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ARTIFICIAL INTELLIGENCE APPLIED TO THE DYNAMIC STABILITY ANALYSIS OF POWER SYSTEMS

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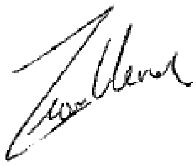
Fdo.:  Fecha: 13/ 06/ 2025

RESUMEN

La creciente complejidad y demanda en los sistemas eléctricos modernos requieren herramientas avanzadas para garantizar su operación fiable y estable. Uno de los aspectos fundamentales en el análisis del sistema eléctrico es el estudio de la estabilidad dinámica, que se refiere a la capacidad del sistema para resistir y recuperarse de perturbaciones a lo largo del tiempo. Los métodos tradicionales de simulación dinámica, aunque son precisos, suelen requerir altos recursos computacionales y tiempos prolongados, lo que limita su aplicación en escenarios de tiempo real o de gran escala.

En este contexto, Red Eléctrica de España, como empresa responsable de la operación y el transporte del sistema eléctrico, ha identificado desde su Departamento de Fiabilidad la necesidad de desarrollar nuevas metodologías que permitan mejorar el análisis y la optimización de diversos aspectos de la estabilidad del sistema. Para ello, se plantea la aplicación de Inteligencia Artificial (IA) en combinación con simulaciones dinámicas, con el objetivo de reducir los tiempos de cálculo y desarrollar modelos sustitutos generalizables que aproximen el comportamiento del sistema bajo distintas condiciones operativas.

En este proyecto se desarrollan y se ponen en práctica estos modelos basados en IA, que tienen el potencial de proporcionar evaluaciones rápidas y fiables sobre la estabilidad del sistema, facilitando la toma de decisiones por parte de los operadores y planificadores de la red. En última instancia, esta metodología busca combinar la precisión de las simulaciones dinámicas con la eficiencia y adaptabilidad de la IA, contribuyendo a la construcción de un sistema eléctrico más resiliente e inteligente.

Además, el marco metodológico propuesto está diseñado para identificar y evaluar contingencias críticas, es decir, aquellas perturbaciones que podrían generar los impactos más severos en la estabilidad del sistema. Gracias a la capacidad de la IA para reconocer patrones y priorizar escenarios, el sistema puede identificar de manera más eficiente los casos de mayor riesgo en comparación con las simulaciones tradicionales exhaustivas.

Esta capacidad es esencial para el análisis preventivo, permitiendo a los operadores reforzar la robustez del sistema y preparar estrategias de mitigación adecuadas ante escenarios de alto riesgo. Con esta nueva metodología, Red Eléctrica de España avanza hacia una gestión más eficiente y proactiva de la estabilidad del sistema eléctrico, optimizando recursos y mejorando la seguridad operativa de la red.

ABSTRACT

The increasing complexity and demand in modern power systems require advanced tools to ensure their reliable and stable operation. One of the fundamental aspects of power system analysis is the study of dynamic stability, which refers to the system's ability to withstand and recover from disturbances over time. Traditional dynamic simulation methods, while accurate, often require high computational resources and long processing times, limiting their applicability in real-time or large-scale scenarios.

In this context, Red Eléctrica de España, as the company responsible for the operation and transmission of the power system, has identified the need within its Reliability Department to develop new methodologies that enhance the analysis and optimization of various aspects of system stability. To achieve this, the application of Artificial Intelligence (AI) in combination with dynamic simulations is proposed, with the goal of reducing computation times and developing generalizable surrogate models that approximate system behavior under different operating conditions.

This project develops and implements these AI-based models, which have the potential to provide fast and reliable assessments of system stability, facilitating decision-making for grid operators and planners. Ultimately, this methodology seeks to combine the precision of dynamic simulations with the efficiency and adaptability of AI, contributing to the development of a more resilient and intelligent power grid.

Additionally, the proposed framework is designed to identify and evaluate critical contingencies, meaning disturbances that could have the most severe impact on system stability. Thanks to AI's ability to recognize patterns and prioritize scenarios, the system can more efficiently identify high-risk cases compared to traditional exhaustive simulations.

This capability is essential for preventive analysis, allowing operators to reinforce system robustness and prepare appropriate mitigation strategies for high-risk scenarios. With this new methodology, Red Eléctrica de España moves toward a more efficient and proactive management of power system stability, optimizing resources and improving the operational security of the grid.

ACKNOWLEDGMENTS

I would like to begin by expressing my deepest gratitude to my supervisor at Red Eléctrica de España, Eduardo Lorenzo Cabrera. From the very first day, he made me feel welcome and integrated within the department, fostering an environment in which I felt comfortable and confident in my work. His willingness to share his extensive knowledge, not only about the project itself but also about the sector and the broader electrical system, has been invaluable. His explanations have helped me understand important ideas, get a clearer picture of how the industry works, and recognize the details that make this field unique. I am especially thankful for the trust he placed in me, enabling me to take ownership of this project and develop it with autonomy and confidence.

I also want to extend my sincere appreciation to all the members of the reliability department, who have played a crucial role in making my experience truly fulfilling. Their warm welcome made me feel like a part of the team from the very beginning. Throughout this journey, they have generously shared their knowledge, provided invaluable advice, and supported me whenever needed. Working with such supportive and dedicated professionals has made my experience much more valuable. I feel lucky to have been part of this team. The time I have spent with all of you has been both rewarding and insightful, and I will always appreciate the conversations, lessons, and moments we shared.

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This experience has been truly enriching, and I am profoundly grateful to everyone who has contributed to it. Thank you all for your generosity, support, and the knowledge you have shared. It has been an honor to be part of this team.

1 CONTENTS

1. INTRODUCTION

The electrical system is a fundamental infrastructure for the development of any country, as it ensures the supply of energy needed for daily life, industry, and services. Its operation is based on four main pillars: generation, transmission, distribution, and electricity consumption.

Electricity generation can come from various sources, such as thermal, hydroelectric, nuclear power plants, and, increasingly, renewable sources like solar and wind energy. These plants convert different types of energy into electricity, which is then transmitted through high-voltage networks to consumption centers. The transmission of electricity requires a robust infrastructure of lines and transformation stations that allow for power reduction and adaptation to homes and businesses.

The distribution process delivers electricity from substations to end consumers, ensuring efficient and safe delivery. This phase involves medium- and low-voltage networks and is complemented by intelligent systems that optimize energy flow and demand response.

1.1 SPAIN'S POWER GRID

In 2024, 56.8% of Spain's electricity came from renewable sources, a 10.3% increase from 2023. Hydroelectric generation grew 35.5%, and solar photovoltaic rose 18.9%, marking its sixth consecutive record year. Spain added 7.3 GW of new solar and wind capacity, with solar energy (25.1%) surpassing wind (24.9%) as the leading power source. These advancements reinforce Spain's commitment to sustainability and reducing fossil fuel dependence. [1]

However, the integration of renewables has increased the complexity of the electrical system. The variability of renewable generation, which depends on climatic factors, requires solutions such as energy storage and interconnection with other European countries to ensure supply stability. Additionally, the Renewable Energy Control Center (Cecre), managed by Red Eléctrica de España, plays a key role in the supervision and coordination of renewable generation.

The modernization of the electricity grid has also been crucial in adapting to this new scenario. Various companies have announced significant investments to reinforce and digitalize Spain's electricity network, implementing technologies such as remote metering, advanced sensor systems, and cybersecurity. Grid automation enables faster responses to failures and optimizes electricity distribution, improving operational efficiency.

The operator of Spain's electrical system is Red Eléctrica de España (REE), whose function is to ensure the balance between electricity supply and demand in real-time, guaranteeing the stability of the supply and the security of the system. REE not only manages the high-voltage transmission network but also oversees the operation of the electrical system through its Electric Control Center (CECOEL).

REE performs multiple essential functions for the proper functioning of Spain's electrical system:

- **Ensuring electricity supply**: Monitors electricity generation and consumption in real-time to prevent imbalances that could affect system stability.

- **Management of the transmission network**: Coordinates the operation of high-voltage lines and electrical substations to ensure efficient energy distribution.
- **Integration of renewable energy**: Through the Renewable Energy Control Center (Cecre), REE supervises renewable generation and facilitates its safe incorporation into the electrical system.
- **International exchanges**: Manages interconnections with other European countries, enabling electricity exchange to improve supply security.
- **Planning and network development**: Designs strategies for the expansion and modernization of electrical infrastructure to adapt to growing demand and the energy transition.

The Electric Control Center is the operational hub of REE, where the Spanish electrical system is monitored and coordinated in real-time. From this center, more than 240,000 data points are received, analyzed, and processed per second, allowing for quick and efficient decision-making to maintain the balance between generation and consumption.

The main functions of CECOEL include:

- **Real-time supervision**: Monitors the status of the electricity network and the electrical parameters of generation and transmission.
- **Demand management**: Coordinates electricity generation to continuously match consumption demands.
- **Incident control**: Detects and manages potential network failures, ensuring a rapid response to minimize disruptions.
- **Production optimization**: Issues operational instructions to ensure the correct scheduling of electricity generation and international exchanges.

CECOEL operates 24 hours a day, 365 days a year, ensuring that electricity reaches supply points when needed. Additionally, REE has specific control centers for the electrical systems of the Balearic and Canary Islands, adapting management to the particularities of these territories.

1.2 STABILITY IN POWER SYSTEMS

Due to the strong interaction between Spain's electrical system and the rest of the European countries' electrical systems, it is important to emphasize the significance of electricity exchanges and the different characteristics of each for an in-depth study of power system stability.

The European Network of Transmission System Operators for Electricity (ENTSO-E) manages an interconnected electrical system designed to ensure a high level of supply security throughout Europe. This interconnection framework allows collaboration among transmission system operators (TSOs), reducing risks associated with isolated failures. However, this connection also presents challenges, as disturbances can propagate through the grid, affecting adjacent areas or even the entire system.

In recent decades, the ENTSO-E electrical system has undergone significant transformations, including the implementation of market rules, the increase in electricity generation from renewable sources, and the geographical expansion of the grid. These changes have led to systems operating closer to their safety margins, increasing the risk of contingencies that exceed design criteria. The growing complexity of the grid requires coordinated planning and harmonized operational measures to prevent extreme contingencies that could lead to blackouts or instability in the network.

Security measures within ENTSO-E are structured around the N-1 rule, which ensures that the loss of a single generation unit or transmission line does not cause severe consequences for the system. However, more severe events, such as simultaneous failures of multiple elements, can trigger emergency conditions requiring specific defense mechanisms. TSOs continuously update their defense plans, incorporating automatic responses designed to limit the spread of disturbances within the grid.

The stability of electrical networks has been a key concern since the early 20th century, with historical blackouts demonstrating the risks of instability. Electrical system stability is fundamental to ensuring a secure and efficient electricity supply. According to CIGRE, system stability is defined as the ability of the system to recover its operational balance after a disturbance, maintaining its variables within acceptable limits to prevent system collapse.

Modern electrical systems are designed to operate safely under common contingencies such as changes in load or generation. However, they may face more severe disturbances, such as short circuits or the loss of large generating units. To manage these risks, system operators must implement control strategies and automatic protection measures.

The classification of stability problems helps to understand the underlying causes of instability and facilitates the design of protection schemes. Several factors are considered in stability assessments, including the physical nature of instability, the magnitude of the disturbance, the involved devices, and the methods for analyzing and predicting stability.

Electrical system stability is a fundamental aspect of power grid operation, ensuring a consistent and secure electricity supply under both normal and disturbed conditions. It is essential for preventing widespread outages and maintaining system reliability. This stability is categorized into three key areas, each addressing different aspects of system behavior and response to disturbances.

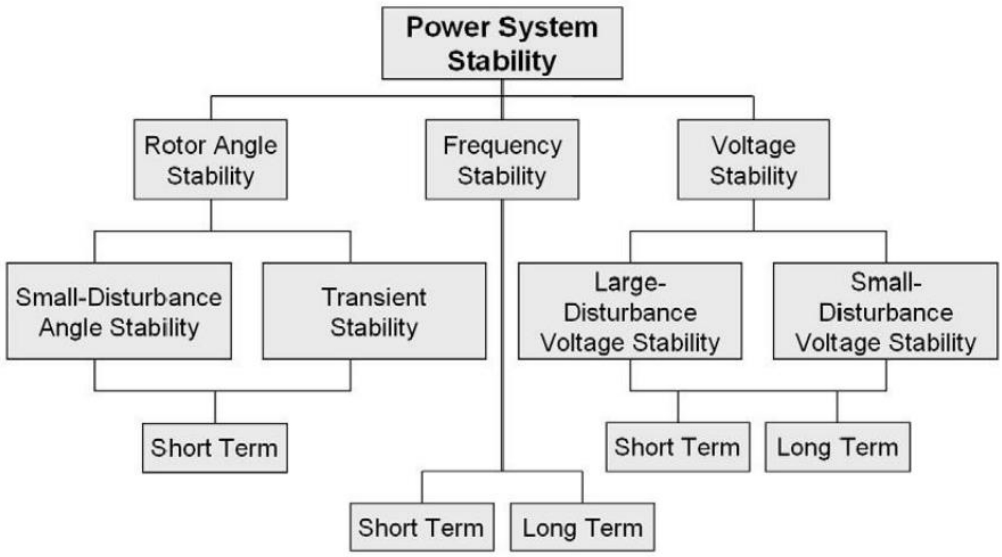

Figure 1: Power system stability diagram. Source: ENTSO-E (2018)

The first is generator synchronization, which ensures that all synchronous machines remain coordinated in phase and frequency. Loss of synchronization can lead to cascading failures, making this stability crucial for the smooth operation of interconnected grids.

The second aspect is frequency control, which maintains a stable balance between electricity generation and demand. Unexpected fluctuations in frequency can trigger automatic disconnections of generators or loads, affecting overall system integrity. Effective frequency regulation mechanisms, including inertia and control responses, help mitigate these risks.

Lastly, voltage stability ensures that all substations and transmission lines maintain adequate voltage levels to support electrical loads efficiently. Voltage collapse can occur when reactive power supply is insufficient, leading to blackouts and operational failures. Maintaining voltage stability requires proper system regulation and dynamic adjustments based on demand variations.

Any disruption in these areas can severely impact system performance, potentially leading to instability, equipment damage, or large-scale outages. Understanding and managing these stability factors is essential for ensuring the reliability and resilience of modern electrical networks. [2]

1.2.1 Types of Rotor Angle Stability

Rotor stability is a critical aspect in the operation of power systems, as it determines the ability of synchronous generators to maintain synchronization with the electrical system after disturbances. It can be classified into two major categories based on the magnitude and nature of the disturbance:

- **Small-Signal Stability:** This type of stability refers to the system's ability to maintain synchronization in response to minor variations in power generation or consumption. It is closely related to the dynamic behavior of generators and their ability to dampen electromechanical oscillations. Small disturbances may arise from changes in electrical load, adjustments in generator operation, or slight fluctuations in system voltage. In this context, stability depends on factors such as the exciter gain, which influences the generator's response to voltage changes; system impedance, which affects the interaction between generators and the transmission network; and active power generation, as variations in this can modify electromagnetic torque and rotor oscillations.

- **Transient Stability:** This type of stability refers to the electrical system's ability to recover from severe disturbances such as short circuits, sudden losses of generation, or failures in transmission lines. Unlike small disturbances, large disturbances can induce significant angular shifts in generator rotors, jeopardizing system stability. When a critical event occurs, the system must ensure that generators can maintain synchronization despite abrupt changes in electromagnetic torque. Transient stability may be influenced by the control system's response speed, the opening time of protective circuit breakers, or the level of distributed generation and interconnection with other networks.

1.2.2 Frequency Stability

Frequency stability refers to the ability of the electrical system to maintain a balance between energy generation and consumption after a significant disturbance. Sudden frequency variations can trigger automatic disconnections of generators or loads, affecting system integrity. In interconnected networks, this issue becomes even more critical during events where the system splits into electrical islands, requiring efficient management to minimize unforeseen load losses. To stabilize frequency, the system has different response levels:

1. **System inertia:** Inertia is the first line of defense against sudden frequency changes. It refers to the ability of synchronous generators to maintain the rotational speed equilibrium of their rotors thanks to the stored kinetic energy. When a disturbance occurs (such as the sudden disconnection of a power plant), the inertia of the generators helps slow down the frequency drop, allowing time for regulation mechanisms to act. However, with the increasing integration of renewable sources like solar and wind, which do not have direct mechanical inertia, electrical systems have begun implementing solutions such as battery storage and fast-response controllers to compensate for this function

2. **Primary regulation:** This mechanism activates immediately after the inertial response, within seconds. Primary regulation is carried out by generators equipped with speed governors, which detect frequency variations and automatically adjust the delivered power. If the frequency drops due to a generation deficit, the governors increase energy injections to compensate for the difference. This control is decentralized, as each generator responds locally without external coordination. It is crucial for stabilizing frequency in the initial moments after a disturbance and preventing uncontrolled fluctuations.

