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RESEARCH ARTICLE

An Open-Source Tool-Box for Asset Management Based on the Asset Condition for the Power System

GOPAL LAL RAJORA[1], MIGUEL A. SANZ-BOBI[1], (Senior Member, IEEE), CARLOS MATEO DOMINGO[1], AND LINA BERTLING TJERNBERG[2], (Senior Member, IEEE)

[1]Institute for Research in Technology, Universidad Pontificia Comillas, 28015 Madrid, Spain
[2]Division of Electric Power and Energy Systems, KTH Royal Institute of Technology Stockholm, 114 28 Stockholm, Sweden

Corresponding author: Gopal Lal Rajora (glrajora@comillas.edu)

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ABSTRACT This Study introduces an open-source toolbox for asset management in power systems developed under the European ATTEST project. This paper focuses on presenting an open-source toolbox for Transmission and Distribution System Operators (TSOs and DSOs) to improve the reliability and efficiency of power networks, including a solution to the difficulties faced by the power industry, such as the aging infrastructure and the growing need for renewable energy integration. The toolbox uses predictive analytics and machine learning to evaluate the health of assets, enhance maintenance plans, and guarantee efficient resource distribution. It evaluates the condition of power grid assets through clustering (K-means, SOM) and reinforcement learning (Q-learning), providing actionable insights for improving asset management. This approach allows TSOs and DSOs to adopt proactive maintenance strategies, reducing the risk of failures, minimizing downtime, and extending the lifespan of critical infrastructure. The toolbox provides actionable insights for planning maintenance strategies and optimizing resource allocation. Scalability tests were conducted using a synthetic power grid of 600 transformers alongside real-world data from five European electrical companies. Due to space constraints, only the results from 92 transformers. This research contributes to achieving sustainable power systems and supporting the energy transition by focusing on intelligent asset management.

INDEX TERMS ATTEST, asset health assessment, condition monitoring, power system asset management, predictive maintenance, reinforcement learning, machine learning, data-driven insights.

I. INTRODUCTION

The global energy system is undergoing a significant transition, driven by climate objectives, sustainable development goals, increasing energy demand, and the electrification of other sectors, such as transportation, thermal heating, and cooling. The United Nations has adopted a resolution for sustainable development, encapsulating 17 goals to be achieved by 2030 [1]. Power systems worldwide must evolve to meet these objectives, minimize environmental impacts, and maintain high technical performance standards. This evolution presents new challenges, requiring innovative approaches to power system asset management, especially in maintenance and optimization. Electrical equipment represents significant economic asset value for Distribution System Operators (DSOs) and Transmission System Operators (TSOs). Many components within the power systems have long intrinsic lifetimes, most exceeding 40 years [2]. However, with technological evolution, new components in smart grids that make intensive use of telecommunications have shorter lives due to the rapid evolution of communications and its protocols and regulatory changes often precipitate the premature obsolescence or replacement of some components [3], [4]. The push for energy transition and advancements in digital techniques and data utilization accelerate the evolution of maintenance and replacement strategies. Moreover, integrating the principles of the circular economy — especially considering the natural resources

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required for manufacturing new equipment — effective Asset Management (AM) emerges as a pivotal strategy for fulfilling the Sustainable Development Goals (SDGs) [5].

In this context, AM plays a crucial role in ensuring the reliable operation of the power grid and energy infrastructure. Given the capital-intensive nature of electric utilities, effectively managing assets, such as power transformers, lines, and switch gears, is crucial. Strategic asset management is essential for enhancing power network reliability, catering to the growing electricity demand, and ensuring efficient and cost-effective operations [6].

The power industry faces multifaceted challenges in maintaining and optimizing asset performance. Factors such as aging infrastructure, geographic dispersion of assets, and evolving operational requirements demand innovative approaches to asset management. Traditional maintenance strategies, often based on fixed schedules or reactive measures, fall short of ensuring the health and reliability of assets. This backdrop underscores the need for intelligent systems to proactively assess the asset conditions, predict failures, and prioritize maintenance activities [7]. Traditional maintenance approaches cannot often integrate data across technical, operational, and economic indicators, limiting their effectiveness. This toolbox fills this gap using clustering and reinforcement learning techniques by providing TSOs and DSOs with a robust framework for medium- and long-term maintenance planning. Tests with synthetic data (600 transformers) and real-world data from five European companies demonstrate its scalability and adaptability. Notably, only results from one company, encompassing 92 transformers, are included here, with all results documented separately.

This paper focuses on the business drivers, challenges, and innovations associated with maximizing power network reliability and availability through AM by developing an open-source toolbox for TSOs and DSOs.This toolbox, which consists of three modules, is a part of the ATTEST (Advanced Tools Towards cost-efficient decarbonization of future reliable Energy SysTems), a European project [8] whose Goal is to develop a secure ICT platform that integrates a set of optimization tools for operating, planning, and managing assets of power systems. It supports coordinated operation, optimal asset maintenance, and integrated planning of transmission and distribution systems, specifically targeting the year 2030 and beyond. It focuses on optimizing power system asset maintenance, integrating state-of-the-art machine learning algorithms for asset health assessment, and prioritizing maintenance strategy.

The following sections of this paper present a generic description of the ATTEST toolbox, a comprehensive examination of the methodology's implementation, and the results from a case study.

II. LITERATURE REVIEW

AM in power systems has evolved with the integration of Artificial Intelligence (AI) and Machine Learning (ML), offering significant advancements in predictive maintenance and condition monitoring. Traditional AM strategies, which relied on fixed schedules or reactive maintenance, are being replaced by AI-driven approaches that utilize predictive analytics to optimize asset health and management.

In [6], it highlights the transformative potential of AI and ML in enhancing asset management through predictive failure analysis and optimized maintenance strategies, showcasing the growing acceptance of AI technologies in the power sector. This shift is crucial as power systems undergo rapid digitalization and face increasing demands for renewable energy integration and sustainability. The ML techniques enable a more data-centric approach to power system management by mitigating the challenges posed by renewable energy integration, cyberattacks, and system volatility [9]. Additionally, hybrid twin models for asset management, merging physical models with ML to optimize the maintenance of critical infrastructure like power transformers, provide a cost-effective approach to asset life extension [10]. In [11], it is demonstrated how machine learning, particularly k-means clustering and artificial neural networks, enhances fault detection in power transformers through Sweep Frequency Response Analysis (SFRA), enabling condition-based maintenance. Similarly, The role of deep learning in various domains within electric power systems, such as load forecasting and fault detection, emphasizes its potential to enhance grid sustainability and resilience through improved asset management practices [12].

Reference [13], discussed the role of machine learning in optimizing Power Management Systems (PMS), showing how blockchain integration can further enhance data reliability in AM processes. Their Study highlights a 14.2% improvement in information collection and a 9.8% enhancement in system control capabilities due to these optimizations. Furthermore, studies on power transformers [14] apply supervised and unsupervised ML algorithms to enhance diagnostics and maintenance planning, showing the potential of AI in optimizing the life cycle of critical assets. These studies collectively underscore the transformative potential of AI/ML in modernizing AM strategies, ensuring that power systems operate efficiently and reliably amidst increasing demands and technological advancements.

Overall, the literature emphasizes the necessity of integrating advanced AI techniques, particularly Machine Learning, for more accurate health assessments, strategic maintenance, and better decision-making in managing power system assets, ultimately ensuring the operational stability of increasingly complex and dynamic power grids.

