

Article

# Industry 4.0 Contribution to Asset Management in the Electrical Industry

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**Abstract:** Industry 4.0 has revolutionized paradigms by leading to major technological developments in several sectors, including the energy sector. Aging equipment fleets and changing demand are challenges facing electricity companies. Forced to limit resources, these organizations must question their method and the current model of asset management (AM). The objective of this article is to detail how industry 4.0 can improve the AM of electrical networks from a global point of view. To do so, the industry 4.0 tools will be presented, as well as a review of the literature on their application and benefits in this area. From the literature review conducted, we observe that once properly structured and managed, big data forms the basis for the implementation of advanced tools and technologies in electrical networks. The data generated by smart grids and data compiled for several years in electrical networks have the characteristics of big data. Therefore, it leaves room for a multitude of possibilities for comprehensive analysis and highly relevant information. Several tools and technologies, such as modeling, simulation as well as the use of algorithms and IoT, combined with big data analysis, leads to innovations that serve a common goal. They facilitate the control of reliability-related risks, maximize the performance of assets, and optimize the intervention frequency. Consequently, they minimize the use of resources by helping decision-making processes.



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**Keywords:** industry 4.0; asset management; electrical networks; decision making; asset life cycle management; risk management; smart grids; complex systems; big data

## 1. Introduction

Asset management (AM) is a topic that has gained popularity in recent years as various challenges force small, medium, and large companies to optimize their AM. For production, transmission, and distribution networks, we recognize several challenges for asset management, such as the aging of equipment fleets and infrastructure [1,2]. Future climate change will also result in the accelerated aging of active equipment on the grid. In addition, climate change increases the risk and the occurrence of climatic events having an impact on network reliability [3].

Furthermore, COVID-19 has also accelerated companies' migration to industry 4.0 tools. For electrical industries, this migration will have consequences for the electricity demand, as well as for grid reliability requirements [4].

As a result, electrical industries must make significant investments in AM to maintain and/or improve electrical network reliability and resilience. However, human and financial resources are limited and insufficient to meet this significant increase. Investments must be prioritized. This prioritization must maximize the achievement of the overall objective of the entire electricity production, transmission, and distribution chain, which is to supply electricity to customers.

For several reasons, this exercise is a challenge. First, AM models and strategies are often defined according to which of the three functions the system belongs to, either production, transmission, or distribution of electricity. This silo approach does not take into account the interrelationships between the equipment as they pertain to the overall objective of this chain.

Second, electrical networks are considered large complex systems. This is due to all the interrelationships between the systems and their composing elements [5,6]. In complex systems, decision making must consider more laborious risk analysis and is subject to more uncertainty. Therefore, managing risks and uncertainty in AM for the electrical industry represent a challenge and a significant part of the decision-making process in terms of prioritization of investments.

In this regard, the arrival of industry 4.0 creates an important shift because it revolutionizes AM paradigms and models. Among other things, it promotes the use of big data in decision making.

As a result, we wonder about the benefits that the arrival of industry 4.0 brings to the management of assets in the electricity industry, mainly for decision making and to achieve the overall goal of the electrical grid. In this regard, although there are several publications relating to industry 4.0 and to AM in the electrical industry, the combination of these topics has not been the concern of any recent publication. Publications are mainly focused on optimizing the AM of particular equipment from one or a few of the tools of industry 4.0 [7]. The objective of this article is, therefore, to detail how industry 4.0 can improve the asset management of electrical networks from a global point of view. To do so, the industry 4.0 tools will be presented, as well as a review of the literature on their application and benefits in this area.

Therefore, the rest of this paper is structured as follows: Section 2 shows the research background by explaining how other researchers treated a similar topic and how this paper contributes to the literature. A definition of asset management and industry 4.0 is also presented to introduce the concept and set the scope of this research. Section 3 details the methodology used to identify and analyze the literature, and Section 4 presents the outcomes of the systematic literature review. Next, Section 5 discuss the results by showing how industry 4.0 benefit AM activities, as well as the challenges in the application of those tools. Finally, a conclusion and future work are presented in Section 6

## 2. Research Background

Some authors carried out a similar exercise. However, those studies focused on the impacts and benefits of a single tool or a particular technology of industry 4.0 on AM of electrical grids. Moreover, two authors [8,9] studied the impact and application of the IoT in electrical networks. In addition, Koziel et al. [10] focused on the contribution of machine learning algorithms and data analytics in AM strategies and power supply reliability. In a second publication, Koziel et al. [11] carried out a review of the literature on the algorithms used in distribution networks precisely for the detection of anomalies, load disaggregation, and fault localization.

Moreover, there are several publications related to the benefits of big data analytics on electricity networks AM [10,12–15]. This puts forwards the idea that this element represents one of the most important pillars of smart grids. In fact, this method allows electrical industries to deal with the complexity related to the network structure, components, constraints, and multiple alternative solutions, as well as uncertainties surrounding predictions and risks [10].

More specifically, Moharm [12] detailed the benefits of big data analytics in micro-grids. In those isolated grids, big data analytics applications are varied, ranging from planning and decision making to maintenance optimization and forecasting customer load and weather. Many of those applications can be transposed to smart grids.

In fact, while Liu and Zou [16] clearly define the use of big data in the operation and control of a distribution network, Stimmel [14] fully explains the integration and the use of big data to benefit smart grid and those applications, and others were also put forwards.

On the other hand, authors that included more than one tool mainly focused on the AM of a particular type of equipment. This is the case of Amadi-Echendu and Mafutsana [7], whose publication focuses on power transmission transformers.