3. **Secondary regulation:** Secondary regulation comes into play after primary regulation, acting within seconds to minutes. Its goal is to restore the system's nominal frequency (e.g., 50 Hz in Europe) and correct potential imbalances in energy generation and consumption. This adjustment is performed centrally through Automatic Generation Control (AGC) systems, which analyze the situation and modify energy production based on demand and system conditions. Secondary regulation also plays a key role in efficiently redistributing generation to reduce the strain on generators that participated in primary regulation.

4. **Tertiary regulation:** Finally, tertiary regulation is the long-term adjustment mechanism, with response times ranging from minutes to tens of minutes. Its function is to optimize the operation of the electrical system after a disturbance, ensuring that the generation dispatch is carried out as efficiently as possible. This regulation involves electrical system operators, who decide which generating units should modify their output to maintain grid stability and ensure energy supply at the lowest possible cost. It is also used to manage demand fluctuations throughout the day and integrate renewable energy into the system. Additionally, one of its key roles is to restore the secondary reserve that may have been used during the initial response to the disturbance, ensuring that the system remains prepared for future imbalances.

1.2.3 Voltage Stability

Voltage stability refers to the ability of the electrical system to maintain adequate voltage levels across all substations. A severe disturbance can trigger a progressive voltage drop at certain nodes, potentially causing blackouts or cascading disconnections of network elements. Voltage stability depends on system regulation and the ability of energy sources to supply both active and reactive power demand. In extreme situations, voltage collapse can occur when the electrical load exceeds the capacity of generators and transmission lines.

Voltage stability relies on several factors within the electrical system, including generation capacity and reactive power supply, which are essential for maintaining proper voltage levels across the grid, as well as load variability, which results from fluctuating demand between industries, households, and transportation systems. [3]

In recent years, due to the increasing presence of artificial intelligence and the use of machine learning models, electrical system operators worldwide, along with multiple companies in the sector, have progressively begun implementing these techniques. The objective of deepening stability studies and often obtaining faster solutions than conventional methods has driven greater participation and integration of these approaches.

2. Dynamic Analysis of Power System Stability

In power system analysis, system stability is one of the most critical areas for ensuring reliable and continuous operation. There are two main approaches to studying this stability: static analysis and dynamic analysis. Both aim to understand system behavior under disturbances, but they differ significantly in nature, objectives, and complexity.

Static analysis focuses on equilibrium conditions within the system, particularly in power flow studies, short circuits, and contingency analysis. This type of analysis does not consider the system’s temporal evolution; instead, it relies on solving nonlinear algebraic equations to determine the system’s stable states (voltages, active and reactive power, etc.). It is useful for evaluating system operation at a given moment, but it does not assess transients or oscillations that may follow events such as faults or disconnections.

Conversely, dynamic stability analysis, which is the focus of this project, examines how the system evolves over time after a disturbance, modeling in detail the dynamic behavior of generators, exciters, governors, loads, and control systems. This type of analysis employs Differential-Algebraic Equations (DAE) to simulate transient responses. It is essential for evaluating transient stability, electromechanical oscillations between synchronous machines, automatic control behavior, and the interaction with renewable energy sources, which exhibit distinct dynamics.

Dynamic simulations are significantly more demanding than static ones due to the greater number of equations (both differential and algebraic), their increased complexity, the small time-step size required for numerical stability (milliseconds), and the detailed modeling of elements such as generators, relays, and regulators. Processing power and memory requirements are substantial, particularly when simulating large networks or multiple contingencies. Therefore, specialized tools such as PSS®E, DIgSILENT PowerFactory, PSCAD, or EMT-type simulators are required due to the complexity and nonlinear nature of these systems.

These programs allow precise modeling of real electrical components and simulate how they respond to various disturbances. Thanks to their ability to solve differential-algebraic equations within milliseconds, they facilitate these procedures, making them viable and significantly more accurate than manual methods or generic tools.

In recent years, artificial intelligence (AI) has gradually integrated into dynamic simulation studies of power systems, revolutionizing both the speed and depth of analysis. With increased computational capacity and automation using languages such as Python, it is now possible to run thousands of dynamic simulations across different scenarios and contingencies, generating a data volume previously unimaginable. Organizations such as CIGRE recognize the increasing use of Artificial Intelligence and Machine Learning (ML) models in power system operation, highlighting their vast potential and impact in enhancing stability, efficiency, and decision-making in electrical networks. [4]

This large-scale data environment enables the application of advanced statistical techniques and AI to detect instability patterns, estimate system responses in real time, reduce simulation time and iterations, or even train surrogate models that accurately replicate the system's dynamic behavior within a fraction of the time required by traditional simulators like PSS®E. Thus, AI serves not only as an analytical tool but also as an accelerator for operational decision-making and power system planning.

2.1 State of the Art

In recent years, numerous projects and studies have begun to explore the synergy between detailed dynamic simulations and AI-based models, with applications ranging from real-time system stability prediction to the creation of surrogate models that replicate system behavior with high precision but significantly lower computational time. This section gathers the most relevant developments in this field, covering recent research, hybrid tools, and real-world use cases that integrate AI to improve transient stability studies in modern power grids.

For the development, training, and deployment of an AI model, a database is required to train the model and enable it to generalize across different scenarios. These databases can be used in a tabular format, meaning they do not consider any underlying structure. In this context, the study by Zhang et al. (2021) proposes a method to evaluate transient stability in electrical systems using active learning, which allows for the intelligent selection of the most representative data to train accurate models with fewer examples. This project develops a machine learning model utilizing deep neural networks to predict the Transient Stability Index (TSI) of a power system after a disturbance. The model's input data consists of system characteristics such as active and reactive power, node voltages, and generation settings, while the output is a binary classification indicating whether the system is stable or unstable. The validation is conducted on the IEEE 39-bus system, a standard in electrical stability research. [5]

Databases obtained from dynamic simulations can be used for AI model applications while considering the structure and topology of the network. This enriches input data while also increasing the complexity of the models used, typically referred to as Graph Neural Networks (GNNs). In this regard, the study by Nauck et al. (2023) presents a GNN-based approach to analyze the dynamic stability of sustainable electrical grids with high penetration of renewable energy sources. The proposed model takes as input a graph representation of the electrical grid, where nodes correspond to system buses and edges to transmission lines, incorporating dynamic variables such as active power, frequency, and rate of change. The model's output is a stability prediction after a disturbance. The approach is applied to the Texas Interconnection, one of the largest and most isolated power grids in the world, allowing researchers to assess the effectiveness of the method under real-world conditions. [6]

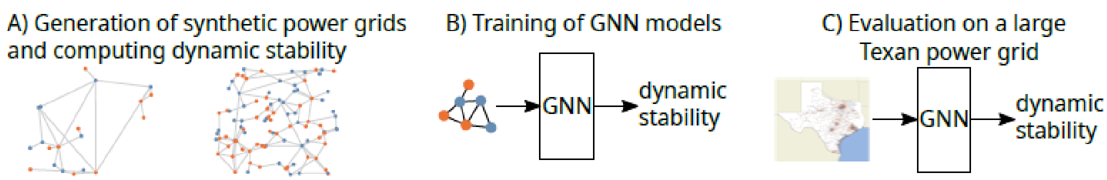

Figure 2: Procedure for deploying a graph neural network model. Source: C. Nauck (2023)

There are multiple differential equations that determine the behavior of the power system being studied. In recent years, neural networks have been developed that combine databases with the governing differential equations of the system in their learning process. These networks are called Physics-Informed Neural Networks (PINNs), which start with more information than standard neural networks but come with increased complexity and computational cost.

The study by Stiasny et al. (2024) presents PINNSim, a simulator designed to predict the dynamics of electrical systems based on PINN-based models. The model is applied to a 9-node test grid, where the inputs include system parameters such as voltages and power, along with the differential equations that define dynamic behavior. The simulator's output is the temporal evolution of system state variables, including frequency and generator angles. [7]

2.2 AIDA

Based on the advances presented in the state of the art, Red Eléctrica introduces AIDA (*Artificial Intelligent Dynamics Assessment*), a tool that combines dynamic simulations with artificial intelligence techniques for the study of transient stability in electrical systems.

AIDA emerges in response to the increasing complexity of power grids, driven by the strong presence of renewable energy due to the ecological transition, as well as factors like the growth of data centers, which introduce new challenges and limitations. These elements require a different analytical approach than traditional methods, and AI plays a crucial role in addressing them.

Due to the significant increase in dynamic simulations, this new methodology is multi-scenario, enabling much more precise regulation of specific aspects of the grid to enhance efficiency and accuracy.

2.2.1 Introduction

AIDA is a multi-purpose program centered on data from the control center of Red Eléctrica de España. Through dynamic simulations, statistical analysis, and artificial intelligence, it optimizes and examines various aspects of transient stability.

The goal is to leverage databases generated from detailed dynamic simulations to train AI models capable of accurately replicating system behavior but with a significantly lower computational cost. The implemented models utilize data in a tabular format, meaning no specific structure is introduced into the model input.

To generate the necessary dynamic simulations, AIDA employs PSS®E (Power System Simulator for Engineering), developed by Siemens PTI, one of the world's most renowned tools for power system stability and operational analysis. PSS®E is widely used by grid operators, electric companies, research centers, and universities due to its ability to model complex systems and conduct precise dynamic studies.

As part of the AIDA project, PSS®E is integrated via its Python scripting interface, allowing automation of simulation execution, results extraction, and post-processing to feed AI models. This integration facilitates a seamless workflow between traditional simulation and predictive model training, maintaining the accuracy of electrical system analysis while optimizing development time.

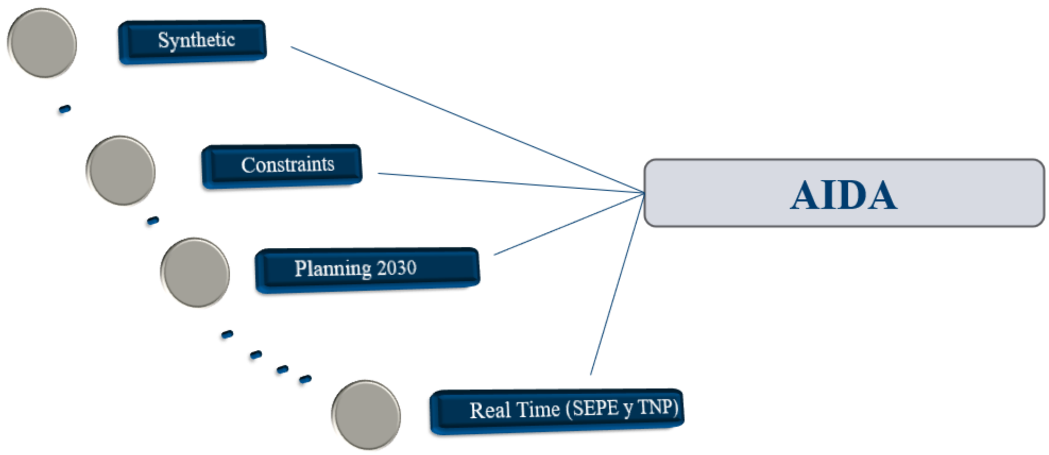

Figure 3: Types of scenarios for dynamic simulation.

The scenarios used for dynamic simulations can be synthetic scenarios, meaning they are generated for evaluation and experimentation without following any real-world structure or scheme. They can also be real-time scenarios received by CECOEL, next-day constraint scenarios, or even future scenarios designed for 2030 horizon planning.

To create a dynamic scenario, the intervention of various programs and databases is required. Starting with a real-time scenario database, to which more specific details can be added, a series of transformations is applied to shift from a static scenario to a dynamic scenario. Using a program that adapts the scenario to dynamic mode—which incorporates both transformations and dynamic models associated with each generator, whether generic or manufacturer-specific, the final dynamic case is generated.

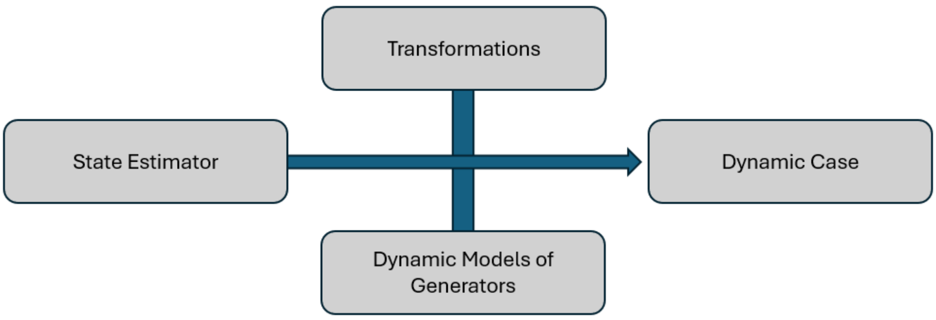

Figure 4: Representation of the shift from steady-state to dynamic.

Processing, storage, and memory resources are fundamental in dynamic simulation projects due to their computational cost. The server specifications are essential for comparing performance with other experiments and for drawing conclusions based on the results obtained. To deploy AIDA and run various simulations, five servers are available, each equipped with 14 physical cores, 20 virtual cores, 3 TB of disk storage, and 16 GB of RAM.

2.2.2 Modules

This program is divided into multiple AI application modules based on their objectives. While they are generally interconnected, it is essential to list them individually and explain their purpose and characteristics in detail. AIDA is a general-purpose program with many functions within dynamic power system studies. Below are its most important functions:

- **Selection of representative scenarios**: One of the most crucial modules, applicable to all others. The objective is to obtain the smallest number of representative cases, allowing a trained model to accurately generalize the remaining dataset. This can be applied to any AI model, as the goal is always to reduce the number of simulations and, consequently, simulation time.
- **Maximum Generation and Maximum Demand Calculation:** Results from dynamic simulations and AI-driven iterations help analyze whether the maximum generation and demand limits, which can be lost at any given moment without critically affecting the system, are correct or need adjustments. The applicable region is influential, differing between island systems and the mainland. This is closely related to dynamic capacity calculations.
- **Disconnected Power Calculation:** Given a contingency and a scenario, accurately determining the disconnected power is vital for evaluating worst-case contingencies or assessing dynamic capacity relative to current limits.
- **Dynamic Capacity Calculation:** This module builds upon previously mentioned ones. Using a set of representative scenarios, a trained model can predict disconnected power given a fault for the remaining sample. Additionally, maximum generation disconnection is calculated for each scenario. Finally, by combining both values, the system's capacity at any given moment is determined, and through statistical analysis of all scenarios, a future capacity benchmark can be selected.
- **Worst Contingency Selection:** The control center faces resource limitations that prevent simulating all possible failures in the grid within a given timeframe. This module was developed to address this limitation, aiming to identify and prioritize the worst contingencies for simulation. This allows for greater flexibility compared to simulating predefined failures, providing better oversight of the most critical faults.

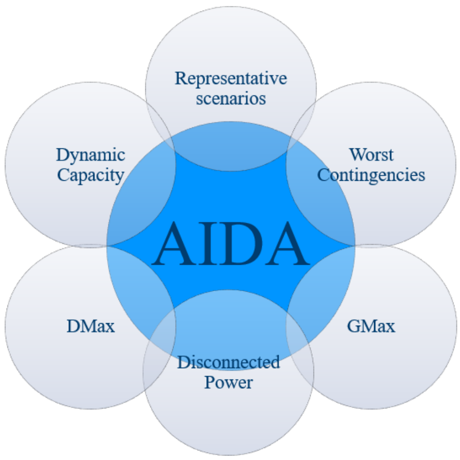

Figure 5: Diagram of AIDA modules

2.2.3 Databases

To implement all the modules presented in the previous chapter, it is necessary to conduct dynamic simulations across multiple scenarios and different contingencies. This process involves transforming the static model into a dynamic one, simulating each scenario, and post-processing the results to create databases used for training various artificial intelligence models.

Since each module serves a different function and objective, not all of them operate within the same analysis space, resulting in distinct databases depending on the application performed. In this project, three separate databases have been utilized, all containing tabular data without considering any network-specific structure.

Although the databases differ, as some focus on the peninsular system while others analyze island systems, the input variables for the models follow a similar structure. In all databases, each scenario includes electric demand, exchanges with bordering countries, or interconnection with the mainland in the case of island systems. Additionally, general characteristics by technology are recorded, such as gross production, the number of connected generators, and inertia in the case of synchronous technology. Furthermore, geographic metrics are collected, 18 zones for the mainland, while in the Balearic Islands, data is separated between Mallorca and Menorca.

The output variables from the dynamic simulation include whether the simulation has completed, the simulated time, binary indicators for static or dynamic inadmissibility, amount of generation disconnected under the given scenario and contingency, and the electrical substation where the fault occurs, among others.

The databases created in this project are as follows:

1. **Database 14:**

This database has been created and processed based on dynamic simulations conducted on 14 electrical substations across the Iberian Peninsula, where a three-phase fault lasting 100 milliseconds was introduced. These 14 pilot nodes serve to analyze the performance of AI models that predict the amount of generation disconnected in the event of such a failure occurring in any given scenario.