III. ASSETS MANAGEMENT WORKFLOW

A. OBJECTIVES OF THE METHOD PROPOSED

The AM method developed in the project ATTEST aims to facilitate the decision-making process about the life and use of the assets in the transmission and distribution of power grids. The AM Modules in the ATTEST project is an open-source toolbox developed according to three different levels of information about the asset conditions that will improve the management of distribution and transmission networks. These three levels are the following:

- The first level consists of identifying the critical information/data to quantify the condition of the asset. Typically, a multiplicity of data is collected during the observed life of the assets. For Example, the Age of the asset, Energy, Failure probability, etc, are some of the available information in the data. This information must be properly handled, converted, and ranked according to its contribution to the condition indicators to be developed at the next level.
- The second level of the smart AM environment entails the definition and development of methods for estimating asset condition indicators. This method is based on the heterogeneous information/data sources selected in the first level. The idea is to obtain comparable condition indicators for different assets, including a factor of certainty (or confidence) regarding the indicators created.
- The third level of this smart AM environment will create a tool to simulate and quantify the evolution of the condition indicator previously defined for the asset under different management strategies.

B. FOUNDATIONS OF THE METHOD PROPOSED

The main principles that inspire the Modules are focused on considering that each asset is evaluated by analyzing four dimensions: life assessment, health condition, maintenance, and economic impacts. These dimensions are supported by data from which fundamental indicators will be calculated. These dimensions are populated by data or variables the power grid company selects according to the data they collect during regular operation. This feature is critical in the AM method proposed to facilitate the use of the tools because they can be adapted easily to any context of data collection in an electrical company. Examples of types of data to be included in the four dimensions are as follows:

1) Life Assessment Dimension: Some variables that can be included for the evaluation of this dimension are the following: Age of the assets, estimation of failure probability, the importance of the asset based on the number of customers connected, energy delivered or served per year, and criticality index in the power grid of the assets. Other similar characteristics can be included in this dimension.
2) Health Condition Dimension: This dimension is used only when periodic or online measurements are collected about the assets. The idea is to evaluate its current condition based on recent observations. Some measurements that can be used for this dimension are internal temperature measurements in the power transformer, dissolved gas analysis, and oil quality. Usually, these types of observations are unavailable in the assets of a distribution power grid but can be available in more extensive and critical transmission power transformers.
3) Maintenance Dimension: This dimension evaluates the maintenance actions applied and their effectiveness through some basic information such as Mean Time To Repair (MTTR) or a similar indicator, Mean Time Between Failures (MTBF), the evolution of the number of work orders for this asset in a given period, and scheduled maintenance cycles.
4) Economic impact Dimension: This dimension considers the consequences of a failure of the assets according to different aspects such as maintenance costs, the cost of the failure, customers affected, the value of the undelivered energy, and environmental damages.

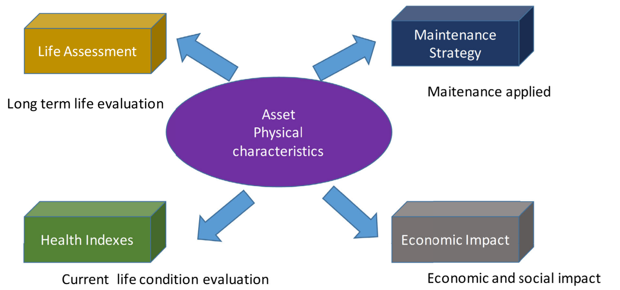


FIGURE 1. Scheme of the basic dimensions of the assets considered in the development of the AM modules.

The data mentioned for each dimension are only examples of the core information that can be managed in the modules.

Fig 2 illustrates the general interaction among the developed modules. First, asset IDs and types are obtained from a power grid description. This leads to a definition of characteristics and data for life assessment, health indexes, maintenance strategy, and economic impact, which characterize the condition of assets in Module I. In Module II, condition indicators are obtained for each asset. Finally, Module III proposes asset management strategies.

IV. IMPLEMENTATION OF THE METHOD PROPOSED

The main features taken into account in the development of the toolbox from an implementation point of view are the following:

- This toolbox is open source and easy to adapt to any new case where this AM module of ATTEST wants to be applied for guiding asset management.
- It is generic to host most data scenarios in power companies in transmission and distribution.
- The design of the toolbox is modular to adapt to the AM user's needs.
- Python is the development language selected for the toolbox. This facilitates easy integration with other platforms.

Several real cases were studied to test the tools. Some examples will be presented in the case study section.

The toolbox is divided into three modules, which are as follows:

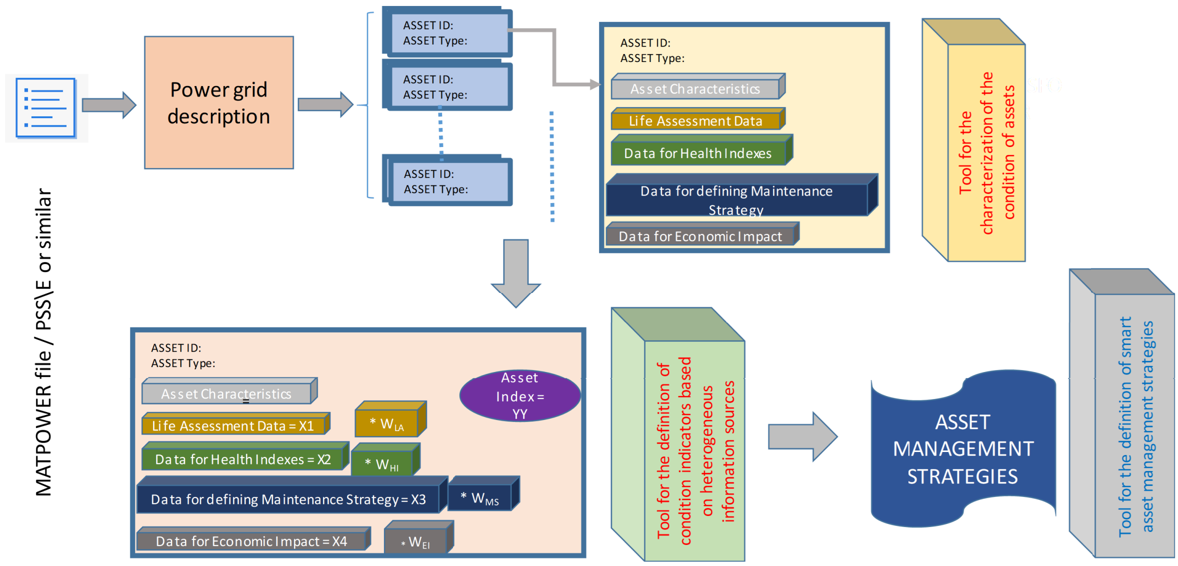


FIGURE 2. **Scheme of the interaction between the different modules.**

A. MODULE FOR THE CHARACTERIZATION OF THE HEALTH CONDITION OF ASSETS

This Module aims to characterize the assets using indicators of their specific properties. It allows for identifying critical information/data to be quantified so the health condition of the assets can be assessed. This information must be appropriately handled, converted, and ranked according to its contribution to the condition indicators. The characterization of the condition of the assets is carried out through a clustering process in which assets with similar features are grouped.

