda_{3_{h,g,s}} - \lambda_{5_{h,g,s}} = 0 \qquad \forall h, g \neq OWF, s \tag{5.35}
$$

$$
\rho_s (f_g \alpha_g + o_g) - \lambda_{1_{\substack{h,i,s \\ i \leftarrow g}}} + \sum_{b} \lambda_{4_{h,g,b,s}} - \lambda_{5_{h,g,s}} = 0 \qquad \forall h, g = OWF, s \tag{5.36}
$$

$$
\sum_{j \in \Theta(i)} \frac{(\lambda_{1_{h,i,s}} - \lambda_{1_{h,j,s}})}{X_{i,j}} + \sum_{j \in \Theta(i)} \frac{(\lambda_{2_{h,i,j,s}} - \lambda_{2_{h,j,i,s}})}{X_{i,j}} = 0 \quad \forall h, i, s \tag{5.37}
$$

And by writing complementarity conditions:

$$\lambda_{2_{h,i,j,s}}\left[\frac{(\theta_{h,i,s}-\theta_{h,j,s})}{X_{i,j}}-F_{i,j}\right]=0 \qquad \forall h,i,j\in\Theta(i),s \tag{5.38}$$

$$\lambda_{3_{h,g,s}}[q_{h,g,s}-(1-y_{h,g,r})\overline{Q}_g]=0 \qquad \forall h,g\neq OWF,s,r \tag{5.39}$$

$$\lambda_{4_{h,g,b,s}}\left[q_{h,g,s}-\sum_k\left[(1-z_{h,k,b,r})\overline{Q}'_{h,g,k,s}\right]\right]=0 \quad \forall h,g=OWF,b,s,r \tag{5.40}$$

$$\lambda_{5_{h,g,s}}(-q_{h,g,s})=0 \qquad \forall h,g,s \tag{5.41}$$

The complementarity conditions, (5.38)-(5.41), and the objective function (5.33a) include nonlinearities. In this regard, the complementarity conditions can be substituted by the strong duality as follows:

$$\begin{aligned}\sum_{h,g,s}\rho_s\left[f_g\alpha_g q_{h,g,s}+o_g q_{h,g,s}\right]&=\sum_{h,i,s}\lambda_{1_{h,i,s}}D_{h,i}\\ &-\sum_{h,i,j\in\Theta(i),s}\lambda_{2_{h,i,j,s}}F_{i,j}-\sum_{h,g\neq OWF,s,r}\lambda_{3_{h,g,s}}(1-y_{h,g,r})\overline{Q}_g\\ &-\sum_{h,g=OWF,b,s,r}\lambda_{4_{h,g,b,s}}\left[\sum_k(1-z_{h,k,b,r})\overline{Q}'_{h,g,k,s}\right]\end{aligned} \tag{5.42}$$

There are two nonlinear terms in the strong duality. The nonlinear term $\lambda_{4_{h,g,b,s}}(1-z_{h,k,b,r})$ can be linearized as:

$$\lambda'_{h,g,k,b,s}=\lambda_{4_{h,g,b,s}}(1-\sum_r z_{h,k,b,r}) \qquad \forall h,g=OWF,k,b,s \tag{5.43}$$

$$\lambda'_{h,g,k,b,s}\leq(1-\sum_r z_{h,k,b,r})M_2 \qquad \forall h,g=OWF,k,b,s \tag{5.44}$$

$$\lambda_{4_{h,g,b,s}}-\lambda'_{h,g,k,b,s}\leq\left[1-(1-\sum_r z_{h,k,b,r})\right]M_2 \qquad \forall h,g=OWF,k,b,s \tag{5.45}$$

$$\lambda_{4_{h,g,b,s}}-\lambda'_{h,g,k,b,s}\geq-\left[1-(1-\sum_r z_{h,k,b,r})\right]M_2 \qquad \forall h,g=OWF,k,b,s \tag{5.46}$$

and the nonlinear term $\lambda_{3_{h,g,s}}(1-y_{h,g,r})$ can be linearized as:

$$\lambda''_{h,g,s}=\lambda_{3_{h,g,s}}(1-\sum_r y_{h,g,r}) \qquad \forall h,g\neq OWF,s \tag{5.47}$$

$$\lambda''_{h,g,s}\leq(1-\sum_r y_{h,g,r})M_3 \qquad \forall h,g\neq OWF,s \tag{5.48}$$

$$\lambda_{3_{h,g,s}}-\lambda''_{h,g,s}\leq\left[1-(1-\sum_r y_{h,g,r})\right]M_3 \qquad \forall h,g\neq OWF,s \tag{5.49}$$

$$\lambda_{3_{h,g,s}}-\lambda''_{h,g,s}\geq-\left[1-(1-\sum_r y_{h,g,r})\right]M_3 \qquad \forall h,g\neq OWF,s \tag{5.50}$$

where M_2 and M_3 are large enough positive constants [349]. Thus, the strong duality renders into:

$$\begin{aligned}\sum_{h,g,s} \rho_s \left[f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}\right] = \sum_{h,i,s} \lambda_{1_{h,i,s}} D_{h,i} - \sum_{h,i,j\in\Theta(i),s} \lambda_{2_{h,i,j,s}} F_{i,j} \\ - \sum_{h,g\neq OWF,s} \lambda''_{h,g,s} \overline{Q}_g - \sum_{h,g=OWF,k,b,s} \lambda'_{h,g,k,b,s} \overline{Q}'_{h,g,k,s}\end{aligned} \tag{5.51}$$

To linearize the term $\lambda_{1_{h,i,s}} q_{h,g,s}$ in the objective function (5.33a), stationarity condition (5.36) is multiplied by $q_{h,g,s}$ as following:

$$\rho_s(f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}) - \lambda_{\underset{i\leftarrow g}{1_{h,i,s}}} q_{h,g,s} + \sum_b \lambda_{4_{h,g,b,s}} q_{h,g,s} - \lambda_{5_{h,g,s}} q_{h,g,s} = 0 \qquad \forall h, g = OWF, s \tag{5.52}$$

The last term in (5.52) should then be omitted due to (5.41). The nonlinear term $\lambda_{4_{h,g,b,s}} q_{h,g,s}$ in (5.52) can also be simplified through (5.40). In addition, by considering (5.43), (5.52) becomes:

$$\lambda_{\underset{i\leftarrow g}{1_{h,i,s}}} q_{h,g,s} = \rho_s(f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}) + \sum_{k,b,s} \lambda'_{h,g,k,b,s} \overline{Q}'_{h,g,k,s} \quad \forall h, g = OWF, s \tag{5.53}$$

which is the linear equivalent of the nonlinear term in the objective function (5.33a).

Those steps convert the BLP in (5.33) into an SLP as follows:

$$\begin{aligned}\max_{q,u,y,z,\theta} \sum_{h,g=OWF,k,b} \left[\sum_s \rho_s \lambda'_{h,g,k,b,s} \overline{Q}'_{h,g,k,s} - \sum_r (u_{h,k,b,r} m_b + z_{h,k,b,r}) C\right] \\ - \sum_{h,g\neq OWF} \left[\sum_s \rho_s (f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}) + \sum_r y_{h,g,r} C\right]\end{aligned} \tag{5.54a}$$

$$\mu_{h,i,s} = \frac{1}{\rho_s} \lambda_{1_{h,i,s}} \qquad \forall h, i, s \tag{5.54b}$$

$$\sum_h y_{h,g,r} - T''_g = 0 \qquad \forall g \neq OWF, r \tag{5.54c}$$

$$\sum_{g\neq OWF} y_{h,g,r} - 1 \leq 0 \qquad \forall h, r \tag{5.54d}$$

$$y_{h+1,g,r} - y_{h,g,r} - y_{h+T''_g,g,r} \leq 0 \qquad \forall h, g, r \tag{5.54e}$$

$$\sum_{h,b} z_{h,k,b,r} - T_k = 0 \qquad \forall k, r \tag{5.54f}$$

$$\sum_{k,b} z_{h,k,b,r} - 1 \leq 0 \qquad \forall h, r \tag{5.54g}$$

$$\sum_r z_{h,k,b,r} - 1 \leq 0 \qquad \forall h, k, b \tag{5.54h}$$

$$\sum_{k,b} u_{h,k,b,r} - 1 \leq 0 \qquad \forall h, r \tag{5.54i}$$

$$\sum_{r} u_{h,k,b,r} - 1 \leq 0 \qquad \forall h,k,b \tag{5.54j}$$

$$z_{h+1,k,b,r} - z_{h,k,b,r} - z_{h+T_k,k,b,r} \leq 0 \qquad \forall h,k,b,r \tag{5.54k}$$

$$z_{h,k,b,r} = 0 \qquad \forall h < T'_{k,b}, k, b, r \tag{5.54l}$$

$$z_{h,k,b,r} = 0 \qquad \forall h > N_h - T'_{k,b}, k, b, r \tag{5.54m}$$

$$z_{h,k,b,r} \leq u_{h,k,b,r} \qquad \forall h,k,b,r \tag{5.54n}$$

$$z_{h,k,b,r} \leq u_{h-T'_{k,b},k,b,r} \qquad \forall h > T'_{k,b}, k, b, r \tag{5.54o}$$

$$z_{h,k,b,r} \leq u_{h+T'_{k,b},k,b,r} \qquad \forall h < N_h - T'_{k,b}, k, b, r \tag{5.54p}$$

$$u_{h+1,k,b,r} - u_{h,k,b,r} - u_{h+T_k+2T'_{k,b},k,b,r} \leq 0 \qquad \forall h,k,b,r \tag{5.54q}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_1, r \tag{5.54r}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_2, r \tag{5.54s}$$

$$\sum_{h,b} u_{h,k,b,r} - (2T'_{k,b} + T_k) \leq 0 \qquad \forall k, b = b_3, r \tag{5.54t}$$

$$\sum_{h,b} u_{h,k,b,r} - 6 \leq 0 \qquad \forall k, r \tag{5.54u}$$

$$z_{h,k,b,r} = 0 \qquad \forall h \in \tau, k, b, r \tag{5.54v}$$

$$z_{h,k,b,r} = 0 \qquad \forall h > h', k = k', b, r \tag{5.54w}$$

$$w_{h,s} + (u_{h,k,b,r} - 1)M_1 \leq L_b \qquad \forall h,k,b,s,r \tag{5.54x}$$

$$-\sum_{g \in \Upsilon(i)} q_{h,g,s} + \sum_{j \in \Theta(i)} \frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} + D_{h,i} = 0 \qquad \forall h,i,s \tag{5.54y}$$

$$\frac{(\theta_{h,i,s} - \theta_{h,j,s})}{X_{i,j}} - F_{i,j} \leq 0 \qquad \forall h,i,j \mid j \in \Theta(i), s \tag{5.54z}$$

$$q_{h,g,s} - (1 - y_{h,g,r})\overline{Q}_g \leq 0 \qquad \forall h, g \neq OWF, s, r \tag{5.54aa}$$

$$q_{h,g,s} - \sum_{k} \left[(1 - z_{h,k,b,r})\overline{Q}'_{h,g,k,s}\right] \leq 0 \qquad \forall h, g = OWF, b, s, r \tag{5.54ab}$$

$$-q_{h,g,s} \leq 0 \qquad \forall h,g,s \tag{5.54ac}$$

$$\rho_s(f_g\alpha_g + o_g) - \lambda_{1_{\substack{h,i,s \\ i \leftarrow g}}} + \lambda_{3_{h,g,s}} - \lambda_{5_{h,g,s}} = 0 \qquad \forall h, g \neq OWF, s \tag{5.54ad}$$

$$\rho_s(f_g\alpha_g + o_g) - \lambda_{1_{\substack{h,i,s \\ i \leftarrow g}}} + \sum_{b} \lambda_{4_{h,g,b,s}} - \lambda_{5_{h,g,s}} = 0 \qquad \forall h, g = OWF, s \tag{5.54ae}$$

$$\sum_{j \in \Theta(i)} \frac{(\lambda_{1_{h,i,s}} - \lambda_{1_{h,j,s}})}{X_{i,j}} + \sum_{j \in \Theta(i)} \frac{(\lambda_{2_{h,i,j,s}} - \lambda_{2_{h,j,i,s}})}{X_{i,j}} = 0 \qquad \forall h,i,s \tag{5.54af}$$

$$\begin{aligned}\sum_{h,g,s} \rho_s \left[f_g \alpha_g q_{h,g,s} + o_g q_{h,g,s}\right] &= \sum_{h,i,s} \lambda_{1_{h,i,s}} D_{h,i} - \sum_{h,i,j \in \Theta(i),s} \lambda_{2_{h,i,j,s}} F_{i,j} \\ &- \sum_{h,g \neq OWF,s} \lambda''_{h,g,s} \overline{Q}_g - \sum_{h,g=OWF,k,b,s} \lambda'_{h,g,k,b,s} \overline{Q}'_{h,g,k,s}\end{aligned} \tag{5.54ag}$$

$$\lambda'_{h,g,k,b,s} \leq (1 - \sum_r z_{h,k,b,r}) M_2 \qquad \forall h, g = OWF, k, b, s \tag{5.54ah}$$

$$\lambda 4_{h,g,b,s} - \lambda'_{h,g,k,b,s} \leq \left[1 - (1 - \sum_r z_{h,k,b,r})\right] M_2 \quad \forall h, g = OWF, k, b, s \tag{5.54ai}$$

$$\lambda 4_{h,g,b,s} - \lambda'_{h,g,k,b,s} \geq -\left[1 - (1 - \sum_r z_{h,k,b,r})\right] M_2 \forall h, g = OWF, k, b, s \tag{5.54aj}$$

$$\lambda''_{h,g,s} \leq (1 - \sum_r y_{h,g,r}) M_3 \qquad \forall h, g \neq OWF, s \tag{5.54ak}$$

$$\lambda 3_{h,g,s} - \lambda''_{h,g,s} \leq \left[1 - (1 - \sum_r y_{h,g,r})\right] M_3 \qquad \forall h, g \neq OWF, s \tag{5.54al}$$

$$\lambda 3_{h,g,s} - \lambda''_{h,g,s} \geq -\left[1 - (1 - \sum_r y_{h,g,r})\right] M_3 \qquad \forall h, g \neq OWF, s \tag{5.54am}$$

5.2.4. Case Study

5.2.4.1. Test System

The proposed SMSOWF model in (5.54) is coded in GAMS v24.7.1 [319] and solved using CPLEX v12.6.2 [320] on a machine running with 144 GB of RAM and an Intel Xeon E5-2660 (2.6 GHz) with 2 processors (20 cores). A 5-bus network (Figure 5.10) is defined to demonstrate applicability of the developed SMSOWF model. Details of the generators are provided in Table 5.8. The inductance and capacity of all transmission lines are correspondingly 0.06 Ω and 60 MW. The considered operating horizon is for 200 hours where it can be scaled up or modified as required based on days, weeks etc.