The Database 14 (BD14) contains hourly records from October 2023 to October 2024, totaling approximately 7,000 cases for each substation where a fault is applied. In total, this results in nearly 100,000 simulations, each spanning 5 seconds.

For each substation, detailed statistical studies have been conducted to analyze behavior patterns in the recorded historical data. This preliminary analysis has helped identify trends, seasonal variations, correlations between variables, and potential anomalies that could influence generation disconnection. These studies are essential for extracting valuable insights from the data and ensuring a deep understanding of the system before applying artificial intelligence techniques. By doing so, the predictive models are built on refined and relevant information, enhancing their accuracy and robustness in anticipating critical events in electricity generation.

The first graph presents an analysis of generation disconnection by hour of the day for a given substation, represented by a bar chart displaying the maximum, average, and minimum values recorded for each time slot. This visualization allows for a clear identification of the hours when the system experiences greater variability or intensity in generation disconnection events.

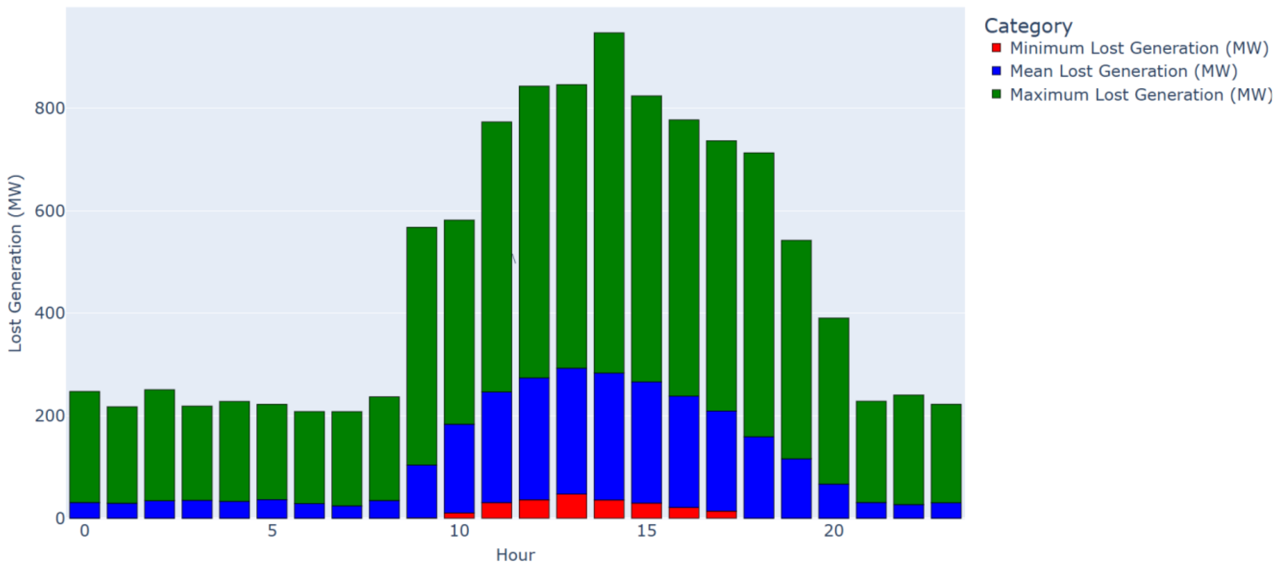

Figure 6: Histogram of disconnected generation by time interval.

It has been observed that certain time slots, seemingly related to sunlight incidence, concentrate in both maximum and average values, suggesting possible patterns linked to external factors such as weather conditions, demand behavior, or substation operations.

The same statistical analysis has been conducted considering monthly variation, evaluating maximum, average, and minimum values of generation disconnected throughout the year. The results reflect a similar pattern to that observed in the hourly analysis, showing a distinct concentration of higher values in specific periods. Notably, during the hottest months, the highest levels of generation disconnection are recorded.

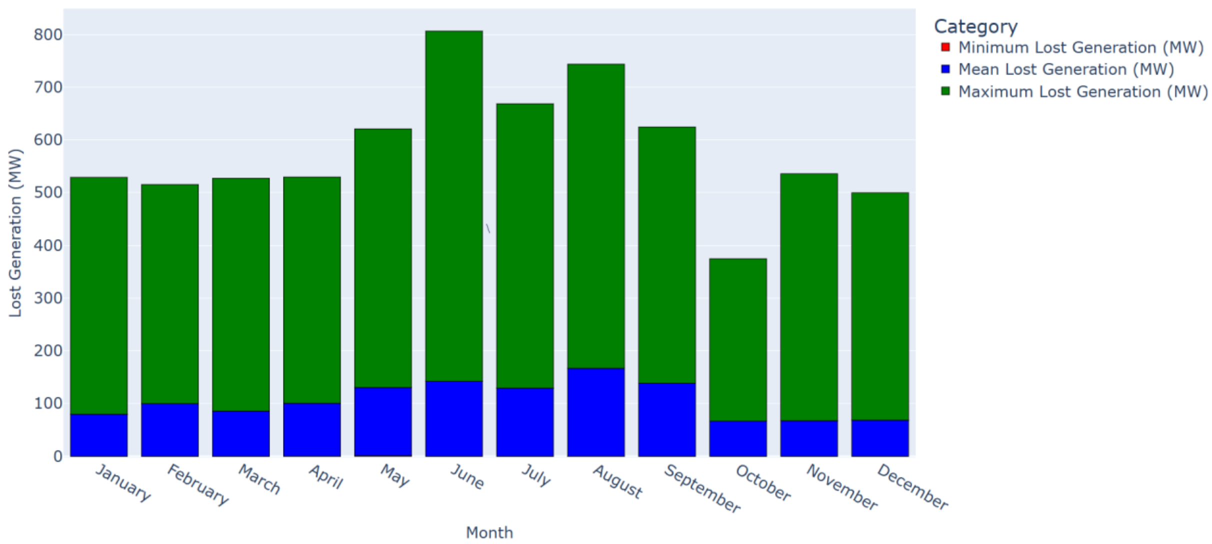

Figure 7: Histogram of disconnected generation by month.

Additionally, a chart has been created for BD14, displaying a monotonically decreasing curve that represents generation disconnection for a specific substation following a 100-

millisecond fault. This graph has been produced for all 14 substations, providing a comprehensive overview of the system's behavior under such contingencies.

Consequently, statistical measures can be applied to assess risks in relation to established limits or to identify irregular variations in specific substations.

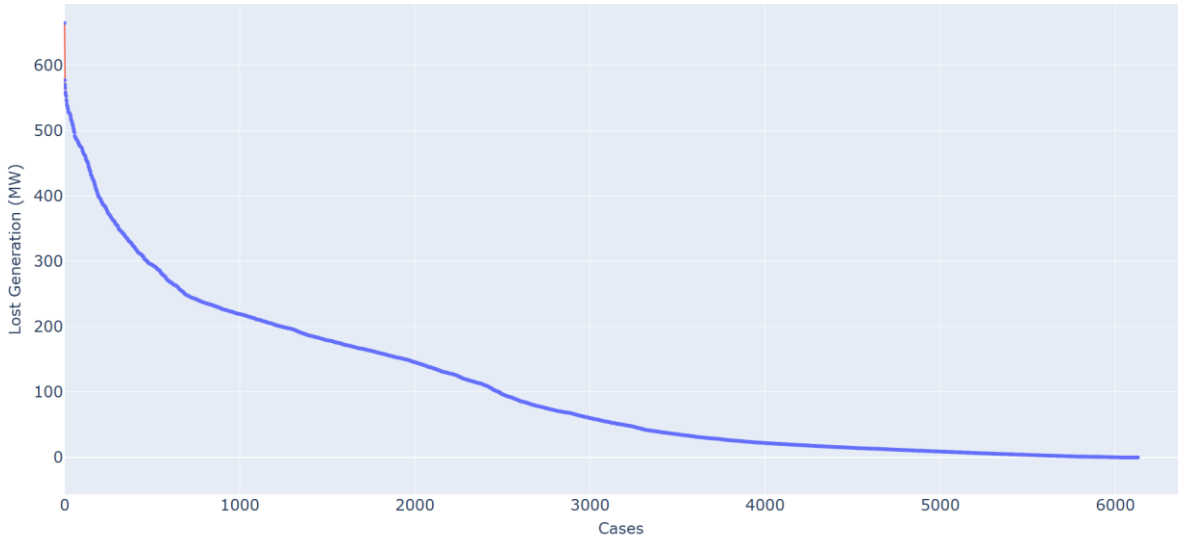

Figure 8: Monotonic curve of disconnected generation.

2. **Database 107:**

Database 107 (BD107) has been designed as a key strategic resource to advance the application of artificial intelligence models in power system operations. This database was built from a series of detailed dynamic simulations, conducted on a set of 107 electrical contingencies, representing potential faults or relevant incidents that could impact the electrical grid.

These contingencies include sudden disconnection of transmission lines, generation units, or substations, where three-phase faults to ground lasting 100 milliseconds were introduced. What makes this database unique is that these simulations were performed for every hour of the year, generating one scenario per hour, totaling approximately 7,000 scenarios. Each scenario reflects the specific generation, demand conditions, and other operational variables explained earlier in this section.

The primary goal of this database is to serve as a training and validation set for an AI-based predictive model capable of identifying, for each hourly scenario, which of the 107 contingencies pose the greatest risk to system stability. In other words, the objective is for the model to learn to recognize the most critical contingencies based on the system's operational context, enabling prioritized classification of faults to be considered.

A preliminary analysis has also been conducted on this dataset to identify which contingencies frequently violate static and dynamic admissibility conditions or have simulation times below a defined threshold, among other aspects. Additionally, generation disconnection distributions by contingency have been evaluated, applying preliminary filtering to eliminate outliers.

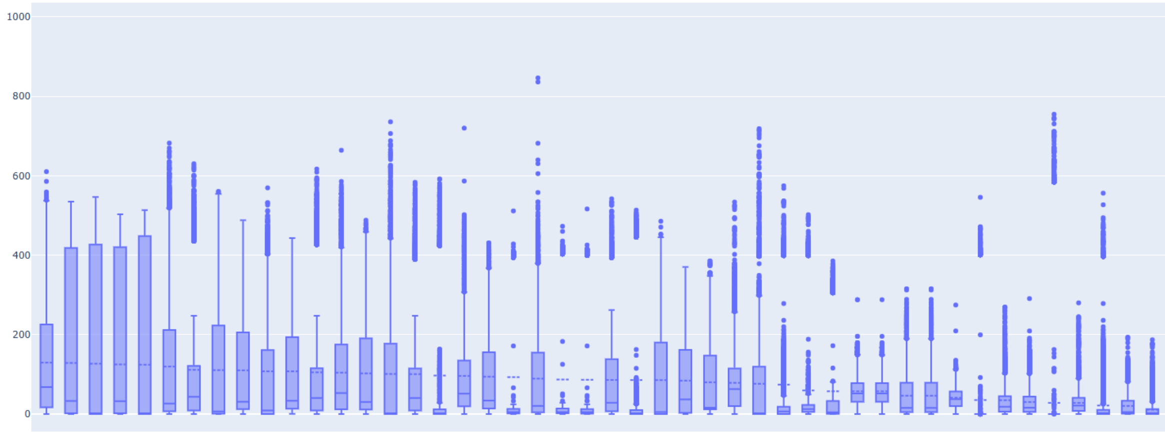

Figure 9: Boxplot of disconnected generation for each contingency.

This chart provides valuable insights prior to model training, allowing verification of whether the classification of worst contingencies aligns with previously analyzed data. While each scenario may vary significantly, in general, the results should correspond to the identified patterns.

3. Database Baleares:

The Baleares Database has been developed based on an extensive set of dynamic simulations conducted specifically on the electrical system of the Balearic Islands. These simulations involve the systematic application of three-phase faults to ground lasting 100 milliseconds across 82 substations distributed throughout the archipelago.

Each of these contingencies has been evaluated for every hour of the year, generating approximately 7,000 scenarios, similar to the other databases, to realistically represent the operational conditions of the system over time. The primary objective of this database is to characterize system behavior during critical events, iterating parameters associated with disconnected power until reaching the threshold linked to load shedding, a sudden and significant loss of demand due to a fault.

This phenomenon is closely related to the nadir frequency value, defined as the lowest frequency level reached after a disturbance. Nadir serves as a key indicator of event severity and the system's ability to withstand disturbances without compromising stability. Using this database enables precise evaluation of operational limits and explores alternative approaches to adjust dynamic generation capacity more realistically for the island system.

As with BD14 and BD107, various statistical studies have been conducted to extract essential insights for interpreting results from AI models that will later be trained. Regarding dynamic capacity calculations in the Balearic Islands, leveraging the multi-scenario nature of the dynamic simulations, monotonically decreasing generation disconnection graphs have been obtained for each substation, allowing for percentile-based risk assessment and the application of a new methodology.

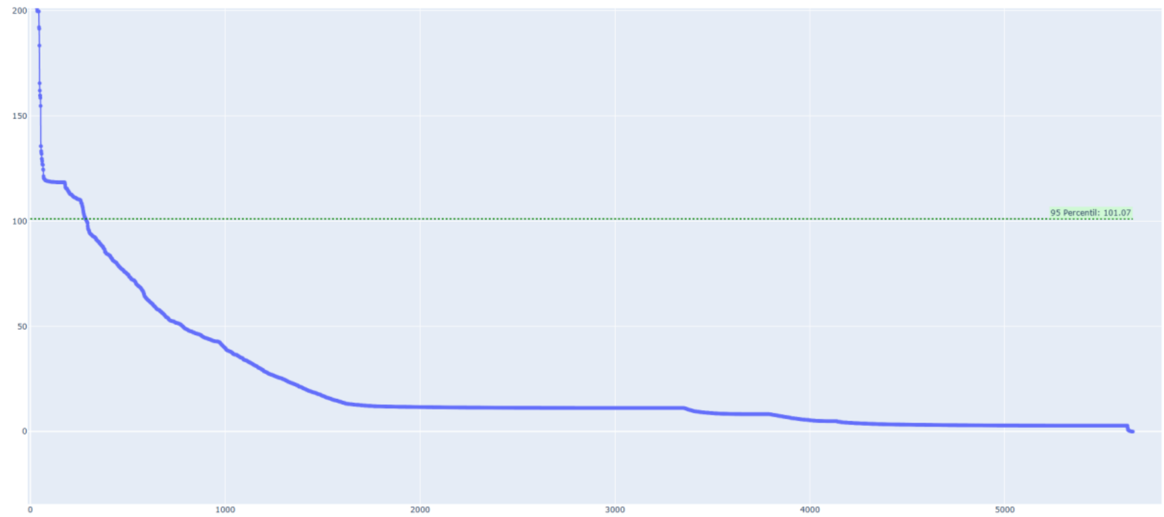

Figure 10: Monotonic curve of disconnected generation for substation in the Balearic Islands.

3. APPLICATIONS

The AIDA project leverages advanced artificial intelligence methodologies to optimize dynamic power system studies by applying predictive modeling across multiple datasets. Building on the datasets presented in the previous chapter, AIDA applies artificial intelligence to optimize scenario selection, contingency analysis, and dynamic capacity calculation while minimizing simulation time.

With Database 14 (BD14), the primary goal is to predict generation disconnection in response to three-phase faults at critical substations across the Iberian Peninsula. To enhance efficiency, representative scenario selection is applied, reducing the number of simulations while maintaining predictive accuracy. This allows AI models to anticipate system behavior, considering seasonal fluctuations and daily variability.

For Database 107 (BD107), the focus shifts to worst-case contingency identification for each scenario. AI models trained on this dataset analyze system conditions at an hourly resolution, classifying and prioritizing faults based on severity and probability. This ensures contingency planning is more targeted and effective, aiding decision-makers in mitigating risks proactively.

Finally, Database Baleares is primarily utilized for dynamic capacity calculation over future planning horizons, providing insights into system resilience under different contingencies. Given the complexity of island grids and their interconnections with Mallorca, Menorca, and the Iberian Peninsula, representative scenario selection is employed to refine predictions while optimizing computational efficiency.

Together, these databases form a powerful analytical framework, streamlining decision-making in power system management. By strategically applying AI-driven methodologies across BD14, BD107, and the Database Baleares, the project enhances predictive accuracy, optimizes resource allocation, and strengthens the resilience of electrical networks in both mainland and island environments.

3.1 ESTIMATION OF DISCONNECTED POWER IN THE IBERIAN PENINSULA

The rapid integration of renewable energy sources has introduced significant complexities in the stability and predictability of the Iberian Peninsula's electrical grid. Unlike traditional generation, renewables such as wind and solar are highly variable, making it increasingly difficult to anticipate system behavior in the event of a fault. This growing uncertainty highlights the need for precise estimation of disconnected generation in each scenario, allowing operators to enhance contingency planning and improve overall system reliability.

Understanding how generation loss propagates across the grid has multiple practical applications. One key implementation is fault monitoring, which identifies disturbances that result in large-scale generation disconnection. This data can be integrated into CECRE, where a gradient map visually represents how generator losses spread throughout the network, enabling better real-time decision-making. Additionally, by studying fault impact propagation, system operators can refine mitigation strategies and improve response protocols.

