POSTPRINT VERSION. The final version is published here :
Gauthier, F., Gaha, M., Amelete, S. G., Vaillancourt, R. et Abdul Nour, G. (2023). Maintenance optimisation using intelligent asset management in electricity distribution companies. International Journal of Product Lifecycle Management (Vol. 15, p. 44-67). doi: 10.1504/IJPLM.2023.10059254

Author's Identification

Sam Gontran Amelete*

Research Chair on Asset Management,
Industrial Engineering Department,
School of Engineering,
University of Quebec at Trois-Rivières,
3351, boul. des Forges, C.P. 500,
Trois-Rivières (Québec), G9A 5H7, Canada
Email: sam.amelete@uqtr.ca
*Corresponding author

Raynald Vaillancourt

Asset Management Team
Grid Strategy
Group - Distribution, supply and shared services
Hydro-Québec
C.P. 10000, succ Pl. Desjardins – 18e étage – Tour Est
Montréal (Québec), H5B 1H7, Canada
Email: raynald.vaillancourt@uqtr.ca

Georges Abdul-Nour*

Research Chair on Asset Management,
Industrial Engineering Department,
School of Engineering,
University of Quebec at Trois-Rivières,
3351, boul. des Forges, C.P. 500,
Trois-Rivières (Québec), G9A 5H7, Canada
Email: georges.abdulnour@uqtr.ca
*Corresponding author

François Gauthier

Research Chair on Asset Management,
Industrial Engineering Department,
School of Engineering,
University of Quebec at Trois-Rivières,
3351, boul. des Forges, C.P. 500,
Trois-Rivières (Québec), G9A 5H7, Canada
Email: francois.gauthier@uqtr.ca

Mohamed Gaha

Hydro-Québec Research Institute IREQ
Hydro-Québec
1800 Bd Lionel-Boulet,

Varennes (Québec), J3X 1S1, Canada
Email: gaha.mohamed@hydroquebec.com

Biographical Statements

Sam Gontran Amelete received an engineering degree from the Université Libre de Tunis (ULT) and a Master's degree in industrial engineering from the Université du Québec à Trois-Rivières (UQTR). He worked as a research assistant in the HQ / NSERC asset management research chair of Professor Georges Abdul-Nour. His fields of interest are Asset Management, Reliability, Intelligent Manufacturing (I4.0), simulation modeling, optimization and Lean-Six Sigma.

Raynald Vaillancourt holds a Bachelor's and a Master's degree in engineering from École Polytechnique de Montréal. He worked for Hydro-Québec for 32 years as head of Reliability and Asset management. He has collaborated with the UQTR School of Engineering for 30 years.

Dr. Georges Abdul-Nour is a professor at the Department of Industrial engineering, Université du Québec à Trois-Rivières, Canada. He received his Bachelor's and Master's Degrees in industrial engineering from the Université de Moncton, N.B. Canada. He completed his PhD at Texas Tech University; Lubbock Texas, U.S.A. Dr. Abdul-Nour authored and co-authored 10 books and books chapters, and more than 450-refereed papers in international journals and conferences proceeding, and technical reports. His research interest is in fields such as Asset Management, Reliability, Intelligent Manufacturing (I4.0), Lean-Six Sigma, Optimization; Simulation modeling; Supply Chain Management; Operations Management; Multiple-criteria decision analysis; Sustainability and JIT. He is an elected member Of the Academy of Industrial Engineering of Texas Tech. Dr Abdul-Nour hold the HQ/NSERC Research Chair in Asset-Management and He is a Fellow of ISEAM.

Dr. François Gauthier joined the Industrial Engineering Department of the Université du Quebec a Trois-Rivieres in 1998. He received his M.Sc. (1994) and Ph.D. (1997) from the Université de Sherbrooke (Canada) in the field of engineering design for safety. His current research interests are in the development and application of ergonomics and safety analysis methodologies for safety of machinery. As co-chairman of the Hydro-Quebec Asset Management Research Chair, he's involved in the risk assessment process in the context of Asset Management.

Dr. Mohamed Gaha received a Master's degree in Computer Science from Université du Québec à Montréal in 2008, and a Ph.D. degree from École Polytechnique de Montréal, QC, Canada, in 2012. From 2008 to 2012, he was affiliated as a Ph.D. scholar with Hydro-Quebec's Research Institute (IREQ). From 2012 he works as a researcher at IREQ. His current research interests include asset management, Monte Carlo simulations and machine learning.

This paper is a revised and expanded version of a paper entitled 'Asset Management, Industry 4.0 and Maintenance in Electrical Energy Distribution' presented at the IFIP (International Federation for Information Processing) International Conference on APMS (Advances in Production Management Systems) 2021: Artificial Intelligence for Sustainable and Resilient Production Systems, Nantes, France, 5 – 9 September 2021.

Maintenance optimization using intelligent Asset Management in electricity distribution companies

Abstract

This article presents the effect of Industry 4.0 (I4.0) combined with Asset Management (AM) in improving the life cycle of complex systems in Electrical Energy Distribution (EED). The boom in smart networks leaves companies in this sector no choice but to adhere to I4.0. The contribution of I4.0 to the progress of AM in maintenance in EED will therefore be demonstrated by a case study using simulation. The case study will concern the benefits of using Advanced Metering Infrastructure (AMI), the heart of smart grids, at Hydro-Québec Distribution (HQD), the primary supply authority in Quebec. The HQD network includes 4.3 million clients, on a territory of approximately 250,000 km^2 and 680,000 overhead transformers. The results are conclusive: the number of outages will drop by 7% annually and maintenance costs will fall by at least 5% per year.

Key Words
asset management; maintenance; industry 4.0; electricity distribution; smart grid; advanced metering infrastructure; AMI; stochastic simulation; artificial intelligence.

1. Introduction
These days, maintenance is considered an integral part of the key processes that make a company competitive and allow it to endure (Al-Najjar et al., 2018). AM, which is related to and supports optimal corporate decision making, is indispensable. The new revolution, known as Industry 4.0 is also required with the current advent of new technologies and the major challenges of the moment, which are due especially to the growing complexity of equipment. With the arrival of new sources of private energy (solar, wind, etc.), climate change, attention to social-environmental protection and safety, the EED sector is perfectly placed in the context stated above. Globalization, labour shortages, the need for even greater network availability and the aging of facilities are other factors that contribute to the need for this transition to excellence in maintenance in EED. It is from this perspective that a good number of companies in this sector are analyzing the possibility of utilizing AM and Industry 4.0 to integrate, optimize and improve their management processes for the life-cycle management of complex systems. The objective will be to demonstrate the efficiency of combining AM and I4.0 in life-cycle management of complex systems in EED companies. Many authors have focused only either on the use of one or a few technologies as part of smart grids, or on AM in EED. This article therefore makes it possible to link technologies in the current context of I4.0 with AM, then show the benefits of such a connection in life-cycle management of complex systems in EED. This link will first be made through a literature review of AM in EED, I4.0 and technological advances in EED. Secondly, a case study at Hydro-Québec Distribution (HQD), the EED company in Quebec, on the use of AMI (Advanced Metering Infrastructure) coupled with the development of customer voltage and consumption monitoring algorithms for the low voltage (LV) overhead network will be outlined. In this case study, maintenance without I4.0 is compared to maintenance with I4.0 through a simulation of discrete events to reveal the potential benefit of moving to I4.0.

2. Literature review
This section describes the state of the art on the application of AM and I4.0 in life-cycle management of complex systems in EED to gather the necessary information for this article.

2.1. Asset Management
Indispensable when it comes to complex system lifecycle management, Asset Management is a business function that allows an organization to extract maximum value from its assets (Shah et al., 2017). It consists of an understandable and fully integrated strategy, process, culture aimed at optimizing the efficiency,

value, profitability and performance of production and manufacturing assets (Komonen et al., 2006). The main standards that discuss AM in general, its terminology and its implementation are the ISO5500X series and PAS55 (Van den Honert et al., 2013). Van den Honert et al. (2013) compare them to reveal their similarities, differences and shortcomings. It appears that the ISO5500X series, the most recent standard, is much more detailed and comprehensive than PAS55, on which it is based (**Figure 1**).