Let denote an asset $a_i \in \{a_1, a_2, \ldots, a_n\}$, where a_i is the asset i belonging to the set of assets A, and each can be evaluated in terms of four dimensions: Life Assessment (L), Health Condition (H), Maintenance (M), and Economic Impacts (E). These dimensions encompass various features (j, k, l, m) unique to each asset according to the previous definitions:

- the features for the dimension L of an asset a_i will be described as $a_{iL1}, a_{iL2}, \ldots, a_{iLj}$
- the features for the dimension H of an asset a_i will be describeproposed dimensionsiH2, $\ldots, a_{iHk}$
- the features for the dimension M of an asset a_i will be described as $a_{iM1}, a_{iM2}, \ldots, a_{iMl}$
- the features for the dimension E of an asset a_i will be described as $a_{iE1}, a_{iE2}, \ldots, a_{iEm}$

The number of features in each dimension could be different, and the assets can have all or only some of the dimensions proposed.

1) NORMALIZATION

Before clustering, normalization is applied to the values of each feature in each dimension using the maximum and minimum values of each feature. This process scales the data from 0 to 1, ensuring comparability. Min-max normalization is applied using observed data and expected extreme values to ensure that all potential asset conditions, from poor to excellent, are represented. By incorporating industry standards and historical data, the method provides accurate normalization, even when the dataset predominantly contains assets in good condition.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x' is the normalized value, x is the original value, x_{min} is the minimum value of the feature, and x_{max} is the maximum value of the feature.

2) CLUSTERING ALGORITHM

The clustering algorithm aims to group assets based on similarity, effectively reducing their quantity for focused attention. The process starts with unsupervised K-means clustering to determine the clusters. The Elbow [15] method aids in determining the optimal cluster count as shown in Equation 2.

$$\min \sum_{i=1}^{k} \sum_{j=1}^{n_i} \|x_j^{(i)} - \mu_i\|^2 \tag{2}$$

where k is the number of clusters, n_i is the number of data points in cluster i, $x_j^{(i)}$ is a data point in cluster i, and μ_i is the centroid of cluster i.

Once the optimal number of clusters is determined, the assets are grouped using Self Organized Maps (SOMs). A self-organizing map (SOM) is an unsupervised machine learning technique used to produce a low-dimensional (typically two-dimensional) representation of a higher-dimensional data set while preserving the topological structure of the data [16]. In addition to the number of clusters, SOMs determine the layout of the clusters. The layout of the clusters defines how the displacement of one cluster impacts the location of its neighbors. If the optimal number of clusters is a prime number (larger than 3), the optimal number is rounded to the previous largest non-prime number. It is shown in Fig 3. The layout should be bi-dimensional if the number of clusters is greater than four to give diversity and more flexibility in the clusters; otherwise, it is unidimensional. The optimal number of clusters is not a deterministic indicator. Its estimated value is obtained through an iterative process. If the initial optimum number of clusters is too large, producing empty clusters, the number of clusters is reduced iteratively until all clusters are full. This iterative process is shown in Fig 4. The identified cluster count is the number of neurons in a Self-Organized Map (SOM). This powerful clustering algorithm enhances visualization and cluster profiling. It provides a deeper understanding of asset characteristics compared to K-means.

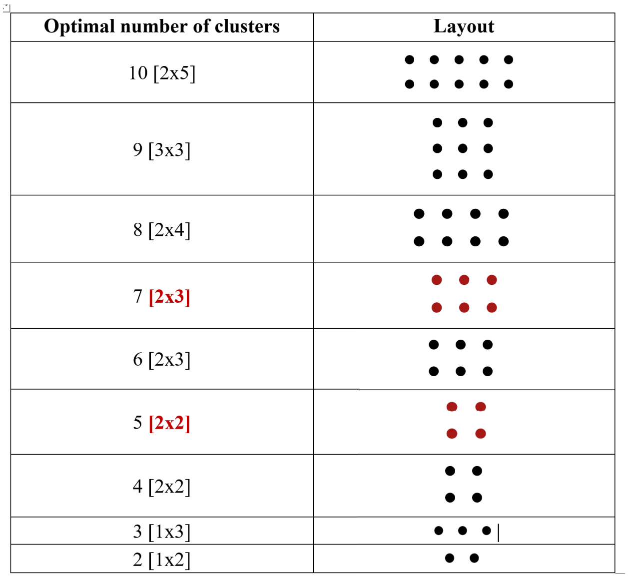


FIGURE 3. Som layout depending on the optimal number of clusters.

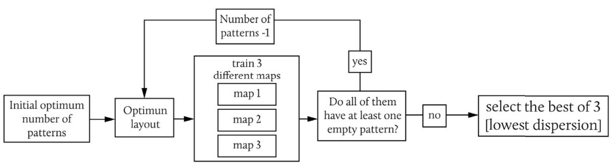


FIGURE 4. Flow chart of the training process of the som.

The SOM algorithm updates weights (W_{ij}) according to Equation 3 for each neuron (i) based on the input data (X_i) to minimize the topological error.

$$\Delta W_{ij} = \eta(t, i, j) \cdot h(i, j, b) \cdot (X_i - W_{ij}) \tag{3}$$

where:

- $\eta(t, i, j)$ is the learning rate.
- $h(i, j, b)$ is the neighborhood function.
- b is the best-matching unit (BMU).

The SOM clusters the assets in a reduced number of groups. Each group has a center representing the typical profile of values of the attributes of each dimension. Inside each group, the assets have similar characteristics in the dimensions analyzed. It allows us to analyze the profiles and identify those clusters representing assets in more critical conditions from the perspective of the dimensions and those in better conditions. At this moment, it is possible to label the groups.

Generally, the set of assets A was reduced to N clusters/Patterns, each containing a subset of assets with similar characteristics. Each profile is represented by a vector with a dimension equal to the number of features used per dimension.

B. MODULE FOR THE DEFINITION OF CONDITION INDICATORS BASED ON HETEROGENEOUS INFORMATION SOURCES

This Module defines an innovative approach to translate the results obtained from the previous Module into a set of harmonized, easily measurable, and comparable indicators for different types of assets, which will allow identifying which assets require special attention from an asset management point of view. This Module entails defining and developing methods for estimating asset condition indicators. These methods are based on the heterogeneous information/data sources selected in Module I. The goal is to obtain comparable condition indicators for different assets.

1) INDEX WEIGHT

The index weight indicates the contribution of the evaluation indicator to the condition indicator. To construct meaningful condition indicators, the user assigns weights (W_i) to each feature (x_i) within a given dimension. These weights are determined based on the importance of the feature, with the constraint that the sum of all weights should be equal to one, as shown in Equation 4 where n is the number of variables in each dimension.

$$\sum_{i=1}^{n} w_i = 1 \tag{4}$$

The condition indicator (I) for each dimension is then calculated using a weighted formula in equation 5.

$$I = \sum_{i=1}^{n} w_i \cdot x_i \tag{5}$$

This process is replicated for all dimensions, yielding specific indicators for each.

2) TOTAL INDICATOR

To arrive at a comprehensive asset performance assessment, we compute a Total Indicator (TI). The Total Indicator is derived by summing the indicators from all dimensions and subsequently dividing by the total number of dimensions.

$$TI = \frac{\sum_{i=1}^{N} I_i}{N} \tag{6}$$

where:

- TI represents the Total Indicator.
- signifies the total number of dimensions.
- I_i corresponds to the indicator for each dimension.