Figure 11: Simulation of the propagation of disconnected generation following a fault.

Another crucial application involves the construction of monotonically decreasing generation disconnection curves for each substation. Unlike traditional capacity assessment methods that evaluate only a single scenario, this approach provides a more dynamic and comprehensive understanding of grid resilience. By recalculating capacity with an expanded dataset, operators gain a clearer picture of system limitations and fault tolerances, leading to more accurate long-term planning strategies.

To achieve these objectives, an AI model will be trained to generalize the system's behavior and the differential equations that govern it. Given the high computational cost of dynamic simulations, one of the primary challenges is identifying the smallest possible set of representative scenarios from which the model can extrapolate system-wide dynamics. By optimizing the selection of scenarios, the project ensures efficient computation while maintaining robust predictive capabilities.

For this purpose, Database 14 (BD14) will be utilized, providing historical records of generation disconnection across multiple substations in the Iberian Peninsula. By applying representative scenario selection techniques to BD14, the AI model will be trained on a refined subset of cases, ensuring that key patterns and system dynamics are accurately captured while significantly reducing the need for exhaustive simulations. This approach enhances both the efficiency and reliability of the predictive model, allowing for robust contingency planning and grid stability assessments.

3.1.1 Selection of Representative Scenarios

In the context of power system analysis, particularly when applying machine learning models, the selection of representative scenarios is a critical step to ensure model performance and generalization. From the original dataset, which contains approximately 6,100 scenarios collected over the course of a year, not all cases contribute equally to the training process. Many of these scenarios may be highly similar to each other or contain limited information value, offering little benefit to the learning process.

On the other hand, certain data points reflect significantly different operating conditions. These diverse scenarios are especially valuable, as they enable the model to learn richer relationships between variables and to capture key system behaviors. This diversity ultimately enhances the model's ability to generalize and accurately predict the target output variable under a wide range of conditions.

The scenario selection process under varying power system operating conditions was based on the methodology proposed by Aththanayake et al., where deep neural networks are employed to analyze system behavior under different operating states. [8]

A total of four different methods have been employed for the selection of representative scenarios, each with distinct characteristics and levels of sophistication. The first method, known as the chronological or equally spaced method, consists of selecting one scenario every n time steps from the full chronological ordered dataset. This approach is simple and computationally efficient, but it does not consider the structure of the data in the input feature space. As a result, it may include redundant or similar scenarios while ignoring rare but informative ones. Its main drawback is that it assumes uniform relevance across all scenarios, which is rarely the case in complex system behavior.

The second method is referred to as the sliding window method. In this approach the dataset is divided into consecutive, non-overlapping windows of n chronologically ordered scenarios. For each window, a clustering process is applied using a simple distance-based metric and the scenario closest to the resulting cluster centroid is selected as the representative. This method introduces a notion of local diversity and helps retain temporal structure while still reducing redundancy within short time frames. However, it may still miss globally distinct behaviors if they occur in different windows.

The third method is the well-known K-Means clustering algorithm, which partitions the dataset into k cluster by minimizing the sum of squared Euclidian distances between data points and their corresponding cluster centroids. This method is well suited for identifying structure in well-distributed dataset. Importantly, the representative scenarios selected using K-Means are not the centroids themselves, which may not correspond to real data points. The representative scenarios are the actual scenarios from the dataset that are closest to each centroid. This ensures that all selected scenarios are realistic and consistent with the physical constraints of the original data. K-Means is effective when clusters are compact and similarly sized, but it may struggle with datasets containing clusters of varying densities or non-spherical shapes.

The fourth and final method is DBSCAN (Density-Based Spatial Clustering of Applications with Noise). This algorithm groups together points that lie in high-density regions while identifying low-density points as outliers. Unlike K-Means, DBSCAN does not require specifying the number of clusters in advance and can identify clusters of arbitrary shape. As with K-Means, the representative scenarios are selected as the real data points closest to the high-density core of each identified cluster, ensuring that the selected samples are physically plausible. DBSCAN is particularly powerful in heterogeneous datasets where clusters differ significantly in density or structure. It also helps to filter out noisy or non-informative scenarios, potentially improving model training by focusing on meaningful patterns.

Each of these four methods provides a unique lens through which to reduce and structure the dataset, aiming to retain the most diverse and informative scenarios for subsequent modeling. In this section, a comparison between the different methods is presented, focusing on their ability to generalize a monotonically decreasing curve of disconnected generation for one of the fourteen substations.

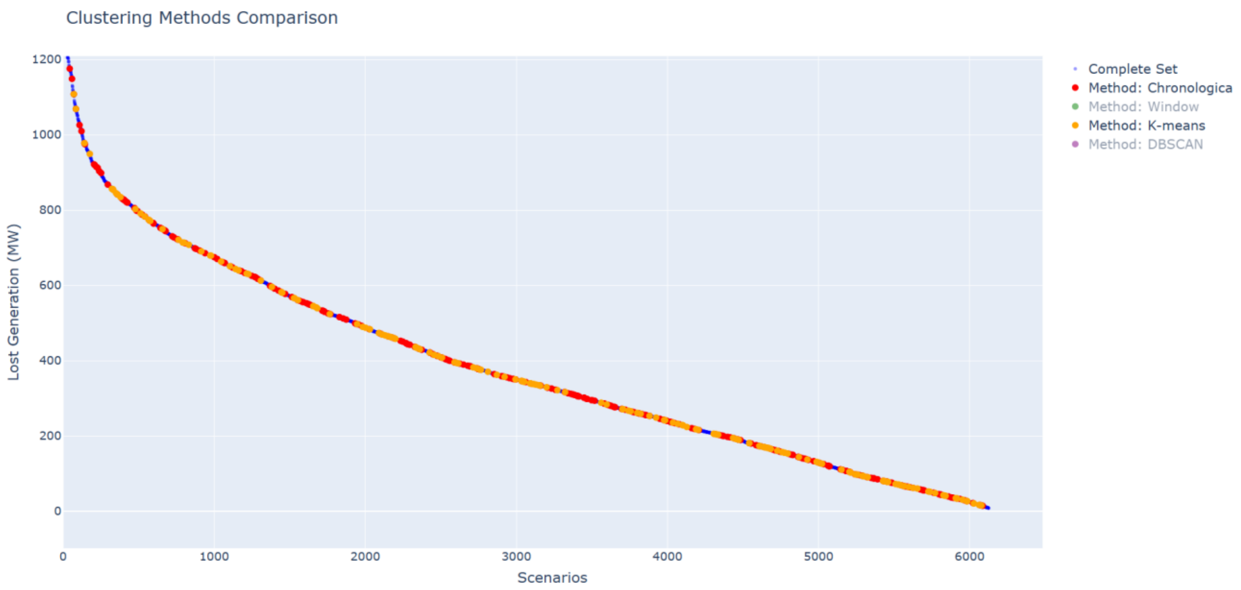

Figure 12: Comparison of Chronological and K-means clustering.

The figure above illustrates how the four clustering methods perform when tasked with generalizing a monotonically decreasing curve of disconnected generation for one of the substations. As observed, some methods are clearly more effective than others in capturing the overall shape and variability of the curve. Among them, the K-Means and Chronological methods demonstrate superior performance in approximating the general trend, particularly in the more challenging region where disconnected generation levels are high. These scenarios are likely rare or atypical, making them harder to capture without a method that ensures adequate representation across the entire feature space.

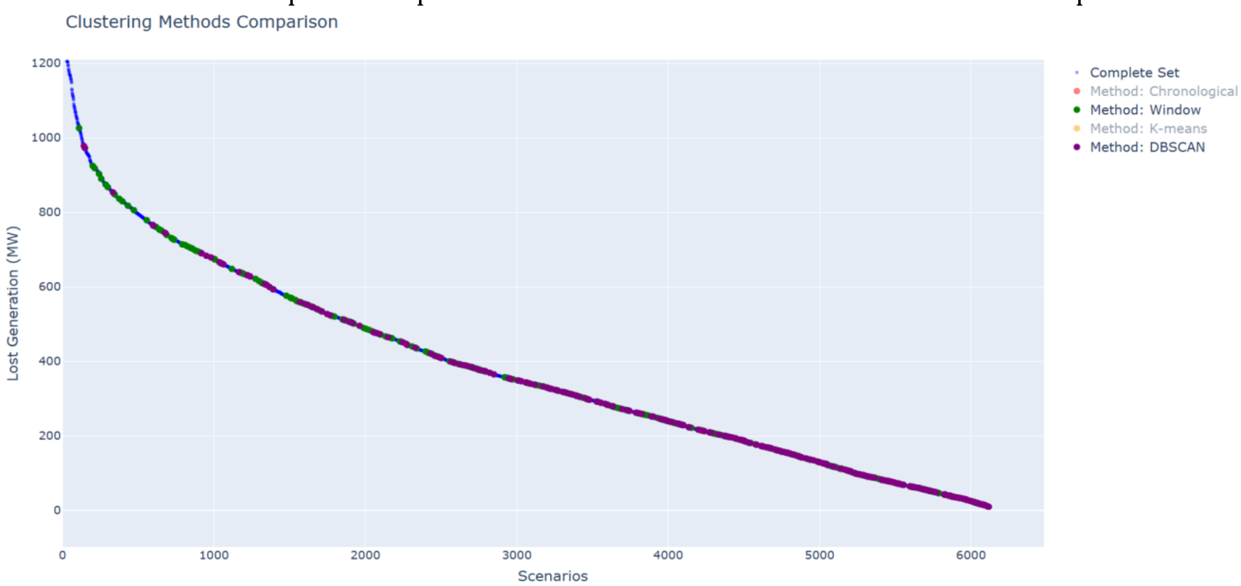

Figure 13: Comparison of Sliding Window and DBSCAN clustering.

In contrast, both the Sliding Window and DBSCAN methods show greater difficulty in identifying representative scenarios in these high-disconnection zones. The Window methods, by focusing on local windows, may fail to detect globally rare but critical events, while DBSCAN's density-based nature tends to underrepresent low-density regions where these edge cases typically lie.

The number of selected representative scenarios varies by method: both the Chronological and Window methods use a step or window size of 20, resulting in approximately 305 representative scenarios each. K-Means clustering was configured with k = 175, providing a balance between coverage and resolution. DBSCAN was applied with epsilon = 19 and minimum number of samples min_samples = 1, specifically chosen to allow detection of outlier points that are distant from dense clusters. However, due to DBSCAN's assumption that low-density areas are noise, it fails to include the most extreme cases, those with very high lost power, which are precisely the most critical to capture for robust generalization.

These differences highlight the importance of scenario selection strategy, particularly when modeling rare but high-impact situations. Methods that ensure a global view of data distribution, such as K-Means or chronological sampling, may be better suited for preserving edge-case behavior in models that aim to generalize across the full operational range.

The next step is to evaluate how well an artificial intelligence model generalizes when trained on the complete dataset of approximately 6,100 scenarios. This initial assessment provides a reference point for the model's ability to learn the relationships between input variables and accurately reproduce the target output across the full range of operating conditions. Once this baseline performance is established, the scenario selection methods are applied in order to determine whether a reduced set of representative scenarios can achieve comparable results. This process aims to assess the trade-off between computational efficiency and model accuracy, and to verify whether the same key insights, such as the reconstruction of monotonically decreasing curves of disconnected generation, can be obtained with significantly fewer dynamic simulations.

3.1.2 Estimation of Disconnected Power

This section presents a model capable of predicting the amount of disconnected generation using a set of input variables. The output variable, disconnected power, is derived from dynamic simulations carried out under a wide range of system disturbance scenarios. By learning the relationships between the input conditions and the resulting power disconnections, the model provides an efficient alternative to computationally expensive dynamic simulations, enabling faster and more scalable analysis of system behavior.

The model selected for this project is LightGBM (LGBM), a highly efficient and scalable gradient boosting framework that builds upon decision tree algorithms. LGBM is particularly well-suited for handling large-scale datasets and complex predictive tasks due to its innovative leaf-wise tree growth strategy. Unlike traditional level-wise approaches, LGBM grows trees by expanding the leaf with the highest potential to reduce loss, which often results in faster convergence and improved predictive accuracy. This method allows the model to focus computational resources on the most informative splits, making it both powerful and resource efficient. Furthermore, LGBM supports a wide range of advanced features, including native handling of categorical variables, built-in regularization techniques to prevent overfitting, and parallel and GPU learning capabilities, all of which contribute to its robustness and adaptability in real-world applications.

To ensure the model's reliability and its ability to generalize well to unseen data, the training pipeline began with a carefully designed validation strategy using TimeSeriesSplit with four splits. This technique is specifically tailored for time series data, where preserving the temporal order of observations is essential. Unlike standard cross-validation methods that randomly shuffle data, TimeSeriesSplit maintains the chronological sequence, ensuring that each training set precedes its corresponding test set in time. This approach not only prevents data leakage but also simulates real-world forecasting scenarios, where future data must be predicted based on past information. Each split incrementally increases the training window while shifting the test window forward, allowing the model to be evaluated across multiple temporal segments. This setup was instrumental not only for assessing model performance but also for guiding the hyperparameter tuning process, ensuring that the selected parameters are robust across different time-based partitions of the data. As a result, the model is better equipped to handle the dynamic nature of time series forecasting tasks.

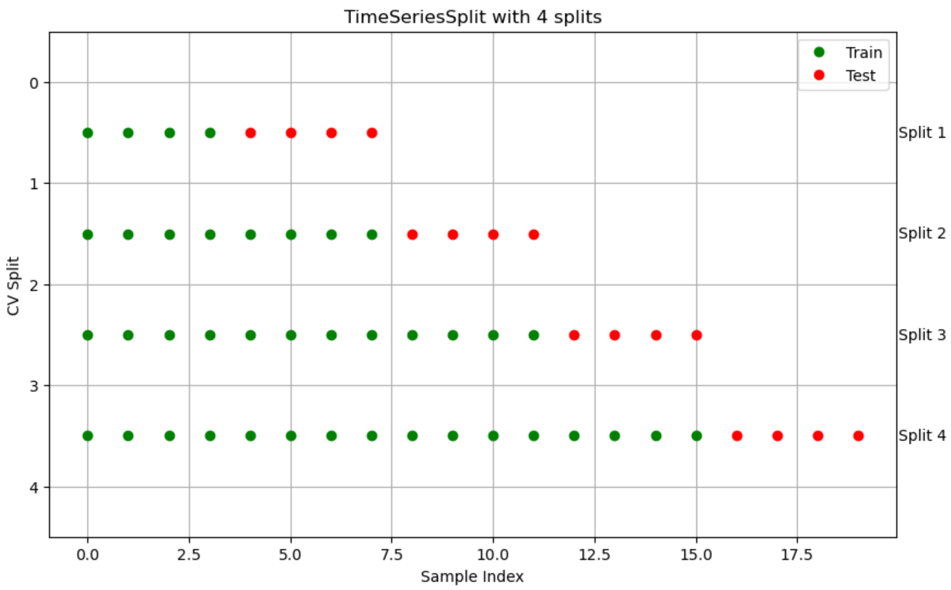

Figure 14: Representation of Time Series Split with 4 splits.

The hyperparameters tested through temporal cross-validation for the LightGBM (LGBM) model are as follows:

- **n_estimators**: [200, 500, 1000] – This parameter defines the number of boosting iterations, meaning the number of trees that will be built in the ensemble. A higher number of estimators can improve model performance by allowing it to learn more complex patterns, but it also increases computational cost and the risk of overfitting.

- **learning_rate**: [0.01, 0.05, 0.1, 0.5] – The learning rate controls the step size at which the model updates weights during training. A lower learning rate (e.g., 0.01) ensures more gradual learning, reducing the risk of overfitting but requiring more iterations.

A higher learning rate (e.g., 0.5) speeds up convergence but may lead to suboptimal solutions if too aggressive.

- **num_leaves**: [10, 15, 20, 40] – This parameter determines the maximum number of leaves per tree, influencing the model's complexity. A higher number of leaves allows the model to capture more intricate relationships in the data, but it also increases the risk of overfitting. A lower number of leaves results in a simpler model that may generalize better but could miss important patterns.

These hyperparameters were systematically evaluated using temporal cross-validation, ensuring that the model is optimized for sequential data while maintaining robustness against overfitting. By testing different configurations, the goal is to find the best balance between predictive accuracy and generalization, particularly in time-dependent datasets where past observations influence future predictions.

Below is a table presenting the five best hyperparameter combinations out of the 48 possible configurations tested. The selection is based on their mean test score, Root Mean Squared Error (RMSE), and ranking. These metrics provide insight into the model's performance, with the mean test score reflecting overall predictive accuracy, RMSE indicating the error magnitude, and the ranking helping identify the most effective parameter settings. This evaluation ensures that the LightGBM model is optimized for temporal data while maintaining a balance between accuracy and generalization.