However, from that literature review, it is observed that there is no summary of the possibilities industry 4.0 offers, along with how it can be used to support the assets management of power grids from a global point of view.

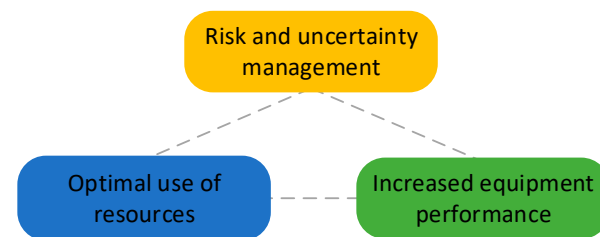
### 2.1. Asset Management Definition

ISO 55000, the international standard for AM, defines this topic as “the coordinated activity of an organization to realize value from assets” [17]. Given the large sphere of application of ISO 55000, establishing the standard’s requirements in a specific sector must be governed more explicitly. The International Infrastructure Management Manual (IIMM) is a guide that defines the implementation steps of the ISO-55000 standard [18].

For the electrical sector, AM is defined as “an organized procedure of operating, maintaining and improving electrical assets by using combined engineering practices and economic analysis along with thorough business practices” [3].

For physical AM, the definition to which we mainly refer is framed by specification PAS-55, a publicly available specification covering AM of physical assets: “Systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan” [19]. This research focuses on physical AM specifically. The definition of AM referred to will therefore be the latter.

The main challenge of AM in the electrical industry is to balance expected performance, costs, and risks [20,21]. Figure 1 shows this relation.



**Figure 1.** Interrelation between performance, risks, and costs (adapted from Biard et al. [21]).

### 2.2. Industry 4.0 Definition

Industry 4.0 is a phenomenon that has emerged from several technological initiatives. It is a hot topic that has been popular in the literature over the past decade. However, we find a great deal of confusion with regard to the framework of industry 4.0 and its underlying technologies.

Despite efforts to establish a clear definition of industry 4.0, a unanimous definition has not emerged to date. In most publications, we find a definition from a list of related technologies. However, by combining the approach of several authors, it is possible to interpret that industry 4.0 represents an environment where the various components of a system or organization collaborate digitally [22], where data is collected, processed, and analyzed automatically. This collaboration promotes the emergence of several technological innovations that make it possible to increase the capacity, efficiency, and flexibility of systems [23].

The rapid evolution of technologies is a challenge for the structure of industry 4.0 and the establishment of a clear definition. As a result, the elements and tools put forward by the authors vary. However, we find two fundamental concepts: the Internet of Things (IoT) and Cyber-Physical System (CPS). Both concepts are made possible through the use of sensors, actuators, control and communication units, etc. [24,25].

Technological possibilities and tools are combined with the two fundamental concepts. Concepts, principal tools, and technologies are defined in Table 1. Several of these technologies are interrelated and must be combined to obtain the results and advantages presented.

Definitions have been developed from publications [22,24–27], most of those publications aim to present the evolution and define industry 4.0.

**Table 1.** Industry 4.0 concepts, technological possibilities, and tools definition.

Concepts, Technological Possibilities, and Tools	Definition
Internet of Things (IoT)	Allows the interoperability of the elements of a system by providing a digital interaction between objects.
Cyber-Physical System (CPS)	Aims to link the physical and virtual environment of the organizations' elements in order to synchronize them in real-time.
Big Data	The key element of industry 4.0. It represents the astronomical quantity and variety of data collected that makes them unusable in their raw state. Proper processing, paired with relevant junctions between types of data, leads to important insights [22].
Cloud	Supports the interconnections between software and data with servers hosted on the web rather than in organizations. It provides higher data storage and calculation capacities as well as accessibility.
Machine Learning	A concept of artificial intelligence, using mathematical algorithms, from the analysis of big data. Over time, the compiled data improves the algorithm calculations and therefore increases the performance of the results.
Simulation and modeling	Used to perform complex analyzes that would be impossible to implement with traditional analytical techniques and to simulate the effect of decisions before applying them.
Digital twin	A simulation tool. It is a digital reproduction of the components or equipment of an organization or system. This virtual copy is designed to react the same way the real machine would.
Augmented Reality	Technology that allows a virtual environment to be linked to the real physical environment, enriching the real environment with additional data and information.
Smart factory	A factory where the production system is decentralized, and the entire value chain is autonomous.
Additive manufacturing	Manufacturing products from 3D printers by juxtaposing multiple layers of raw materials based on a virtual design of the final product.

An essential component of industry 4.0 is the fact that the technological innovations that it encompasses are not limited to facilitating an increase in production capacity or organizational efficiency. It is a revolution in the management model, through which the analysis of big data contributes to organizational decision making [22]. The main characteristic of industry 4.0 is its resulting paradigm shift, causing companies to move from centralized management to decentralized organization [24].

### 3. Research Methodology

The present research aims to synthesize current knowledge and to determine the technologies of industry 4.0 having a significant positive impact on the management of the assets of the electricity industry. To do this, the research method is based on the systematic literature review (SLR) method. This method helps to identify what is known about a topic and provides a reproducible and transparent process [28]. This method has been used by many authors in the field of AM and in industry 4.0 impact analyses.

In the field of AM, Gavrikova et al. [29] apply this method to increase understanding of strategic aspects of AM. This study and the present research have similar goals. They tend to synthesize current knowledge, which is based on specific applications, rather

than a holistic approach. Similarly, the SLR method is also used by Polenghi et al. [30] to determine the factors that influence the achievement of AM goals.