3) ASSET EVALUATION

The evaluation of asset performance hinges on the Total Indicator value. Assets are categorized as requiring priority attention and maintenance when the Total Indicator is nearly or exactly equal to one. After computing condition indicators for each dimension, the same clustering methodology as in Module 1 is employed. The objective is to group assets with similar characteristics, focusing on those exhibiting critical indicators. The approach involves the simultaneous integration of heterogeneous information sources from four key dimensions: Life Assessment (L), Health Condition (H), Maintenance (M), and Economic and Environmental Impacts (E). Each asset's condition is evaluated by aggregating these dimensions into a singular, comprehensive condition indicator. For each asset(a_i), the condition indicators for each dimension are calculated as:

$$I_L(a_i) = \sum_{j=1}^{n_L} w_{Lj} a_{iLj}$$
$$I_H(a_i) = \sum_{k=1}^{n_H} w_{Hk} a_{iHk}$$
$$I_M(a_i) = \sum_{l=1}^{n_M} w_{Ml} a_{iMl}$$
$$I_E(a_i) = \sum_{m=1}^{n_E} w_{Em} a_{iEm} \tag{7}$$

where w_{Lj}, w_{Hk}, w_{Ml}, and w_{Em} are the weights assigned to the features in the Life Assessment, Health Condition, Maintenance, and Economic Impact dimensions, respectively. Finally, the Total Indicator for each asset a_i is computed by averaging the condition indicators across all dimensions as per Equation 6. The Module comprehensively evaluates asset conditions by implementing these steps and equations, facilitating effective prioritization and decision-making for maintenance and management strategies.

C. MODULE FOR THE DEFINITION OF SMART ASSET MANAGEMENT STRATEGIES

This Module compares assets from different perspectives of operation and maintenance by elaborating sorted lists of assets and recommending the most convenient actions to take according to the indicators obtained. Also, it can simulate and quantify the evolution of the condition indicator previously defined for the assets under different management strategies proposed by the user. It presents a novel approach to smart asset management in a power system, leveraging reinforcement learning for decision-making. This method aims to optimize the performance and maintenance of power system assets based on their current and projected states. The framework consists of two main analysis options and uses reinforcement learning to suggest optimal actions.

1) **Short-term Analysis**: Utilizes the current state of the asset, termed the 'Reference Scenario,' derived from module 2 output.
2) **Long-term Analysis**: Extends the short-term Analysis by incorporating future scenarios, each spanning five years, which can be customized and created using a Monte Carlo parameter selection method.

This Module provides a novel approach to smart asset management by:

1) **Analyzing Asset Conditions**: Using data from the previous Module II, it assesses the current state of each asset across multiple dimensions (life assessment, maintenance strategy, economic impact).
2) **Label Assignment**: Each asset is evaluated and labeled based on its condition in each dimension (L for low, M for medium, H for high).
   a) L for [0,0.25]
   b) M for (0.25,0.5]
   c) H for (0.5,1]
3) **Action Selection**: Optimal actions are determined using a Q-matrix derived from a reinforcement learning algorithm (Q-learning), which suggests actions with the highest potential reward. The detailed methodology for this process is explained in section IV-C1.

The Fig 5 shows the main elements of the methodology followed for the short-term Analysis. The next step is to select

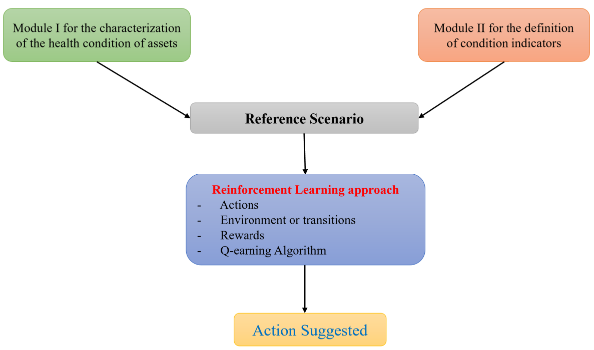


FIGURE 5. Elements of the methodology used in short-term analysis.

the action according to the asset labels. The action selection is obtained from a Q-matrix resulting from a previous execution of a reinforcement learning algorithm (Q-learning), which will be described later. The Q-matrix comprises all the possible combinations of three labels placed in its rows and suggested actions in its columns. The intersection of each row and column has a numeric value called Q-value. The action selected will have the highest Q value in a row.

The methodology for the long term is similar but extends to future scenarios. There are six scenarios(Which can be configurable), each spanning five years. These scenarios are created from the reference scenario using a Montecarlo parameter selection method. The Montecarlo method uses configuration files that allow for the definition of the interval

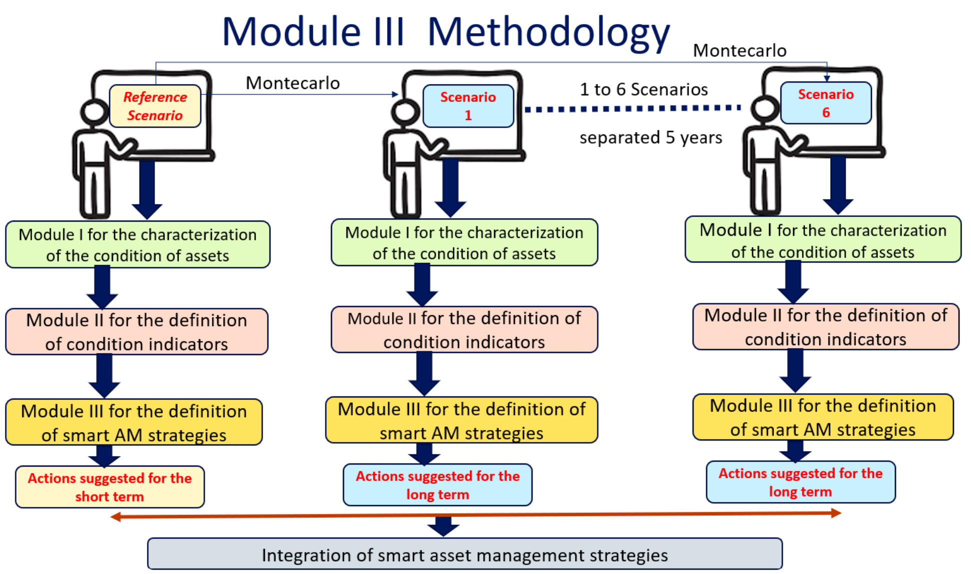


FIGURE 6. Elements of the methodology used in long-term analysis.

of values for variables. Once the scenarios are created, each is treated as indicated for the reference scenario. Fig 6 shows the elements and information flow in a Long-term methodology analysis.

1) REINFORCEMENT LEARNING AND Q-LEARNING

Reinforcement Learning (RL) is a machine learning technique that enables an agent to learn in an interactive environment by trial and error using feedback from its actions and experiences. According to [17], reinforcement learning is learning what to do — how to map situations to actions— to maximize a numerical reward signal. The learner is not told which actions to take but must discover which ones yield the most reward by trying them. In the most exciting and challenging cases, actions may affect not only the immediate reward but also the next situation and, because of this, all subsequent rewards. These two characteristics—trial-and-error search and delayed reward—are the most important distinguishing features of reinforcement learning.