Rank	learning_rate	n_estimators	num_leaves	mean_test_score	RMSE
1	0.1	500	10	-6,510.4171	80.6871
2	0.1	1000	10	-6,520.9205	80.7522
3	0.05	1000	10	-6,561.4393	81.0027
4	0.1	200	10	-6,588.4422	81.1692
5	0.05	500	10	-6,609.3052	81.2976

Table 1: Comparison of different hyperparameter configurations.

As shown, the best results were consistently achieved using a learning_rate of 0.1 or 0.05. Lower values, such as 0.01, likely caused underfitting due to slower convergence, while higher values like 0.5 may have led to overfitting or unstable behavior. Regarding the number of estimators, configurations with 500 or 1000 trees performed better, particularly when paired with smaller learning rates, which require more boosting rounds to reach optimal performance.

A particularly striking result was that all top-performing models used num_leaves = 10. None of the configurations using 15, 20, or 40 leaves appeared among the best results, suggesting that simpler, shallower trees work better with this dataset. These smaller tree structures likely help the model generalize more effectively and avoid overfitting.

The best configuration overall combined learning_rate = 0.1, n_estimators = 500, and num_leaves = 10, resulting in the lowest RMSE of 80.6871. Considering this, future tuning efforts should focus on refining the learning rate and number of estimators within these promising ranges, while keeping the number of leaves fixed at 10 to preserve model simplicity and robustness.

Now that the best hyperparameter configuration has been identified, the model is trained using 80% of the data and tested on the remaining 20%. This corresponds approximately to training on scenarios from October 2023 to August 2024 and testing from August 2024 to October 2024.

To ensure a proper separation between training and testing data and avoid potential correlation, a gap of 12 records is applied between the two sets. This gap acts as a buffer, preventing data leakage and ensuring that the model does not inadvertently learn patterns that directly influence the test set. By introducing this separation, the model is evaluated on truly unseen data, improving its ability to generalize to future scenarios.

This approach is particularly important in time-series modeling, where consecutive observations are often highly correlated. Without a gap, the model might benefit from short-term dependencies that do not reflect real-world forecasting challenges. By enforcing this separation, the evaluation process becomes more realistic, ensuring that the model's performance is assessed under conditions similar to actual deployment.

A separate model is trained for each substation, ensuring that the predictions are tailored to the specific characteristics and patterns of each location. However, to keep the presentation concise and avoid excessive data, the results shown will focus on one specific substation. This allows for a detailed analysis of the model's performance while maintaining clarity and readability in the report. The insights gained from this substation can be extrapolated to the others, as the same methodology has been applied across all models.

For this specific substation, the model achieves the following performance metrics: RMSE Train: 18.39, R^2 Train: 0.99, RMSE Test: 66.29, and R^2 Test: 0.92. While there is some degree of overfitting, as indicated by the lower error in the training set compared to the test set, the model still demonstrates a strong ability to generalize. The high R^2 Test score of 0.92 suggests that the model effectively captures the underlying patterns in the data and maintains reliable predictive performance, even when applied to unseen scenarios.

In the following graph, the model's predictions for the test set are displayed, allowing for a visual assessment of its performance. The predicted values closely follow the actual data, demonstrating that the model can generalize correctly to unseen scenarios.

This aligns with the previously discussed performance metrics, where the R^2 Test score of 0.92 indicates a strong correlation between predictions and actual values, and the RMSE Test value of 66.29 reflects a reasonable level of error. While some degree of overfitting was observed, given the lower RMSE in the training set, the model still effectively captures the underlying patterns in the data.

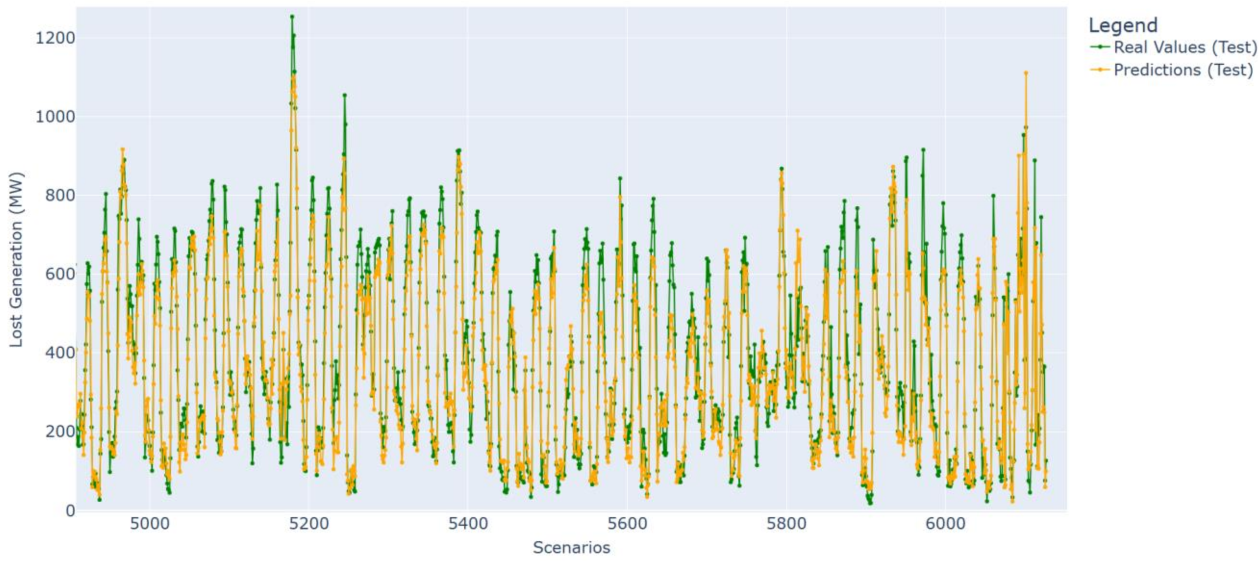

Figure 15: Prediction of the LGBM model on the test set.

The graph serves as further validation of the model's ability to adapt to new data while maintaining predictive accuracy. The consistency between the visual representation and the numerical metrics confirms that the model is well-calibrated, making it a reliable tool for forecasting within this specific substation.

Having observed the performance of a model with such strong metrics, it is important to further analyze how different factors influence its effectiveness. To gain deeper insights, a study will be conducted to examine the impact of training set size and the gap between training and test data on the model's evaluation metrics.

The size of the training set plays a crucial role in model performance, as larger datasets typically allow the model to learn more complex patterns, but they may also introduce noise or outdated trends. Conversely, smaller training sets might lead to underfitting, limiting the model's ability to generalize.

Similarly, the gap between training and test data is essential in preventing data leakage and ensuring realistic evaluation. A larger gap reduces correlation between the two sets, making the test results more representative of real-world forecasting challenges. However, an excessively large gap might lead to a loss of valuable temporal dependencies.

By systematically varying these parameters and analyzing their effect on RMSE, R^2, and other evaluation metrics, this study aims to determine the optimal balance between training data size and separation gap, ensuring the best possible generalization and predictive accuracy for future implementations.

Using optimized hyperparameters, the model is first trained to evaluate the impact of training set size on performance, aiming to determine the minimum amount of data required while still achieving satisfactory metrics. To do this, the training set size has been systematically varied across different time spans, ranging from long periods such as nine months and six months to shorter durations like three months, one month, two weeks, and one week. Additionally, even smaller training windows have been tested, including five days, three days, and two days, to assess how the model performs with extremely limited historical data.

By analyzing the results across these different training durations, the goal is to identify the point at which the model maintains high predictive accuracy while minimizing unnecessary data usage. A larger training set generally allows the model to learn more complex patterns, but it may also introduce outdated trends or noise. On the other hand, a smaller training set might limit the model's ability to generalize, potentially leading to underfitting.

The following graph presents the R^2 values for each training set size, providing insight into how the amount of training data influences the model's ability to generalize effectively.

Figure 16: Comparison of model performance by training set size.

From the graph, it is observed that the model's R^2 value remains stable between two weeks and one month, indicating that within this range, the model maintains its predictive accuracy without significant deterioration. Based on this evaluation, a training set size of 400 data points or representative scenarios, approximately three weeks, has been selected as the optimal amount necessary for the model to generalize effectively and extrapolate the rest of the dataset.

With this determined training size, the next step is to analyze how the gap size between training and test data affects the evaluation metrics. By varying the gap, the goal is to understand its influence on model performance, ensuring that the separation is sufficient to prevent data leakage while still allowing the model to capture relevant temporal patterns.

In the following graph, the variation of R^2 is observed as the gap size between training and test data is adjusted, ranging from 12 records to 2500 records. This analysis helps evaluate how the separation between the two datasets impacts the model's ability to generalize.

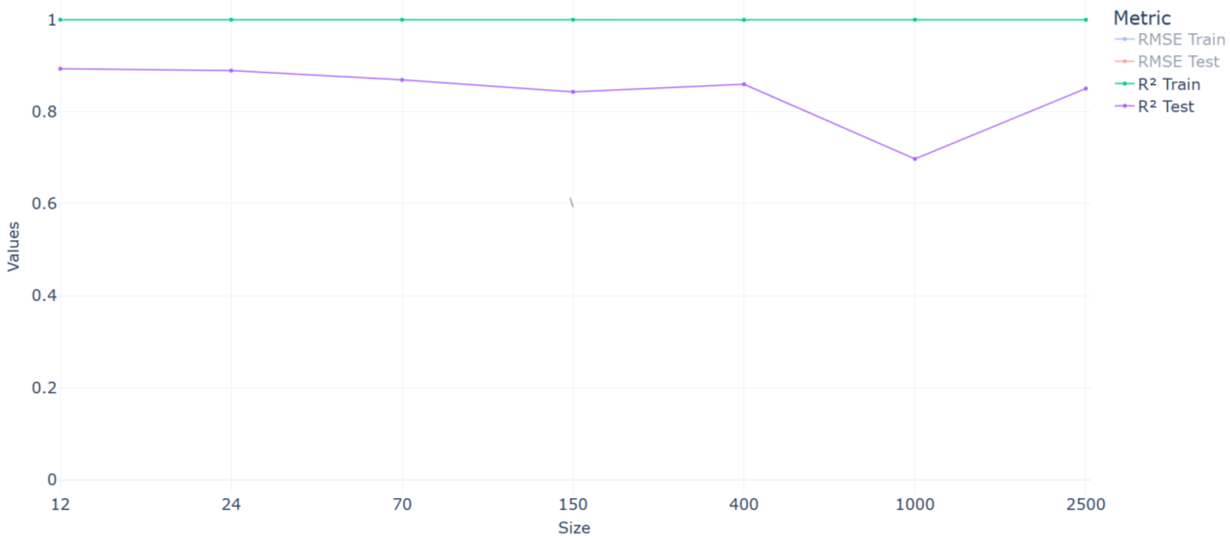

Figure 17: Comparison of model performance by gap size.

From the graph, it can be observed that, in general, the R^2 value remains stable across different gap sizes, except for the case of 1000 records, where a noticeable drop occurs. This decline suggests that the model may struggle to generalize effectively when this specific gap size is applied.

One possible explanation for this behavior is that the model benefits from having access to data from different stations, which might provide essential variability and context for learning. When a gap of 1000 records is introduced, it could be removing crucial information, making it harder for the model to capture broader patterns. This indicates that incorporating diverse station records is important for maintaining predictive accuracy, as excluding them might limit the model's ability to generalize effectively.

Now that all the necessary steps have been completed to apply the selection of representative scenarios, the optimal training set size has been determined, ensuring that the model can generalize effectively. With this foundation, the next section integrates the findings from the previous analyses, combining the insights on training size and gap selection to build a refined model.

This model will estimate the disconnected power for the entire dataset using a training set composed of representative scenarios, rather than relying on a continuous time window. The objective is to construct the monotonically decreasing curve of disconnected generation for this specific substation, providing a comprehensive view of how power disconnection evolves under different conditions.

3.1.3 Modeling the Disconnected Generation Curve

Now that the optimal hyperparameters have been determined, learning rate = 0.1, num_leaves = 10, and n_estimators = 500, the model is applied to a carefully selected sample of 400 data points. These points are chosen using the K-Means clustering method, as previously explained, ensuring that the most representative scenarios are used for training. Specifically, the actual data points closest to the 400 centroids identified by K-

Means are selected, providing a diverse and compact training set that captures the essential variability of the dataset.

The selection of these representative points is a crucial step in the process, as it allows the model to learn from a balanced and well-distributed subset of the data rather than relying on a continuous time window. This ensures that the training set includes a wide range of possible scenarios, improving the model's ability to generalize across different conditions. By focusing on a condensed and highly informative dataset, the model is expected to maintain strong predictive accuracy while reducing computational complexity.

Once the model has been trained using this optimized subset, it is then applied to estimate the disconnected power across the remaining scenarios in the dataset. This step extends the model's predictions beyond the initial training set, allowing it to provide estimates for situations it has not directly seen before. The ability to extrapolate effectively is a key indicator of the model's robustness, demonstrating that it can capture the underlying patterns in the data rather than simply memorizing specific instances.

Following this estimation process, various evaluation metrics are computed to assess the model's performance. The results show that the model achieves an RMSE of 73.0792 and an R^2 of 0.92, indicating a high level of accuracy and reliability. These strong metrics validate the effectiveness of the approach, demonstrating that the combination of representative scenario selection and optimal hyperparameter tuning has significantly improved the model's ability to generalize. The careful selection of training data has ensured that the model learns from the most relevant patterns, while the hyperparameter optimization has fine-tuned its predictive capabilities.

With these predictions in place, the next step is to construct a monotonically decreasing curve of disconnected generation, which will be compared against the actual observed curve. The primary objective of this comparison is to determine whether the model can replicate the real curve using fewer steps, effectively capturing the essential trends in power disconnection while minimizing unnecessary complexity. If successful, this approach would allow for a more efficient representation of the disconnection process, reducing the number of required scenarios while still maintaining an accurate depiction of the system's behavior.

This methodology not only enhances the efficiency of the estimation process but also provides valuable insights into how representative scenarios can be leveraged to streamline forecasting. By reducing the number of required steps while maintaining accuracy, the approach ensures that the model remains both robust and scalable, making it a practical tool for future applications in power system analysis. Additionally, this strategy could be extended to other substations or similar datasets, demonstrating its versatility and potential for broader implementation in predictive modeling tasks.

Next, the graph will be presented, showing both the actual monotonically decreasing curve and the predicted curve for a specific substation. This comparison will allow for a visual assessment of how well the model replicates the real trend of disconnected generation, highlighting its ability to generalize and accurately estimate power disconnection using a reduced set of representative scenarios.

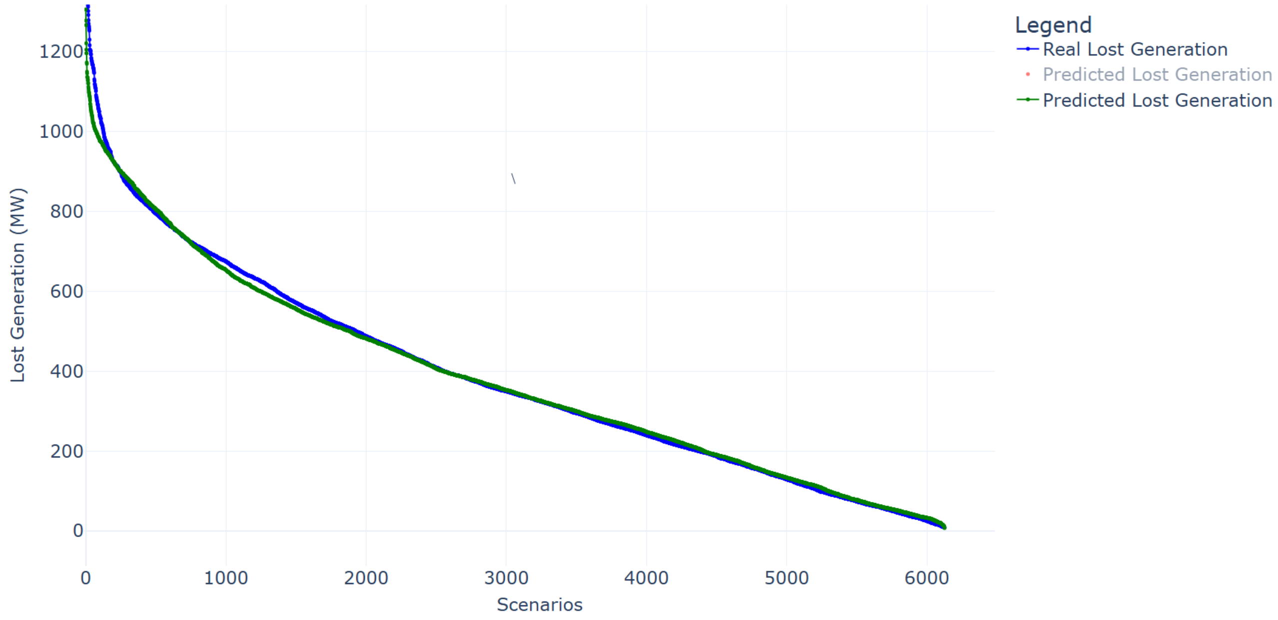

Figure 18: Prediction of the monotonic disconnected generation curve from the model trained with representative scenarios.