Then, with regard to industry 4.0, Salvadorinho and Teixeira [31] uses the SLR method to study how manufacturing companies can make a digital shift without hampering the integration of lean principles currently in force. In addition, Beltrami et al. [32] use this approach to analyze the impact of industry 4.0 tools on sustainability. Again, this study aims at a similar objective, but the current study focuses on the electrical industry and improving the management of their assets from innovative digital tools.

### 3.1. Literature Identification

The publications of the digital database Scopus and IEEE Explore were used to retrieve articles that best suit the topic. The initial search targeted the main keywords, i.e., “Industry 4.0”, “Asset Management”, and “Electrical network” (and synonyms) in the *Title*, *Abstract*, and *Keywords* fields. This combination did not return any results in both databases. Therefore, the term industry 4.0 has been replaced by all the main tools it represents. The terms of Table 1 were used to complement the term “Industry 4.0”.

This change to the search terms identified several publications in both databases. Then, inclusion and exclusion criteria were established to target the most relevant publications, as prescribed by the SLR method. As a result, the literature review includes 76 articles. Figure 2 shows the steps of the methodology and the inclusion and exclusion criteria.

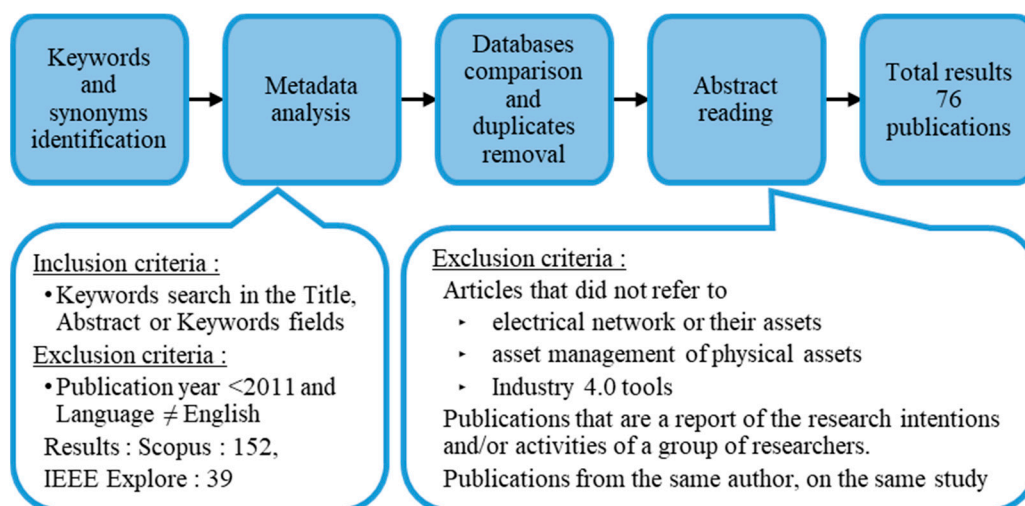


Figure 2. Systematic literature review process.

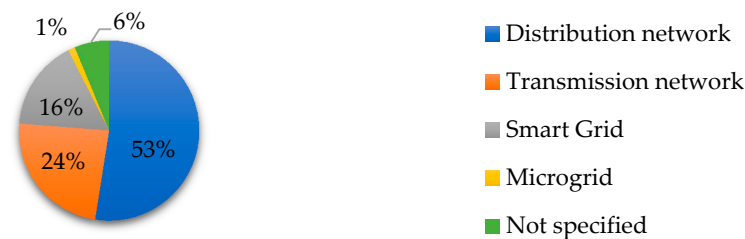
### 3.2. Literature Analysis Process

As a first step, the results of the literature review were analyzed according to their metadata, such as the publication year, the keywords used, and the field of application. Then, an observation of how technologies and innovations are applied in a specific field was conducted.

To evaluate the impact of industry 4.0 tools to AM from a global point of view, an AM model must be considered. The model referred to is the IIMM [18]. Although the PAS-55 standard refers to the management of physical assets, this standard is no longer renewed. However, it inspired the ISO-55000 standard. The ISO-55000 standard details the elements to be introduced into an asset management system, but especially at the information management level. The IIMM model proposes for its part the key steps be implemented in order to integrate ISO-55000 standard elements into the management of infrastructure assets. The application framework is, therefore, the one that best suits the context of this research.

#### 4. Results

It was noted that most of the publications analyzed were from distribution and transmission networks. Figure 3 reflects the proportion of publications according to the function that suits best the sector targeted.

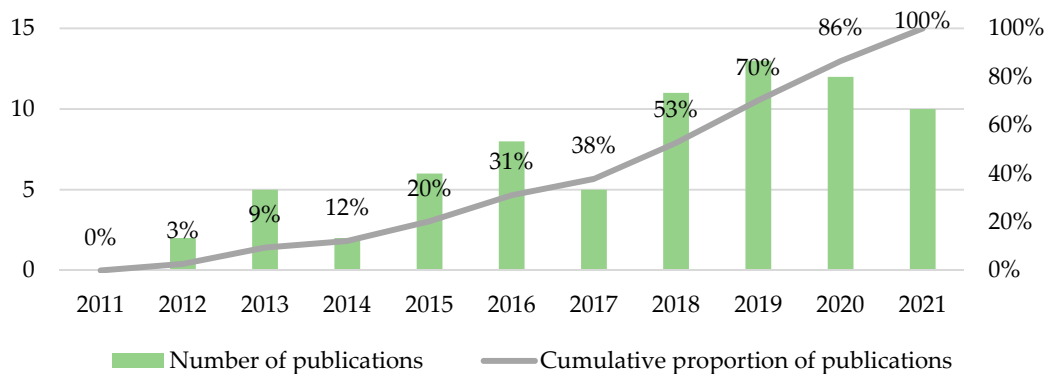


**Figure 3.** Proportion of publications according to the function that suits best the sector targeted.

It can be observed that only a few were intended for production assets. In fact, production assets were included in publications intended for smart grid specifically or in publication related to the electrical network in general (i.e., “Not specified” in Figure 3)