At the core of reinforcement learning is an agent, environment, states, actions, and rewards. The agent observes the current state of the environment, selects an action and receives a reward as feedback from the environment. The goal of the agent is to learn a policy that maximizes the long-term sum of rewards (called the return) by exploring and exploiting the environment.

Fig 7 illustrates the action-reward feedback loop of a generic RL model.

An agent is in an environment and in a state in reference time is S_t. The agent can perform an action in the environment A_t, and as a consequence of this, the state changes to S_{t+1}, and at the same time, a reward is obtained R_{t+1}. This reward could be positive or negative. Negative means the effect is not desired, and positive means the effect is desired. The agent wants the highest possible value of cumulative rewards and

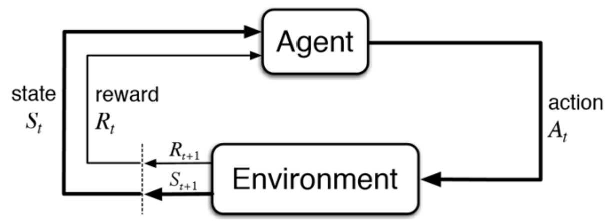


FIGURE 7. Basic elements of reinforcement learning.

will try to prevent actions from causing a negative reward (penalization). In essence, positive values guide the agent through actions that can contribute to reaching the Goal, and negative values deviate the agent from the way to reach the Goal.

One of the main advantages of this method is that it does not require historical information for learning, unlike other machine learning approaches. In the context of the ATTEST project and the Module to be developed, reinforcement learning has been considered an appropriate method to associate the condition of the assets with actions to be taken. Also, the algorithm is estimated to be very flexible and can easily adapt to new asset management strategies. The alternative to using RL could be associating rules previously defined connecting conditions of the assets and actions. Still, any modification in the strategy of the company should involve a rewriting of these rules.

There are a lot of different ways/algorithms to implement the ideas of reinforcement learning in the machine learning area. However, in this Module, the Q-learning algorithm was selected for its straightforward implementation and popularity due to its efficiency in learning optimal action-selection policies in reinforcement learning settings. Its advantage over other algorithms lies in its simplicity and ability to efficiently handle environments with discrete states and actions, making it a versatile choice for many problems without requiring complex adjustments or extensive tuning. Q-learning updates its Q-values using the Bellman equation:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\right] \tag{8}$$

where $Q(S_t, A_t)$ is the current Q-value for state S_t and action A_t, α is the learning rate, R_{t+1} is the reward for moving to the next state, γ is the discount factor and $\max_a Q(S_{t+1}, a)$ is the maximum predicted reward for the next state.

The Q-learning algorithm has been implemented through the following steps:

1) Environment: The environment in our problem is the condition of the power grid system observed by us, which includes all assets such as transformers, lines, and switchgear. This environment interacts with the RL agent by providing current states of assets and receiving maintenance actions.
2) State (S): The state represents the current condition of an asset across multiple dimensions. For each asset ai, the state includes its life assessment, health condition, maintenance status, and economic impact. States are labeled as L (low), M (medium), or H (high).
$$S = (L, H, M) \tag{9}$$
In this Module, An asset can be in one of the states L, M, and H for each dimension, yielding 27 possible states.
3) Action Space: Defined actions include replacement, maintenance adjustments, inspection, use rate modification, asset addition or removal, and digitalization, as shown in table 1.
4) The reward is the feedback received after performing an action. It quantifies the immediate impact of the action on the asset's state. Rewards are designed to reflect the cost-effectiveness and benefit of the action, with penalties for actions leading to undesirable states. The maximum and minimum rewards are set between 1000 and -1000, respectively, but these values can be configured based on the specific needs of the system.
$$r(s,a) = \begin{cases} +1000, & \text{for actions leading to optimal states (L, L, L, L)} \\ -1000, & \text{for actions leading to critical states (H, H, H, H)} \\ \text{Near zero values} & \text{for other state transitions} \end{cases} \tag{10}$$
5) Transition Rules: Govern the change from state S_t to $S(t+1)$, with permissible and forbidden transitions represented in the model.
6) Policy: The policy is a strategy defining the action for each state to maximize the cumulative reward. It maps states to actions based on learned experiences.
$$\pi(s) = a \tag{11}$$
7) Value: The value function estimates the expected cumulative reward for each state, guiding the RL agent to prioritize actions that lead to better long-term outcomes.
$$V(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right] \tag{12}$$
8) Goal: Achieving a state of L in all dimensions.

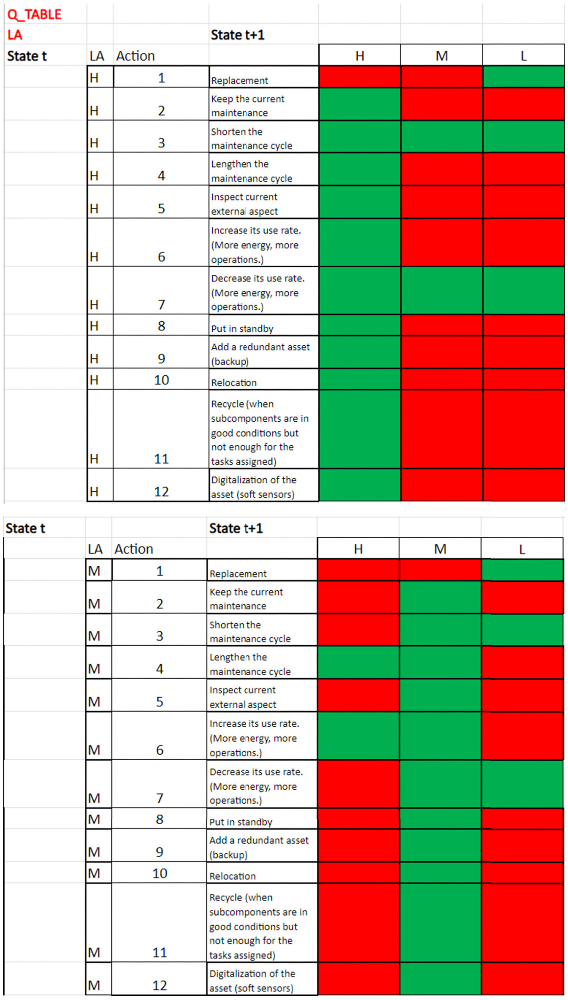
TABLE 1. The list of actions used in module III.

Action	Description/Comments
Replacement	Replace the asset with a new one if it's deemed more cost-effective or necessary due to failure or obsolescence.
Keep the current maintenance	Maintain the asset according to its regular maintenance schedule.
Advance maintenance	Perform maintenance earlier than scheduled to prevent potential issues or extend the asset's lifespan.
Delay maintenance	Postpone maintenance to a later time, potentially to align with other operational needs or budget constraints.
Inspect current external aspects	Assess the external condition of the asset to determine if any immediate actions are needed or for documentation purposes.
Increase its use rate	Increase the operational load of the asset, subject to network conditions and asset capacity.
Decrease its use rate	Decrease the operational load of the asset, potentially reducing wear and tear or energy consumption.
Put on standby	Temporarily deactivate the asset, perhaps due to low demand or pending further decisions on its usage.
Add a redundant asset	Introduce a backup asset to ensure continuity of operations in case of failure or increased demand.
Relocation	Transfer of the asset to a different location, possibly to optimize resource allocation or mitigate environmental stress.
Recycle	Dismantle the asset and reuse its components, typically when certain parts are still functional, but the whole asset is no longer viable.
Digitalization of the asset	Installation of sensors or other digital tools to monitor the asset's performance and gather data for Analysis.