From the visual representation, it is evident that the predicted monotonically decreasing curve closely follows the actual curve, demonstrating the model's strong ability to replicate the real trend of disconnected generation. The two curves are practically overlapping, indicating that the model successfully captures the overall behavior across all segments, even in the areas where the disconnection values fluctuate more significantly. This suggests that the methodology used, combining representative scenario selection with optimized hyperparameters, has been highly effective in ensuring accurate predictions while maintaining computational efficiency.

One of the most notable aspects of this result is the model's ability to preserve the trend across all sections of the curve, even in the regions where the disconnection values exhibit more pronounced variations. This means that the model is not only capable of estimating average behavior but also of adapting to more extreme fluctuations, which is crucial for real-world applications where power disconnection does not always follow a perfectly smooth pattern.

This high level of accuracy allows for valuable applications in dynamic capacity evaluation for future horizons. By reliably estimating the trend, the model enables the calculation of percentiles, which can be used to assess potential risks and determine the likelihood of extreme scenarios. Additionally, this approach provides a structured way to evaluate the percentage of scenarios that could pose operational challenges, ensuring that power system planning accounts for possible disconnection events effectively.

Furthermore, the ability to construct a monotonically decreasing curve with fewer steps while maintaining precision offers significant advantages in terms of forecasting efficiency. Instead of requiring many individual simulations, this methodology allows for a more streamlined approach, reducing computational demands while still providing a highly accurate representation of disconnected generation behavior. This makes it a valuable tool for decision-making processes, enabling operators to anticipate potential risks and optimize system performance with greater confidence.

3.2 SELECTION OF THE WORST CONTINGENCIES

Due to resource limitations and the vast number of possible failures that can occur within the system, it is not feasible to dynamically calculate and simulate all contingencies within a short time window. The complexity and computational demands of evaluating every potential fault make it necessary to prioritize the most critical scenarios. In large-scale power systems, thousands of possible contingencies can arise, each with varying degrees of impact on grid stability, reliability, and operational efficiency. Attempting to analyze all of them in real time would require an immense amount of computational power and time, making it impractical for immediate decision-making.

This chapter focuses on how AI-driven models can be applied to select the worst contingencies, ensuring that the most impactful failures are identified efficiently. By leveraging machine learning techniques, the goal is to provide decision support to the control center, helping operators determine which faults should be simulated at any given moment. Instead of relying on exhaustive simulations, AI models can intelligently filter, and rank contingencies based on their potential severity, allowing operators to focus on the most critical cases that could pose a significant risk to system stability.

The ability to automate the selection process is crucial for enhancing situational awareness in real-time operations. AI models can analyze historical data, system topology, and real-time measurements to predict which contingencies are most likely to lead to severe disruptions. This enables a proactive approach to contingency analysis, where the control center can anticipate and prepare for high-risk scenarios before they escalate into major failures.

Furthermore, by integrating AI-based contingency selection into the decision-making workflow, operators can optimize the allocation of computational resources, ensuring that simulations are conducted on the most relevant cases rather than wasting time on low-impact failures. This improves the overall efficiency of contingency analysis, allowing for faster response times and more effective mitigation strategies.

For the selection of the worst contingencies, Database 107 (BD107) is used, as previously explained. This data set serves as the foundation for training a neural network model built using PyTorch, designed to estimate the disconnected generation for each possible failure scenario. The neural network is structured so that its output layer contains as many neurons as there are contingencies, meaning that for each input scenario, the model will produce an estimate of the disconnected generation for every possible failure.

The objective of this approach is to introduce a set of input variables into the neural network and allow it to learn the complex relationships between these variables and the resulting disconnected generation. By doing so, the model can efficiently determine which contingencies lead to the most severe disconnections, enabling the identification of the worst-case scenarios for each given set of conditions. Instead of manually simulating every possible failure, the AI-driven model provides a prioritized ranking, allowing operators to focus on the most critical cases.

The contingencies analyzed in this study consist of three-phase faults to ground lasting 100 milliseconds, occurring on substations, generation units, and transmission lines. These faults represent severe disturbances that can significantly impact system stability and operational reliability.

The input data fed into the neural network includes a wide range of variables that characterize the state of the power system at any given moment. These variables encompass both global system conditions and regional factors, ensuring that the model captures the full complexity of contingency behavior. Among the key inputs are:

- **Total demand**: which reflects the overall electricity consumption at the time of analysis.
- **Interconnection flows**: with France, Portugal, and Morocco, representing the exchange of power between Spain and neighboring countries. These values are crucial for understanding cross-border dependencies and their impact on system stability.
- **Tabular values by technology**: which provide detailed information on the contribution of different generation sources, such as nuclear, hydro, wind, solar, and thermal power plants.
- **Regional data for 18 zones across the Iberian Peninsula**: ensuring that the model accounts for localized variations in generation and demand.

By incorporating this diverse set of inputs, the neural network is trained to recognize patterns and relationships that determine the severity of each contingency. Once trained, the model can process new scenarios and estimate the disconnected generation for every possible failure, effectively ranking them based on their impact. This allows for a data-driven selection of the worst contingencies, ensuring that control center operators can focus their simulations on the most critical cases.

The ability to automate this selection process significantly enhances operational efficiency, reducing the computational burden associated with exhaustive contingency analysis. Instead of manually evaluating thousands of potential failures, the AI model provides a targeted approach, identifying the most severe cases in real time. This methodology not only improves decision-making but also strengthens grid resilience, ensuring that the system remains prepared for the most impactful disruptions.

The first step before constructing the final model that predicts the disconnected power for each failure in every scenario is to determine the optimal neural network architecture. Selecting the right structure is crucial to ensuring that the model effectively learns the complex relationships between input variables and contingency outcomes while maintaining computational efficiency.

This process involves evaluating different configurations, including the number of layers, neurons per layer, activation functions, and regularization techniques, to find the best balance between accuracy and generalization. A well-structured network will allow the model to capture the underlying patterns in the data without overfitting or underfitting, ensuring reliable predictions across diverse operating conditions.

3.2.1 Optimizing Neural Network Architecture and Hyperparameters

To develop a robust predictive model for estimating disconnected power in different contingency scenarios, several neural network configurations have been designed and tested. These architectures progressively increase in complexity, incorporating additional layers, activation functions, dropout regularization, batch normalization, and residual connections to enhance learning stability and prevent overfitting. Each configuration brings specific improvements aimed at optimizing predictive accuracy while maintaining computational efficiency.

The first models, NeuralNet and NeuralNet2, represent basic feedforward networks with three to five hidden layers. They utilize ReLU activation functions, which help maintain non-linearity and prevent vanishing gradients, along with dropout regularization to reduce overfitting. NeuralNet2 introduces an additional hidden layer with 86 neurons, refining feature extraction and allowing for a more nuanced representation of input data.

Moving towards more advanced architectures, ComplexNeuralNet and ComplexNeuralNet2 incorporate batch normalization, which stabilizes training and accelerates convergence by normalizing activations across mini-batches. These models also introduce LeakyReLU and ELU activation functions, which improve gradient propagation and prevent neurons from becoming inactive. Additionally, residual connections are implemented, allowing information to flow more effectively across layers, ensuring that deeper networks retain meaningful features from earlier layers.

The most sophisticated configurations, ComplexNeuralNet3, ComplexNeuralNet4, and ComplexNeuralNet5, expand the architecture to six hidden layers, significantly increasing model capacity. These models integrate SELU activation functions, which maintain self-normalizing properties, improving gradient flow and ensuring stable training. They also include dropout layers to enhance generalization and prevent overfitting, while residual connections further optimize learning efficiency by preserving information flow across layers.

Each of these architectures is designed to progressively refine the neural network's ability to predict disconnected power for different contingencies, ensuring a balance between accuracy, generalization, and computational efficiency. By leveraging these configurations, the model can effectively capture complex relationships within the dataset, providing reliable estimations that support decision-making processes in contingency analysis.

All neural network architectures are evaluated using 450 epochs, with the Adam optimizer set to a learning rate of 0.01. The chosen loss function is global RMSE (Root Mean Squared Error), meaning that the error is computed across all outputs collectively, rather than individually for each contingency. This approach provides a comprehensive measure of overall prediction accuracy, ensuring that the model effectively captures the general trend of disconnected power across multiple failure scenarios.

This evaluation process aims to determine whether a more complex network or one with specific architectural features is necessary to improve performance. By analyzing the results across different models, we can assess how factors such as layer depth, activation functions, dropout regularization, and residual connections impact the model's ability to generalize and accurately predict disconnected power for each contingency scenario.

In the table below, the global RMSE and R^2 metrics are presented for both training and test datasets. These values provide a comprehensive evaluation of each model's performance, allowing for a comparison of how well the different neural network architectures generalize and predict disconnected power across multiple contingencies.

Model	RMSE Train	RMSE Test	R^2 Train	R^2 Test
NeuralNet	93.2979	133.6252	0.9021	0.8196
NeuralNet2	88.4303	128.6044	0.9121	0.8329
ComplexNeuralNet	121.0629	127.3832	0.8352	0.8361
ComplexNeuralNet2	130.0583	128.8292	0.8098	0.8324
ComplexNeuralNet3	115.0281	123.2473	0.8512	0.8466
ComplexNeuralNet4	115.9652	125.3527	0.8488	0.8413
ComplexNeuralNet5	121.6135	126.5786	0.8337	0.8382

Table 2: Comparison of model performance across different neural network architectures.

From the results presented in the table, we can observe a clear trend in how model complexity affects performance. The simpler architectures, such as NeuralNet and NeuralNet2, exhibit higher RMSE values on the test set compared to the training set, indicating a tendency toward overfitting. These models achieve high R^2 scores on the training data but experience a noticeable drop in performance when evaluated on unseen test data. This suggests that while they learn well from the training set, they struggle to generalize effectively to new scenarios.

On the other hand, the more complex architectures, such as ComplexNeuralNet, ComplexNeuralNet2, ComplexNeuralNet3, ComplexNeuralNet4, and ComplexNeuralNet5, show less overfitting. Their RMSE values for training and test sets are much closer, and their R^2 scores remain more stable, indicating better generalization. Among these, ComplexNeuralNet3 stands out as the best-performing model, achieving the lowest test RMSE (123.2473) and the highest test R^2 score (0.8466).

The ComplexNeuralNet3 model is structured with six hidden layers, incorporating batch normalization, dropout regularization, and residual connections to enhance stability and learning efficiency. The first layer consists of 512 neurons, with batch normalization applied to stabilize activations and a LeakyReLU activation function to prevent dead neurons. The second layer has 256 neurons, also with batch normalization, and uses an ELU activation function, which helps maintain smooth gradients. Additionally, dropout (0.3) is applied to reduce overfitting.

The third layer contains 128 neurons, again with batch normalization and ELU activation, along with dropout (0.3) to further improve generalization. The fourth layer introduces a residual connection, allowing information to flow more effectively across the network. This layer has 128 neurons, with batch normalization and a ReLU activation function to enhance learning stability. The fifth layer consists of 64 neurons, with batch normalization and a SELU activation function, which helps maintain self-normalizing properties. A dropout rate of 0.2 is applied to further prevent overfitting. Finally, the output layer is a fully connected linear layer, mapping to the number of outputs required for the prediction task.

The ComplexNeuralNet3 model demonstrates the best balance between accuracy and generalization, making it the most suitable architecture for predicting disconnected power across different contingencies. Its combination of batch normalization, dropout regularization, and residual connections ensures stable training while minimizing overfitting, leading to more reliable predictions in real-world applications.

It is important to highlight that the RMSE and R^2 values obtained in this evaluation are worse compared to the previous chapter, where the estimation of disconnected generation was performed. This difference is expected, as the current approach optimizes a single model to predict the output for all failures simultaneously, rather than using a separate model for each contingency. Given this broader scope, a slight decrease in accuracy is natural. However, despite this, the results remain strong, with an R^2 consistently above 0.8, indicating that the model still captures the underlying patterns effectively and provides valuable predictions for contingency analysis.

3.2.2 Estimating the Worst Contingencies via Disconnected Generation Prediction

Now that we have determined the optimal architecture and hyperparameters for the neural network, we can proceed with the training and evaluation phase. The model will be trained using 80% of the available data, allowing it to learn the complex relationships between system variables and the resulting disconnected generation for each contingency. Once the training is complete, the remaining 20% of the data will be used for testing, providing an independent evaluation of how the model operates in real scenarios and how it could be integrated into decision-making processes.

This phase is essential for demonstrating how the model can support the control center by providing rapid estimations of disconnected generation for different contingencies. By analyzing its predictions, we can observe how it processes new data and identifies critical failures, offering valuable insights into system behavior under different conditions. The ability to quickly estimate the impact of contingencies allows operators to prioritize simulations, focusing on the most relevant cases without the need for exhaustive manual analysis.

Additionally, this evaluation will highlight the practical benefits of using AI-driven contingency analysis in real-time operations. By integrating this model into the control center workflow, operators could gain a data-driven tool that enhances situational awareness and improves response strategies. The results obtained from the test set will provide a clear picture of how the model functions in practice, illustrating its potential to streamline contingency selection and optimize decision-making processes.

The following visualization presents the estimated disconnected generation for 15 contingencies, as predicted by the trained neural network, over a 10-scenario time window. This visualization provides insight into how the model responds to different contingencies across multiple scenarios, illustrating the variations in disconnected power over time. By analyzing these estimations, we can observe how the impact of each contingency evolves depending on the scenario, offering a valuable perspective for contingency assessment and decision-making in the control center.

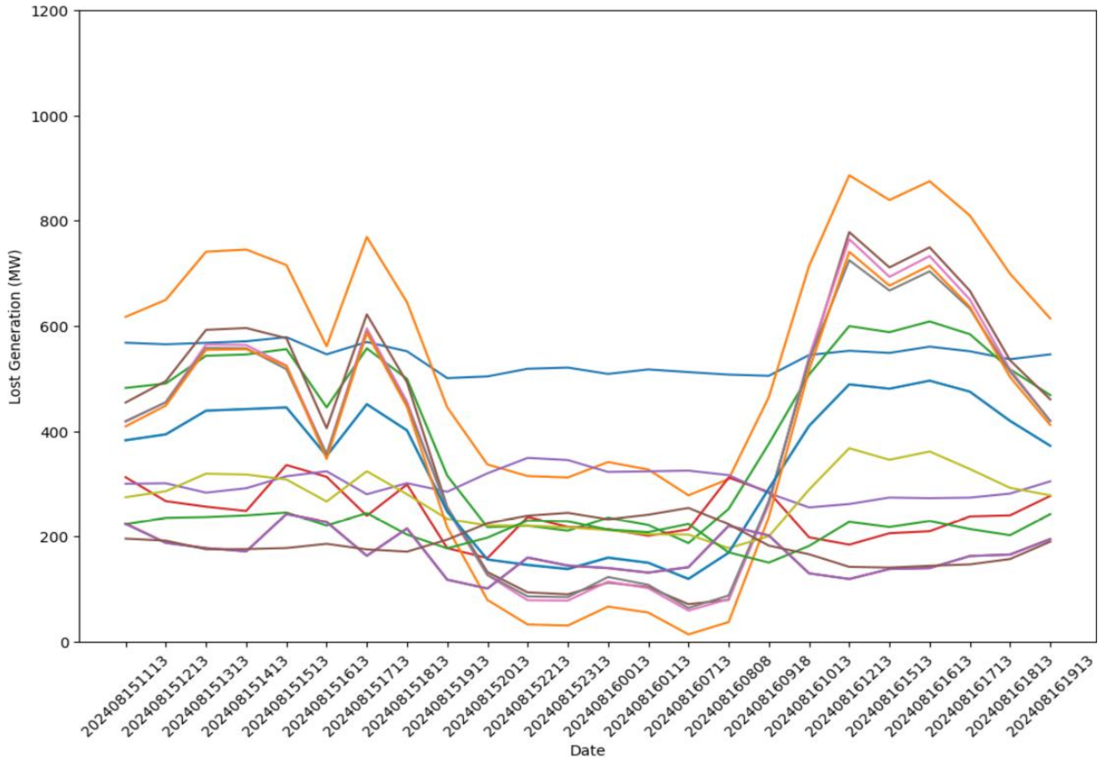

Figure 19: Prediction of disconnected generation caused by 15 contingencies over time.

In certain scenarios, specific contingencies rise to high-impact positions, meaning they cause significant generation disconnection and require immediate attention. However, in other scenarios, these same contingencies become less relevant, with minimal or almost no disconnected generation. This variability highlights the complex nature of contingency analysis, where the severity of failures is not fixed but rather depends on the operating conditions and interactions within the power system.

This behavior underscores the importance of adaptive contingency assessment, where different failures must be prioritized based on the specific scenario rather than relying on a static ranking. Some contingencies may consistently pose a high risk, while others may only become critical under certain conditions. The ability to capture these fluctuations through a trained neural network provides valuable insights for control center operations, allowing operators to focus on the most relevant contingencies at any given moment.