##### 4.1. Evolution of Publications

As industry 4.0 is a revolution that occurred in the last decade, most of the publications are dated from 2018 and over (62%). Figure 4 shows the evolution of the number of publications by year. It should be noted that the 2021 year represents only the first 6 months.



**Figure 4.** Evolution of the number of publications related to the topic by year.

##### 4.2. Keywords Analysis

In order to determine the main fields of application, as well as the predominant industry 4.0 tools, a keyword occurrence analysis was carried out. The results are presented in Tables 2 and 3.

**Table 2.** Occurrence of keywords in industry 4.0 applications in the electrical industry.

Keywords	Freq.	Prop.
Algorithms	17	22%
Big data	14	18%
Modeling	13	17%
Simulation	11	14%
IoT	9	12%
Artificial intelligence	2	3%
Cloud	2	3%
Virtual reality	1	1%
Real-time systems	1	1%

**Table 3.** Occurrence of keywords from industry 4.0 application domains in the electrical industry.

Keywords	Freq.	Prop.
Information and data management	22	29%
Budget, investment, and cost management	22	29%
Reliability	18	24%
Anomaly, outages and failure detection/analysis	17	22%
Decision making	15	20%
Smart grid	15	20%
Optimization	12	16%
Maintenance and health management	12	16%
Risk management	12	16%
Load forecasting and management	11	14%
Monitoring	11	14%
Planning	10	13%
Demand response	6	8%
Forecasting	6	8%

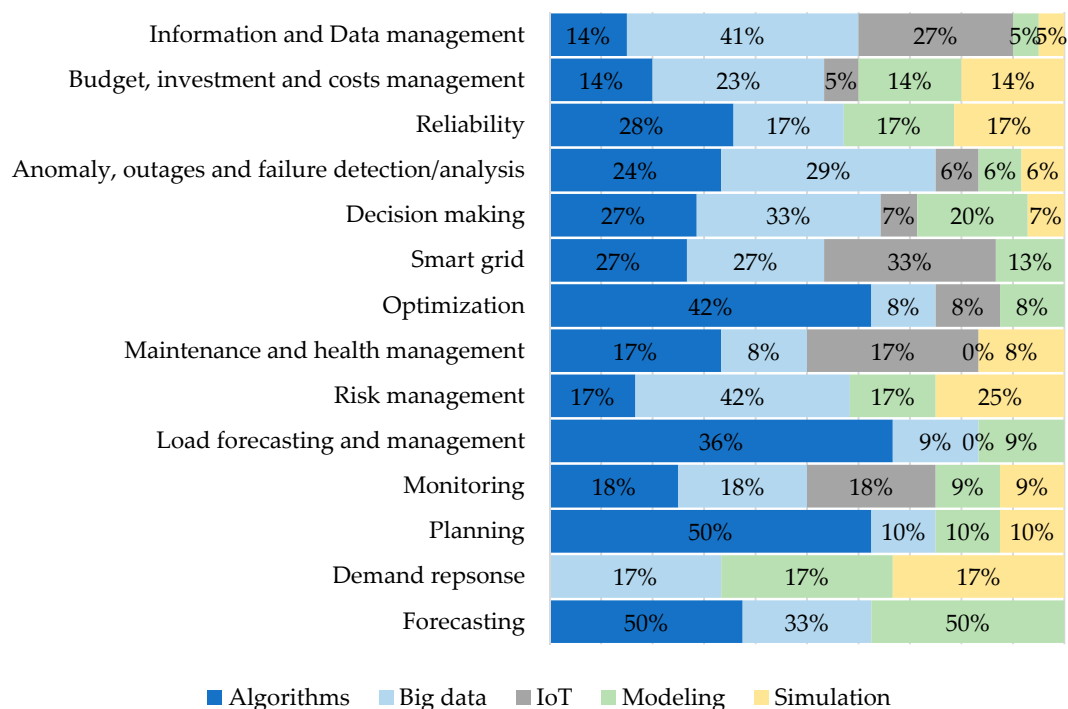
Table 2 presents the occurrence of keywords belonging to industry 4.0 applications in publications studied. The keywords mentioned in Table 1 that do not appear in the table below are keywords that did not appear in any of the publications.

Table 3 represents the application domains in the electrical industry from which industry 4.0 keywords were mostly used.

Briefly, we can see that electrical industries use various algorithms to treat and analyze smart grid data in order to optimize investments, reliability, and load forecasting while improving the decision-making process and risk management.

#### 4.3. Application Field Analysis

Another interesting approach to enhance the understanding of the use of industry 4.0 technologies to benefit AM is to compare which tools or technology are used the most to meet the application field needs. Figure 5 presents this analysis. For this analysis, only the most used keywords (>2 occurrences) were kept.