The allowed transitions are defined for all the dimensions and all the states. Fig 8 gives an example of this definition for the life assessment dimension. The green color is used for the permitted transition from a State in t to another in t+1. Red is used for forbidden transitions. This allows us to model how each action impacts the indicator of each dimension.

V. CASE STUDY: IMPLEMENTATION OF THE ATTEST ASSET MANAGEMENT TOOL

The toolbox was tested on real-world data from five European TSOs and DSOs, with results from 92 transformers presented here for brevity. The case study highlights the toolbox's effectiveness in clustering assets, calculating condition indicators, and providing maintenance recommendations. Synthetic datasets with 600 transformers were also used to validate


Q_TABLE
LA

State t	LA		Action	State t+1 H	M	L
	H	1	Replacement			
	H	2	Keep the current maintenance			
	H	3	Shorten the maintenance cycle			
	H	4	Lengthen the maintenance cycle			
	H	5	Inspect current external aspect			
	H	6	Increase its use rate. (More energy, more operations.)			
	H	7	Decrease its use rate. (More energy, more operations.)			
	H	8	Put in standby			
	H	9	Add a redundant asset (backup)			
	H	10	Relocation			
	H	11	Recycle (when subcomponents are in good conditions but not enough for the tasks assigned)			
	H	12	Digitalization of the asset (soft sensors)			

State t	LA		Action	State t+1 H	M	L
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	M	11	Recycle (when subcomponents are in good conditions but not enough for the tasks assigned)			
	M	12	Digitalization of the asset (soft sensors)			

FIGURE 8. Example of transitions between states in t and t+1.

scalability. The toolbox has been designed to handle noisy or incomplete datasets effectively. The algorithm relies on the available data to form clusters if specific variables are missing for any dimension. While this may reduce the distinctiveness of clusters, it does not disrupt the overall process. If data is incomplete, users can supplement missing values based on similarities with other assets and historical data trends to enhance the outcomes. This approach ensures robustness and adaptability to varying data conditions. Through this Analysis, we aim to demonstrate the practical benefits and insights the tool offers in enhancing asset reliability and operational efficiency, thereby underscoring its value in addressing contemporary challenges power systems face.

A. INTEGRATION WITH INDUSTRY STANDARDS AND EXISTING GRID MANAGEMENT SYSTEMS

The toolbox was developed with a strong emphasis on handling heterogeneous data sources and formats, a critical challenge in transmission and distribution systems. Rather than being restricted to a specific industry standard, the toolbox is designed to accept data from multiple formats, requiring only preprocessing to ensure compatibility. It has been successfully tested with real-world data from utility providers and fed with power flow data in the MATPOWER format. Additionally, the toolbox is flexible enough to process data from IEEE test feeders and power flow models such as PSS/E. Moreover, it can integrate with data adhering to industry standards like CIM, IEC 61850, and IEEE standards related to power system modeling and asset management. This flexibility ensures that the toolbox remains adaptable to grid configurations and utility requirements, enhancing its usability across various operational environments. During the ATTEST project, the toolbox was integrated into a broader platform developed by Partner (SoftLab) [18] and successfully incorporated into the operational systems of other partners(TSOs and DSOs). This integration allowed the toolbox to interact with existing SCADA and ERP systems, demonstrating its ability to support real-world grid operations. This platform implemented additional tools to support day-ahead and real-time operation planning and network planning optimization. The toolbox was crucial in facilitating seamless data exchange and workflow automation. Interfaces and interactions between the toolbox and other tools were developed and tested to ensure smooth interoperability between system components. By demonstrating its compatibility with industry standards and successful integration into operational platforms, the toolbox has proven its ability to function effectively within existing industrial ecosystems. These integrations confirm that the toolbox can be adapted to various operational environments, ensuring its practical applicability across different power system infrastructures. The ability to ingest and process diverse data formats makes it a versatile solution for asset management, supporting transmission and distribution system operators in improving decision-making and maintenance strategies.

B. DATASET

This case study includes a real scenario corresponding to the assets of a distribution power grid, particularly its power transformers. In total, this scenario contains historical data on 92 power transformers. Each transformer is characterized using multiple indicators or variables that depend directly on the nature of the Analysis (life assessment, maintenance strategy, or economic impact). Indicators and variables available for each dimension are shown in the table 2.

C. MODULE FOR THE CHARACTERIZATION OF THE HEALTH CONDITION OF ASSETS

Fig 9 presents the result of applying module 1 to assess the health conditions of the Power Transformers for Life Assessment Dimensions. Each cluster is defined as a pattern containing those assets with similar features. Each pattern is represented using box diagrams, including the number of assets in the same pattern. In this figure, it can be seen how the Module is capable of detecting four different patterns.

The added value of using patterns instead of just considering individual values for each of their features is

TABLE 2. Overview of data.

Dimension	Indicator / Variable	Description
Life Assessment	Age (years)	Provides characterization of the state and operation of the component.
	Failure probability [0-1]	Indicates the likelihood of a component failing within a specified period.
	Criticality [0-100]	Measures the impact of a component's failure on the system's performance.
	Energy (MWh)	Reflects the operation of the component in terms of energy handled.
Maintenance Strategy	Fault Duration	Attributes related to the asset's condition and failure impact.
	Number of Faults	Reflects the frequency of faults within a specified timeframe.
	Number of Defects	Indicates the total number of defects identified in the asset.
	Defect Severity	Measures the severity of defects identified in the asset.
Economic Impact	Number of Important Customers	Considers the number of critical customers affected by service interruptions.
	Power Contracted	Reflects the total amount of power the utility has committed to providing.
	Power Cut	Indicates the total amount of power not supplied due to service interruptions.

the identification of disassociation between features. For Example, older assets do not always have the highest fault, and assets with a high energy demand are not always the most critical. These relationships can only be detected efficiently using unsupervised learning algorithms like the ones applied in this Study.

The interpretation of each pattern is shown in Fig 10, allowing the user to detect which assets present worse conditions in terms of their state and operation.

D. MODULE FOR THE DEFINITION OF CONDITION INDICATORS BASED ON HETEROGENEOUS INFORMATION SOURCES

The same scenario and dataset were applied in Module II as in the first Module. This section presents the results of this Analysis, focusing on identifying and evaluating condition indicators that provide insights into the health and performance of the assets.

The result of this Module is shown in Table 3. In general, Assets are in good condition, but asset 28CDR2 is in critical condition as the total indicator value is 0.77, higher than the threshold of 0.75. The company planning can configure the threshold. On the other hand, Asset 28PCAT, while presenting an overall good condition with a Total Indicator of 0.58, is flagged for critical attention in the Maintenance Strategy dimension with a score of 0.8. This discrepancy highlights the importance of evaluating assets across multiple dimensions to pinpoint specific areas of concern that may not immediately reflect in the overall Total Indicator but indicate a significant need for maintenance intervention. This higher value of the total indicator has been affected by all the dimensions since all three dimensions have high values, which automatically results in an increased total indicator.