Two boats and a helicopter are considered as transportation mediums (vessels) for performing the maintenance actions. The vessels are differentiated by transportation time (Table 5.9), operation cost and wave height limitations (Table 5.10). The helicopter can travel the distance faster than the boats, has the highest cost and no wave height limitation. The maintenance actions are allowed to be carried out only between 05:00 a.m. and 08:00 p.m. as day working shift.

This case study also considers a simplified version of wake effect in the maintenance scheduling problem. Wind direction is assumed fixed and shown in Figure 5.10 (wind blows from the West to the East). To add the wake effect, it is considered that the available wind power of each column of WTs reduces as the wind travels through the farm based on the wind direction. Thus, it is assumed that WT_1, WT_2, WT_3 have the hourly maximum available wind power based on Figure 5.13. This maximum reduces by one unit for WT_4, WT_5, WT_6, by two units for WT_7, WT_8, WT_9 and by three units for $WT_{10}, WT_{11}, WT_{12}$, as displayed in Table 5.9. These are implemented in the model through the $\overline{Q}'_{h,g,k}$ parameter. The wind and wave data can be found online [383] where for simplicity, the wind speed is approximated as output power as illustrated in Figure 5.13. To account for variations in the wind and wave in the environment, stochasticity is also considered for them. In this regard, the variations range from -3 to +3 standard

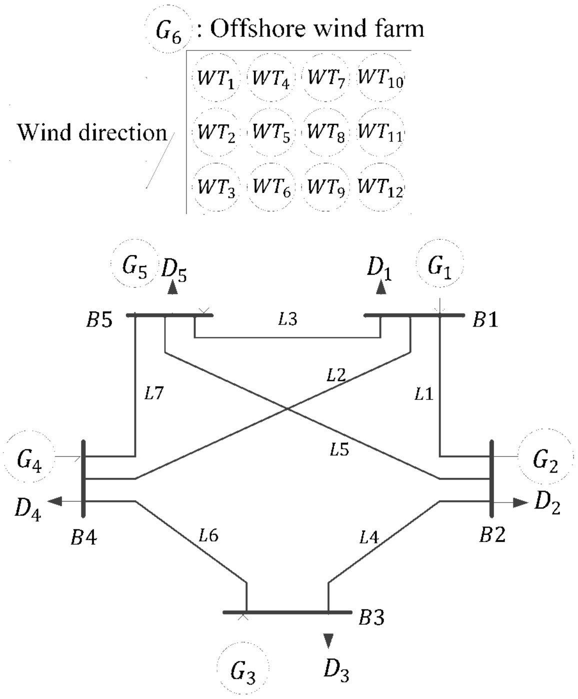


Figure 5.10: The Utilized 5-Bus Test System

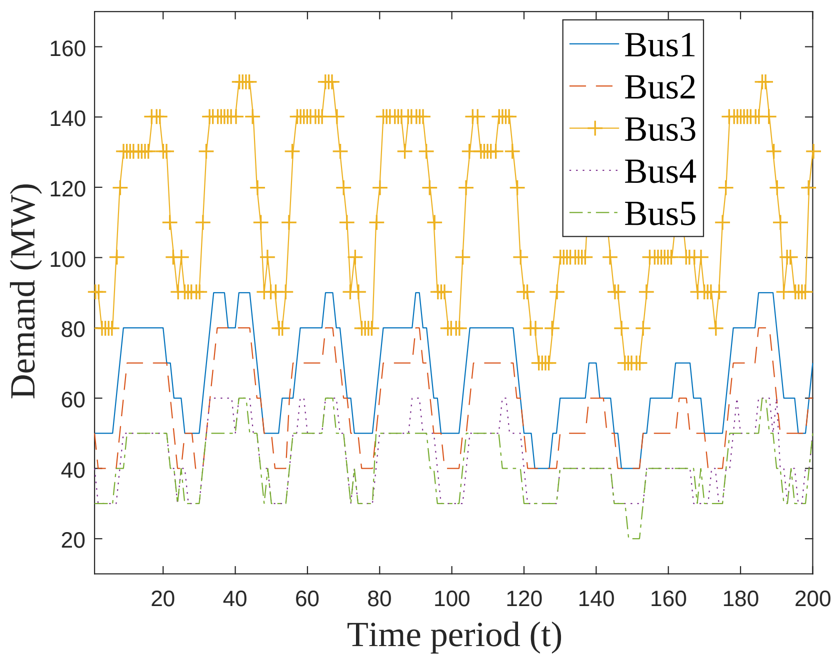


Figure 5.11: Load profile in the test system

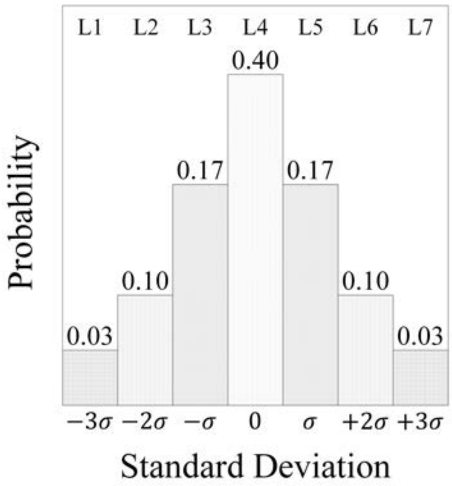


Figure 5.12: Stochasticity defined for wind and wave

Table 5.8: Operational and maintenance information of generators

Generator	$\overline{Q}_g(\overline{Q}'_{h,g,k,s}{}^{a})$	α_g	f_g	o_g
G1	100	0.3	5	7
G2	90	0.5	10	9
G3	160	0.7	15	11
G4	80	0.9	20	13
G5	70	1.1	25	15
G6	108[a]	0	0	10

[a] Set based on Figure (5.13) and reference in stochastic scenarios

deviations through seven levels (L1-L7) for each of wind and wave data. The probability of each level is illustrated in Figure 5.12. It should be mentioned that the reference data in the stochastic case (L4) for wind and wave is the data in the Figure 5.13 where the considered standard deviations are 1.00 and 0.15 units for each of the wind and wave data, respectively.

After developments and advancements in CMSs of WTs, the wind farm operators can receive signals regarding the real-time health condition of the WTs. Assuming the signal indicates an approaching failure, the operator should schedule a PM action as soon as possible. This issue puts that particular WT in front of the line for receiving the maintenance and assigns a priority to that WT. For instance, through the supervisory control and data acquisition (SCADA) system, it is assumed that WT_1 has received an alarm where it expresses that if WT_1 does not have a maintenance in the following 2 days (48 hours), it will fail.

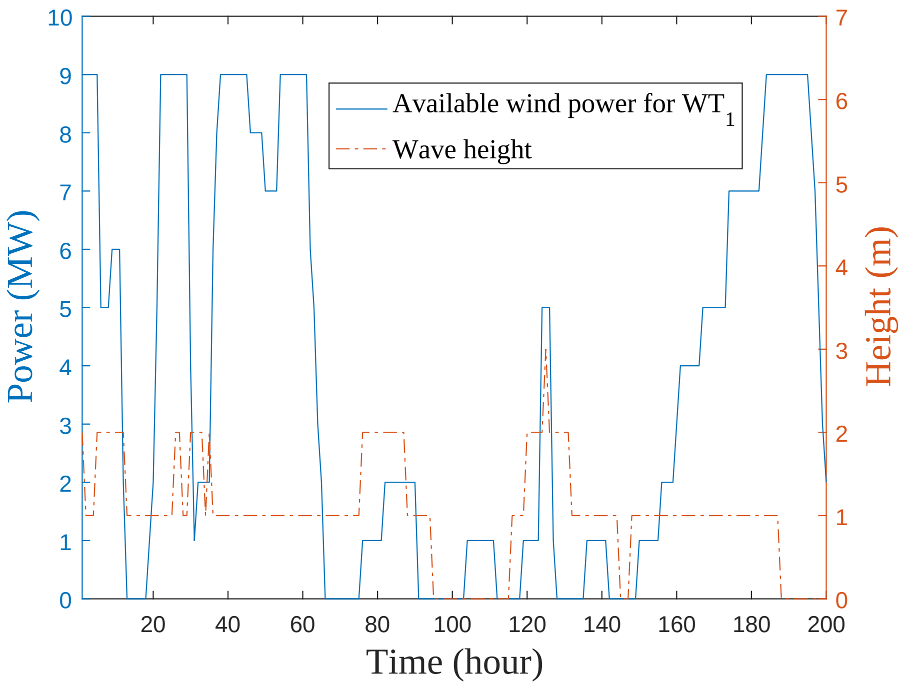


Figure 5.13: Available wind power and wave height in deterministic cases

5.2.4.2. Cases

In order to demonstrate features and applicability of the developed SMSOWF model, nine cases are defined.

5.2.4.2.1. Case I This case introduces a cost-minimization problem where the maintenance scheduling is performed for all the power plants with the objective of achieving the least operation cost for the test system through (5.32).

5.2.4.2.2. Case II This case introduces a profit-maximization problem where the best time window for the PM schedule of each WT in the OWF along with its corresponding transport vessel is found through (5.54). In addition, the maintenance schedule for other generators is also decided. The objective is that these decisions should be in line with each other so that the profit of the OWF is maximized.

5.2.4.2.3. Case III In this case, the maintenance schedules of all power plants (except the OWF) that are obtained in *Case I* are considered the same ($y_{h,g}$ is fixed for G_1 to G_5). Then, a profit-maximization problem is carried out for the OWF through (5.54).

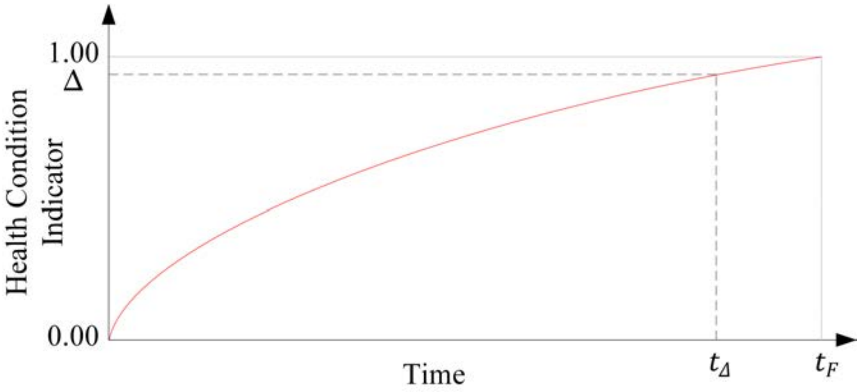


Figure 5.14: The defined anomaly model from the CMS

5.2.4.2.4. Case IV *Case IV* proposes a case where after receiving the failure (or anomaly) alarm, PM of all WTs are re-scheduled (assuming WTs did not have their PM performed by that time) and the maintenance of the WT_1 is prioritized. However, the maintenance of other power plants is already decided ($y_{h,g}$ is fixed for G_1 to G_5 from *Case II*).

In order to demonstrate the possibility of integration of CMSs with the maintenance planning, a simple anomaly model is defined as in Figure 5.14. The anomaly model receives the health condition of the WT (e.g. from a SCADA system) and updates the health condition indicator that displays the status of the WT. In this example, 0.00 means WT is in a good operational state and 1.00 means the WT is in an anomaly or failure state. Due to the high costs of anomaly and failure conditions, the OWF operator would like to prevent any WT to reach the failure state. Therefore, whenever the health condition indicator reaches a predefined threshold, Δ (which can be set based on experience), it is assumed that the WT must undergo maintenance by the time t_F. Otherwise, the WT may face an anomaly or a failure. Interested readers can refer to [38, 39, 153] for detailed analyses on the developments of such CMSs and anomaly models.

5.2.4.2.5. Case V *Case V* assumes that WT_1 requires a prioritized action and planning of PM schedules for other WTs is already outlined ($y_{h,g}$ is fixed for G_1 to G_5; $z_{h,k,b}$ and $u_{h,k,b}$ are fixed for WT_2 to WT_{12} from *Case II*). Hence, only the PM of WT_1 needs to be re-scheduled to an earlier time within the next 2 days after receiving the alarm. It should be noted that the priority constraint, (5.54w), is only considered in *Case IV* and *Case V* ($h' = 48, k' = WT_1$). Based on Figure 5.14, in this example, $t_F - t_\Delta$ can be considered as the remaining time for the WT until it faces an anomaly or failure with $h' = 48$ hours, since the time it received the anomaly signal.

5.2.4.2.6. Case VI In order to show the difference that addition of wake effect delivers, *Case VI* neglects the impact of the wake effect where it is assumed that available

Table 5.9: Vessel transfer time, wake effect and FOR

Wind Turbine	Vessel Transfer Time (hr.) b_1	b_2	b_3	Wake Effect (MW) (hourly measure)	FOR (p.u.)
WT_1, WT_2, WT_3	2	1	0	Figure (5.13)	0.02
WT_4, WT_5, WT_6	2	1	0	Figure (5.13) - 1	0.02
WT_7, WT_8, WT_9	2	1	0	Figure (5.13) - 2	0.01
$WT_{10}, WT_{11}, WT_{12}$	2	1	0	Figure (5.13) - 3	0.01

producible power for all the WTs follows the same pattern depicted in Figure 5.13. Then, a profit-maximization problem is carried out through (5.54).

5.2.4.2.7. Case VII This case modifies *Case II* and considers the model without night work-shift limitation which provides the possibility of performing maintenance at any hour of the day. To this aim, (5.54v) is disregarded in this case as it only enforces the day shift.

5.2.4.2.8. Case VIII To account for the unexpected failure in the study, *Case III* is updated where the forced outage rate (FOR) is considered as well. The assumed FOR values are displayed in Table 5.9 [384, 385]. Moreover, since the wake effect can impact the performance of the WTs as the loading on them increases, the FOR for the WTs that are affected more by the wake effect is higher than the other WTs. The calculation of unexpected outage times based on FOR for the WTs is performed through Monte Carlo technique where 2000 scenarios were simulated and one scenario was randomly selected to show the unexpected outage period for each WT based on its considered FOR. For simplicity, the FOR is solely considered for the WTs and only the deterministic study is carried out for this case.

5.2.4.2.9. Case IX There may be a situation where the WTs or generators require more than one maintenance action (e.g. on different sub-assemblies). Such possibility is also implemented in the model by updating *Case VI* and its application is demonstrated through *Case IX*. For simplicity, only the deterministic study is carried out and the number of required maintenance actions is set to two, $N_r = 2$, for each generator and WT.