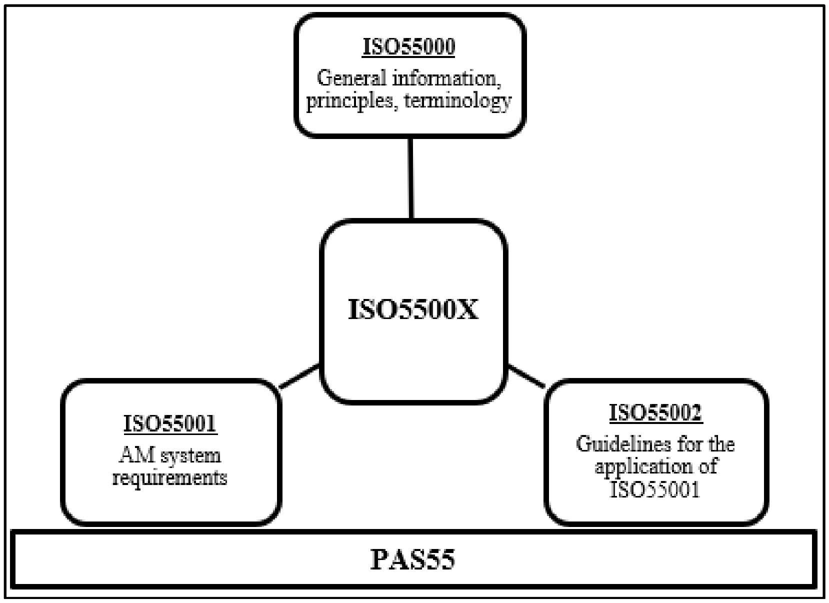

Figure 1: ISO5500X series based on PAS55

According to the ISO5500X series, AM involves a balance between costs, opportunities and risks in relation to the desired performance of assets with the goal of achieving the organization's objectives (Nieto et al., 2017). This same series of standards defines an asset as something with a potential value for an organization and for which it is responsible (Shah et al., 2017). AM is a company function that allows an organization to extract maximum value from its assets. The work of Shah et al. (2017) also reveals that AM is a mix between the fields of engineering and management that must be based on reliable, relevant and timely information while taking into account strategic business objectives. This relation with information processing was confirmed by Khuntia et al. (2016), who link AM and data management. These same authors also list the different techniques, methods and philosophies that comprise AM. They especially evoke in the EED field RCM (Reliability Centred Maintenance), CBM (Condition Based Maintenance), TBM (Time Based Maintenance), RBM (Risk Based Maintenance), and LCCA (Life Cycle Cost Analysis).

2.2. Industry 4.0 and Maintenance

Based on the literature review, the most widespread and general definition of I4.0 is the one in which Industry 4.0 would be a collective term, a revolution, grouping technologies and value chain organization concepts (Al-Najjar et al., 2018, Wang, 2016). Just as for AM, data processing is essential in I4.0. Bengtsson and Lundström (2018) observe that the new challenge for engineers is data processing in the current fourth industrial revolution. Industry 4.0 is applicable to all the processes in a company, not simply maintenance. Maintenance systems in the current framework must be sustainable, agile and interoperable. It is essential that these systems also possess the ability to manage disparate data in real time thanks particularly to I4.0 tools such as e-maintenance, smart sensors, IOT, Big Data and augmented reality. These tools are associated with AM best practices such as CBM and LCCA. According to Dąbrowski and Skrzypek (2018), smart predictive maintenance, which is simply the improvement of CBM, is a key element in the new industrial revolution. They emphasize that smart predictive maintenance makes it possible to predict the risk of failure in real time while taking into account the remaining useful life and relying on efficient data collection. Wang (2016) continues along the same lines and adds that this type of maintenance uses the tools of I4.0 [CPS (Cyber Physical Systems), IOT (Internet Of Things), Big Data and Data Mining, IOS (Internet Of Service) or Cloud Computing] to detect signs of failure, predict the future behaviour of an asset and thereby optimize operation of the asset. Nonetheless, Bengtsson and Lundström (2018) recall that the basic concepts and techniques of maintenance (lubrication, cleaning, inspection, etc.) should not be neglected in the current context of the fourth industrial revolution. They propose combining the old maintenance methods with the new emerging technologies of Industry 4.0 for a more efficient maintenance process.

2.3. Link between AM and I4.0

In general, AM includes acquisition, operation, maintenance and decommission. I4.0 allows to be proactive in context of AM. One of the links that can be established between AM and I4.0 is that AM encompasses the various maintenance policies (Germán et al., 2014, Khuntia et al., 2016), while I4.0 makes it possible to move toward predictive maintenance and, thus, to maximize an asset's productivity time and life span (Dąbrowski and Skrzypek, 2018). This section is summarized in **Figure 2**; the table below is taken from Dąbrowski et al. (2018).

AM includes maintenance policies

Destination with 4.0

Maintenance	corrective	predetermined	based on condition	predictive
Characteristics	Performed after failure	Performed at predefined intervals	Performed after observing certain conditions on an asset	**Completed on the most profitable date after the asset's RUL forecast**
Requirements	Competent staff, spare parts available, quick reactions	Deep knowledge of asset life, accurate staff planning and spare parts supply	Monitoring equipment/systems, IT infrastructure, competent staff	**Surveillance systems, IT infrastructure, data, models and algorithms**
Advantages	Maximizing asset life, no planning costs	Minimizes asset downtime, fewer wear-and-tear failures, high level of planning	Maximizes the productivity time of assets, maximizes the life of an asset	**Maximizes asset productivity time, maximizes asset life, high level of planning**
Disadvantages	Significant costs related to failure, costs due to unplanned outages	Waste of the RUL (Remaining Useful Life) of the asset, planning is expensive, it does not prevent random failures, requires intensive work	High investment in monitoring and prognostic equipment	**High investment in monitoring, prognostic and diagnostic equipment, emerging technology**

Figure 2: Link between AM and I4.0

2.4. I4.0 technologies used in EED

In the field of EED, with the advent of smart grids, and for their efficient operation, IOT, Big Data Analytics and Cloud Computing appear indispensable and encompass the other technologies.

Before turning to tools that make the network smart, it is important to understand the concept of the smart grid. Smart grids emerged with the adoption of automatic meter readers, which subsequently were improved and resulted in Advanced Metering Infrastructure (AMI) (Živic et al., 2015). AMI are considered the backbone of this new type of grid. These grids make it possible to proactively steer the EED system.

Compared to a traditional grid where only the electrical flow circulates, the smart grid disseminates not only the electrical flow but also the bidirectional information flow between EED companies and clients through AMI (Anita and Raina, 2019, Sulaiman et al., 2019). For Jaradat et al. (2015), two of the main objectives of the so-called smart grid are grid reliability and short lag time in data transmission. The characteristics listed above in such a grid result in the need for reliable monitoring in real time.

The IOT is a network of devices able to connect, interact and exchange data with each other. For Jaradat et al. (2015), its purpose is to automate operations on the network. Anita and Raina (2019) note, for example, that IOT devices like Smart Metering Architectures (SMA) or AMI allow smart grids to inform users of their consumption and to quickly detect a failure. They also make it possible to control the quality of energy, identify unauthorized uses of energy, monitor the condition of the network and quickly reconfigure it. The use of IOT such as AMI generates a significant volume of different types of data sets in real time that must be analyzed (Dudek et al., 2018, Luan et al., 2015).

Analytics is the way these data are interpreted and their meaning is communicated to the appropriate user (Khuntia et al., 2017). According to Liboni et al. (2018), new electrical engineers must possess advanced data science skills. Sulaiman et al. (2019) add that analyzing data transmitted by AMI that are in the realm of Big Data, is a data-science problem. Big Data applications require a flexible, evolving platform with large storage space (Khuntia et al., 2017).

Cloud Computing is based on the delivery of computing as a service over the Internet. The Cloud provides the interface desired and the storage space necessary to support ICT (Internet and Communication Technology) applications and manage IOT devices on smart grids. It plays a key role in obtaining upgradability, interoperability, flexibility and the integration of various services to automate the network. Cloud Computing nonetheless has a few security gaps (hacking, pirating, data theft, etc.). Big structures are advised to develop private clouds.

The emphasis must also be put on certain tools listed below that support the three leading technologies of Industry 4.0 in the EED sector. SCADA (Supervisory Control and Data Acquisition) is a real-time monitoring and control tool for the electrical network (Khuntia et al., 2017). Geographic Information System (GIS) allows a spatial representation of the electrical network in real time on a geographic map, which makes it possible to define sufficient maintenance policies for each area. AMI make it possible to collect, record and instantly transmit network measurements and a two-way communication between the customer and the supplier (Anita and Raina, 2019, Dudek et al., 2018, Živic et al., 2015, Jaradat et al., 2015). Radio-Frequency Identification (RFID) tags and Wireless Sensor Network (WSN) intervene in data collection. Block Chain is used for the secure transmission of this data (Anita and Raina, 2019). **Figure 3** summarizes the use of I4.0 in the EED sector covered in this and the preceding paragraphs.