Assets with Total Indicator values significantly below the critical threshold (e.g., 28CHQD, 28CZP5, 28CUB0, etc.) are likely considered acceptable to good condition with less immediate need for intervention. However, these assets still require regular monitoring to ensure they do not deteriorate to a critical condition over time.

The varying scores across different dimensions for each asset highlight the importance of a multifaceted approach to asset management, considering not just the physical condition (Life Assessment) but also the strategic (Maintenance Strategy) and financial (Economic Impact) aspects. This comprehensive view allows for more informed decision-making regarding maintenance priorities and investment.

TABLE 3. List of total indicators.

Asset ID	Life Assessment	Maintenance Strategy	Economic Impact	Total Indicator
28CDR2	0.793	0.711	0.807	0.77
28CYL3	0.649	0.675	0.53	0.618
28PCAT	0.65	0.8	0.3	0.58
28CHHS	0.594	0.724	0.414	0.577
28CQPQ	0.542	0.512	0.309	0.454
28CIA7	0.478	0.388	0.286	0.384
28CDR5	0.316	0.682	0.135	0.377
28CHQD	0.269	0.038	0.475	0.26
28CZP5	0.41	0.126	0.229	0.255
28CUB0	0.428	0.097	0.216	0.247
28CNTW	0.181	0.267	0.288	0.245
28AGM9	0.174	0.04	0.513	0.242
28CXN2	0.406	0.167	0.152	0.242

These results have been transformed in the Clusters using the same methodology as Module I, shown in Fig 11. The below depicts clusters in the form of patterns for indicators, with each pattern showing the performance of each indicator and the percentage of assets it includes. For instance, Pattern 1 encompasses six assets, which, from a Maintenance perspective, are in critical condition and require immediate attention. This conclusion is made because the value of the maintenance indicator is near one. So, if any indicator has a value near one, it is in critical condition and needs maintenance immediately. Suppose an indicator has a value near 0. In that case, it means that it is in good condition and does not require any maintenance or extra attention from caretakers, as it is adequately maintained.

E. MODULE FOR THE DEFINITION OF SMART ASSET MANAGEMENT STRATEGIES

The results in the table 4 showcase the practical application of this methodology of Module 3. Actions recommended by the Q-learning algorithm, such as replacement, maintenance

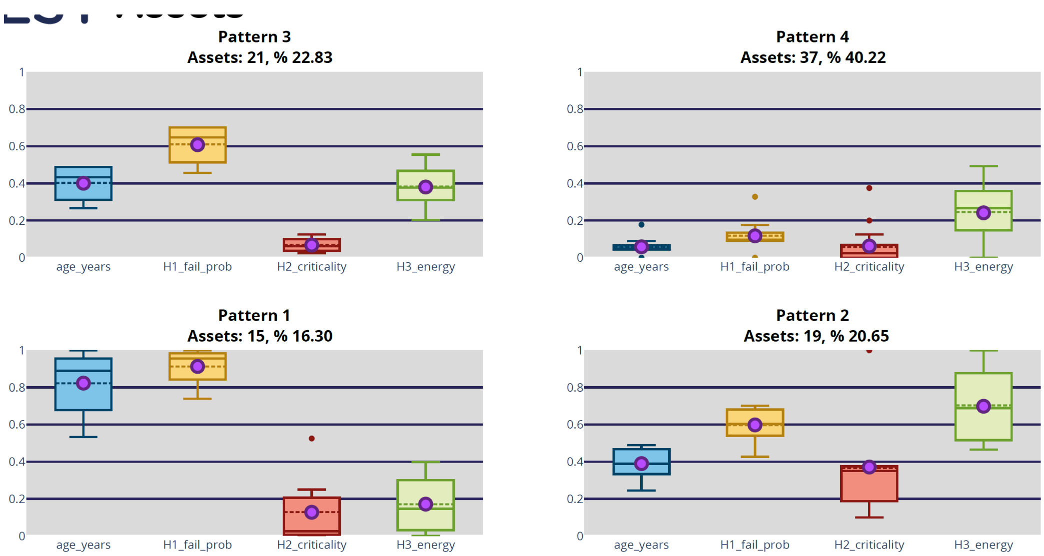

FIGURE 9. Results obtained for the life assessment of 92 power transformers.

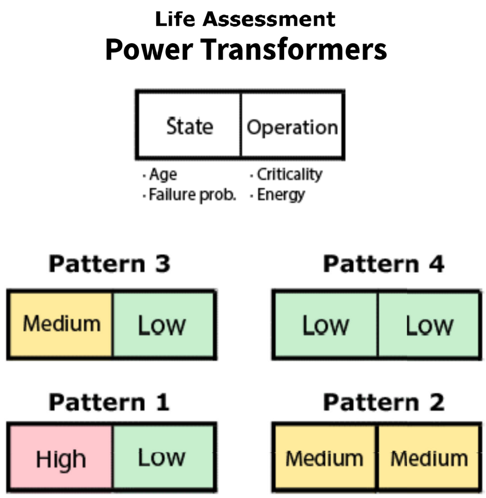

FIGURE 10. Analysis of the results obtained for the life assessment of 92 transformers.

adjustments, and asset relocation, are tailored to each asset's specific condition to achieve the optimal state of low (L) risk or concern across all dimensions. For instance, asset 28CDR2, characterized by high (H) Economic Impact and medium (M) scores in both Life Assessment and Maintenance Strategies, is recommended for a replacement to address its critical condition effectively. Conversely, assets with low (L) scores across all dimensions, such as 28PCKK and subsequent entries, are advised to maintain their current maintenance schedules, reflecting their optimal state and negating immediate intervention. These recommendations highlight the capacity of the Module to discern and prescribe specific actions based on the unique conditions of each asset, demonstrating a significant advancement in asset management strategies. The flexibility and adaptability of the Q-learning algorithm enable it to accommodate changes in asset management strategies without necessitating the rewriting of predefined rules. This approach not only enhances the efficiency of managing power system assets but also supports the proactive identification and mitigation of risks, ensuring the reliability and sustainability of the power system.

TABLE 4. Recommended action.

Name	EI	LA	MS	Action
28CDR2	H	M	M	Replacement
28CHHS	L	M	M	Shorten the maintenance cycle
28CQPQ	L	M	M	Relocation
28CYL3	M	M	M	Installing soft sensors for monitoring
28PCAT	L	H	M	Replacement
28PCKK	L	L	L	Keep the current maintenance
28PFQB	L	L	L	Keep the current maintenance
28PJTZ	L	L	L	Keep the current maintenance
28PLPZ	L	L	L	Keep the current maintenance
28PNG6	L	L	L	Keep the current maintenance
28PNG7	L	L	L	Keep the current maintenance
28PNG9	L	L	L	Keep the current maintenance
28PNNZ	L	L	L	Keep the current maintenance
28PPE4	L	L	L	Keep the current maintenance
28PPE7	L	L	L	Keep the current maintenance
28PPF1	L	L	L	Keep the current maintenance
28PPF2	L	L	L	Keep the current maintenance
28PRQP	L	L	L	Keep the current maintenance

F. COMPUTATIONAL EFFICIENCY AND CLUSTERING PERFORMANCE

To evaluate the computational efficiency of the toolbox, we conducted performance measurements using specified hardware and software configurations. Since the implemented clustering algorithm is unsupervised, conventional prediction accuracy metrics do not apply. Instead,