5.2.5. Results

Profit of the OWF in each case is exhibited in Table 5.11. In the deterministic study, a comparison between *Case I* and *Case II* shows that there is a large potential for the OWF to increase its profit by participating in the market and considering the electricity

Table 5.10: Vessel cost and transportation limit

Vessel	Vessel Cost Factor m_b	Wave Height Limit (m) L_b
b_1	0.1	0.5
b_2	0.2	1.5
b_3	0.8	-

prices in the decision making process. In other words, if the wind farm decides to plan the PM of its WTs by considering the actual electricity prices, it could raise its profit by more than double. On the other hand, *Case III* shows that if the OWF cannot affect maintenance schedules of other power plants, it could still increase its profit by about 11%.

Interestingly, it can be seen that in the stochastic study, the profits follow the same trend as in the deterministic study. It should also be mentioned that the maximum available power in the stochastic study (144) is more than in deterministic study (108). This is the main reason of rather high profits in comparison with the deterministic cases. Another important point that must be mentioned here is that this addition of power in the stochastic case can present the OWF with more capability in influencing the market (e.g. prices, costs). Hence, the analysis of the strategic behavior is more prominent in the stochastic study than the deterministic one.

Case IV and *Case V* are of particular importance since they directly integrate the performance analysis and anomaly detection (AD) information extracted from the SCADA system of the WT into the operation and decision making process. As expected, the profits in Table 5.11 show that if a sudden anomaly occurs and a PM action is required, the best option (from the profit-maximization perspective) would be to re-schedule the maintenance of all the WTs in the farm, *Case IV*. This is due to the reason that in the *Case II*, the WT_1 was scheduled for maintenance through vessel type b_1 (which is the cheapest vessel). In *Case IV*, all maintenance schedules were re-arranged and other WTs were able to increase their use of the cheap vessel b_1. In *Case V*, since there was no available period for using vessel b_1 (in the 48 hours after the alarm), vessel b_2 was ordered to be used in the emergency maintenance situation which caused higher costs and thus, lower profit for the OWF. On the other hand, it can be seen that the difference in the profit reduces in the stochastic study and the impact is less. This means that in a more realistic case, due to the uncertainty in wind and wave, in such conditions, there is less opportunity for profiting in comparison with the deterministic study.

On consideration of the wake effect in the analyses, while *Case VI* neglects the influence of wake effect, *Case VII* disregards the impact of daily working shift. Interestingly, the results show that ignoring the wake effect brings about outcomes which are very different from when the wake effect is considered, Table 5.11. Comparing *Case II* with *Case VI* shows that by neglecting the wake effect, the earned profit is \$28204 which is nearly 3 times (2 times in the stochastic study) more than the profit when the wake

Table 5.11: Summary of profit and vessel utilization; deterministic(stochastic)

	Number of Vessel Utilizations			
	b1	b2	b3	Profit ($)
Case I	3 (2)	9 (10)	0 (0)	4716 (9875)
Case II	3 (3)	9 (9)	0 (0)	10769 (11410)
Case III	3 (2)	9 (7)	0 (3)	5220 (10423)
Case IV	3 (2)	9 (10)	0 (0)	10483 (10632)
Case V	2 (2)	10 (10)	0 (0)	9810 (10607)
Case VI	3 (2)	9 (10)	0 (0)	28204 (25489)
Case VII	4 (4)	8 (8)	0 (0)	10867 (17104)
Case VIII	3 (-)	9 (-)	0 (-)	3498 (-)
Case IX	6 (-)	18 (-)	0 (-)	14954 (-)

Table 5.12: Summary of electricity price and operation cost; deterministic(stochastic)

	Avg. Price ($/MWh)	Operation Cost ($)
Case I	23.310 (23.112)	929069 (923347)
Case II	23.722 (23.211)	930450 (924639)
Case III	23.373 (23.855)	929221 (924250)
Case IV	23.681 (23.755)	930299 (924687)
Case V	23.688 (24.090)	930471 (923995)
Case VI	22.948 (22.357)	908732 (900718)
Case VII	23.675 (23.892)	930222 (925036)
Case VIII	23.363 (-)	930855 (-)
Case IX	25.855 (-)	919536 (-)

effect is considered. This is very important as it can result in a planning strategy where it is far from the reality.

Regarding work shifts, the results show that providing the possibility of carrying out maintenance at any hour of day does not increase the profit significantly, Table 5.11. For instance, by providing the 24/7 maintenance crew in *Case VII*, the profit has only increased around 1% when compared with *Case II* with only daily working shift. It should be reminded that this change is more bold in the stochastic study as the maximum available wind power has increased. On the other hand, having around-the-clock maintenance crew results in higher costs which then will reduce the additionally earned profit. Furthermore, the proposed SMSOWF model provides a way to study and find the optimum daily work shift for the maintenance crew which can be of great assistance for the asset management and maintenance department.

Table 5.12 displays the average electricity price and the operation cost of the system. It should be mentioned that the operation cost is defined as shown in (5.32a) where costs related to maintenance actions are not included. Moreover, the variable operation cost for the OWF is also considered to be 0, Table 5.2. *Case VI* exhibits the lowest average price and operation cost in both deterministic and stochastic studies which is due to the high level of integration of wind in the operation of the power system. *Case I* has the second lowest average electricity price and operation cost in both deterministic and stochastic studies. This is because of the fact that the problem in *Case I* is a cost-minimization problem, (5.32).

Consideration of unexpected outages for the WTs in *Case VIII* shows that the profit can be rather significantly decreased, Table 5.11. This is due to the fact that more outages result in less production and hence more loss in profit for the OWF. This is also in line with the increase in the operation cost when compared with *Case III*, Table 5.12.

While *Case VI* considers only one maintenance action for the WTs and generators, *Case IX* assumes that each of them requires two maintenance actions. This increase in the number of maintenance actions has reduced the profit for the OWF by more than half.

A comparison between the operation costs of three profit-maximization cases of *Case II*, *Case IV* and *Case V* in the deterministic study shows that whenever an anomaly occurs for a WT in the wind farm, the best case from the perspective of the system is to re-schedule the maintenance of all WTs (*Case IV*); otherwise, both the average price and operation cost increase. However, the stochastic study shows that considering the stochasticity can change the outcomes, although the change is not significant. Interestingly, this move (choosing *Case IV*) is also the best option for the wind farm operator as then the operator endures the lowest loss in the profit in the deterministic study, Table 5.11. This is due to the fact that re-scheduling maintenance of all the WTs will help the model to obtain the next-best-optimum solution and this prevents the system to deviate from the optimal operation. It should be reminded here that in this model, the cost of the maintenance action is not considered as part of the operation cost of the system. If only the perspective of the system as a whole is considered, one could also study the impact of an emergency situation through the cost-minimization model presented in (5.32).

Figure 5.15 displays the electricity prices in the test system during the study period for cases $I-VII$ in the deterministic study. The maximum electricity price (58.1 \$/MWh) occurs in *Case IV* at hour $h=46$ where the available wind power at the OWF is 78 MW and the overall demand is 350 MW. The reason for this peak price is that at this hour, G_3 undergoes maintenance and G_5, the most expensive generator, enters the system to keep the load balance. It should be reminded that in this case, the maintenance schedules of all power plants (except the OWF) are fixed and considered the same as in *Case II* for the sake of comparing the impact of a sudden anomaly.

Although *Case VI* delivers the lowest electricity average price and operation cost in the deterministic study, few peak values in the prices occur. For instance, during hours 42-43 where G_2 is scheduled for maintenance, the OWF does not dispatch its full power causing the most expensive generator to produce and increase the price. Similar behavior is observed with more prominent impact in *Case VI* in the stochastic study as the available power in the OWF has increased. On the other hand, the increase in the

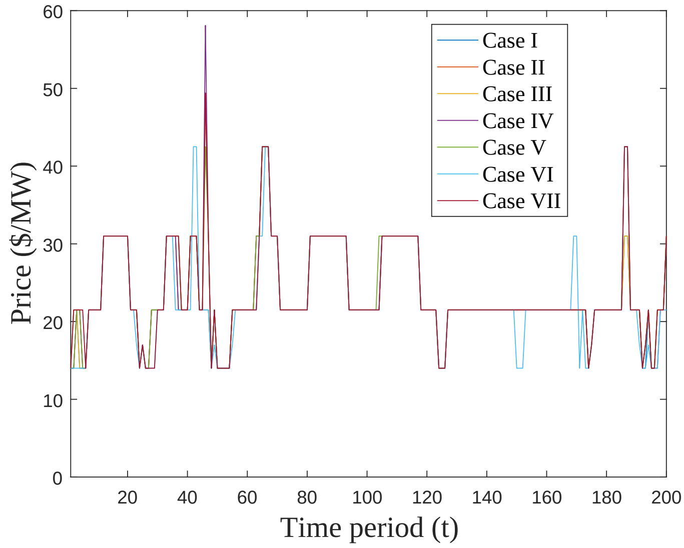


Figure 5.15: Electricity prices over study period for deterministic Cases $I-VII$

number of maintenance actions in *Case IX* has also increased the operation cost in comparison with *Case VI* as it has caused more downtime for the OWF. This means that production of conventional generators has increased and this results in higher operation costs. Indeed, one can advance this study by introducing the game theory and obtaining the NE in order to evaluate the market power and behavior of other players in the system.

Table 5.13 shows the frequency of utilization of the vessel types in the case studies *I* - *VII*. Please notice that in the proposed model, the vessel type does not impact the duration of the maintenance action itself and only affects the transportation time. Therefore, there is no conflict between the vessel optimization and the operation cost; the vessels are only selected based on their cost and optimized based on their availability. Hence, from arranging vessels point of view, this part only exhibits applicability of the model with integration of various vessels and the environmental limitations (wave height). It should also be reminded that there is no difference between the WTs in the same column, Figure 5.10. The results in both deterministic and stochastic studies show that the system tends to associate the cheaper vessels with the more profitable WTs; in other words, the WTs that are less influenced by the wake effect. As mentioned earlier, the justification for this planning is based on the environmental conditions, the costs of the vessels and the time they require for transferring the maintenance crew to and from the OWF.

Regarding the vessel type b_3, the helicopter, in addition to the mentioned case studies, several other cases were analyzed. For instance, a sensitivity analysis was performed on the cost of the vessels through the deterministic study. In *Case I* where it is a cost-minimization case, the helicopter was only deployed when its cost became less than twice of the most expensive boat, b_2. Hence, with low cost, such case resulted in

Table 5.13: Summary of vessel utilization based on WTs in cases $I-VII$; deterministic(stochastic)

	b_1	b_2	b_3
WT_1	3 (1)	4 (6)	0 (0)
WT_2	0 (1)	7 (6)	0 (0)
WT_3	3 (2)	4 (4)	0 (1)
WT_4	5 (2)	2 (5)	0 (0)
WT_5	2 (1)	5 (5)	0 (1)
WT_6	1 (1)	6 (5)	0 (1)
WT_7	3 (4)	4 (3)	0 (0)
WT_8	0 (1)	7 (6)	0 (0)
WT_9	1 (1)	6 (6)	0 (0)
WT_{10}	1 (1)	6 (6)	0 (0)
WT_{11}	1 (1)	6 (6)	0 (0)
WT_{12}	1 (1)	6 (6)	0 (0)

utilization of vessel b_3 for the majority of the maintenance of the WTs and the other WTs used the vessel type b_1. This also brought about higher profit for the OWF and lower operation cost for the system.

Indeed, the most significant value of a helicopter can be considered when boats cannot work due to wave limitations or when there is an urgent need for a maintenance. With this aim, *Case IV*, amongst the profit-maximization cases, was analyzed where the helicopter was deployed and came into operation with the cost of three times more expensive than the most expensive boat, b_2. An interesting observation was made as the helicopter was only deployed in the stochastic cases. This shows that addition of stochasticity could bring about more realistic scenarios where the deterministic study almost disregarded the helicopter completely.

5.2.6. Case Study Conclusion

Strategic maintenance scheduling of an OWF in a deregulated power system is studied in this case study through the proposed SMSOWF model. The model includes practical constraints from the system and the OWF such as maintenance working shift, environmental limitation and wake effect. In addition, the SMSOWF model has the capability of integrating condition monitoring information in the operation and planning of the OWF. The proposed model is assessed from various perspectives through multiple case studies. For instance, the results show that actively considering market in the operation can bring about significant profit for the OWF. On the other hand, it is shown that simplifications in terms of neglecting wake effect and working shifts cause the results to deviate from practical outcomes where wake effect displayed the highest impact.

5.3. Strategic Islanded Microgrid Maintenance Optimization

The third study proposes a model to analyze strategic maintenance scheduling problem for an islanded MG. Similar to the first and second studies, strategic maintenance scheduling of microgrid (SMSOMG) model compares this problem from centralized and decentralized perspectives while accounting for various uncertainties. It also investigates impact of the market operations on the maintenance scheduling considering RES and storage units. This study is published by the author in [147].