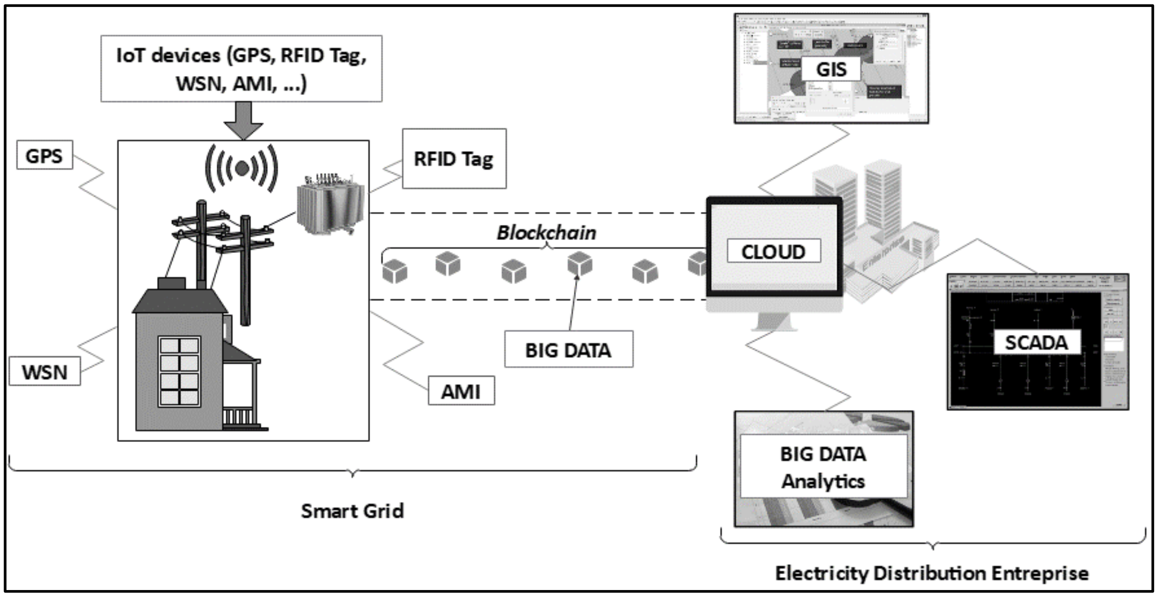

Figure 3: I4.0 technologies in EED

2.5. AI in AM and maintenance of EED networks

Mattioli et al. (2020) defined Artificial Intelligence as a branch of computer science that integrates cognitive abilities, perception, learning, abstraction, reasoning, decision, dialogue and the ability to move and manipulate objects. A more simplistic definition is given by Ochella and Shafiee (2019) which defines AI as the ability of a machine to display human-like intelligence, particularly in response to its surroundings. Ochella and Shafiee (2019) raise the importance of AI for predictive maintenance whose primary goal in this context would be the prediction of the remaining useful life of an asset for better decision making. The remaining useful life has a stochastic nature and it would be possible to predict it with advanced AI algorithms according to some confidence. The authors discussed the difference in the use of AI for the maintenance of new or modified equipment with a considerable operating time interval. The latter would use data driven AI given the availability of historical data while for new equipment it would be the symbolic AI as recommended by Mattioli et al. (2020) in the absence of data. Symbolic AI mainly concerns expert systems and rule-based engines that rely on human expert knowledge. The **Table 1** below summarizes the characteristics of data driven AI and Symbolic AI. According to a survey from McKinsey Global Institute it emerged that AI is very promising for the energy and utilities sector, especially in the areas of maintenance and optimization of assets exploitation as well as prediction of consumer behavior and energy use patterns (Ochella and Shafiee, 2019).

Table 1: Characteristics of the 2 main types of AI

AI type	**Data driven AI**	**Symbolic AI**
Framework	Historical data present	Few or no historical data
Foundation	Learning	Reasoning
Equipment type	Considerable operating time interval, Existing failures databases	New, Modified
Examples	Machine learning, Deep learning	Ontologies, Semantic graphs

The use of AI in EED maintenance is growing in importance. Mukti et al. (2014) use the ANN (Artificial Neural Network) which is an AI technique for monitoring (diagnosis) of the health status of transformers. It was noted that transformers are among the most expensive and critical components of an electrical network. Xia et al. (2018) propose the use of the deep learning techniques association that are the Convolutional Neural Network (CNN) and the Recurrent Neural Network (RNN) combined with the use of patrol robots and unmanned aerial vehicles to determine failures on power network using image recognition. This would reduce the costs generated by visual inspection patrols of lines which require considerable human and material resources. Arif and Wang (2018) used AI through the machine learning technique DNN (Deep Neural Network) to predict repair and recovery times for clients of a distribution network after the occurrence of major climatic events which most of the time cause a considerable number of interrupted customers and major planning problems in the deployments of the repair team. Motepe et al. (2019) used hybrid AI techniques to predict load in electrical power distribution while integrating temperature as a climatic parameter in order to improve the maintenance planning. Zinflou et al. (2019) use deep learning technique applied to thermal inspection of the underground distribution cable to improves the safety and the reliability of the network by detecting the potential defects of junctions based on the thermal characteristics. Gaha et al. (2021) developed a holistic framework based on Symbolic and data Driven AI for Asset Management for power utility. It analyses asset performance and grid reliability according to grid topology and customer profiles. Finally Žarković et al. (2020) rely on unsupervised machine learning and artificial neural network to create optimal maintenance plan by measuring polarization index, dielectric loss factor, idle current, short-circuit impedance. Their algorithms are trained on big data obtained during power transformer exploitation.

3. Case study: use of AMI

3.1. General information on AMI

In general, I4.0 makes it possible, in almost real time, to collect and analyze a large volume of data and develop models for predictive maintenance. The EED-specific framework is that the data to collect comes from Advanced Metering Infrastructure (AMI) that measure consumption at customer premises. HQD's benefit is that AMI is already installed and, therefore, no installation costs are incurred (**Figure 4**).

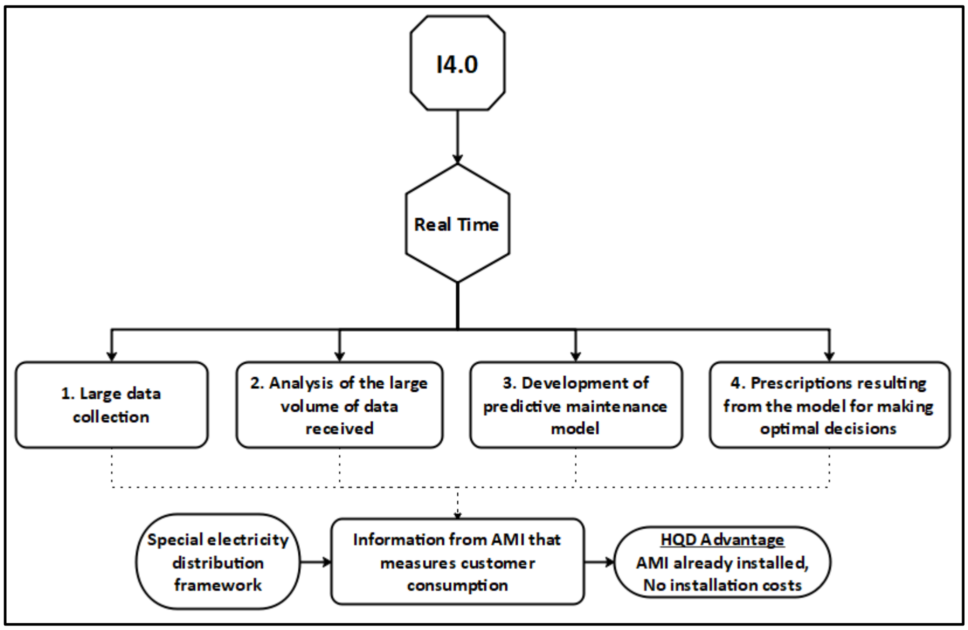

Figure 4: HQD advantage with regard to evolution to I4.0

AMI is considered to be the backbone of smart grids (Sulaiman et al., 2019). As mentioned above, they allow smart grids to educate the user on his consumption, to quickly detect a failure, to control the quality of the energy, to detect unauthorized energy uses, to monitor the network state and quickly reconfigure it (Pau et al., 2018, Anita and Raina, 2019).

Hydro-Quebec Distribution (HQD), the main distributor of electricity in the province of Quebec in Canada, supplies 4.3 million customers spread over an area of 250,000 km2. Its multi billion-dollar assets include millions of equipment, mainly structures (wooden poles, vaults and underground pipes) and electrical equipment (conductors, cables, transformers, etc.) including more than 700,000 transformers (Hydro-Québec Distribution, n.d.).

In the 2010s, HQD replaced the electricity meters used to measure the consumption of all its customers with an AMI. This infrastructure was intended to ensure the sustainability of its equipment which had reached the end of their useful life, to achieve efficiency gains with the automation of consumption reading and to integrate technological developments (Hydro-Québec Distribution, n.d.).

One of the main advantages of this new infrastructure is the measurement of the quality of the electrical supply such as the continuity of supply and the quality of the voltage. The analysis of the voltage at the customers by transformer makes it possible to identify degradations and to define actions to replace problematic equipment. **Figure 5** shows an example where the voltage at the transformer is above the nominal threshold. This voltage results from a degradation of the transformer. **Figure 6** illustrates another example where the transformer was damaged following a lightning strike that struck the distribution line (Hydro-Québec Distribution, n.d.).