By leveraging this predictive capability, system operators can enhance decision-making, ensuring that resources and mitigation strategies are allocated efficiently. Instead of relying solely on predefined worst-case scenarios, this approach enables a data-driven evaluation, adapting to real-time conditions and improving overall system reliability.

By utilizing all the visualizations like those above, which highlight the worst contingencies, it becomes possible to monitor the most critical failures in real time. This approach allows for a continuous assessment of how contingencies evolve under different scenarios, enabling operators to quickly identify and respond to the most severe cases. Real-time monitoring of these contingencies enhances situational awareness, improves decision-making, and ensures a more proactive approach to system reliability and stability.

3.3 DYNAMIC CAPACITY CALCULATION IN THE BALEARIC ISLANDS

The dynamic capacity calculation in the Balearic Islands is based on an iterative process over dynamic simulations, aimed at determining the necessary disconnected power to achieve a 10% load shedding of total demand. In practice, this load shedding is associated with a minimum frequency threshold reached after a contingency. Specifically, if the system frequency drops to approximately 48.8 Hz, a 10% load shedding is triggered to stabilize the grid. This value represents the maximum generation that can be tripped at any given moment, ensuring system stability under severe contingencies. Since this amount fluctuates over time, it becomes crucial to evaluate the capacity limits at each substation, allowing for a more precise assessment of system resilience.

Li et al. conducted a similar study in Frontiers in Energy Research, exploring data-driven approaches for predicting frequency nadir using power-frequency polynomial fitting and neural networks. These methodologies closely align with the iterative process in this chapter, reinforcing the role of AI-driven techniques in stability assessments and system optimization under contingencies. [9]

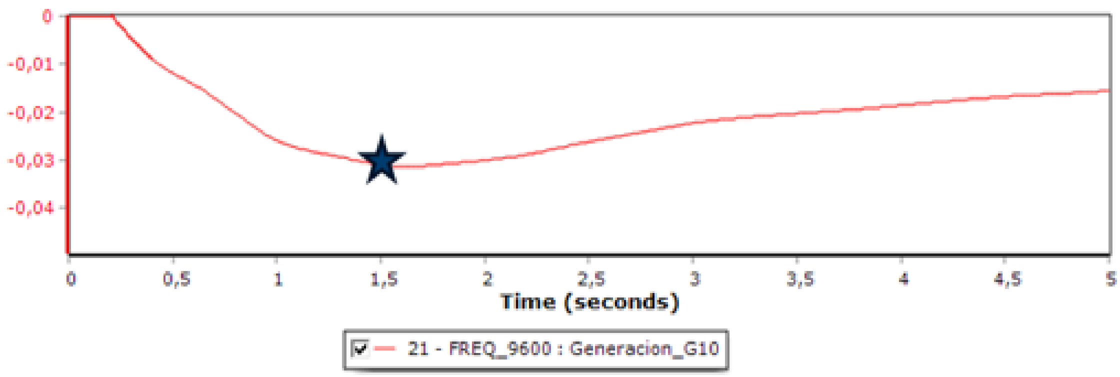

Figure 20: Representation of the minimum frequency achieved following a fault.

To obtain these values, two artificial nodes, one representing generation and the other demand, both with equal power, are introduced into the network to ensure that the system remains unaltered. A fault is then applied to one of these nodes, allowing for the evaluation of the disconnected power required to reach the expected nadir (minimum frequency). This approach ensures that the system response is accurately assessed without modifying the existing network structure.

Once these power values are obtained, the next step is to develop an AI-based model, specifically a neural network for each substation, capable of extrapolating the maximum generation that could be tripped in any given scenario. This methodology enables a more efficient estimation process, reducing the need for extensive dynamic simulations while maintaining high accuracy in predicting system behavior under different conditions.

By leveraging a reduced training dataset, these neural networks can predict the required disconnected power without the need for an extensive number of dynamic simulations, significantly reducing computational time and improving efficiency. This approach offers a new methodology for evaluating system capacity, differing from the traditional method, which selects a single scenario and applies the same criteria uniformly across all substations. The conventional approach tends to be overly cautious, assuming worst-case conditions across the board, whereas this AI-driven method allows for a more granular analysis, tailoring capacity assessments to each substation individually.

By adopting this methodology, it becomes possible to refine contingency planning, ensuring that substations with excessively conservative assumptions can have their capacity limits adjusted, while those facing higher risks receive the necessary attention. This data-driven approach enhances system reliability, optimizes operational decisions, and provides a more adaptive framework for managing dynamic capacity in the Balearic Islands.

The first step in the process is to perform iterative simulations until the disconnected power, referred to as G10, associated with the minimum frequency threshold of 48.8 Hz is determined for each scenario. By systematically adjusting the disconnected power in each simulation, the exact G10 value for each scenario can be identified, providing a solid foundation for further analysis and model development. This G10 metric represents the maximum generation that can be tripped while ensuring system stability, making it a crucial parameter for evaluating dynamic capacity in the Balearic Islands.

3.3.1 G10 Calculation Through Iterative Dynamic Simulations

Since the G10 power associated with the minimum frequency threshold of 48.8 Hz is initially unknown, it is necessary to test with a couple of initial power values to establish a reference. The relationship between disconnected power and frequency is assumed to be linear, allowing for the application of linear regression techniques to estimate the required power level. However, this process requires multiple iterations, as different scenarios do not behave identically, and in some cases, the linearity is not perfectly maintained.

Due to these variations, adjustments must be made iteratively to refine the estimation and ensure accuracy across all scenarios. The following representation illustrates the different points obtained through interpolation, showing the process of reaching the 48.8 Hz frequency threshold in five different scenarios.

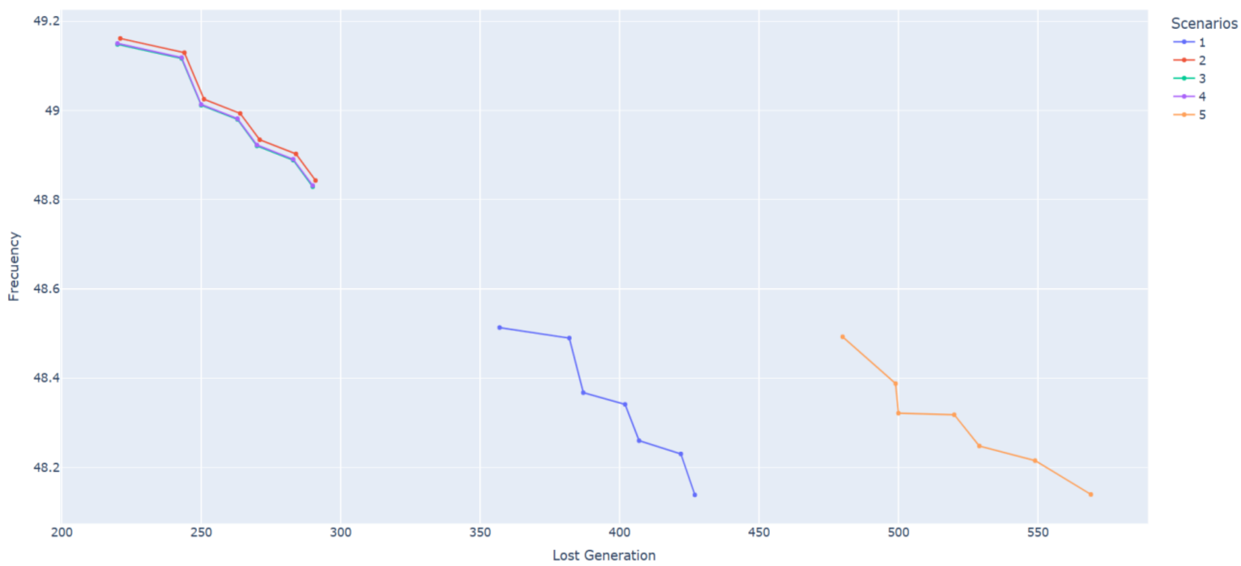

Figure 21: Relationship between disconnected power and minimum frequency for 5 scenarios.

Once the iterative process has been completed and values have been obtained for each scenario that sufficiently approach the 48.8 Hz threshold, the necessary information and data are now available to train a model capable of generalizing the maximum generation that can be tripped. This model will allow for a significant reduction in the number of required simulations, optimizing the process by providing reliable estimations without the need for exhaustive dynamic simulations for every new scenario.

3.3.2 G10 Calculation Using Neural Networks

In this section, a neural network-based approach is introduced to generalize the G10 value across different scenarios, leveraging previously computed data. The G10 represents the maximum amount of generation that can be disconnected, associated with a minimum frequency reached after a contingency, and linked to a 10% load shedding of the total demand. Since this concept has been explained earlier, it will not be reiterated here.

The primary objective of training a neural network model is to significantly reduce the number of dynamic simulations required to obtain G10 for all possible scenarios. Traditionally, determining G10 for each scenario necessitated running extensive dynamic simulations, which is computationally expensive and time-consuming. However, by training the model with a carefully selected set of representative scenarios, it becomes possible to generalize the G10 estimation across the entire dataset. This approach ensures that the model learns the underlying patterns and dependencies between system parameters and contingency outcomes, allowing it to predict G10 values with high accuracy for scenarios beyond the training set.

Once the trained model provides G10 estimations for each scenario, the next step involves calculating the dynamic capacity of each substation. This is achieved by subtracting the G10 value for a given scenario from the power tripped at each substation due to a 100-millisecond three-phase fault to ground. By performing this calculation across all scenarios, a comprehensive dataset of dynamic capacity values for each substation is obtained.

With this dataset, a monotonic capacity analysis can be conducted for each substation, enabling the definition of a new dynamic capacity using percentile-based thresholds. This statistical approach ensures that the capacity assessment accounts for variations across multiple scenarios, providing a more refined and realistic evaluation of each substation's ability to withstand disturbances.

One of the key advantages of this methodology is its multi-scenario nature, which enhances precision compared to previous approaches. Traditional methods relied on a single scenario, adopting a more general and conservative perspective that, while ensuring system security, lacked the granularity needed for substation-specific risk assessment. In contrast, the neural network-based approach allows for a detailed evaluation of each substation's dynamic capacity, facilitating a more tailored risk assessment aligned with operational strategies.

This section presents a comparative analysis of two neural network models designed to estimate the G10 value across different scenarios. The first model serves as a baseline, trained without representative scenarios and using a reduced set of selected variables. The second model, in contrast, incorporates a carefully chosen set of representative scenarios to enhance generalization and reduce the number of required dynamic simulations. By comparing these two approaches, the impact of scenario selection on estimation accuracy and computational efficiency can be assessed.

The baseline model is designed to provide a reference for evaluating the benefits of incorporating representative scenarios. It operates with a reduced set of selected variables, making it easier to interpret the results and identify the most influential factors affecting G10 estimation. This simplification allows for a more transparent analysis of the model's predictions, facilitating a better understanding of the relationships between input variables and contingency outcomes.

Structurally, the model is a feedforward neural network composed of three fully connected layers. The first layer takes the input variables and maps them to 64 neurons, followed by a second layer with 32 neurons, and a final output layer that produces the G10 estimation. Each hidden layer applies a ReLU activation function to introduce non-linearity, allowing the model to capture complex relationships between the input features and the target variable. The architecture consists of an input layer that receives the selected variables relevant to G10 estimation, a first hidden layer with 64 neurons followed by ReLU activation, a second hidden layer with 32 neurons also followed by ReLU activation, and an output layer with a single neuron producing the estimated G10 value. The model is trained using the ADAM optimizer with a learning rate of 0.001 for 200 epochs and a batch size of 16, ensuring stable convergence and efficient parameter updates throughout the training process.

However, since this model does not leverage representative scenarios, it requires a significantly larger training set to achieve accurate generalization across different conditions. Each scenario is treated independently, meaning the model must learn from a broader dataset to capture the full range of possible variations. While this approach ensures reliable G10 estimations, it increases computational demands due to the need for a more extensive training process.

The following graph illustrates how the prediction is performed for the baseline model. The model is trained using 80% of the available data, allowing it to learn the underlying patterns and relationships necessary for estimating G10. Once training is complete, the model is evaluated on the remaining 20% of the data, which is displayed in the graph. This evaluation phase provides insight into the model's ability to generalize to unseen scenarios, demonstrating how well it can estimate G10 based on new inputs that were not part of the training process.

Figure 22: Prediction of G10 using the model trained with the full dataset.

The visualization above shows that the baseline model generally achieves strong generalization across the evaluated data. The predicted values closely follow the actual values, indicating that the model effectively captures the underlying patterns necessary for estimating G10. This is further supported by the obtained R^2 score of 0.88, which reflects a high degree of correlation between predictions and real values. The model demonstrates reliable performance, confirming that despite using a larger training set, it successfully generalizes well to unseen scenarios.

Now that the scope and performance of the model have been evaluated using 80% of the full dataset, the next step will be to train the same model again under different conditions. This time, instead of using a large portion of the dataset, the training will be conducted with a reduced training set carefully selected to include representative scenarios. The objective is to analyze how the model adapts to a more constrained dataset while maintaining its ability to generalize effectively across different cases.

For the selection of representative cases, a subsample of the dataset is chosen, consisting of records with a step size of 12. Given that the data is chronologically ordered, this approach ensures a structured selection process. As a result, the training set will be composed of approximately 300 data points, allowing the model to learn from a diverse yet representative subset while maintaining temporal coherence.

In the following visualization, the performance of the same model, maintaining the same structure as the previously trained baseline model, is presented. This version has been trained using the reduced dataset and evaluated on the test set, allowing for a direct comparison of its effectiveness under different training conditions. The objective is to assess how the reduction in training data impacts the model's ability to generalize and maintain predictive accuracy.

Figure 23: Prediction of G10 using the model trained with representative scenarios.

The graph illustrates that the model maintains a strong ability to generalize the output, even when trained on a reduced dataset. This result confirms that representative scenarios can be effectively used to minimize both simulation time and the number of dynamic simulations required, without significantly compromising performance. The model achieves an R^2 of 0.77 on the test set, which, as expected, is lower than that of the previous model trained on the full dataset.

However, despite having fewer data points to learn from, it still reaches a satisfactory evaluation metric. This demonstrates that a carefully selected subset of representative cases can provide enough variability and information for the model to make accurate predictions. By reducing the amount of training data while maintaining predictive quality, this approach offers a practical solution for optimizing computational efficiency, making it possible to streamline the simulation process while preserving reliable results.

While the model demonstrates a strong ability to generalize its predictions, it is important to recognize that neural networks are inherently complex and often lack intuitive interpretability. Unlike simpler models, where the influence of each variable can be directly observed through coefficients or feature weights, neural networks operate as black-box systems, making it difficult to understand how they process and prioritize information. This complexity arises from their layered structure, nonlinear interactions, and the way they learn patterns from data, which can make it challenging to determine the exact contribution of each input variable to the final prediction.

To gain deeper insight into the model's decision-making process, additional methodologies must be applied. One widely used approach for interpreting machine learning models is SHAP (Shapley Additive Explanations) values. SHAP values are based on cooperative game theory and provide a theoretically grounded measure of feature importance. They quantify how much each variable contributes to a model's predictions by calculating the marginal impact of each feature across different combinations of inputs. This method ensures a consistent and fair attribution of importance, helping to reveal which variables play a crucial role in shaping the model's output.

By analyzing SHAP values, we can better understand the inner workings of the neural network and validate whether the model is relying on meaningful patterns rather than spurious correlations. This interpretability is particularly valuable in applications where understanding the reasoning behind predictions is essential for trust, transparency, and decision-making.

Moreover, SHAP values not only provide a ranking of feature importance but also offer insights into the direction and magnitude of their impact on predictions. Unlike traditional feature importance methods that simply indicate whether a variable is influential, SHAP values show whether a feature positively or negatively affects the model's output and by how much. This allows for a more detailed interpretation of the relationships between input variables and predictions, helping to identify potential biases, dependencies, or unexpected interactions within the data. By visualizing SHAP values, we can observe how different features contribute across various instances, enabling a more transparent and interpretable understanding of the model's behavior. [10]

The following graph presents the importance of the model's input variables using SHAP values. Specifically, it highlights the 20 most influential variables out of the 30 used in training, providing a detailed view of how the model prioritizes different features. This visualization offers a clear representation of how various inputs affect the model's predictions, helping to interpret its reasoning and assess the relevance of the selected data. By leveraging SHAP values, we can gain a more comprehensive understanding of the model's behavior, ensuring that its predictions align with domain knowledge and expected patterns. Additionally, this analysis helps identify whether certain variables have an outsized impact, allowing for further refinement of the model and potential improvements in feature selection.