5.3.1. Nomenclature

Indexes:	
h	Index for hour
g	Index for houses and diesel generator
j	Index for distributed energy resources
b	Index for battery storage system
Sets:	
$\Gamma(g)$	Houses in the microgrid
Parameters:	
α_g	Cost of operating diesel generator (\$/kWh)
C_j	Cost of maintenance action for distributed energy resource (DER) j (\$)
B	Life-cycle cost factor for battery (\$/kWh)
$T_{g,j}$	Required maintenance time for DER j in house g (h)
N_h	Number of hours
E_j	Limit on the simultaneous maintenance actions of DER j
L	Maximum number of DERs that can go under maintenance simultaneously
h'	Maximum limit of time to have maintenance after the alarm
g'	The house that has received the alarm signal
j'	The DER system that has received the alarm signal
$D_{h,g}$	Demand at house/generator g at hour h (kW)
$Q'_{h,g,j}$	Maximum available power for DER j in house g at hour h (kW)
$Q''_{h,g}$	Maximum available power in generator g at hour h (kW)
M_1, M_2, M_3	Large enough numbers used in linearization
Variables:	
$x_{h,g,j}$	Binary variable for maintenance status of DER j, in house g at hour h
$q_{h,g}$	The produced power by diesel generator g at hour h (kW)
$q'_{h,g,j}$	The produced power by DER j in house g at hour h (kW)
$y_{h,g}$	Charge of battery in house g at hour h (kW)
$z_{h,g}$	Discharge of battery in house g at hour h (kW)
λ_{1_h}	Lagrange multiplier of demand balance
$\lambda_{2_{h,g,j}}$	Lagrange multiplier of maximum capacity limit for houses

$\lambda_{3_{h,g}}$	Lagrange multiplier of maximum capacity limit for diesel generator
$\lambda_{4_{h,g,j}}$	Lagrange multiplier of battery charge/discharge connection
$\lambda_{5_{h,g,j}}$	Lagrange multiplier of battery maximum charge
$\lambda_{6_{h,g,j}}$	Lagrange multiplier of battery maximum discharge
$\lambda_{7_{h,g,j}}$	Lagrange multiplier of battery charge link
$\lambda_{8_{h,g,j}}$	Lagrange multiplier of battery discharge link
$\lambda_{9_{h,g}}$	Lagrange multiplier of battery charging positivity
$\lambda_{10_{h,g}}$	Lagrange multiplier of battery discharging positivity
$\lambda_{11_{h,g,j}}$	Lagrange multiplier of power positivity for houses
$\lambda_{12_{h,g}}$	Lagrange multiplier of power positivity for diesel generator
$\lambda_{13_{h,g,j}}$	Lagrange multiplier of battery initial/final condition
$\mu_{1_{h,g,j}}$	Variable for linearization of $\lambda_{2_{h,g,j}}$
$\mu_{2_{h,g,j}}$	Variable for linearization of $\lambda_{5_{h,g,j}}$
$\mu_{3_{h,g,j}}$	Variable for linearization of $\lambda_{6_{h,g,j}}$

5.3.2. Introduction

The conventional electric power system is changing its form due to efforts such as reducing the greenhouse gas emissions, future scarcity of fossil fuel, shun substantial investments in power generation, deregulation, increasing the integration of DER (e.g. solar, wind, storage) and large deployment of advanced metering infrastructure [386]. Such transition brings about several challenges from different perspectives (e.g. integration, operation, stability, protection). In particular, rapid growth in utilization of DERs in the electric power distribution systems is gaining attention as it provides the customers with more control and flexibility on their operation and opportunity to earn profit. Therefore, the connected topics should also try to follow with this quick development. One of these topics that helps the components keep their stable operational level and contribute to acceptable reliability constraints in a power system is PM. As an example, avoiding significant investments in the electric grid by distributing the energy generation and high integration of DERs result in increased utilization of the equipment in MG and thus, higher wear in the components [387]. Therefore, a MG requires optimum PM planning and operation scheduling; otherwise, maloperation of DERs (e.g. due to abnormal condition or failure) can endanger the security of power delivery and reduce the reliability and satisfaction of the customers from the services [388].

As mentioned in section 5.2.2, PM scheduling can be divided into two categories of passive and active. Passive maintenance scheduling considers that the maintenance outages are planned without considering the electricity market and the prices while the active maintenance scheduling considers that the outages are planned considering the change in the electricity prices. With this classification, most of the research studies in the electric power systems have been focused on the passive maintenance scheduling [325–329]. Moreover, because of the complexity of the problem, several simplifications are always considered (e.g. forecasted electricity prices, neglecting RES, disregarding storage systems, ignoring health condition information). [389] proposes a maintenance scheduling model in a distribution system with the objective of minimizing total operation cost of the system. The generation companies suggest their favorable maintenance time-window and the system operator verifies whether these plans fall within considerations of distribution system (e.g. economic, security). There are also several similar works where the focus of the problem is solely on the grid [125, 339].

MGs can be considered as entities that coordinate the operation of DERs [390]. This coordination can be performed by an independent microgrid operator (IMGO) in a centralized or decentralized manner [391, 392]. MGs have become extremely popular due to their positive role in speeding up the transformation of the power system because of the mentioned challenges. As a result, there have been many studies on their operations and many MG projects have been developed [393–395]. For instance, [396] surveys trends for integration of wind and solar power generators from power electronics point of view and concludes that modern power electronic technologies can assist in achieving high efficiency and reliability at low costs for MGs. [397] optimizes operation of a grid-connected MG by minimizing maintenance related and operation costs of the DERs through economic dispatch formulation. It shows that when all types of sources are considered, the O&M costs are high, thus, emphasizing on importance of analyzing this topic. However, although storage can alleviate the intermittent problem of solar and wind by introducing time-shift in the energy consumption [398–400], it requires additional investments and increased operational costs. For instance, [398] shows that different types of storage systems (which can be classified based on the number of charge/discharge cycles) can have different influence on the costs and profit as the profit they bring about may not be financially better than the costs they impose. [401] minimizes the net present cost of a MG where they take into account capital, replacement, and O&M costs. It demonstrated that as the amount of interruptible load increases (e.g. load shedding due to failures or abnormal condition of equipment), the total cost of the MG decreases. However, this also reduces the satisfaction of the customers and PM can help to overcome such shortcomings by assisting in maintaining the condition of the equipment at an acceptable level. [402] proposes a three-layer architecture for operation of a MG. The proposed energy management system that schedules the operation receives the maintenance outages as inputs to the model. The maintenance is planned if the forecast results in excess power in the MG. [403] proposes a two-stage optimization model for dispatch in order to maximize the profit of a MG including storage, wind and solar. In a theoretical approach, [404] introduces a bi-level control scheme to increase reliability in a grid by taking advantage of bulk generation units. All these models neglect the mutual impact of the maintenance scheduling on the actual operation and the electricity prices.

Integrating electricity market into the operation of MG is gaining attention [405]. Performing operation of a MG through a cost-minimization framework has become very popular as it results in the least cost operation [394, 406]. [407] considers a balancing market in a grid-connected MG where the users act independently and an energy manager sets the price for energy by considering the intersection of the generation and demand. The simulation model considered three consumers and DERs and set an upper limit on the price during the operation. It shows how the operation of DERs can directly affect the electricity prices while connected or in islanded mode. [408] proposes an optimization model for optimal operation of a MG with the objective of running with the least operational costs. The load curtailment is introduced as a penalty factor that displays the importance of considering the outages, which may be avoided if an efficient condition monitoring and PM planning strategy is applied. [409] evaluates sustainability and reliability of MGs in an electricity market. It discusses how the reliability can be impacted by introducing MGs and the importance of studying other aspects of reliability such as outages which can be planned or unexpected. [410] analyzes interactions among agents in MGs through a cooperative game theoretic approach and shows how forming a MG can influence different agents in the system. It demonstrates that regulating price based on service cost can bring about market failures (i.e. misalignment between maximization of social welfare and maximization of objectives of other agents). This shows the importance of analysis of strategic behavior of all agents in a MG. [411] reviews the performed research on MGs in terms of scheduling where it is mentioned that reliability related matters require further investigations. [412] proposes a predictive-based operation strategy in an off-grid MG and shows that there is 2-7% potential of saving costs. All these studies analyzed the MG without addressing active PM scheduling. In other words, they neglect the opportunity for the agents in making any profit through maintenance scheduling.

The focus of this case study is on the decision-making problem in the context of active PM scheduling. While an IMGO seeks for maintenance and operation schedules that reduce the electricity prices and operation cost (cost-minimization problem) in a perfectly competitive market scenario, the other agents pursue scenarios to increase their profit (profit-maximization problem). Active PM scheduling can bring about cases where the maintenance plans could cause a MG deviate from its optimum operation and different agents exercise market power. Therefore, such a study is of importance for the regulators to detect market failures, for the policy makers to identify beneficiaries of their policies, and to the agents to study their possible planning arrangements in order to gain additional profit within the operational range defined by the IMGO.

To this aim, this case study proposes two formulations with regard to maintenance scheduling and operation of MGs. It extends the idea mentioned in [413] on the operation and management of isolated MGs by integrating maintenance scheduling and surveying the horizon of agents on making profit. In the first formulation, a cost-minimization problem in an SLP is formulated where it considers that the IMGO operates the MG and ensures that the generation meets the demand with the least operational cost objective. This formulation is considered as the benchmark and state-of-the-art in the passive PM scheduling. The cost-minimization problem neglects the strategic behavior of the agents (e.g. houses) in the MG and disregards their profit-making goal. Moreover, in the cost-minimization formulation, the IMGO schedules the PM actions for the houses which is similar to the centralized operation framework [335, 414]. In the second formulation, a profit-maximization problem in bi-level form (BLP) is formulated where it considers that the houses schedule the required PM of their DER systems with the objective of maximizing their profit. The IMGO runs an auxiliary supply (diesel generator) and ensures the security of supply. The lower-level problem in the BLP tries to minimize the operation cost of the MG while the upper-level maximizes the profit of the houses. The BLP is transformed into an SLP by applying KKT conditions. The final SLP is considered as a SMSOMG and is the state-of-the-art in active PM scheduling field. The considered islanded MG can consist of houses where each house has a battery storage, solar and wind system. In addition, since the lifetime of the battery is impacted by different parameters such as charge/discharge rate, maintenance, depth of charge [415, 416], an intuitive life-cycle cost factor is also assigned to the operation of the battery systems in maintenance scheduling. Finally, the SMSOMG model also incorporates condition monitoring information into the decision-making process. The contribution of this case study can be summarized as following: passive and active PM scheduling models (centralized and decentralized), incorporation of maintenance decision-making into the electricity market in a MG with solar, wind and storage that integrates a factor for life-cycle of the storage system, application of submitting condition monitoring data into the operation of a MG and analysis of strategic behavior of agents in order to assess the operation and the deviation from an optimal operation.

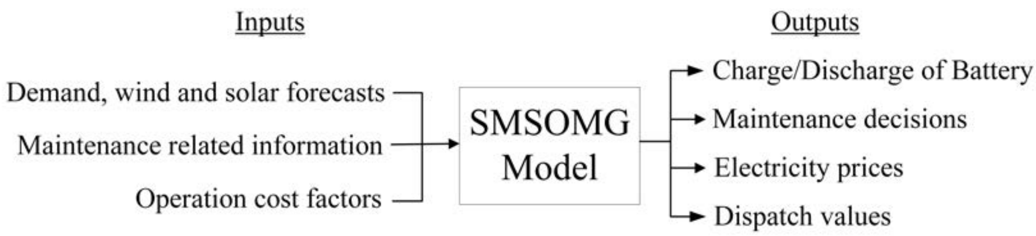


Figure 5.16: The general SMSOMG model

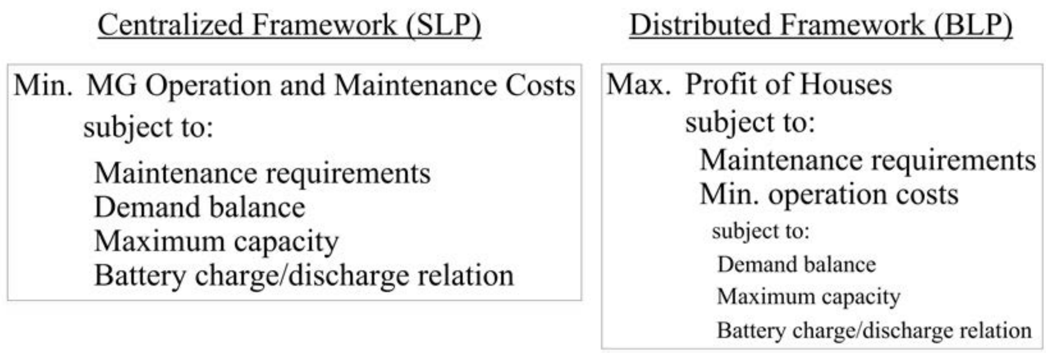


Figure 5.17: The flowchart of proposed SLP and BLP for SMSOMG

5.3.3. Problem Formulation

The overall model is displayed in Figure 5.16 where the inputs and outputs are mentioned. An overview on the defined cost-minimization and and profit-maximization models can be seen in Figure 5.17.

5.3.3.1. Cost-Minimization Maintenance Scheduling

Based on the perspective that the objective of the IMGO is to operate the MG with the least operation cost, a cost-minimization formulation is considered in section 5.3.3.1 where this cost-minimization scenario does not take into account the profit of the houses in the MG. The SLP is defined as following:

$$\min_{q,q',x,y,z} \sum_{h,g\notin\Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g\in\Gamma(g),j} \alpha_g q'_{h,g,j} + \sum_{h,g\in\Gamma(g),j} x_{h,g,j} C_j + \sum_{h,g\in\Gamma(g)} (y_{h,g} + z_{h,g}) B \tag{5.55a}$$

$$\sum_h x_{h,g,j} - T_{g,j} = 0 \qquad \forall g \in \Gamma(g), j \tag{5.55b}$$

$$x_{h+1,g,j} - x_{h,g,j} - x_{h+T_{g,j},g,j} = 0 \qquad \forall h < N_h, g \in \Gamma(g), j \tag{5.55c}$$

$$\sum_{g\in\Gamma(g)} x_{h,g,j} - E_j \leq 0 \qquad \forall h, j \tag{5.55d}$$

$$\sum_j x_{h,g,j} - L \leq 0 \qquad \forall h, g \in \Gamma(g) \tag{5.55e}$$

$$x_{h,g,j} = 0 \qquad \forall h > h', g = g', j = j' \tag{5.55f}$$

$$\sum_{g\notin\Gamma(g)} q_{h,g} + \sum_{g\in\Gamma(g),j\neq b} q'_{h,g,j} - \sum_g D_{h,g} - \sum_{g\in\Gamma(g)} (y_{h,g} + z_{h,g}) = 0 \qquad \forall h \tag{5.55g}$$

$$q'_{h,g,j} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 \qquad \forall h, g \in \Gamma(g), j \tag{5.55h}$$

$$q_{h,g} - Q''_{h,g} \leq 0 \qquad \forall h, g \notin \Gamma(g) \tag{5.55i}$$

$$q'_{h+1,g,j} - q'_{h,g,j} - y_{h+1,g} + z_{h+1,g} = 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.55j}$$

$$y_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.55k}$$

$$z_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.55l}$$

$$y_{h+1,g} - Q'_{h,g,j} + q'_{h,g,j} \leq 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.55m}$$

$$z_{h+1,g} - q'_{h,g,j} \leq 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.55n}$$

$$-y_{h,g} \leq 0 \qquad \forall h, g \in \Gamma(g) \tag{5.55o}$$

$$-z_{h,g} \leq 0 \qquad \forall h, g \in \Gamma(g) \tag{5.55p}$$

$$-q'_{h,g} \leq 0 \qquad \forall h, g \in \Gamma(g), j \tag{5.55q}$$

$$-q_{h,g} \leq 0 \qquad \forall h, g \notin \Gamma(g) \tag{5.55r}$$

$$q'_{h=1,g,j} - q'_{h=N_h,g,j} = 0 \qquad \forall g \in \Gamma(g), j = b \tag{5.55s}$$

The first two terms in the objective function (5.55a) account for the cost of producing power through the diesel generator and the DER systems in each house. The third term accounts for cost of PM actions and the last two terms account for the life-cycle cost of battery storage systems. Please notice that the B coefficient also assists in preventing the charge/discharge action to occur simultaneously. Constraint (5.55b) ensures that the minimum required PM time for each DER system at each house is met where constraint (5.55c) monitors the continuity of that maintenance action. Constraint (5.55d) limits the number of houses that can simultaneously perform maintenance on any of the DER systems at each hour. Constraint (5.55e) limits the number of DER systems that can have maintenance in each house at each hour. Integration of health condition monitoring information into the maintenance scheduling is introduced through constraint (5.55f). The demand balance, maximum DER producible power and maximum diesel generator capacity are enforced in (5.55g), (5.55h) and (5.55i), respectively. Constraint (5.55j) provides the relation between charged and discharged power in the battery system. Constraints (5.55k) and (5.55l) provide the maximum limitation on power charge and discharge in a battery. Constraint (5.55m) ensures that the amount of power to be charged in the battery cannot be more than the available capacity and similarly, constraint (5.55n) ensures that the amount of power to be discharged from the battery cannot be more than the available power in the battery. While constraints (5.55o), (5.55p), (5.55q) and (5.55r) provide positivity control for the defined variables, constraint (5.55s) forces the initial and final available power in the battery systems to be the same.