**Figure 5.** Proportion of publications by industry 4.0 elements used by application fields.

Then, by analyzing the combination of the different application fields in the same publication, we can observe that some of them include or has an impact on others, and some are mutually dependent. For example:

- *Demand response* is assured by enhanced *Reliability* and accurate *Load forecasting*;
- *Optimization* is often combined with *Planning* or *Budget, investments, and cost management*;
- *Monitoring* needs *Information and data management* processes to manage the voluminous amount of data it generates;
- *Information and data management* leads to an improved *Decision-making* process;
- *Risk management* is assured by an appropriate *Decision-making* process, improved *Forecasting* methods, and enhanced *Maintenance and health management*;
- *Monitoring* leads to *Anomaly, outages, and failure detection and analysis* improvement, which helps *Maintenance and health management*;
- *Optimal Planning, Decision making, and Risk management*, as well as the integration of refined *Forecasting* methods, contribute to efficient *Budget, investments, and cost management*.

The next section details how the industry 4.0 tools and technology are used to benefits the main application fields. For the purpose of this study, the application fields may differ from the ones identified in Table 3. Clustering is established following the reading of the publication.

#### 4.3.1. Information and Data Management

The data generated by smart grids have the characteristics of big data. Big data is the key element of industry 4.0. To use the data to its full potential, its optimal management is a critical element. Investments in data quality are also proven to be beneficial for AM [33]. Koziel et al. [33] even developed a framework for data quality management that can measure the impact of poor data quality and identify data quality improvement opportunities.

Several experts studied existing methods for structuring and analyzing big data from electrical industries. Firstly, McDonald [34] presents the method to transform a public utility to data-driven utility, as well as its benefits from case studies in transmission and distribution networks. Following the same idea, Gil et al. [35] developed the *EIoT* platform, whose objective is to manage smart grids data based on IoT. Simultaneously, Qian et al. [36] elaborated an architecture of an AM system for a distribution network that relies on the use of RFID sensors to manage assets' data.

Liu et al. [37] also used RFID technology in order to improve data management of distribution networks, but more specifically for operation and maintenance. These authors define the advantage of RFID technology in distribution networks as:

*"[RFID] can achieve [ . . . ] real-time access, maintenance and data verification [ . . . ], ensure the consistency, [ . . . ] synchronization of [ . . . ] information, reduce the workload of [ . . . ] information management, and can significantly improve the accuracy of asset information and the ease of control in the process of operation and maintenance."*

(Liu et al. [37])

In addition, the accessibility of data with mobile tools and applications for workers in the field represents efficiency gains [38].

However, one of the challenges of managing data from the cloud and wireless architecture is cybersecurity. The confidentiality of data collected and transmitted in the communication network must be assured. Therefore, an architecture that maintains data privacy and provides an architecture resistant to hackers must be implemented. Thus, Liu et al. [39] define a method to enhance the cyber security of data transmission in the electrical grid by security encryption method.

In brief, properly managed data generated by smart grids and data compiled for several years in electrical networks leave room for a multitude of possibilities for comprehensive analysis and highly relevant information. This crucial element must not be



neglected from AM models. Industry 4.0 tools, such as cloud computing and IoT, both help *Information and Data Management*. These application fields form the basis for other application fields.

#### 4.3.2. Budget, Investment and Cost Management

Optimizing expenses is one of the core functions of most electrical industries. In fact, budget is one of the main factors that lead most of the decisions regarding AM. As a result, many innovative methods aim to efficiently manage budget, investments, and costs.

The following section focuses on publications whose objective is to manage investments only. For the purposes of this literature review and to ensure consistency, models, methods, and processes that result in optimizing costs through, for example, improving maintenance practices, are treated in sections that fit the most their main objective (e.g., maintenance and health management).

Consequently, Butans and Orlovs [40] offer an innovative tool that optimizes investment in distribution networks based on modeling and simulation. The model considers the network evolution based on changing demand, new energy network, and storage, as well as network failures. A distinction is also made between CAPEX and OPEX expenditures.

Furthermore, Zhang et al. [41] developed an innovative method that deals with the complexity of evaluating and controlling the project cost level of transmission networks. The method is based on the k-means clustering algorithms and classification algorithm random bit forest and allows accurate cost-level evaluation.

Thus, one of the main objectives of resource management is to find the optimal level of investment that is needed to ensure long-term reliability and performance without compromising risk. Modeling and simulation combined with the use of algorithms are ways to reach this objective.

#### 4.3.3. Decision Making

Considering market evolution, aging assets, future climate change, and electrical networks being considered large complex systems, decision making in AM must include a risk analysis and is subject to uncertainty.

- Many methods and processes detailed in other application fields aim to enhance decision making. For example:
- The use of big data analytics and algorithms to establish the health index of assets contributes to decision making regarding equipment replacement and maintenance actions [42,43];
- Optimizing investments from modeling and simulation support decision making regarding budget [27];
- Simulating the long-term impact of the maintenance strategy also influences decision making relating to maintenance policies [44];
- Improving maintenance activities helps decision making related to resource constraints [45].

#### 4.3.4. Load Forecasting and Management

Big data analysis can be used to forecast electricity demand. Several authors use machine learning algorithms to forecast demand [46]. In many cases, the purpose of identifying load profiles and forecasting demand is to increase demand response along with investment and network configuration optimal planning.

#### 4.3.5. Reliability Improvement

Industry 4.0 tools help to increase grid reliability. Clements and Mancarella [45] demonstrated that automation of the grid can lead to substantial gains in reliability, especially for grids where staff availability is an issue. Their model shows a reduction in energy loss up to 24%. Those gains are even higher for networks where asset condition is critical.