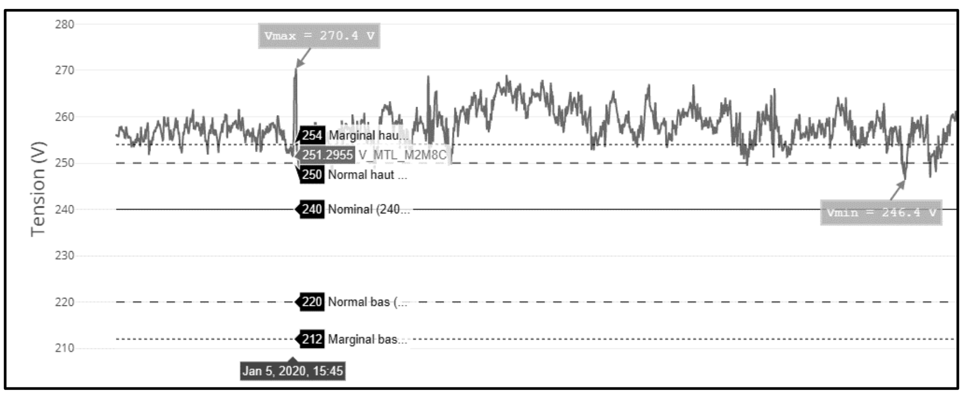

Figure 5: 100 kWa transformer with overvoltage

Analyzing the load on transformers can allow to identify overloaded ones (**Figure 7**). Overloading accelerates the aging of the transformer. In periods of extreme cold (winter peak) or following a prolonged interruption in winter (temperature ≤ -12ºC), the demand may cause an excessive overload greater than the capacity of the fuse (200% of the nominal capacity of the transformer), causing a breakdown among customers. In some cases, not knowing that the transformer is overloaded, repair is limited to changing the fuse and, consequently, customers risk another failure due to overload (Hydro-Québec Distribution, n.d.).

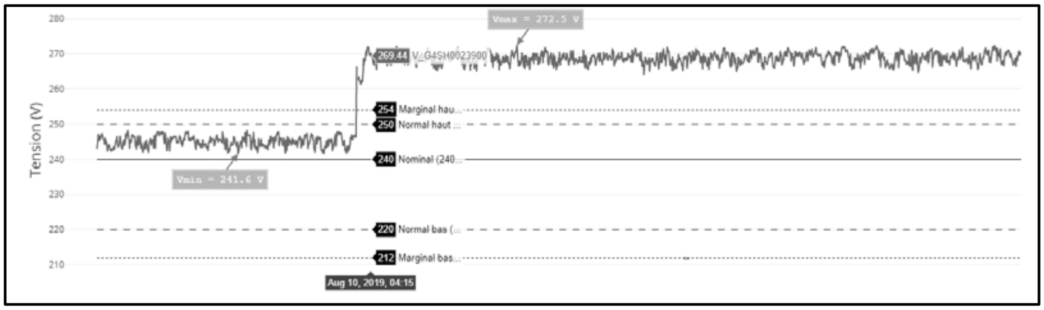

Figure 6: 25 kWa transformer damaged by lightning causing voltage problems

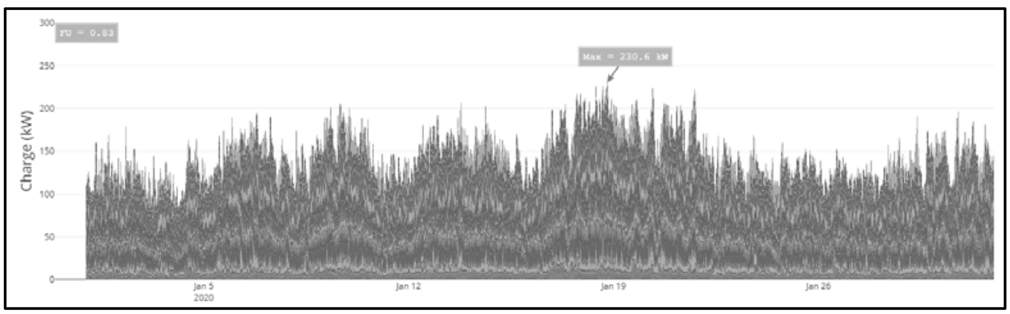

Figure 7: 100 kWa transformer overloaded

The availability of consumption per transformer every 15 minutes also improves the data used in network analysis tools. One of these data is the association of customers with transformers. **Figure 8** illustrates an association error. All customers on the same transformer should have similar voltage. However, on this transformer, there are customers with different voltages. An analysis of the transformers neighboring the customers' addresses makes it possible to find the right transformer and to correct the association (Hydro-Québec Distribution, n.d.).

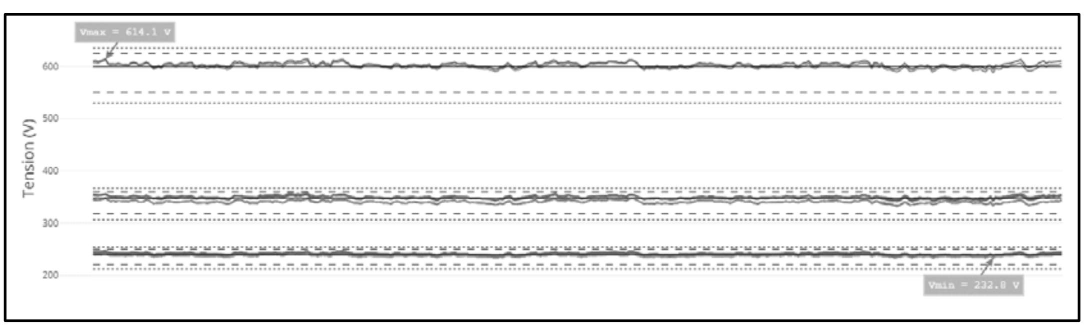

Figure 8: Transformers with an error in the association of customers and transformers

Another advantage of AMI is the possibility of knowing the status of equipment and the need for maintenance such as, for example, regulators. Prior to this system, this equipment had to be removed from the network for inspection on a regular basis. This system makes it possible to monitor their performance and initiate their maintenance at the appropriate time (Hydro-Québec Distribution, n.d.).

Given these functionalities offered by AMI, the study will make it possible to establish the profitability of their use coupled with the development of Artificial Intelligence (AI) algorithms to monitor customer voltage and consumption. This will help to identify the problems listed above before outages and breakages and will constitute the I4.0 maintenance case.

3.2. Case study

The project that consists in demonstrating the benefits of implementing I4.0 for the HQD electrical grid was the result of need combined with opportunity. The need is the necessity in the current context of AM to migrate toward predictive maintenance. The opportunity is that the data permitting this migration are available thanks to AMI installed at customer premises.

As explained above, it consists in comparing maintenance without I4.0 to maintenance I4.0 by simulating a concrete example. The simulation consists in replacing an existing system by a simpler computer model with similar behaviour. The existing system is HQD's overhead low voltage (LV) distribution system. It was selected because it is more convenient to estimate the parameters to consider such as the number of customers interrupted (CI) following an outage. The computer models were created on the Rockwell Arena simulation software. Maintenance without I4.0 is represented by an initial model illustrating the current LV overhead network, with the presence of AMI only. The maintenance I4.0 model integrates the AI algorithms discussed above. Outages as well as customers interrupted, repair time based on the type of day when the outage occurred (ND = normal day, CWD = day with a critical weather event) and the costs resulting from these outages are taken into account. The two models are compared to reveal which is most beneficial as well as the scale of the benefits.

3.3. Building the simulation model

Due to a data nondisclosure agreement with HQD, we cannot provide in-depth details on the distributions used, model logic, and what-if scenarios.

<u>**Model without I4.0**</u>

The number of failures according to the different causes from 2015 to 2019 was used. These data have been grouped according to the families of equipment and causes. The equipment families (**Table 2**) have been established in accordance with HQD. The same for **Table 3** serving as a basis for the grouping of causes, inspired by the standards of the Institute of Electrical and Electronics Engineers (IEEE) std 1366, IEEE std 1782 and the Canadian Electricity Association (CEA). Numbers in parentheses represent HQD ratings.

Table 2: Grouping of equipment

Families	Equipments	
Driver	(10) Driver (13) Tie wire	(15) Connector (16) Insulator
LV cable	(12) Low voltage network	
Surge arrester	(17) Surge arrester (30) Circuit breaker (33) Voltage regulator	(34) Capacitor (35) Stepper
Fuse	(18) Fuse	
Switching device	(20) Circuit breaker (21) Disconnector (23) Automatic disconnector	(22) Three-pole switch (31) Automatic switch
Overhead transformer	(32) Overhead transformer	
Post	(40) Post (41) Anchor and shroud	(42) Traverse (44) Aerial accessory
Unknown	(45) None (aerial)	(46) Others (aerial)

Source: (Hydro-Québec Distribution, n.d.).

Table 3: Grouping of the causes of failures

Root causes (IEEE std 1782-2014)	HQD causes	
Equipments	(11) Default (12) Overload (13) Assembly (14) Protection	(15) Non-quality (33) Obsolete (wear and tear) (57) Customer equipment
	(31) Substance (salt)	(32) Industrial pollution
Public	(34) Fire / gas leak (54) Vehicle	(55) Purpose (56) Vandalism
Wildlife	(52) Bird	(53) Animal
Lightning	(21) Lightning	
Atmospheric conditions	(22) Precipitation (24) Natural disaster	(25) Wind (26) Extreme temperature
Vegetation	(51) Vegetation	
Others	(41) Maneuver error (42) Accidental contact	(43) Tests (44) Sec. unplanned
Unknown	(58) Undetermined	(59) Info not provided
Scheduled outages	(60) Review (61) Maintenance (62) Network modification (63) Safety work (64) Safe maneuvers	(65) Maneuvers (66) Public safety (67) Customer request interruption (68) Network strengthening (69) Special program
Loss of power	(70) Critical MOT (71) Scheduled (72) Faults	(73) Remote load shedding (74) Cyclic load shedding (79) Other producer

Source: (Hydro-Québec Distribution, n.d.).