5.3.3.2. Profit-Maximization Maintenance Scheduling

A profit-maximization formulation is proposed through BLP in section 5.3.3.2. The objective of the profit-maximization formulation is for the houses to maximize their profit while maintaining the least operation cost in the system. The BLP in the profit-maximization scenario is transformed into an SLP by deriving the KKT conditions for the problem. The BLP is defined as following:

$$\begin{aligned} \max_{x,y,z} \; & \sum_{h,g \in \Gamma(g), j \neq b} \lambda_{1_h} q'_{h,g,j} + \sum_{h,g \in \Gamma(g)} \lambda_{1_h} (z_{h,g} - y_{h,g}) - \sum_{h,g,j} x_{h,g,j} C_j \\ & - \sum_{h,g} (y_{h,g} + z_{h,g}) B \end{aligned} \tag{5.56a}$$

$$\sum_{h} x_{h,g,j} - T_{g,j} = 0 \qquad \forall g \in \Gamma(g), j \tag{5.56b}$$

$$x_{h+1,g,j} - x_{h,g,j} - x_{h+T_{g,j},g,j} = 0 \qquad \forall h < N_h, g \in \Gamma(g), j \tag{5.56c}$$

$$\sum_{g \in \Gamma(g)} x_{h,g,j} - E_j \leq 0 \qquad \forall h, j \tag{5.56d}$$

$$\sum_j x_{h,g,j} - L \leq 0 \qquad \forall h, g \in \Gamma(g) \tag{5.56e}$$

$$x_{h,g,j} = 0 \qquad \forall h > h', g = g', j = j' \tag{5.56f}$$

$$\min_{q,q'} \sum_{h,g \notin \Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g \in \Gamma(g),j} \alpha_g q'_{h,g,j} \tag{5.56g}$$

$$\sum_{g \notin \Gamma(g)} q_{h,g} + \sum_{g \in \Gamma(g), j \neq b} q'_{h,g,j} - \sum_g D_{h,g} - \sum_{g \in \Gamma(g)} (y_{h,g} + z_{h,g}) = 0 : \lambda_{1_h} \quad \forall h \tag{5.56h}$$

$$q'_{h,g,j} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 : \lambda_{2_{h,g,j}} \qquad \forall h, g \in \Gamma(g), j \tag{5.56i}$$

$$q_{h,g} - Q''_{h,g} \leq 0 : \lambda_{3_{h,g}} \qquad \forall h, g \notin \Gamma(g) \tag{5.56j}$$

$$q'_{h+1,g,j} - q'_{h,g,j} - y_{h+1,g} + z_{h+1,g} = 0 : \lambda_{4_{h,g,j}} \quad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.56k}$$

$$y_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 : \lambda_{5_{h,g,j}} \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.56l}$$

$$z_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \leq 0 : \lambda_{6_{h,g,j}} \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.56m}$$

$$y_{h+1,g} - Q'_{h,g,j} + q'_{h,g,j} \leq 0 : \lambda_{7_{h,g,j}} \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.56n}$$

$$z_{h+1,g} - q'_{h,g,j} \leq 0 : \lambda_{8_{h,g,j}} \qquad \forall h < N_h, g \in \Gamma(g), j = b \tag{5.56o}$$

$$-y_{h,g} \leq 0 : \lambda_{9_{h,g}} \qquad \forall h, g \in \Gamma(g) \tag{5.56p}$$

$$-z_{h,g} \leq 0 : \lambda_{10_{h,g}} \qquad \forall h, g \in \Gamma(g) \tag{5.56q}$$

$$-q'_{h,g,j} \leq 0 : \lambda_{11_{h,g,j}} \qquad \forall h, g \in \Gamma(g), j \tag{5.56r}$$

$$-q_{h,g} \leq 0 : \lambda_{12_{h,g}} \qquad \forall h, g \notin \Gamma(g) \tag{5.56s}$$

$$q'_{h=1,g,j} - q'_{h=N_h,g,j} = 0 : \lambda_{13_{h,g,j}} \qquad \forall g \in \Gamma(g), j = b \tag{5.56t}$$

5.3.3.3. Karush–Kuhn–Tucker Conditions

In order to transform the BLP (5.56) into an SLP, KKT conditions are applied to the lower-level problem (5.56g)-(5.56t). These conditions are: stationarity (gradient of Lagrangian with respect to lower-level variables), complementary slackness, primal constraints (original inequalities) and dual constraints [348]. Forming the Lagrangian function ($\mathscr{L}$) provides:

$$\begin{aligned}
\mathscr{L}(q, q', y, z, \lambda) = & \sum_{h,g \notin \Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g \in \Gamma(g),j} \alpha_g q'_{h,g,j} + \sum_h \lambda_{1_h} \Bigg[- \sum_{g \notin \Gamma(g)} q_{h,g} \\
& - \sum_{g \in \Gamma(g), j \neq b} q'_{h,g,j} - \sum_{g \in \Gamma(g)} z_{h,g} + \sum_{g \in \Gamma(g)} y_{h,g} + \sum_g D_{h,g} \Bigg] + \sum_{h,g \in \Gamma(g),j} \lambda_{2_{h,g,j}} \big[q'_{h,g,j} \\
& - (1 - x_{h,g,j}) Q'_{h,g,j} \big] + \sum_{h,g \notin \Gamma(g)} \lambda_{3_{h,g}} \big[q_{h,g} - Q''_{h,g} \big] + \sum_{h < N_h, g \in \Gamma(g), j = b} \lambda_{4_{h,g,j}} \big[q'_{h+1,g,j} \\
& - q'_{h,g,j} - y_{h+1,g} + z_{h+1,g} \big] + \sum_{h,g \in \Gamma(g), j = b} \lambda_{5_{h,g,j}} \big[y_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \big]
\end{aligned}$$

$$+\sum_{h,g\in\Gamma(g),j=b}\lambda_{6_{h,g,j}}\left[z_{h,g}-(1-x_{h,g,j})Q'_{h,g,j}\right]+\sum_{h<N_h,g\in\Gamma(g),j=b}\lambda_{7_{h,g,j}}\left[y_{h+1,g}\right.$$
$$\left.-Q'_{h,g,j}+q'_{h,g,j}\right]+\sum_{h<N_h,g\in\Gamma(g),j=b}\lambda_{8_{h,g,j}}\left[z_{h+1,g}-q'_{h,g,j}\right]+\sum_{h,g\in\Gamma(g)}\lambda_{9_{h,g}}[-y_{h,g}]$$
$$+\sum_{h,g\in\Gamma(g)}\lambda_{10_{h,g}}[-z_{h,g}]+\sum_{h,g\notin\Gamma(g)}\lambda_{11_{h,g}}[-q_{h,g}]+\sum_{h,g\in\Gamma(g),j}\lambda_{12_{h,g,j}}[-q'_{h,g,j}]$$
$$+\sum_{h,g\in\Gamma(g),j=b}\lambda_{13_{h,g,j}}\left[q'_{h=1,g,j}-q'_{h=N_h,g,j}\right] \tag{5.57}$$

Stationarity conditions are written as follows:

$$\frac{\partial\mathscr{L}(q,q',y,z,\lambda)}{\partial q}=\alpha_g-\lambda_{1_h}+\lambda_{3_{h,g}}-\lambda_{11_{h,g}}=0 \qquad \forall h,g\notin\Gamma(g) \tag{5.58}$$
$$\frac{\partial\mathscr{L}(q,q',y,z,\lambda)}{\partial q'}=\alpha_g+\lambda_{1_{\substack{h\\ j\neq b}}}+\lambda_{2_{h,g,j}}+\lambda_{4_{h-1>1,g,j=b}}-\lambda_{4_{h<N_h,g,j=b}}$$
$$+\lambda_{7_{h<N_h,g,j=b}}-\lambda_{8_{h<N_h,g,j=b}}-\lambda_{12_{h,g,j}}+\lambda_{13_{h=1,g,j=b}}-\lambda_{13_{h=N_h,g,j=b}}=0$$
$$\forall h,g\in\Gamma(g),j \tag{5.59}$$
$$\frac{\partial\mathscr{L}(q,q',y,z,\lambda)}{\partial y}=\lambda_{1_h}-\lambda_{4_{h-1>1,g,j}}+\lambda_{5_{h,g,j}}+\lambda_{7_{h-1>1,g,j}}-\lambda_{9_{h,g}}=0$$
$$\forall h,g\in\Gamma(g),j=b \tag{5.60}$$
$$\frac{\partial\mathscr{L}(q,q',y,z,\lambda)}{\partial z}=-\lambda_{1_{h,g}}+\lambda_{4_{h-1>1,g,j}}+\lambda_{6_{h,g,j}}+\lambda_{8_{h-1>1,g,j}}-\lambda_{10_{h,g}}=0$$
$$\forall h,g\in\Gamma(g),j=b \tag{5.61}$$

And from complementarity conditions:

$$\lambda_{2_{h,g,j}}\left[q'_{h,g,j}-(1-x_{h,g,j})Q'_{h,g,j}\right]=0 \qquad \forall h,g\in\Gamma(g),j \tag{5.62}$$
$$\lambda_{3_{h,g}}\left[q_{h,g}-Q''_{h,g}\right]=0 \qquad \forall h,g\notin\Gamma(g) \tag{5.63}$$
$$\lambda_{4_{h,g,j}}\left[q'_{h+1,g,j}-q'_{h,g,j}-y_{h+1,g}+z_{h+1,g}\right]=0 \qquad \forall h<N_h,g\in\Gamma(g),j=b \tag{5.64}$$
$$\lambda_{5_{h,g,j}}\left[y_{h,g}-(1-x_{h,g,j})Q'_{h,g,j}\right]=0 \qquad \forall h<N_h,g\in\Gamma(g),j=b \tag{5.65}$$
$$\lambda_{6_{h,g,j}}\left[z_{h,g}-(1-x_{h,g,j})Q'_{h,g,j}\right]=0 \qquad \forall h<N_h,g\in\Gamma(g),j=b \tag{5.66}$$
$$\lambda_{7_{h,g,j}}\left[y_{h+1,g}-Q'_{h,g,j}+q'_{h,g,j}\right]=0 \qquad \forall h<N_h,g\in\Gamma(g),j=b \tag{5.67}$$
$$\lambda_{8_{h,g,j}}\left[z_{h+1,g}-q'_{h,g,j}\right]=0 \qquad \forall h<N_h,g\in\Gamma(g),j=b \tag{5.68}$$
$$\lambda_{9_{h,g}}\left[-y_{h,g}\right]=0 \qquad \forall h,g\in\Gamma(g) \tag{5.69}$$
$$\lambda_{10_{h,g}}\left[-z_{h,g}\right]=0 \qquad \forall h,g\in\Gamma(g) \tag{5.70}$$
$$\lambda_{11_{h,g}}\left[-q_{h,g}\right]=0 \qquad \forall h,g\notin\Gamma(g) \tag{5.71}$$
$$\lambda_{12_{h,g,j}}\left[-q'_{h,g,j}\right]=0 \qquad \forall h,g\in\Gamma(g),j \tag{5.72}$$
$$\lambda_{13_{h,g,j}}\left[q'_{h=1,g,j}-q'_{h=N_h,g,j}\right]=0 \qquad \forall h,g\in\Gamma(g),j=b \tag{5.73}$$

The nonlinearities in the complementarity conditions (5.62)-(5.73) can be linearized through disjunctive constraints by new additional binary variables [349]. However, this will extremely complicate the problem. Therefore, since the lower-level problem, (5.56g)-(5.56t), is convex, as the commitment decisions (start-up and shut-down) of the distributed resources are not considered and $x_{h,g,j}$ in lower-level acts as a parameter, these complementarity conditions are substituted by strong duality (5.74).

$$
\begin{aligned}
&\sum_{h,g\notin\Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g\in\Gamma(g),j} \alpha_g q'_{h,g,j} = \\
&\sum_{h,g} \lambda_{1_h} D_{h,g} - \sum_{h,g\in\Gamma(g),j} \lambda_{2_{h,g,j}} (1-x_{h,g,j}) Q'_{h,g,j} - \sum_{h,g\notin\Gamma(g)} \lambda_{3_{h,g}} Q''_{h,g} \\
&- \sum_{h<N_h,g\in\Gamma(g),j=b} \lambda_{5_{h,g,j}} (1-x_{h,g,j}) Q'_{h,g,j} - \sum_{h<N_h,g\in\Gamma(g),j=b} \lambda_{6_{h,g,j}} (1-x_{h,g,j}) Q'_{h,g,j} \\
&- \sum_{h<N_h,g\in\Gamma(g),j=b} \lambda_{7_{h,g,j}} Q'_{h,g,j} \qquad (5.74)
\end{aligned}
$$