Reliability is a topic ensured by many application fields. For example, most *Anomaly, outages, and failure detection and analysis* methods improve fast outage recovery and lead to minimized downtime and increased service availability.

Moreover, reliability is a factor in risk management. Many risk management applications involve reliability enhancement. Moreover, appropriate maintenance and health management of assets lead to enhanced reliability as well. Methods, processes, and publications that were associated with those keywords were presented in those respective categories.

Specifically for reliability improvement, some authors use algorithms based on neuro-fuzzy inference to assess the state of components, equipment, and complex systems [47]. Simulation is also used to predict the impact of maintenance strategy on long-term network reliability [44]. Moreover, big data from historical weather data is used, in combination with other data sources, to optimize vegetation management and minimize the risk related to the latter on the reliability of the network [48]. This optimized tree trimming planning helps to reduce by the third the risk of outages caused by vegetation and cost related to corrective actions on those outages by approximately the same proportion.

#### 4.3.6. Anomaly, Outages, and Failure Detection/Analysis

In addition to enhancing reliability and providing accurate forecasts, machine learning algorithms are used for the purposes of identifying and anticipating failures.

In literature, we recognize many innovative methods related to *Anomaly, outages, and failure detection and analysis*. First, partial discharge detection can be obtained by the combination of monitoring and algorithms that merge big data retrieved from network equipment [49].

Moreover, anomalies and faults localization of distribution networks are facilitated by the combination of IoT and faults indicators in the AM systems [50]. Hydro Ottawa also uses monitoring and big data analyses to locate faults on their distribution network. Their system combines distribution circuit data with geographic information to display the exact location of the failure [51].

Lamberti et al. [52] bring the innovation further with the development of a software architecture that allows automatic fault detection and switching operations to isolate the fault area, in a fully automated approach, without human intervention.

In brief, most *Anomaly, outages, and failure detection and analysis* innovative methods lead to enhanced reliability by ensuring fast outage recovery with a minimum of resources. Risk related to critical failures is also controlled. Ultimately, customer satisfaction is increased by this approach.

#### 4.3.7. Increase Efficiency of Inspection and Maintenance Activities

Traditional inspection techniques are improved by the use of industry 4.0 tools. In fact, IoT technology, such as RFID tags, can ensure real-time synchronization and information access [37] when combined with an efficient *Information and Data management system*. The use of algorithms also helps to optimize resources assignment to scheduled inspection [53].

By using a genetic algorithm, De Vasconcelos et al. [53] developed a model to improve inspection scheduling using network segment priority indexes. The inspection scheduling optimization leads to a reliability index augmentation of 51 percentage points. The reliability index is developed by the author, but this significant augmentation reflects the impact of using algorithms to optimize inspection scheduling.

Moreover, augmented reality can simplify and accelerate the completion of maintenance activities as it allows workers to obtain the real-time information required for maintenance activities (instructions, status data, production data, etc.).

#### 4.3.8. Maintenance and Health Management

In the electrical industry, there is a shift in maintenance practices from systematic and time-based maintenance to predictive maintenance, with industry 4.0 innovations.

Predictive maintenance can be achieved by:

- Appropriately processing heterogeneous big data;
- The IoT, as devices installed on equipment, send data that can predict necessary maintenance activities before failure [22];
- The use of algorithms and simulation methods to support the calculation of the equipment's residual life.

In brief, analyzing the real-time condition of the equipment by monitoring contributes to the maintenance policy optimization and to maintenance activities efficient planning.

Moreover, simulation is often used to compare and improve maintenance strategies in terms of reliability maximization and cost minimization [54–56]. The simulation conducted by Fleckenstein and Balzer [54] demonstrates that a risk-based maintenance model can reduce 8% of the network overall risk with a similar investment level.

Modeling also helps to analyze the electrical complex system and interdependencies while making it possible to prioritize maintenance activities depending on resource constraints [45]. As a result, industry 4.0 technologies provide appealing advantages for preventive maintenance, which contributes to minimizing the resources required and the risk of failures.

Another application of industry 4.0 tools to support maintenance and health management is to implement risk-based maintenance strategies. Risk-based maintenance strategies are an application field straddling *Risk Management* and *Maintenance and health management* as it improves the maintenance strategy and minimizes risk. Health index calculation supports risk-based maintenance strategies, and industry 4.0 tools significantly benefit the health index calculation. In fact, criticality and health index calculation can be obtained using algorithms, such as the weighted sum algorithm [57], the linear programming algorithm [42], and the k-means clustering algorithm [58]. Authors often use those algorithms to calculate the health index of a single type of equipment [42,57,58].

As a result, improvements that bring industry 4.0 tools benefit the *Maintenance and Health management* of electrical networks assets.

#### 4.3.9. Risk Management

Climate change and the effect of weather events on network reliability forces electrical industries to manage risk related to meteorological conditions. To help with this process, Clements and Mancarella [59] developed a model that predicts the reliability and resilience risk of the distribution network in extreme weather conditions and in the presence of resource constraints. Similarly, Youssefi and Moselhi [60] use artificial neural network algorithms to forecast the risk of outages from weather conditions analysis.

Risk management also includes the asset replacement strategy optimization in order to minimize the risk of critical failure and to ensure that investments are directed to assets that contribute the most to maintain an acceptable level of risk. To this aim, Johnson et al. [61] developed a framework for risk planning based on asset degradation forecast modeling and its impact on risk assessment. Goyal et al. [43] developed a similar approach to prioritize maintenance actions according to health score and risk assessment, based on big data analytics and the implementation of an algorithm. Health index calculation is also used for that purpose.