For the predictive part of the simulation models (from 2020), it was assumed that the number of failures increases each year since the improvement projects which could take place during these years and which could cause a consequent decrease of failures are not taken into account. To represent this increase in the models, a triangular distribution (TRIA) was chosen. This distribution has for parameter the minimum, the equiprobable which was confused with the mean and the maximum. It will be noted TRIA (minimum, equiprobable, maximum).

Two types of failure occurrence days are to be distinguished. The repair time varies according to this type of day and follow a Triangular Distribution TRIA (minimum, equiprobable, maximum). The type of day was fit to a Discrete distribution DISC(%ND, ND, %CWD, CWD). The likelihood to have a failure a Normal Day (ND) or a Critical Weather event Day (CWD) depend on the equipment and the cause of the failure. The repair time on a ND is obviously less important than CWD one.

The number of interrupted customers (we are talking here about unplanned interruptions leading to a decrease in customer satisfaction) per failure follows a TRIA(minimum, equiprobable, maximum) customers.

The cost data for poles follows a TRIA(minimum, equiprobable, maximum) $. As only breakdowns are considered, only corrective repair orders have been taken into account.

Transformer costs are allocated according to the cause of the failure and the type of transformer.

Costs for other families of equipment vary depending on the ease of access to the equipment and the type of day when the outages occurred.

Impact of I4.0

Maintenance I4.0 will make it possible to reduce a certain number of failures in the fuse equipment family and to switch a certain number of failures in the transformer, LV cable equipment families to planned interruptions. These failures are mainly due to the overload cause which belongs to the equipment cause group. Indeed, the algorithm will make it possible to detect the overload of a transformer and to replace it preventively (which generates a planned interruption) before the occurrence of the failure. Some irregularities in the LV cable due to this transformer overload can also be resolved in planned interruptions before they cause outages. For the fuse, it blows very often due to overload of the transformer and prevents the transformer from failing, so it can blow several times and each time be replaced correctively before the overloaded transformer eventually fails. By detecting transformer overload earlier, these repetitive failures on the fuse can be avoided.

We made the assumption that the failures that occurred during the CWD are all due to the type of cause overload. The failures to be avoid or to be placed in planned interruptions are in priority those which arrived during CWD. Failures occurring during ND's are only involved if the total number of failures to be avoid or to be placed in planned interruptions exceeds the number of CWD day type failures. These assumptions come from the fact that during major meteorological events, it very often happens that several customers who have been deprived of power are restored simultaneously. If these customers switch on their devices at almost the same time, this causes a peak in consumption and, subsequently, the overloading of the transformers.

For transformer, failures preventable by I4.0 will be caused to change into planned interruptions. These interruptions involve costs. We made the assumption that we will use the costs of the type of cause = burned for the framework of the type of cause = overload.

The I4.0 will make it possible to prioritize failures with the type of cause = overloaded [burned] into planned interruptions. If there are still failures to be transferred to planned interruptions, the failures due to other causes will also be transferred until the total number of failures to be changed to planned interruptions is reached for the transformer equipment family.

Failures that can be avoided by I4.0 on the LV cable are led to switch to planned interruptions. These interruptions involve costs. An estimate (expert opinion) according to which the reduction in cost by going from failure to planned interruption for the LV cable is proportional to that of the transformer, whatever the type of cause on average is made. It is assumed that this decrease varies from 20% to 30% (expert opinion). A uniform distribution (UNIF) of parameter (minimum, maximum) can therefore be modeled on this reduction.

The I4.0 will prioritize failures occurring during major events to planned interruptions, for the cause type = overloaded [equipment]. If there are still failures to be transferred to planned interruptions, the failures arriving on normal days will also be transferred until the total number of failures to be transferred to planned interruptions is reached for the LV cable equipment family.

Failures preventable by I4.0 for the fuse are made to disappear. The cost for these failures will therefore be null. The I4.0 will eliminate faults occurring during major events as a priority, for the type of cause =

overloaded [equipment]. If there are still failures to be saved, the failures appearing during normal days will also be subtracted until the total number of failures to be saved is reached for the fuse equipment family.

The number of failures, cost and interrupted customers related to these failures of other equipment are not modified in this specific case of use of I4.0 (AMI + development of AI to monitor customer voltage and consumption). Comparison of the model without I4.0 and with I4.0 for transformers, LV Cables and fuses is summarized in **Figure 9**.

3.4. Model logic

The programming logic of simulation models without and with I4.0 under Arena is represented by the Unified Modeling Language (UML) activity diagrams in **Figure 10** and **Figure 11** to **Figure 14** respectively.