At this step, there are four nonlinearities in the problem where $\lambda_{2_{h,g,j}}(1-x_{h,g,j})$, $\lambda_{5_{h,g,j}}(1-x_{h,g,j})$ and $\lambda_{6_{h,g,j}}(1-x_{h,g,j})$ are in the strong duality (5.74); and the nonlinear terms $\lambda_{1_h} q'_{h,g,j} + \lambda_{1_h}(z_{h,g} - y_{h,g})$ are in the objective function of the upper-level problem, (5.56a). The first three nonlinearities are linearized through some large positive numbers as follows [349]:

$$
\begin{aligned}
&\mu_{1_{h,g,j}} = \lambda_{2_{h,g,j}}(1-x_{h,g,j}) && \forall h,g\in\Gamma(g),j && (5.75)\\
&\mu_{1_{h,g,j}} \leq (1-x_{h,g,j})M_1 && \forall h,g\in\Gamma(g),j && (5.76)\\
&\lambda_{2_{h,g,j}} - \mu_{1_{h,g,j}} \leq \left[1-(1-x_{h,g,j})\right]M_1 && \forall h,g\in\Gamma(g),j && (5.77)\\
&\lambda_{2_{h,g,j}} - \mu_{1_{h,g,j}} \geq -\left[1-(1-x_{h,g,j})\right]M_1 && \forall h,g\in\Gamma(g),j && (5.78)\\
&\mu_{2_{h,g,j}} = \lambda_{5_{h,g,j}}(1-x_{h,g,j}) && \forall h,g\in\Gamma(g),j=b && (5.79)\\
&\mu_{2_{h,g,j}} \leq (1-x_{h,g,j})M_2 && \forall h,g\in\Gamma(g),j=b && (5.80)\\
&\lambda_{5_{h,g,j}} - \mu_{2_{h,g,j}} \leq \left[1-(1-x_{h,g,j})\right]M_2 && \forall h,g\in\Gamma(g),j=b && (5.81)\\
&\lambda_{5_{h,g,j}} - \mu_{2_{h,g,j}} \geq -\left[1-(1-x_{h,g,j})\right]M_2 && \forall h,g\in\Gamma(g),j=b && (5.82)\\
&\mu_{3_{h,g,j}} = \lambda_{6_{h,g,j}}(1-x_{h,g,j}) && \forall h,g\in\Gamma(g),j=b && (5.83)\\
&\mu_{3_{h,g,j}} \leq (1-x_{h,g,j})M_3 && \forall h,g\in\Gamma(g),j=b && (5.84)\\
&\lambda_{6_{h,g,j}} - \mu_{3_{h,g,j}} \leq \left[1-(1-x_{h,g,j})\right]M_3 && \forall h,g\in\Gamma(g),j=b && (5.85)\\
&\lambda_{6_{h,g,j}} - \mu_{3_{h,g,j}} \geq -\left[1-(1-x_{h,g,j})\right]M_3 && \forall h,g\in\Gamma(g),j=b && (5.86)
\end{aligned}
$$

Thus, the linearized strong duality becomes:

$$
\begin{aligned}
&\sum_{h,g\notin\Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g\in\Gamma(g),j} \alpha_g q'_{h,g,j} = \\
&\sum_{h,g} \lambda_{1_h} D_{h,g} - \sum_{h,g\in\Gamma(g),j} \mu_{1_{h,g,j}} Q'_{h,g,j} - \sum_{h,g\notin\Gamma(g)} \lambda_{3_{h,g}} Q''_{h,g} \\
&- \sum_{h<N_h,g\in\Gamma(g),j=b} \mu_{2_{h,g,j}} Q'_{h,g,j} - \sum_{h<N_h,g\in\Gamma(g),j=b} \mu_{3_{h,g,j}} Q'_{h,g,j} \\
&- \sum_{h<N_h,g\in\Gamma(g),j=b} \lambda_{7_{h,g,j}} Q'_{h,g,j}
\end{aligned}
\tag{5.87}
$$

For linearization of the nonlinear terms in the objective function (5.56a), the previously defined variables suffice. Hence, at first, (5.59) is multiplied by $q'_{h,g,j}$. After updating the indexes of the variables with leading and lagging subscripts, the following is obtained:

$$
\begin{aligned}
&\lambda_{1_{\substack{h\\ j\neq b}}} q'_{h,g,j} = \\
&\alpha_g q'_{h,g,j} + \lambda_{2_{h,g,j}} q'_{h,g,j} + \lambda_{4_{h-1>1,g,j=b}} q'_{h,g,j} - \lambda_{4_{h<N_h,g,j=b}} q'_{h,g,j} + \lambda_{7_{h<N_h,g,j=b}} q'_{h,g,j} \\
&- \lambda_{8_{h<N_h,g,j=b}} q'_{h,g,j} - \lambda_{12_{h,g,j=b}} q'_{h,g,j} + \lambda_{13_{h=1,g,j=b}} q'_{h,g,j} - \lambda_{13_{h=N_h,g,j=b}} q'_{h,g,j} \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \forall h,g\in\Gamma(g),j
\end{aligned}
\tag{5.88}
$$

where (5.88) can be simplified through (5.62), (5.64), (5.72), (5.73) and (5.75) and transform into (5.89):

$$
\begin{aligned}
&\lambda_{1_{\substack{h\\ j\neq b}}} q'_{h,g,j} = \\
&\alpha_g q'_{h,g,j} + \mu_{1_{h,g,j}} Q'_{h,g,j} + \lambda_{4_{h,g,j=b}} y_{h+1,g} - \lambda_{4_{h,g,j=b}} z_{h+1,g} + \lambda_{7_{h<N_h,g,j=b}} q'_{h,g,j} \\
&- \lambda_{8_{h<N_h,g,j=b}} q'_{h,g,j} \qquad\qquad\qquad\qquad\qquad\qquad \forall h,g\in\Gamma(g),j
\end{aligned}
\tag{5.89}
$$

In order to substitute the last four nonlinear terms in (5.89) with linear terms, additional mathematical processes are required. Hence, at first, (5.60) and (5.61) are multiplied by $y_{h,g}$ and $z_{h,g}$, respectively, and then summed together. Next, by considering (5.65), (5.66), (5.69), (5.70), (5.79) and (5.83), the subsequent term results into (5.90):

$$
\begin{aligned}
&\lambda_{4_{h<N_h,g,j}} y_{h+1,g} - \lambda_{4_{h<N_h,g,j}} z_{h+1,g} - \lambda_{7_{h<N_h,g,j}} y_{h+1,g} - \lambda_{8_{h<N_h,g,j}} z_{h+1,g} \\
&- \mu_{2_{h,g,j}} Q'_{h,g,j} - \mu_{3_{h,g,j}} Q'_{h,g,j} - \lambda_{1_{h,g}} y_{h,g} + \lambda_{1_{h,g}} z_{h,g} = 0 \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \forall h,g\in\Gamma(g),j=b
\end{aligned}
\tag{5.90}
$$

In addition, substituting (5.67) and (5.68) in (5.90) delivers (5.91):

$$
\begin{aligned}
&\lambda_{4_{h<N_h,g,j}} y_{h+1,g} - \lambda_{4_{h<N_h,g,j}} z_{h+1,g} + \lambda_{7_{h<N_h,g,j}} q'_{h,g,j} - \lambda_{8_{h<N_h,g,j}} q'_{h,g,j} = \\
&\lambda_{7_{h<N_h,g,j}} Q'_{h,g,j} + \mu_{2_{h,g,j}} Q'_{h,g,j} + \mu_{3_{h,g,j}} Q'_{h,g,j} + \lambda_{1_{h,g}} y_{h,g} - \lambda_{1_{h,g}} z_{h,g}
\end{aligned}
$$

$$\forall h, g \in \Gamma(g), j = b \quad (5.91)$$

Finally, by substituting (5.91) into (5.89), the linearized form of the nonlinear terms in the objective function (5.56a) renders to (5.92):

$$\begin{aligned}
&\lambda_{1_{\substack{h \\ j \neq b}}} q'_{h,g,j} + \lambda_{1_h} z_{h,g} - \lambda_{1_h} y_{h,g} = \\
&\alpha_g q'_{h,g,j} + \mu_{1_{h,g,j}} Q'_{h,g,j} + \lambda_{7_{h<N_h,g,j=b}} Q'_{h,g,j} + \mu_{2_{h,g,j=b}} Q'_{h,g,j} + \mu_{3_{h,g,j=b}} Q'_{h,g,j} \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \forall h, g \in \Gamma(g), j \qquad (5.92)
\end{aligned}$$

In the end, the BLP (5.56) is converted into an SLP, (5.93), as following:

$$\begin{aligned}
\max_{q,q',x,y,z} \; & \sum_{h,g \in \Gamma(g),j} \left[\alpha_g q'_{h,g,j} + \mu_{1_{h,g,j}} Q'_{h,g,j}\right] \\
& + \sum_{h,g \in \Gamma(g), j=b} \left[(\lambda_{7_{h<N_h,g,j}} + \mu_{2_{h,g,j}} + \mu_{3_{h,g,j}}) Q'_{h,g,j}\right] \\
& - \sum_{h,g \in \Gamma(g),j} x_{h,g,j} C_j - \sum_{h,g \in \Gamma(g)} (y_{h,g} + z_{h,g}) B \qquad (5.93a)
\end{aligned}$$

$$\begin{aligned}
&\sum_h x_{h,g,j} - T_{g,j} = 0 && \forall g \in \Gamma(g), j && (5.93b) \\
&x_{h+1,g,j} - x_{h,g,j} - x_{h+T_{g,j},g,j} = 0 && \forall h < N_h, g \in \Gamma(g), j && (5.93c) \\
&\sum_{g \in \Gamma(g)} x_{h,g,j} - E_j \le 0 && \forall h, j && (5.93d) \\
&\sum_j x_{h,g,j} - L \le 0 && \forall h, g \in \Gamma(g) && (5.93e) \\
&x_{h,g,j} = 0 && \forall h > h', g = g', j = j' && (5.93f)
\end{aligned}$$

$$\begin{aligned}
&\sum_{g \notin \Gamma(g)} q_{h,g} + \sum_{g \in \Gamma(g), j \neq b} q'_{h,g,j} - \sum_g D_{h,g} - \sum_{g \in \Gamma(g)} (y_{h,g} + z_{h,g}) = 0 \qquad \forall h && (5.93g) \\
&q'_{h,g,j} - (1 - x_{h,g,j}) Q'_{h,g,j} \le 0 \qquad \forall h, g \in \Gamma(g), j && (5.93h) \\
&q_{h,g} - Q''_{h,g} \le 0 \qquad \forall h, g \notin \Gamma(g) && (5.93i) \\
&q'_{h+1,g,j} - q'_{h,g,j} - y_{h+1,g} + z_{h+1,g} = 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b && (5.93j) \\
&y_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \le 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b && (5.93k) \\
&z_{h,g} - (1 - x_{h,g,j}) Q'_{h,g,j} \le 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b && (5.93l) \\
&y_{h+1,g} - Q'_{h,g,j} + q'_{h,g,j} \le 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b && (5.93m) \\
&z_{h+1,g} - q'_{h,g,j} \le 0 \qquad \forall h < N_h, g \in \Gamma(g), j = b && (5.93n) \\
&-y_{h,g} \le 0 \qquad \forall h, g \in \Gamma(g) && (5.93o) \\
&-z_{h,g} \le 0 \qquad \forall h, g \in \Gamma(g) && (5.93p)
\end{aligned}$$

$$-q'_{h,g,j} \leq 0 \qquad \forall h, g \in \Gamma(g), j \tag{5.93q}$$

$$-q_{h,g} \leq 0 \qquad \forall h, g \notin \Gamma(g) \tag{5.93r}$$

$$q'_{h=1,g,j} - q'_{h=N_h,g,j} = 0 \qquad \forall g \in \Gamma(g), j = b \tag{5.93s}$$

$$\alpha_g - \lambda_{1_h} + \lambda_{3_{h,g}} - \lambda_{11_{h,g}} = 0 \qquad \forall h, g \notin \Gamma(g) \tag{5.93t}$$

$$\alpha_g + \lambda_{1_{\substack{h \\ j \neq b}}} + \lambda_{2_{h,g,j}} + \lambda_{4_{h-1>1,g,j=b}} - \lambda_{4_{h<N_h,g,j=b}} + \lambda_{7_{h<N_h,g,j=b}} - \lambda_{8_{h<N_h,g,j=b}}$$
$$-\lambda_{12_{h,g,j}} + \lambda_{13_{h=1,g,j=b}} - \lambda_{13_{h=N_h,g,j=b}} = 0 \qquad \forall h, g \in \Gamma(g), j \tag{5.93u}$$

$$\lambda_{1_h} - \lambda_{4_{h-1>1,g,j}} + \lambda_{5_{h,g,j}} + \lambda_{7_{h-1>1,g,j}} - \lambda_{9_{h,g}} = 0 \quad \forall h, g \in \Gamma(g), j = b \tag{5.93v}$$

$$-\lambda_{1_{h,g}} + \lambda_{4_{h-1>1,g,j}} + \lambda_{6_{h,g,j}} + \lambda_{8_{h-1>1,g,j}} - \lambda_{10_{h,g}} = 0 \quad \forall h, g \in \Gamma(g), j = b \tag{5.93w}$$

$$\sum_{h,g \notin \Gamma(g)} \alpha_g q_{h,g} + \sum_{h,g \in \Gamma(g), j} \alpha_g q'_{h,g,j} =$$
$$\sum_{h,g} \lambda_{1_h} D_{h,g} - \sum_{h,g \in \Gamma(g), j} \mu_{1_{h,g,j}} Q'_{h,g,j} - \sum_{h,g \notin \Gamma(g)} \lambda_{3_{h,g}} Q''_{h,g}$$
$$- \sum_{h<N_h, g \in \Gamma(g), j=b} \mu_{2_{h,g,j}} Q'_{h,g,j} - \sum_{h<N_h, g \in \Gamma(g), j=b} \mu_{3_{h,g,j}} Q'_{h,g,j}$$
$$- \sum_{h<N_h, g \in \Gamma(g), j=b} \lambda_{7_{h,g,j}} Q'_{h,g,j} \tag{5.93x}$$

$$\mu_{1_{h,g,j}} = \lambda_{2_{h,g,j}}(1 - x_{h,g,j}) \qquad \forall h, g \in \Gamma(g), j \tag{5.93y}$$

$$\mu_{1_{h,g,j}} \leq (1 - x_{h,g,j}) M_1 \qquad \forall h, g \in \Gamma(g), j \tag{5.93z}$$

$$\lambda_{2_{h,g,j}} - \mu_{1_{h,g,j}} \leq \left[1 - (1 - x_{h,g,j})\right] M_1 \qquad \forall h, g \in \Gamma(g), j \tag{5.93aa}$$

$$\lambda_{2_{h,g,j}} - \mu_{1_{h,g,j}} \geq -\left[1 - (1 - x_{h,g,j})\right] M_1 \qquad \forall h, g \in \Gamma(g), j \tag{5.93ab}$$

$$\mu_{2_{h,g,j}} = \lambda_{5_{h,g,j}}(1 - x_{h,g,j}) \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ac}$$

$$\mu_{2_{h,g,j}} \leq (1 - x_{h,g,j}) M_2 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ad}$$

$$\lambda_{5_{h,g,j}} - \mu_{2_{h,g,j}} \leq \left[1 - (1 - x_{h,g,j})\right] M_2 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ae}$$

$$\lambda_{5_{h,g,j}} - \mu_{2_{h,g,j}} \geq -\left[1 - (1 - x_{h,g,j})\right] M_2 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93af}$$

$$\mu_{3_{h,g,j}} = \lambda_{6_{h,g,j}}(1 - x_{h,g,j}) \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ag}$$

$$\mu_{3_{h,g,j}} \leq (1 - x_{h,g,j}) M_3 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ah}$$

$$\lambda_{6_{h,g,j}} - \mu_{3_{h,g,j}} \leq \left[1 - (1 - x_{h,g,j})\right] M_3 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93ai}$$

$$\lambda_{6_{h,g,j}} - \mu_{3_{h,g,j}} \geq -\left[1 - (1 - x_{h,g,j})\right] M_3 \qquad \forall h, g \in \Gamma(g), j = b \tag{5.93aj}$$

5.3.4. Case Study

In order to evaluate the proposed SMSOMG model and assess the performance and behavior of the agents in the MG, several case studies are considered in a test system. The proposed SMSOMG model is coded in GAMS v24.7.1 [319] and solved using CPLEX v12.6.2 [320] on a machine running with 144 GB of RAM and an Intel Xeon E5-2660

(2.6 GHz) with 2 processors (20 cores).