#### 4.3.10. Network Configuration Optimization

The optimal configuration, in terms of quantity and location of distribution network equipment and substation, is the subject of several studies [62–65]. The aim of this exercise is to maximize the network reliability while keeping the cost at its minimal level. For switches, the optimization model proposed by Zhang and Crossley [62] leads to an investment and maintenance cost reduction of more than 40% on a 15-year period. Then, the optimization model developed by Pouya and Javad [65] shows even higher savings, but the methodology differs as only the critical loads are considered in the optimal configuration.

The use of algorithms such as ant colony optimization algorithms [62] or imperialist competitive algorithm [63,64], along with modeling and simulation tools [65,66], contributed to upgrading this process. Life cycle cost (LCC) [66], as well as load forecasting [63], must be taken into account in this exercise.

#### 4.3.11. Electricity Consumption Optimization

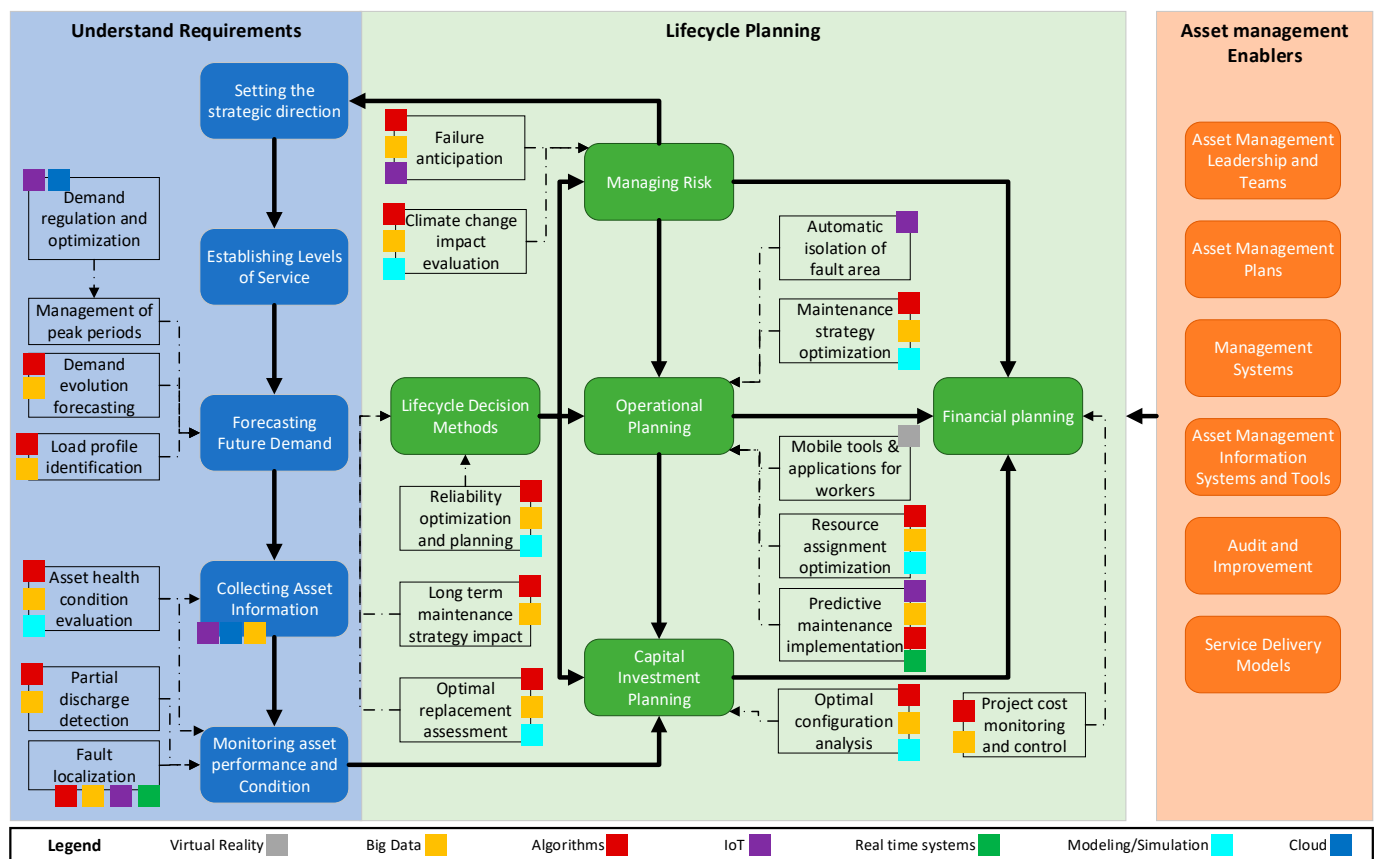
Optimization of electricity consumption affects and regulates the electricity demand. Regulating consumption makes it possible to adapt the network more easily to variations. As a result, the management of peak periods can be improved.

To do so, with the growth of the IoT, more and more household equipment contains smart electronic devices that make remote control possible. These devices promote the regulation of consumption and demand planning in an automated fashion, or not, to balance the load. Therefore, these technologies have significant impacts on electricity demand.

### 5. Discussion

#### 5.1. Industry 4.0 Impact to AM Model, from an Electrical Industry Point of View

To assess the impact on AM in the electrical industry sector from a global point of view, application fields and innovations have been matched to IIMM AM model elements [18]. Figure 6 shows the results. In this figure, industry 4.0 tools that are used in literature to achieve the activity presented are represented by a colored legend in order to simplify the visualization of the model.