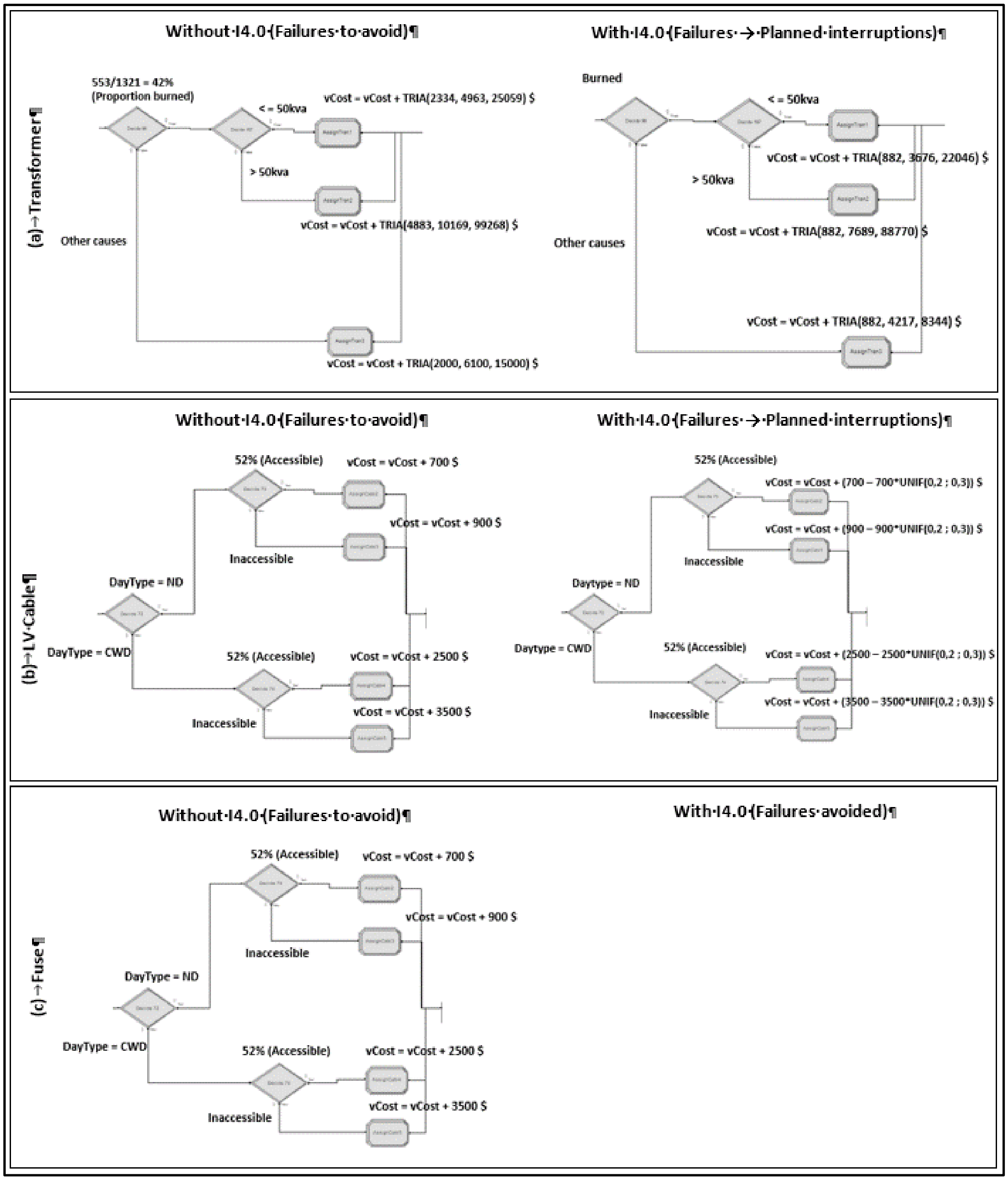

Figure 9: Effect of I4.0 on (a) transformers, (b) LV cables and (c) fuses

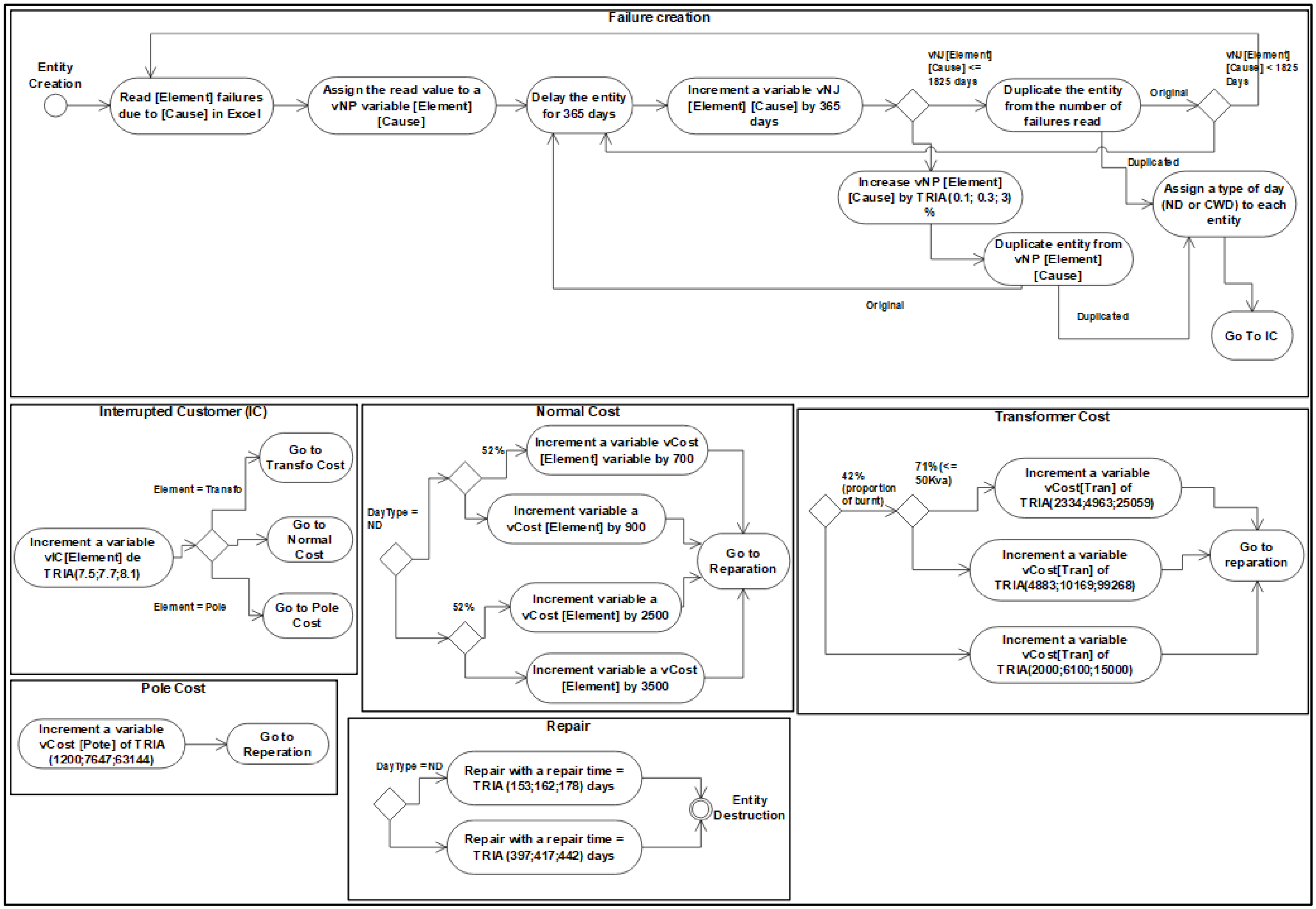

Figure 10: UML activity diagram of model without I4.0

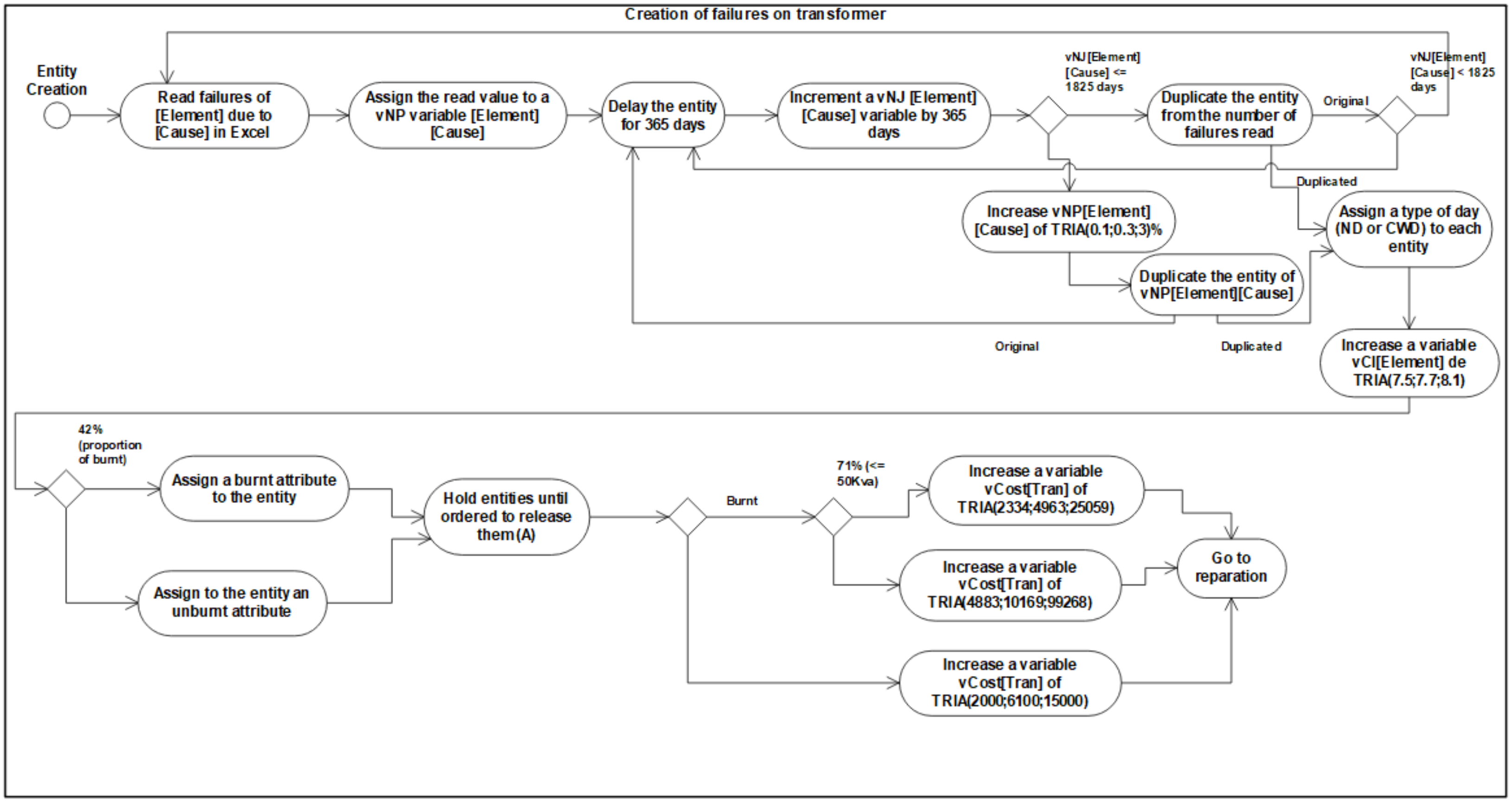

Figure 11: UML activity diagram of the effect of I4.0 on transformer 1

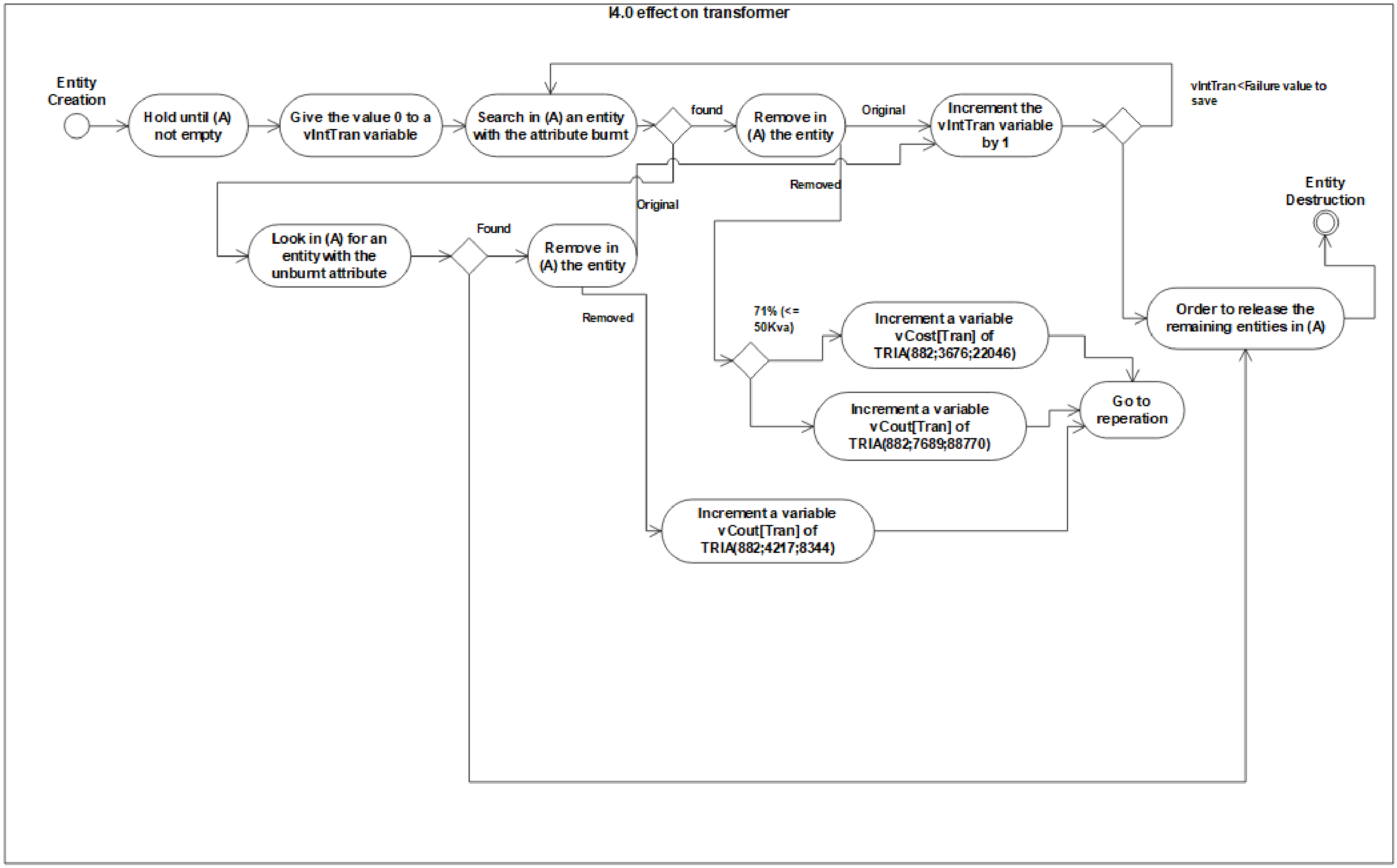

Figure 12: UML activity diagram of the effect of I4.0 on transformer 2

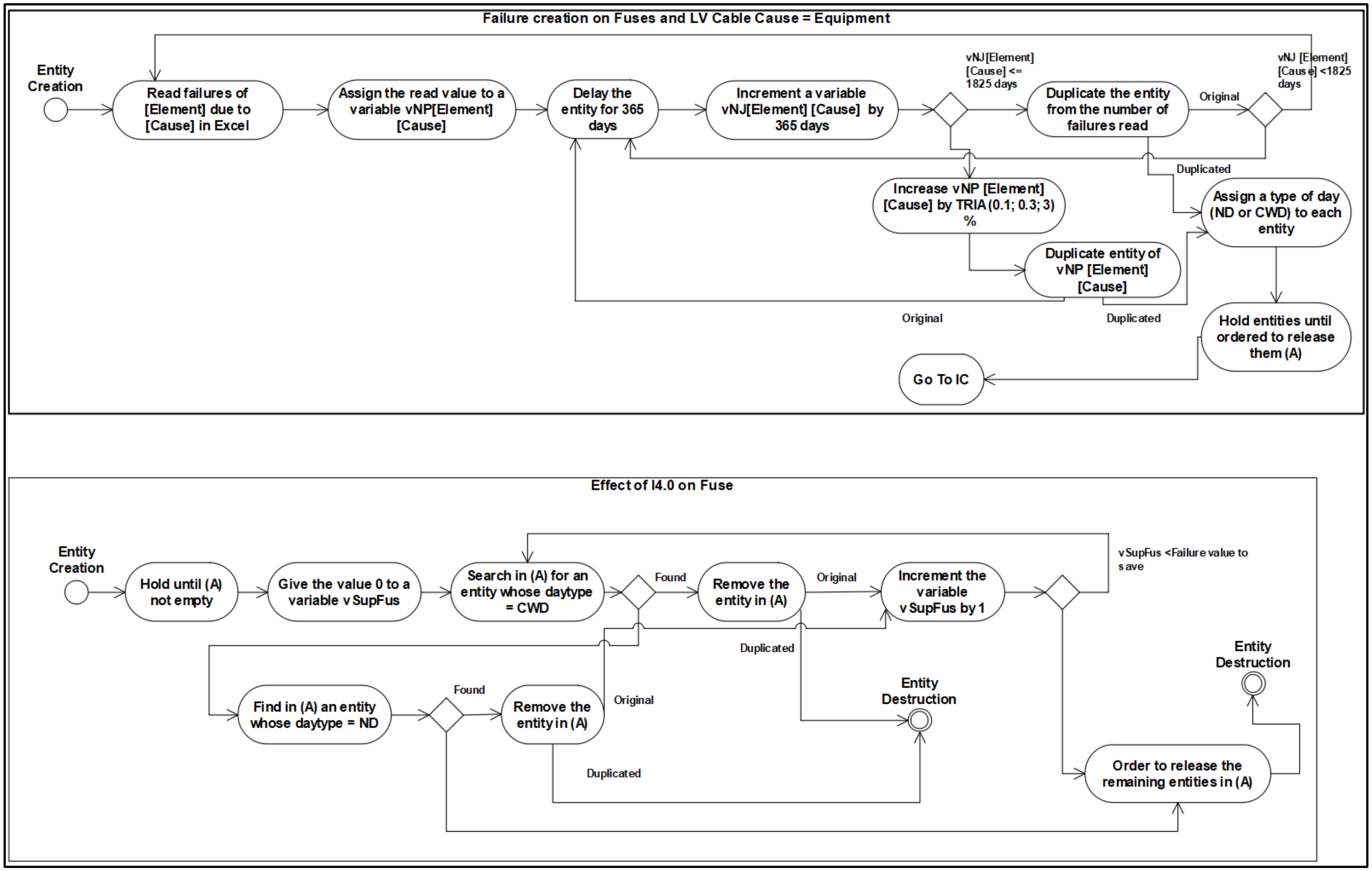

Figure 13: UML activity diagram of the effect of I4.0 on fuse and LV cable 1

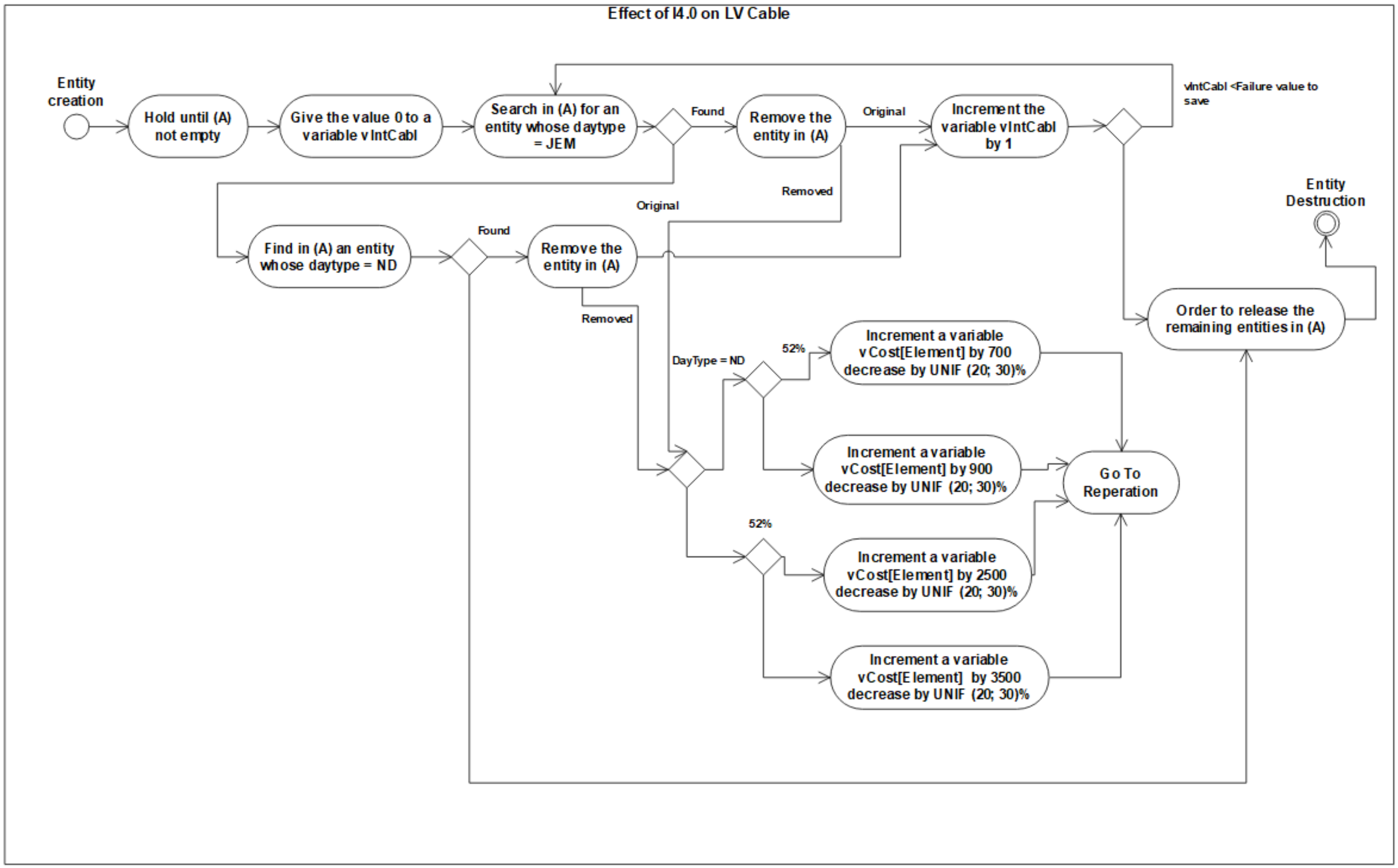

Figure 14: UML activity diagram of the effect of I4.0 on fuse and LV cable 2

3.5. Steady state and validation

As simulation models are finite horizon, the steady state is implemented from the beginning of the simulation (**Figure 15**). The main outcomes (number of outages, number of CI, costs) are incremented every year. The number of replications was set at 30. With these 30 replications, the percentage of error (half width interval) in the outcomes was cumulatively less than 1% at the end of 2019 (**Table 4**). The models were configured to roll from 2015 to 2024. The period from 2015 to 2019 made it possible to verify that the program indeed behaves like HQD's actual LV overhead