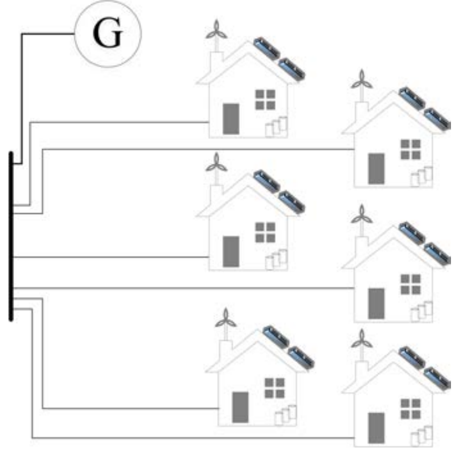


Figure 5.18: The utilized test system as isolated MG

5.3.4.1. Test System

An islanded MG with 6 houses and a diesel generator is considered as the test system, Figure 5.18, to demonstrate applicability of the developed SMSOMG model. Each of the houses is supplied with solar panels, WTs and battery storage systems. Table 5.15 displays the cost of producing energy for each house and the generator as well as the required time to carry out the PM for each type of the generation resource. Figure 5.19 illustrates the considered demand for all the houses over the study period. Figure 5.20 plots the assumed available power that can be extracted from solar panels and WTs. Please notice that these values are simply for the purpose of demonstration of applicability of the model. It should be mentioned that the maximum capacity of electric energy storage in battery at each hour for all the houses is limited to 3 kW ($Q'_{h,g\in\Gamma(g),j=b} = 3$) and the maximum capacity of the generator is limited to 10 ($Q''_{h,g\notin\Gamma(g)} = 10$). Also, the limit on simultaneous maintenance actions on each of the battery, solar and wind systems is set to 6 ($E_j = 6$). On the other hand, at each house, the number of distributed power sources that can go under maintenance is set to 3 ($L = 3$). The parameter for demonstrating the charge and discharge impact on lifetime of the battery system is set to 1 ($B = 1$). Finally, the maintenance cost (C_j) for the battery, solar and wind is considered 1, 3 and 2 units, respectively.

5.3.4.2. Case Studies

Four main case studies are developed here to simulate the applicability of the developed SMSOMG model.

Table 5.15: Information of the houses (G1-G6) and the generator (G7)

	Cost $\alpha_g(\$/kWh)$	Maintenance Time $T_{g,j}$ (h)		
		Battery	Solar	Wind
Generator1 (House1)	1	1	2	2
Generator2 (House2)	1	1	2	2
Generator3 (House3)	2	1	2	2
Generator4 (House4)	2	1	2	2
Generator5 (House5)	3	1	2	2
Generator6 (House6)	3	1	2	2
Generator7 (Independent)	10	-	-	-

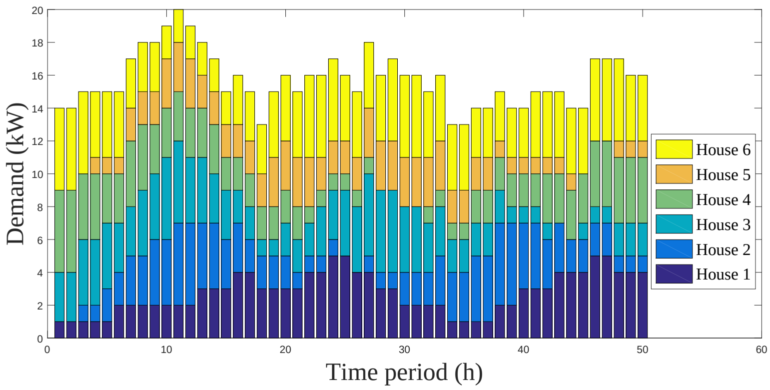


Figure 5.19: Considered demand at each house, $D_{h,g\in\Gamma(g)}$

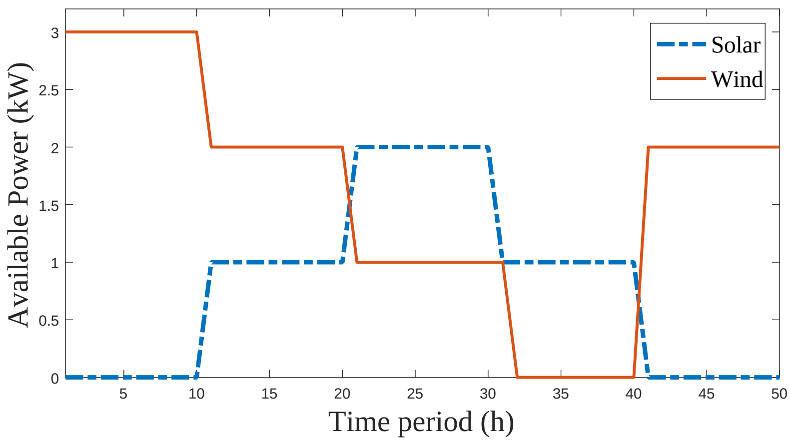


Figure 5.20: Available energy from solar and wind at each house, $Q'_{h,g\in\Gamma(g),j=s,w}$

5.3.4.2.1. Case I This case solves the maintenance scheduling problem through the formulation provided in (5.55) with the objective of minimizing the operation cost. This means that the schedules of the maintenance actions are decided by the IMGO and the capability of the houses in earning any profit is neglected. *CaseI* that follows state-of-the-art passive maintenance scheduling is considered as the benchmark in this case study.

5.3.4.2.2. Case II On the other hand, *CaseII* lays out the problem in a bi-level structure so that all houses collaborate with each other in order to maximize their profit while maintaining the least operational costs. In this case, the houses choose their desired times of the maintenance plans. This stat-of-the-art formulation of active PM scheduling provides the possibility for the regulators or the system operators to monitor the performance of the system and identify the weak points. These weak points could be in operational term or market failures as mentioned in section 5.3.2.

5.3.4.2.3. Case III This case incorporates the health condition data extracted from the CMSs installed on battery storage, solar panels and WTs. These new information directly affect the maintenance plans, performance and profit of each house. For this purpose, *CaseIII* assumes that when an anomaly signal is received from any of the condition monitoring signals, the system has to schedule a PM action by time h' for that particular system. It is also assumed that no PM action has been carried out since the beginning until receiving the alarm signal. Since the scope of this case study is on the utilization and integration of the outcomes of CMSs, interested readers can refer to [38, 39, 153] for more information on developing the AD signals.

5.3.4.2.4. Case IV This case follows a similar path as *CaseIII*. The only difference is that in *CaseIV*, it is assumed that after receiving the anomaly signal, the maintenance actions of all systems (except the system that has received the signal) are confirmed and cannot be changed. Thus, only the maintenance action of the system with high risk of failure should be modified. This situation may be more realistic in practice as anomaly or failure signal can occur at any moment and the planning may need to be modified accordingly.

5.3.5. Results and Discussion

Table 5.16 shows a summary of the four cases and Figure 5.21 displays the electricity prices for the two main cases. *CaseI* demonstrates the lowest operation cost and average price for the system as the objective is the minimization of the operation cost. This also results in the lowest profit for the houses as the maintenance decisions are all made by the IMGO. These outcomes are under centralized framework with passive PM scheduling.

The houses may be interested in maximizing their profit by participating in the market and performing active PM planning. Considering strategic behavior of the houses, *CaseII* solves the maintenance scheduling problem with the objective that the houses try to maximize their profit while maintaining the lowest operational costs. Although this kind of planning increases the operation cost and average price in the system, the profit increases significantly. Such results give motivation to the houses to consider strategic PM scheduling.

Table 5.16: Summary of results

	Profit ($)	Operation Cost ($)	Average Price ($/kWh)
CaseI	2577	2430	6.42
CaseII	4875	2507	9.28
CaseIII	4873	2509	9.28
CaseIV	4505	2509	8.88

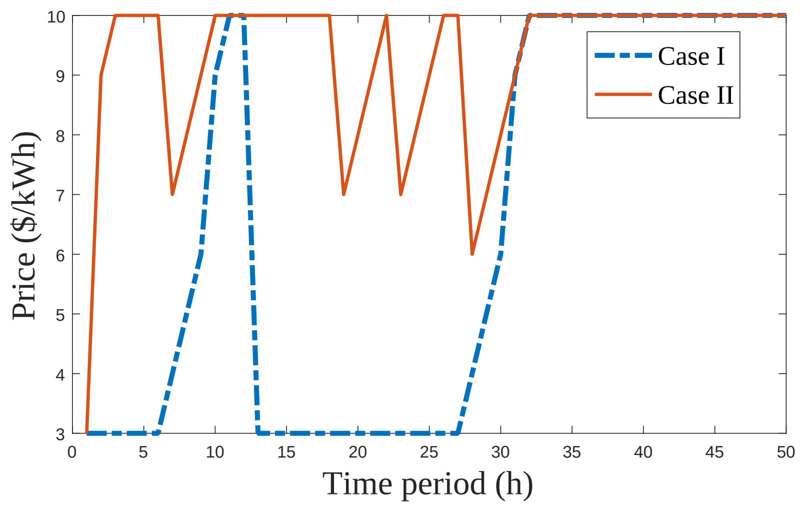
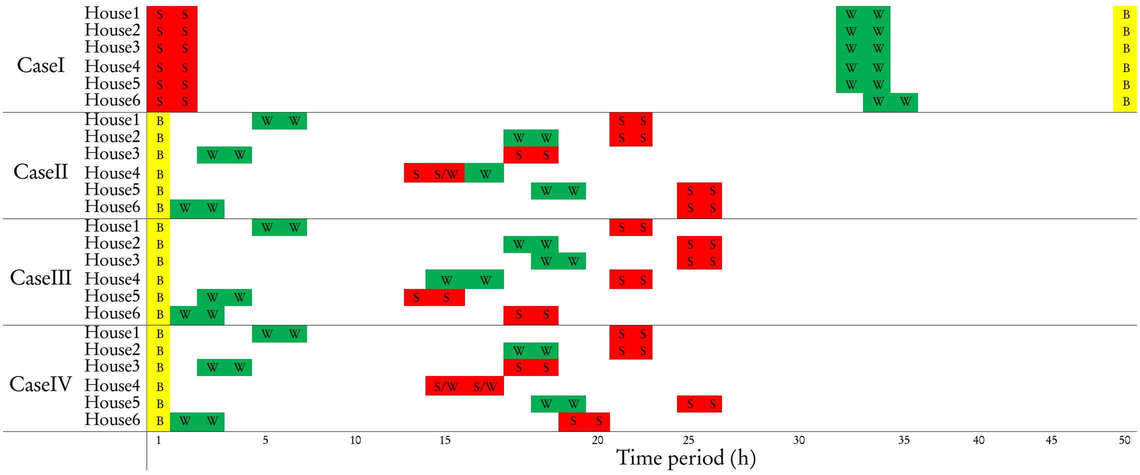


Figure 5.21: Hourly electricity prices

The health condition information is integrated in the operation in *CaseIII*. As expected, through Table 5.16, a sudden occurrence of an anomaly and thus the need for change in the maintenance planning reduces the profit of the houses and increases the operation cost of the MG, *CaseIII*. However, a single anomaly event is not significant enough to impact the average electricity prices within this time horizon.

CaseIII considered that after receiving an anomaly signal, maintenance schedules of all systems can be modified. However, if the anomaly signal does not happen early in the operation, this may not be a practical case. Therefore, *CaseIV* assumes that some of the systems may have carried out their PM actions by the time the anomaly signal is received. Hence, the maintenance decisions for all the systems, except the system that has received the anomaly signal, is assumed to be fixed. This results in a case where the houses try to maximize their profit by finding the best maintenance schedule solely for the system which is the recipient of the alarm signal. As expected, Table 5.16 shows that the reduction in the profit for the houses is much more than *CaseIII* where all maintenance decisions can still be modified.

Table 5.17: Maintenance schedules of battery (B), solar (S) and wind (W) systems



From the maintenance decisions perspective, Table 5.17 illustrates the schedules of PM for the battery, solar and wind systems. As it can be seen and expected in *CaseI*, the maintenance schedules for solar and wind systems are at the times where the available solar and wind are the lowest. However, the strategic behaviors of the houses change the PM schedules through *CaseII* to *CaseIV*. In these cases, the PM actions are scheduled in a way to force the diesel generator to operate (to maintain the generation-demand balance) so that the prices increase. For instance, the maintenance schedules of wind systems are moved to the times with high availability of wind where similar behavior is observed for solar systems. It should be noted that the houses are considered to act together and collaboratively in order to maximize their profit. Thus, only a number of them can go under maintenance and the rest can produce with high electricity price; later, the profit is shared among them.

In *CaseIII*, it is assumed that the solar system ($j = 2$) in House 6 ($g = 6$) has received an anomaly signal and its maintenance must be carried out by the hour 20 ($h' = 20$). While the maintenance schedules of all systems in all houses are relaxed in *CaseIII* (except for solar system in House 6), *CaseIV* fixes these schedules (based on *CaseII*) and solely allows the solar system in House 6 to be modified. As it can be seen, the optimum maintenance solution in *CaseIV* differs from *CaseIII*. From the results it can be seen that the houses compensate for the lost profit by reducing the utilization of the battery systems, Table 5.19. The degree of the change in the profit, operation cost and the average price can be seen in Table 5.16.

From the charge and discharge perspective of the battery storage systems, it should be mentioned that since a cost factor is considered in order to intuitively add the life-cycle expenses, the system tries to find the optimum solution by using the battery system as low as possible. As a result, it is observed that solely battery storage systems in House 1 and House 2 have been engaged in the operation. Indeed, different load, renewable portfolio and life-cycle cost factor will result in different participation degree from the systems. In this regard, Figure 5.22 and Figure 5.23 display the dispatched power by all the agents in the MG in *CaseI* and *CaseII*, respectively. An interesting interaction is observed through comparison of Figure 5.21 with these figures. It can be seen that the charge and discharge of the battery stopped by the hour 32 which corresponds with the beginning of the period of steady high prices as well.