**Figure 6.** Contribution of industry 4.0 tools and application fields in the electrical industry to IIMM AM model. (Model adapted from IPWEA [18]).

This analysis does not represent the exhaustive list of all benefits innovative tools bring to AM activities in electrical networks, but rather the main elements, as well as their interrelationships. The purpose of this representation is to demonstrate how the application

of a tool for a specific application area can influence the entire AM model. Thus, improving one item is beneficial for AM at the aggregate level.

It is noted that the main input of these AM solutions and improvements is big data and its pairing with adequate algorithms to ensure appropriate treatment. Big data is the key element of this fourth industrial revolution. Therefore, it could be argued that the first step to achieving industry 4.0 benefits on AM of electrical grids is to establish an efficient data management system.

Moreover, big data processing is possible through the use of artificial intelligence (AI) algorithms. Indeed, AI models are developed using data, and the more the database is fed, the more efficient the model and, moreover, the smarter. Thus, artificial intelligence and big data are two technologies that are mutually supportive. The contribution of industry 4.0 to AM will, therefore, undoubtedly go through AI.

Then, critical assets, both for system operation and risks being related to them, can benefit from IoT technology to transmit, in real-time or not, health and state data. This way, lifecycle planning can be optimized by integrating relevant algorithms based on the data collected and properly structured.

Asset lifecycle planning is a crucial part of the AM. This is the process by which we optimize the activities related to the lifecycle so as to minimize the total costs related to holding an asset. The life cycle includes the stages of acquisition, operations, maintenance, and disposal of assets. This cycle must offer optimal asset performance based on tolerated risk and minimal use of resources. Lifecycle improvement leads to optimal financial planning and resource usage. In brief, improving the life cycle of physical assets is one of the main benefits of integrating industry 4.0 tools into electrical industries.

### *5.2. Challenges in the Application of Industry 4.0 Tools*

Proper processing of big data, coupled with relevant junctions between types of data, can lead to important insights, enabling highly informed decision making and rapid reactions [22]. Electrical network data already has the hallmarks of big data. They are therefore of significant value for the company, and their management is a priority for benefiting from the advantages of those innovations.

However, one of the main challenges in the implementation of industry 4.0 tools in electrical industries is processing historical data. Issues relating to data quality as well as multiple databases, whether they are interconnected or not, are recognized. The methodology suggested by Koziel et al. [33] is a suitable first step to assess which data should be prioritized in improving their quality. Then, big data must be supported by an efficient and adequately structured management process.

Another challenge relates to risk management. Optimization models are often based on prioritizing critical loads or critical equipment. This requires comprehensive risk analysis and management to ensure that the risk related to less critical customers or assets is not significantly increased. The establishment of tolerance levels is then a crucial element for optimization models implementation.

Finally, data collected and transmitted through cloud and IoT leads to a cybersecurity challenge. There are several methods proposed in the literature to strengthen cybersecurity, but their long-term performance must be maintained and constantly improved.

## **6. Conclusions**

In the context of climate change, aging assets, and increasing reliability requirements, there are several interrelated challenges in electrical industries AM. Among these, we find:

- Significant increase in investment in assets;
- Limited financial and human resources;
- A need to prioritize investments to maximize performance while minimizing costs and risks for the entire electricity production, transmission, and distribution chain.

To overcome these issues, the objective of this publication is to conduct a literature review on the impact of industry 4.0 tools on the AM of electrical industries. Considering

the results, it can be argued that the main tools that would make it possible to overcome AM issues and the application of an integrated AM model by the energy producer, the transmission provider, and the energy distributor are:

- Modeling and simulation of the entire complex system reliability, considering:
  - o The residual life of aging equipment;
  - o Outage forecasting;
  - o Extreme weather conditions and network resilience.
- Integration of machine learning algorithms based on properly structured data from systems and equipment of these three functions to improve simulation models;
- Integration of predictive maintenance methods;
- Prioritize investments from the calculation of the health index carried out with appropriate algorithms.

These elements can minimize the use of limited resources and target investments in critical equipment and systems. They must then be integrated into an overall AM model for the entire chain. Simulation models can also prioritize maintenance actions and optimize asset replacement and maintenance strategy.

To conclude, we see that industry 4.0 is revolutionizing the traditional industry by bringing about major changes in both operational activities and business models and processes. It can support maintenance-related activities, enhance failure prediction and detection, optimize resource assignment, and enable predictive maintenance. Industry 4.0 tools also make an important contribution to risk management, performance, and resource allocation. Therefore, it benefits the balance between the three elements of the interrelation triangle presented in Figure 1.

## 7. Future Research

This exploratory research provided the basis for further analysis. Future research may help fill in the gaps in this research. First, this article presents the impact of the fourth industrial revolution on the AM of the power industry from a global perspective. Therefore, each of the application field categories could consequently be developed. For instance, preventive maintenance methods, as well as the optimization of replacement strategies, could be the subject of a specific literature review.

In addition, considering that most of the publications were from distribution and transmission networks. An additional literature review could fill that gap by precisely targeting keywords related to production assets.

Also, noting that algorithms based on big data are a key element application field, A study related to which algorithms suits best the AM activities should be conducted.

Finally, industry 4.0 tools applied in AM of other public utilities, but which, according to this literature review, are not applied in the electrical industry, could be analyzed. This analysis should make it possible to establish how these practices could be transposed to electrical industries.

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