network. The Real/Simulated relationship is presented in **Table 5** for the cumulative outcome values from 2015 to 2019. We note that it is very close to 1 for the number of outages and the number of customers interrupted. Regarding costs, the values and distributions selected were estimated based on equipment samples. These estimates are supposedly representative of reality, as are the costs resulting from the models.

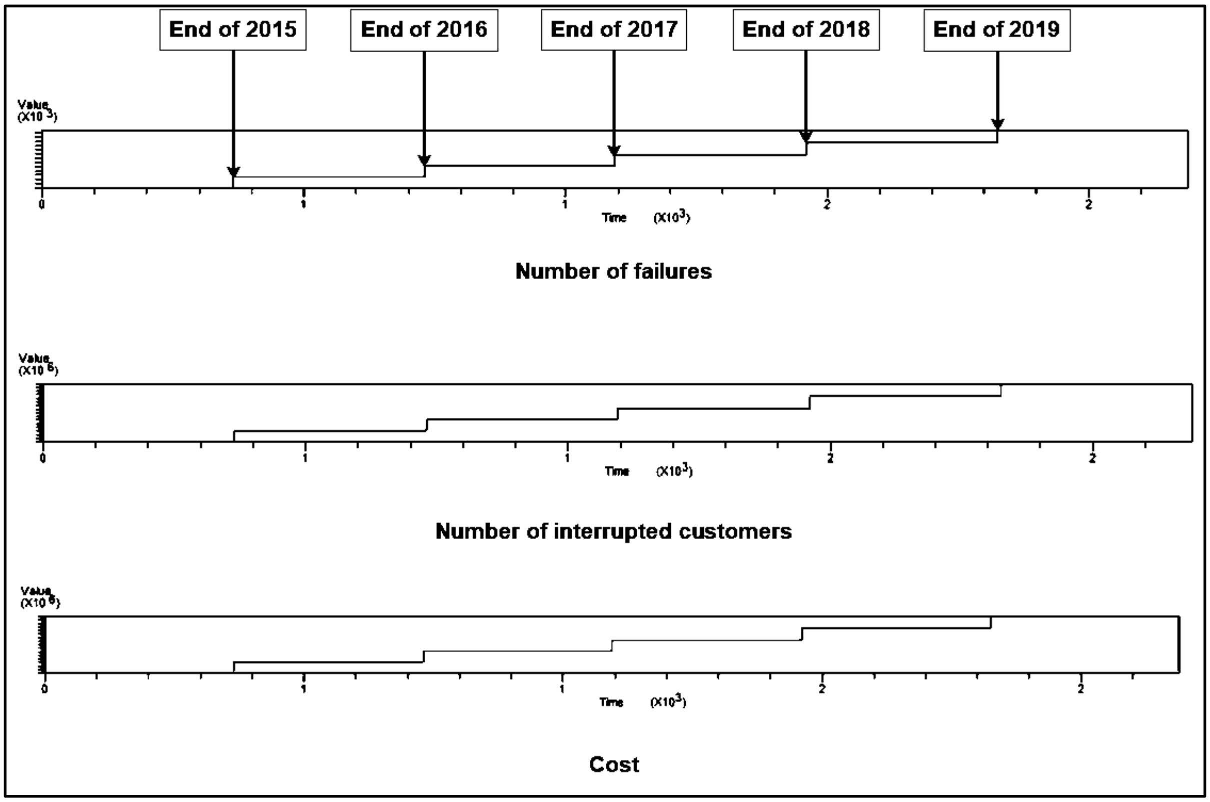

Figure 15: Justification of the steady state from the launch of the simulation

Table 4: Percentage of error in quantitative outcome

Quantitative outcome	Error (Half width)/Average(%)
Total number of outages	0%
Total CI	0.001%
Costs	0.116%

Table 5: Real/Simulated Relationship

Quantitative outcome	Real/Simulated Relationship
Outages	0.982
Customers interrupted	1.016
Costs	The values and distributions selected were estimated based on equipment samples that are representative of reality

3.6. Results and discussion

The main outcomes quantified were the number of outages, the number of customers interrupted and maintenance costs. **Figure 16 to 18** present these outcomes for maintenance without I4.0 and maintenance with I4.0. For the figures, the y-axes are not filled in and the results are presented as a percentage, still in the context of the non-disclosure of data.