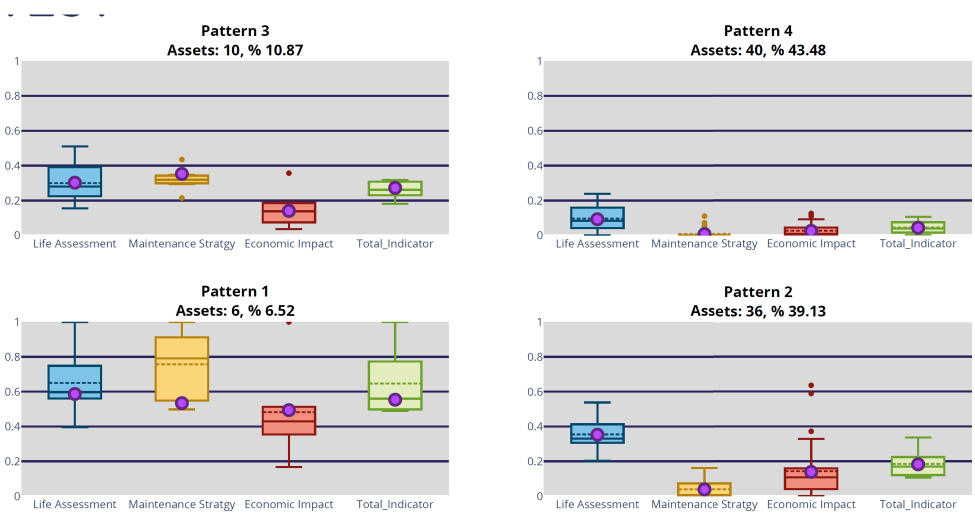

FIGURE 11. Health indicators of 92 assets.

we assessed clustering quality using quantization error and computed iteratively to minimize discrepancies before generating the final results. The quantization error is calculated in three attempts, denoted as q1, q2, and q3, where each attempt aims to lower the error further and refine the clustering process before finalizing the results. These iterative computations ensure that the clusters are as distinct as possible while capturing meaningful patterns in the data. The computational efficiency of different processes was measured in terms of runtime on specified hardware. The results in Table 5 show the execution times for Self-Organizing Map (SOM) clustering and Q-learning-based decision optimization. The SOM clustering process, applied to a dataset of 92 assets, took approximately 12.3 seconds on an Intel i7 Processor with 32 GB RAM. The quantization error was minimized through three iterative attempts (q1, q2, q3) before finalizing the clusters.

TABLE 5. Computational efficiency and clustering performance.

Process	Runtime	Hardware	Quantization Error (q1, q2, q3)
SOM Clustering (92 Assets)	12.3 seconds	Intel i7, 32 GB RAM	0.2071, 0.2068, 0.2065
SOM Clustering (600 Assets)	67.7 seconds	Intel i7, 32 GB RAM	0.2176, 0.2176, 0.2173
Q-Learning (92 Assets)	14.2 seconds	Intel i7, 32 GB RAM	-
Q-Learning (600 Assets)	58.5 seconds	Intel i7, 32 GB RAM	-

These results confirm that the toolbox achieves computational efficiency while maintaining high clustering quality. The iterative quantization error calculations ensure that the best clustering results are selected after multiple attempts, thereby improving decision support for asset management.

VI. CONCLUSION

This Study presents a robust, open-source toolbox for asset management in power systems, integrating machine learning and data analytics to support Transmission and Distribution System Operators (TSOs and DSOs) in proactive maintenance and resource optimization. The ATTEST toolbox enhances standard asset management approaches using reinforcement learning for strategic decision-making and clustering assets based on multi-dimensional health assessments. The case study on power transformers demonstrated the ability of the tool to enhance operational efficiency by identifying critical assets in need of maintenance and recommending tailored actions based on real-time data insights.

The modular design of the toolbox ensures adapting across different power system contexts and asset types. It includes asset condition assessment, condition indicator computation, and strategy definition. Furthermore, the reinforcement learning module supports dynamic, data-driven decision-making, allowing operators to optimize maintenance schedules, predict asset failures, and plan long-term interventions.

Future work could explore integrating more sophisticated machine learning models, such as deep learning algorithms, to improve predictive capabilities and refine maintenance recommendations. Additionally, expanding real-time analytics could provide TSOs and DSOs with immediate insights, enhancing the toolbox's responsiveness to dynamic power system conditions. By advancing asset management practices, the ATTEST toolbox contributes to the reliability and sustainability of power systems and aligns with broader goals of sustainable energy transition and environmental responsibility.

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GOPAL LAL RAJORA received the bachelor's degree in electronic instrumentation and control engineering from the Government Engineering College, Bikaner, Rajasthan, India, in 2015, the Master of Science degree in applied telecommunications and engineering management from Universitat Politécnica de Catalunya, Spain, in 2020, and the master of Science degree in finance from the University of Siena, Italy. Since November 2020, he has been a Predoctoral Researcher and a Ph.D. Student with the Institute of Technological Research (IIT), Universidad Pontificia Comillas, Madrid, Spain.

MIGUEL A. SANZ-BOBI (Senior Member, IEEE) is currently a Professor with the Telematic and Computer Science Department and a Researcher with the Engineering School, Institute for Research and Technology (IIT), Universidad Pontificia Comillas, Madrid, Spain. He divides his time between teaching and research in the artificial intelligence field applied to diagnosing and maintaining industrial processes. He has been a Main Researcher in more than 40 industrial projects more than the last 25 years, related to the diagnosis in real time of industrial processes, incipient detection of anomalies based on models, knowledge acquisition and representation, and reliability and predictive maintenance. All these projects have been based on artificial intelligence, new information technologies, and data mining techniques.

CARLOS MATEO DOMINGO received the degree in industrial engineering from Universidad Pontificia Comillas, the Diploma degree in computer engineering from UNED, in 2000, and the Ph.D. degree in industrial and computer engineering from the Institute for Research in Technology (IIT), in 2007.

He coordinates the Smart and Sustainable Grids area at IIT, specializing in electricity power systems, distribution network modeling, and the impact of distributed energy resources. He has contributed to several European research projects (MERGE, IMPROGRESS, ADVANCED, SUSTAINABLE, and PV-GRID) and worked with industry partners, such as CNMC, Iberdrola, and Ormazabal. Internationally, he has collaborated with MIT, NREL, and the World Bank. He helped create the DSO Observatory for the European Commission and participated in the SMART-DS project for U.S. Department of Energy. He also worked with the World Bank on demand response in Central America and MIT on electrification solutions for developing countries.

LINA BERTLING TJERNBERG (Senior Member, IEEE) is currently a Professor of power grid technology with KTH Royal Institute of Technology, Stockholm, Sweden. She is the Deputy Head of the School of Electrical Engineering and Computer Science (EECS), focusing on research conditions and impact. She is a fellow of IVA and the Royal Swedish Academy of Engineering. Her research and teaching are focused on applying mathematics (e.g., statistics, optimization, and life cycle assessment) to predict and model reliability and the impact of maintenance efforts for various electric power system applications. Her research interests include system analysis of future technologies (e.g., microgrids, battery storage, high voltage direct current (HVDC), nuclear/hydro/wind/solar power, and hydrogen), designs, power grid operation, and electrified transportation.