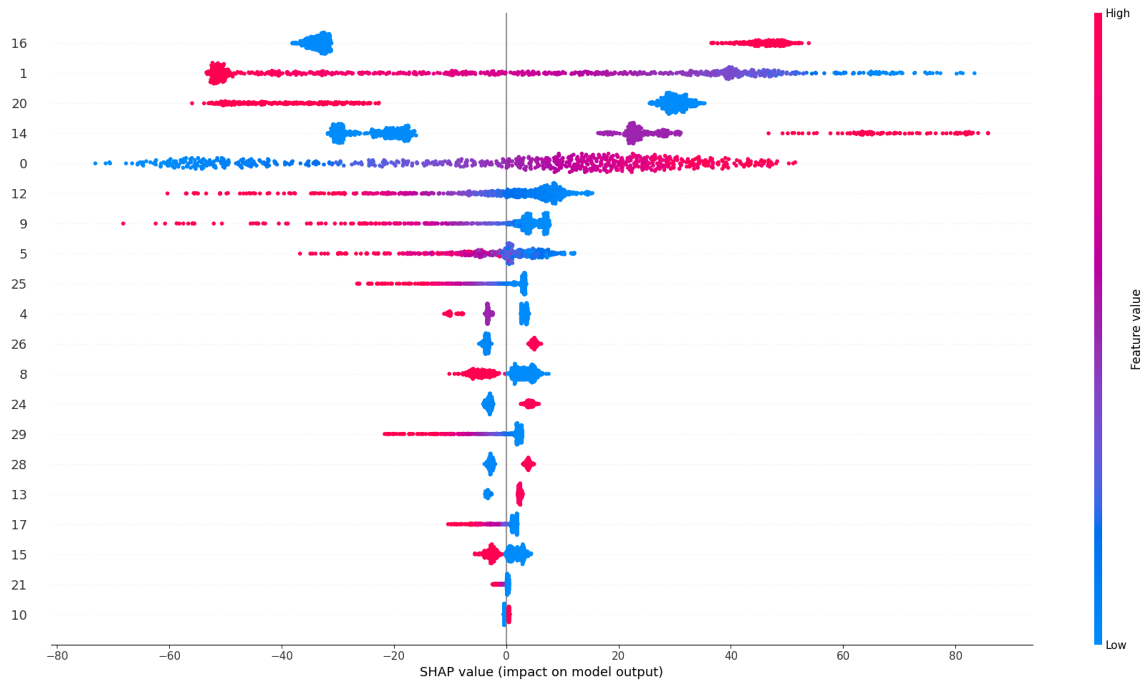

Figure 24: Plot of the top 20 most important features based on SHAP values.

The SHAP values graph provides valuable insights into how different input variables influence the model's predictions. Notably, it reveals that certain features have a clear directional impact on the output variable, G10. For instance, when the inertia of synchronous groups increases, it leads to a corresponding rise in G10, suggesting a strong positive relationship between system inertia and the model's output. Similarly, an increase in demand also results in a higher G10, reinforcing the idea that greater energy consumption contributes to this effect.

On the other hand, the graph shows an inverse relationship between photovoltaic generation and G10. Specifically, when gross photovoltaic production increases, G10 tends to decrease. This indicates that higher levels of solar energy generation contribute to a reduction in the model's output, likely due to the characteristics of renewable energy integration and its impact on system dynamics.

These observations highlight the importance of key variables in shaping the model's predictions and provide a deeper understanding of the underlying relationships within the dataset. By analyzing SHAP values, we can confirm that the model captures meaningful patterns, ensuring that its predictions align with expected physical and operational behaviors.

3.3.3 Dynamic Capacity Calculation

The urgency to accelerate the development of renewable energy investments has never been greater, as many projects remain stalled due to regulatory, technical, or economic constraints. The growing pressure to integrate clean energy sources into the grid is driven by ambitious decarbonization targets, increasing electricity demand, and the need for energy security. At the same time, investment trends are shifting toward large-scale projects, such as data centers, which require substantial and stable power supplies, further intensifying the demand for efficient grid planning and capacity assessment.

Given this evolving landscape, it is crucial to explore new methodologies for calculating system capacity that allow for a more dynamic and adaptive approach. Traditional methods often rely on conservative assumptions, potentially underutilizing available grid resources. By refining capacity assessment techniques, it may be possible to push system limits further while maintaining a controlled level of risk. This approach would enable decision-makers to optimize grid utilization, unlock additional capacity for renewable integration, and accelerate stalled projects without compromising system stability.

Now that G10 can be calculated more efficiently by combining dynamic simulations and leveraging AI models to reduce the number of iterations required to reach the desired values, it is now possible to determine the dynamic capacity of each substation for every scenario in the dataset. This approach enhances computational efficiency while ensuring accurate assessments of system behavior under varying conditions.

To calculate the dynamic capacity, the estimated G10 for each scenario must be adjusted by subtracting the power disconnected in that same scenario due to a 100ms three-phase fault to ground. This approach enables the identification of the additional generation that could be accommodated or connected to each substation while maintaining system stability. By applying this methodology across different scenarios, it becomes possible to construct capacity monotonic curves, offering a clearer understanding of the operational limits and potential expansion opportunities for each substation.

The following visualization represents a dynamic capacity monotonic curve for a specific substation, ordered from highest to lowest capacity to facilitate statistical analysis and the determination of capacity values for substations. This approach allows for the use of multiple scenarios in selecting the appropriate capacity value, ensuring a more robust and data-driven decision-making process.

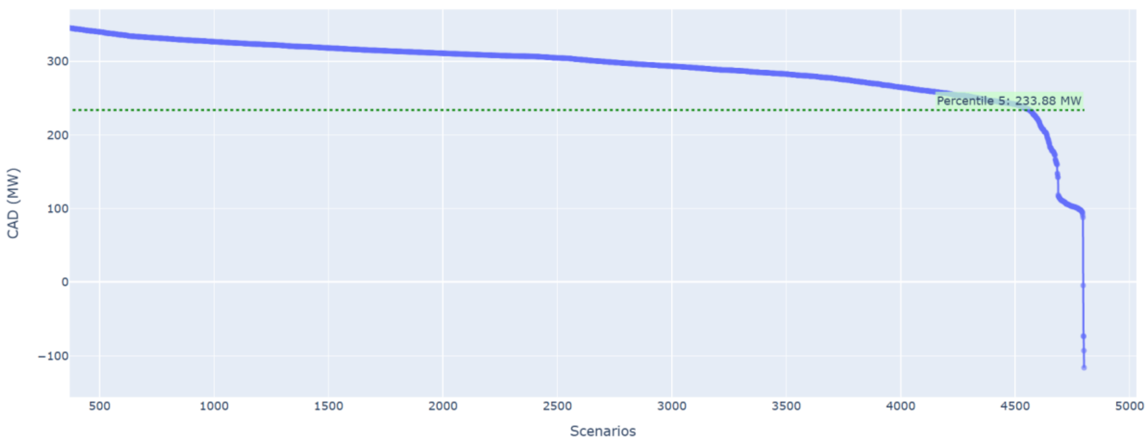

Figure 25: Monotonic dynamic capacity curve for a substation in the Balearic Islands.

By applying statistical analysis to the data, it is possible to select a specific percentile to define the dynamic capacity of the substation. In the graph, the 5th percentile is shown, but any desired percentile could be chosen depending on the level of risk that is considered acceptable. This approach ensures that a significant portion of the scenarios guarantee having more than a specified amount of capacity, making it a reliable reference for determining the operational limits of the substation. By selecting an appropriate percentile, decision-makers can balance risk and system utilization, ensuring that the specified capacity reflects realistic and achievable conditions across multiple scenarios.

3.3.4 Comparison Between Gmax and Dmax

The study of maximum allowable disconnected generation (Gmax) and maximum allowable disconnected demand (Dmax) is essential for assessing the stability and resilience of the electrical system. These two parameters define the limits within which the system can operate without reaching a critical state. When generation is lost, the system frequency decreases due to an imbalance between supply and demand. Conversely, when demand is disconnected, the frequency increases as the available generation exceeds consumption.

Traditionally, stability analyses have focused primarily on generation losses, as sudden drops in generation can lead to severe frequency deviations and potential system failures. However, with the growth in electricity demand and the ongoing energy transition, the grid has become more complex and vulnerable. The increasing integration of renewable energy sources, such as wind and solar, introduces variability and reduces system inertia, making frequency regulation more challenging. As a result, it is no longer sufficient to study only generation losses, demand disconnections must also be considered to ensure a comprehensive understanding of system behavior.

A critical aspect of this analysis is determining whether a loss of generation and a loss of demand of the same magnitude result in the same maximum absolute deviation from 50 Hz. If the system response is symmetrical, meaning that both types of disturbances lead to identical maximum frequency deviations in absolute terms, then studying one of them is sufficient to define operational limits. In this case, analyzing either Gmax or Dmax would provide enough information to establish stability thresholds.

However, if demand disconnections prove to be more restrictive, meaning that frequency deviations are larger or more difficult to control when demand is lost, then this factor must be carefully considered in capacity planning and risk assessment. A more restrictive demand response would imply that the system is less tolerant to sudden drops in consumption, requiring additional measures to mitigate risks. This could influence decisions related to reserve capacity, demand-side management strategies, and infrastructure investments aimed at improving system flexibility.

By thoroughly analyzing the relationship between Gmax and Dmax, operators and planners can make more informed decisions about grid stability, capacity expansion, and risk mitigation strategies. Understanding these dynamics is essential for optimizing system operations and ensuring a reliable and resilient electrical network in the face of evolving energy demands and technological advancements.

To perform the comparison, the first step was to leverage the iterations carried out for the calculation of G10. Once all G10 values were obtained, each associated with a frequency of 48.8 Hz, the next step was to evaluate whether the same power value, but applied to demand disconnection, would result in a maximum frequency of 51.2 Hz, or if the system response is asymmetric. This analysis helps determine whether generation and demand losses of equal magnitude lead to identical absolute frequency deviations or if one has a more restrictive impact on system stability. Understanding this asymmetry is crucial for refining capacity planning and ensuring a balanced approach to risk assessment in grid operations.

The following graph presents a histogram representing the difference between the absolute frequency deviations caused by demand and generation disconnections. This visualization helps assess whether the system response is symmetric or if one type of disconnection has a greater impact on frequency stability.

If the histogram is skewed to the right, it indicates that demand disconnections result in larger absolute frequency deviations, meaning that demand is more restrictive in terms of system stability. Conversely, if the histogram is skewed to the left, it suggests that generation losses lead to greater deviations, making generation the more restrictive factor. This analysis provides valuable insights for capacity planning and risk assessment, ensuring that the most critical constraints are properly accounted for in grid operations.

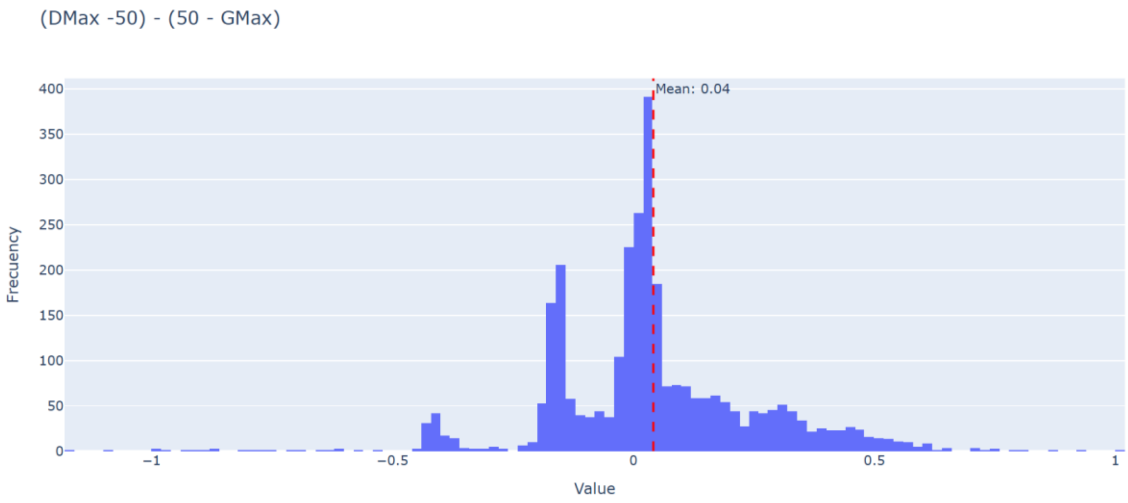

Figure 26: Histogram of the distribution of Gmax versus Dmax.

The graph appears to be centered, though slightly skewed to the right, indicating that demand disconnections may have a somewhat greater impact on frequency deviations compared to generation losses. While the difference is not extreme, this slight asymmetry suggests that demand could be more restrictive in certain scenarios.

For future studies, it would be beneficial to test with a wider range of power values to confirm whether the system response remains balanced or if demand disconnections consistently result in larger deviations. If the trend persists, it may be necessary to prioritize demand constraints in capacity planning and risk assessments to ensure system stability is properly accounted for.

4. CONCLUSIONS

The integration of artificial intelligence with dynamic simulations has significantly impacted the study of transient stability in power systems. One of the most notable advantages is the acceleration of analytical processes. Traditionally, obtaining accurate stability assessments require extensive simulations with large datasets. However, AI-driven approaches have enabled the training of models using representative scenarios, allowing researchers to achieve the desired results with a reduced amount of training data. This reduction in dataset size translates into fewer dynamic simulations needed to reach the same conclusions, optimizing computational resources and time.

Furthermore, AI facilitates the use of surrogate simulators, which operate at a much faster pace than conventional methods. This capability is particularly valuable for control centers, as it enables real-time stability assessments, enhancing decision-making processes and system reliability.

Beyond efficiency improvements, AI models also provide deeper insights into the relationships between input variables and the resulting system behavior. By analyzing these connections, researchers and operators can gain a better understanding of the underlying dynamics of the electrical grid, leading to more informed strategies for maintaining stability and optimizing performance.

In summary, AI has revolutionized transient stability studies by streamlining simulations, enabling real-time assessments, and offering valuable insights into system behavior, ultimately contributing to a more resilient and efficient power grid.

Artificial intelligence has played a crucial role in optimizing the simulation processes required for both estimation of disconnected power in the Iberian Peninsula and dynamic capacity calculation in the Balearic Islands. By leveraging AI-driven methodologies, these applications have significantly reduced the time needed to perform complex stability assessments and capacity calculations.

Traditionally, these studies relied on extensive dynamic simulations, which required substantial computational resources and time. However, AI models have introduced a more efficient approach by training on representative scenarios, allowing for accurate estimations with a reduced dataset. This methodological shift has led to a considerable decrease in the number of simulations necessary to achieve reliable results.

In the estimation of disconnected power in the Iberian Peninsula, artificial intelligence has significantly improved efficiency by drastically reducing the number of required simulations. The trained AI model estimates the monotonic curve of disconnected generation using only 400 points from the total sample of 6,100, achieving accurate results with over 10 times fewer data points than traditional methods.

This reduction translates directly into a 10-fold decrease in the number of dynamic simulations needed to process the entire dataset. As a result, the methodology not only accelerates the estimation process but also minimizes computational costs associated with cloud-based simulations and high-performance hardware.

A striking example of this efficiency gain is the time reduction in database generation. While the traditional approach required four months to generate the full dataset, the AI-driven methodology enables the estimation of the monotonic curve in just 10 days for all 14 substations in the database. This dramatic improvement underscores the transformative potential of AI in power system analysis, making large-scale stability assessments more feasible, cost-effective, and operationally efficient.

In the dynamic capacity calculation in the Balearic Islands, artificial intelligence has similarly led to a significant reduction in computational effort. By training an AI model with only 300 points from the total dataset of 6100, the methodology enables highly accurate estimations of values close to G10 for each scenario throughout the year.

This approach drastically minimizes the number of required dynamic simulation iterations, as the trained model can predict results with high precision without the need for exhaustive computations. It significantly reduces the number of simulations necessary to determine the value associated with minimum frequency, streamlining the entire process. The reduction is approximately 10 times fewer simulations, leading to substantial efficiency gains.

The primary objective of this project was to analyze the potential of artificial intelligence models to assist dynamic simulations and to study and optimize various aspects of stability in the electrical system. Beyond simply assessing the feasibility of AI-driven methodologies, the project has demonstrated strong performance in evaluation metrics, with trained models using tabular data yielding highly accurate results.

While significant progress has been made, there are several AI approaches that have not yet been applied but should be considered for future implementation. One key area for further exploration is the use of models that incorporate internal structural representations, which can enrich the information extracted from the data. A particularly promising technique is Graph Neural Networks (GNNs), where a graph serves as an equivalent representation of the electrical grid. By embedding network topology into neural models, GNNs can provide deeper insights into system behavior, capturing complex relationships between different components of the grid.

Moreover, GNN-based simulators align closely with reinforcement learning (RL) methodologies, enabling the development of control policies that can actively ensure system stability, minimize overload occurrences, or maximize operational benefits. By combining GNNs with RL, AI models can learn optimal strategies for managing the electrical grid dynamically, adapting to real-time conditions and improving overall efficiency.

Integrating such advanced AI methodologies could further enhance the accuracy and efficiency of stability assessments, making them even more valuable for real-time applications and operational decision-making. This project has laid a strong foundation for AI-assisted dynamic simulations, and future advancements in model architecture will continue to push the boundaries of what is possible in power system analysis.

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