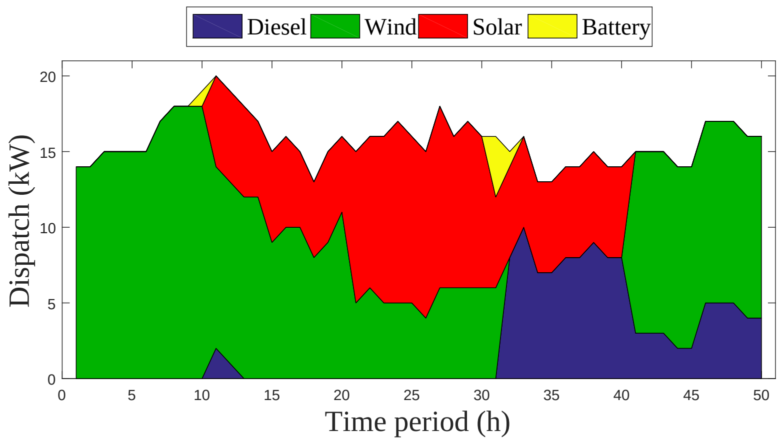


Figure 5.22: Production share *CaseI*

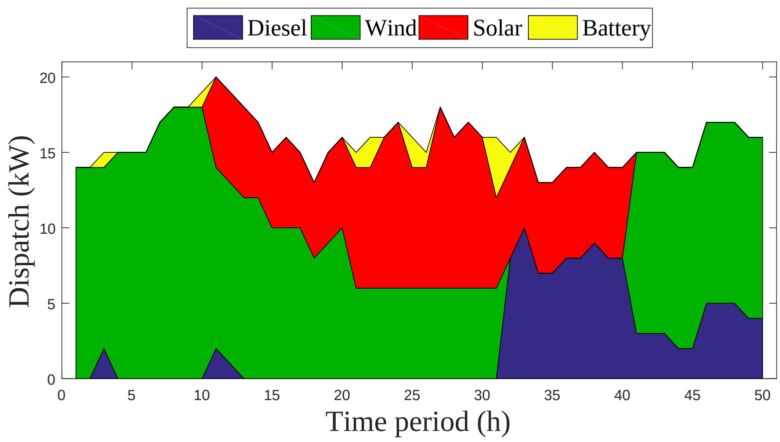


Figure 5.23: Production share *CaseII*

As an example of exercising market power by the houses, the results show that at hour 3 where there is sufficient wind power to supply the demand, House 3 and House 6 carry out PM on their wind systems and force the diesel generator (with higher operation cost) to come into operation. This act increases the electricity prices where higher electricity prices bring about more profit for the houses. Table 5.18 presents a summary of dispatched power of all agents in all cases. As expected, the lowest value of the power produced by the diesel generator is at *CaseI* and the highest value occurs in *CaseIV*. On the other hand, while the produced power by the wind and battery systems has increased from *CaseI* to the other cases, the share of the produced power by the solar system has decreased. A comparison between Table 5.18, Figure 5.22 and Figure 5.23 shows that in this study, the batteries joined the operation and reduced the solar production in strategic cases where the share of the power from the batteries raised by more than double. It should be reminded that no difference between the power produced by the wind and solar systems is considered in this study. Additionally, the operation does not become profitable enough for houses 3-6 to deploy the battery, Table 5.15. Therefore, the houses should keep in mind when investing on the new systems whether they will be able to compensate for the expenses by analyzing the capability and capacity of the market.

Table 5.18: Share of dispatched power by all sources

	Production Share (%)			
	Diesel	Wind	Solar	Battery
Case I	14.2	56.5	28.5	0.8
Case II	14.5	56.9	27.0	1.7
Case III	14.5	56.9	27.0	1.7
Case IV	14.6	56.9	27.4	1.1

Table 5.19: Charge and discharge of battery storage systems

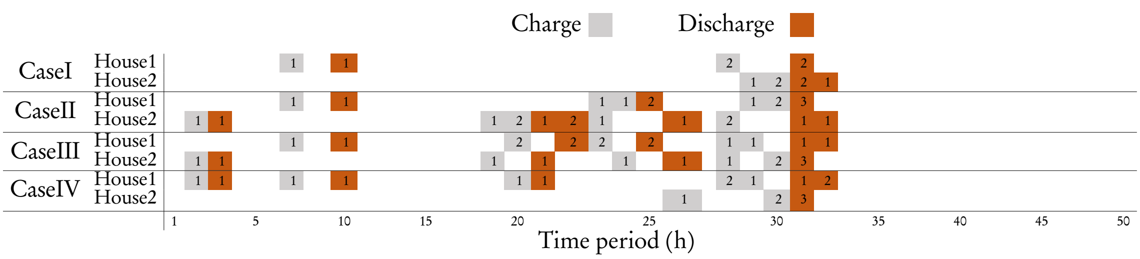


Table 5.19 displays the outcomes of the operation of the battery systems. At first, it can be seen that the charge and discharge of the battery systems are not continuous. This means that the charging and discharging are made at different points and not at once. In particular at *CaseII* to *CaseIV*, this is rational as the charging is made at times when the electricity prices are low and there is enough power to support the demand. The discharge is also made at times when the electricity prices are high so that the the houses can increase their profit. It should be reminded that the houses are assumed to operate in cooperation with each other and are price-makers. Increase in the number

and amount of charge and discharge operations in these cases in comparison with *CaseI* demonstrates the strategic behaviors of the houses in the MG.

One interesting observation is the comparison of *CaseII* and *CaseIII* in Table 5.19. Although *CaseIII* incorporates the condition monitoring information and there is a need for a forced maintenance action, the number and amount of charge and discharge are almost the same in these two cases (number of charge actions = 10, number of discharge actions = 9, amount of charge/discharge = 13 kW). This is due to the fact that the maintenance actions of all the systems in all the houses are not fixed. However, these values decrease by about 50% in *CaseIV* where the maintenance actions are fixed. These outcomes show that when maintenance schedules are confirmed and cannot be changed, it may not be necessary to strategically operate the battery in order to increase the profit and compensate for the lost optimum maintenance window. The developed case studies were solved in about 1 minute and reached below 6% optimality gap.

5.3.6. Case Study Conclusion

This case study proposes analysis of strategic maintenance scheduling for an islanded MG. The SMSOMG model takes into account multiple DERs as well as their corresponding constraints such as charge and discharge of the battery storage system. The deregulated electricity market is introduced through a bi-level formulation. Active and passive PM scheduling formulations have been derived under two centralized and decentralized frameworks. While the passive PM scheduling considers that the maintenance schedules and operation are planned by an independent microgrid operator, the active PM scheduling considers cooperative operation of the houses in order to maximize their profit. The SMSOMG provides capability of evaluating strategic behavior of the market participants in the MG which can assist in diagnosing market failures as well. In addition, with progress in CMSs, SMSOMG implements integration of the information received from CMSs into the operation. The results demonstrate how the agents in the MG can influence the prices, the system operation costs and the profit through the required PM scheduling of the DERs. By consideration of a battery life-cycle cost factor, the results show that if houses consider the electricity market into their operation and planning, they can significantly increase their profit. Study through some case scenarios demonstrated that even if additional limitations are applied on the maintenance in the operation, there still exist chances for the agents to gain from the operation by actively participating in the market.

5.4. Chapter Conclusion

This chapter considers PM scheduling from two main perspectives of centralized and decentralized. It compares the two modes of operation and investigates strategic operation of the agents under various conditions. It also enables integration of health condition information from component level into the system level operation and provides insights on possible improvements in decision making process. In particular, a game theoretic approach as well as specific models for an OWF and an islanded MG are developed and analyzed. Although the models demonstrated advancement on the current state-of-the-art algorithms, the main drawback is their need of high computational power in order to obtain an optimum solution.

6 Conclusion and Future Works

6.1. Concluding Remarks

This dissertation provides a link between operation data recorded at the sub-assembly level in a component and maintenance scheduling in the system. It starts by considering the collected data and developing normal behavior model (NBM)s for components. In chapter 3, four distinct data-driven models are developed to assess performance of components and analyze their maintenance strategies. In the first study in section 3.1, an NBM based on neural network (NN)s is developed. The model detects abnormalities in the operation. Then, through principal component analysis (PCA), the sub-assembly that caused the abnormality is detected. In the second study in section 3.2, a data-driven Markov model is presented to detect under-performance of the component. By considering the historical operation of the component, it analyzes the performance and proposes maintenance suggestions. The model is applied to nine components and the results are compared. In the third study in section 3.3, a model is proposed to evaluate the applied maintenance strategies for several components. The model assists in comparing components from operation and maintenance (O&M) perspective and provides suggestions on improving the maintenance scheduling. In the fourth study in section 3.4, a parametric model is developed for a component where the relationship among the variables is demonstrated through several statistical techniques. Such a model assists in addressing issues such as scalability in large systems with multiple similar components by reducing the number of NBMs for each individual component.

Next in chapter 4, the dissertation demonstrates how an electric power system can benefit from integration of health condition indicators (as developed in chapter 3). This is performed by providing a link from operational data in the sub-assembly level to the system level. The results show that consideration of such data provides profitability and increased reliability chances.

Finally in chapter 5, the dissertation develops models where they address centralized and decentralized maintenance scheduling in electric power system generation. The models individually consider game theory in power system generation context in section 5.1, study strategically how generation maintenance scheduling (GMS) can be improved in an offshore wind farm (OWF) in section 5.2, and an islanded microgrid (MG) in section 5.3. renewable energy sources (RES) are considered in all these three main models where condition monitoring and anomaly detection (AD) models developed in chapter 3 are also incorporated in the models.

6.2. Future Works

This dissertation opens several new lines for future research. For the model developed in section 3.2, future works could perform the analysis based on each sub-assembly and compare it with the overall performance of the component as the developed model address the component itself. Besides, collecting more detailed information on maintenance actions (e.g. costs) and failures can provide additional knowledge when combined with this model.

For the model developed in section 3.3, two areas that could benefit from further research as future works are:

- Development of an operational dynamic threshold for the health condition model (Figure 3.24) so that whenever the function crosses the threshold, the operator could pay additional attention to the operating condition of the component. Such work will result in a parametric model for condition monitoring of the component which can be used for real-time AD.
- Development of a maintenance threshold for individual years (Figure 3.26). For instance, the threshold for each year will increase by some degree (as natural degradation), and when set, maintenance actions can be scheduled to be performed whenever the model approaches the threshold.

For the model developed in section 3.4, the model shows strength in the following areas that can be further analyzed in future studies:

- Adaptability: As most of the models utilized so far are based on NNs, there exists adaptability issue which NN-based models of individual components cannot be used interchangeably. However, a parametric model has the advantage in this regard which parameters could be modified and the model can be used for another component. Indeed, further investigation would need to be carried out in order to test the new parameters.
- Scalability: In a wind farm with a large number of similar components, creating one NN model for each component where the similarities between models cannot be easily investigated is an obstacle for the asset owner and operator. Through the proposed model, such study can be performed and comparisons of the models between few number of components could approach to a general model for the system.
- Remaining useful life estimation: The parametric model developed here is for one year study period during which the component did not suffer any major anomaly. This denotes that the observed behavior and model can be used as a reference. Later, performance of each year can be compared with these results. From another view, for each year, a similar model can be developed where comparisons among the parameters of the models might deliver findings on the degradation matter. Indeed, this can also result in advancements in maintenance scheduling.

For the model developed in chapter 4, detailed analysis of maintenance scheduling and studying its impact on the electricity market in the power system are some of the future works.

For the models developed in chapter 5, the main issue is application of the models for larger systems where several suggestions such as use of snapshots, dimensionality reduction techniques and decompositions techniques are provided. In particular, one could further investigate the possibility of studying the impact of postponing a maintenance action in future studies through the proposed models.

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Curriculum Vitae

Peyman Mazidi was born in 1987 in Iran. He received the Bachelor of Technology degree in electrical engineering from the Islamic Azad University, Aliabad, Iran in 2009. The thesis was titled “simulation of 20KV electric power grid of Aliabad city with MATLAB and DigSilent software” that included analysis of the network. Load-flow and short-circuit studies were performed by hand and software calculations and finally results were compared. He received the Master of Technology degree in electrical power engineering from Jawaharlal Nehru Technological University, Hyderabad, India in 2011. The thesis was titled “reliability assessment of a distributed generation connected radial distribution system”. It analyzed a network with RES from customer and system reliability perspectives while considering different levels of protecting devices and their failure patterns. Since 2013, he holds an Erasmus Mundus Joint Doctorate (EMJD) Fellowship in Sustainable Energy Technologies and Strategies (SETS) awarded by European Commission; a joint program between Comillas Pontifical University in Spain, TUDelft University in Netherlands and KTH Royal Institute of Technology in Sweden where he is pursuing his PhD degree.

In his PhD, he started the research from traditional maintenance and reliability concepts. Next, he transitioned into upgrading some of these areas by bringing in operational data that are collected during the operation of equipment. Then, he developed several data-driven models for analysis of performance and maintenance of industrial assets. Moving forward from component-level to system-level analysis, he continued the research by improving the conventional preventive maintenance scheduling by linking it to the market. He analyzed the advancements in this area and compared centralized and decentralized maintenance planning strategies and compared their advantages and disadvantages. Finally, he combined the developed data-driven models of the assets in the decision-making process and evaluated their influence from system-level perspective.

During his PhD, along with the research, he passed more than 60 credits, worked on UPGRID, a European project funded by European Commission on advancements in smart grid context, and participated several international forecasting competitions where their team ranked among top contestants. The competitions included predicting wind power of a wind farm in Europe and predicting the electricity demands in the UK and the US. Lastly, as first author, he published 6 JCR journal articles and presented 7 papers in conferences and workshops.

His research is focused on condition monitoring, anomaly detection, performance and maintenance management through data analysis and optimization in electric power systems.

List of Publications during PhD

Journal Articles:

[A1] **P. Mazidi**, Y. Tohidi, A. Ramos, and M. A. Sanz-Bobi, "Profit-maximization generation maintenance scheduling through bi-level programming," *European Journal of Operational Research*, vol. 264, no. 3, pp. 1045-1057, 2018.

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Pending:

[A8] I. Dimoulkas, **P. Mazidi**, and L. Herre, "GEFCom2017: A simple neural network based approach to long-term probabilistic load forecasting," Invited paper to be submitted to *International Journal of Forecasting*, 2018.

Conference Papers:

[B1] **P. Mazidi**, Y. Tohidi, and M. A. Sanz-Bobi, "Offshore wind farm preventive maintenance scheduling in a deregulated power system," in *International Conference Windfarms*, Madrid, Spain, 2017.

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Peyman Mazidi
peyman@comillas.edu
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Madrid, Spain