The simulation shows that with I4.0, outages would be reduced by an average of 7% per year (**Figure 16**). The number of customers interrupted also fell by an average of 7% annually (**Figure 17**), which is because the number of outages and customers interrupted are correlated [1 outage corresponds to a triangular distribution of parameters 7.5 (minimum), 7.7 (equiprobable), and 8.1 (maximum) of customers interrupted].

Costs would be reduced by 5% per year on average with I4.0 (**Figure 18**). In fact, for LV cables and transformers, with I4.0, replacement of the equipment for which failure can be predicted should be planned. Maintenance would therefore be performed on a regular basis and would make it possible to avoid costs related to overtime for corrective maintenance. Regarding fuses, a proportion of outages would be totally avoided with I4.0. Maintenance activities that could result in this proportion of outages would therefore be avoided along with the related costs.

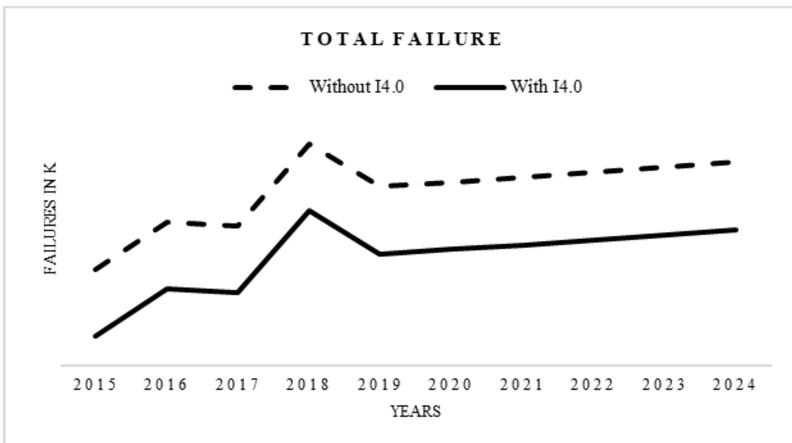

Figure 16: Comparison between Maintenance without and with I4.0 in term of outages

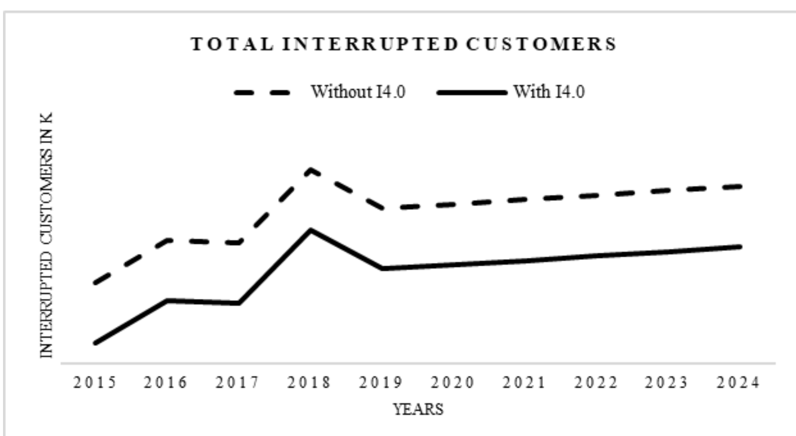

Figure 17: Comparison between Maintenance without and with I4.0 in term of customers interrupted

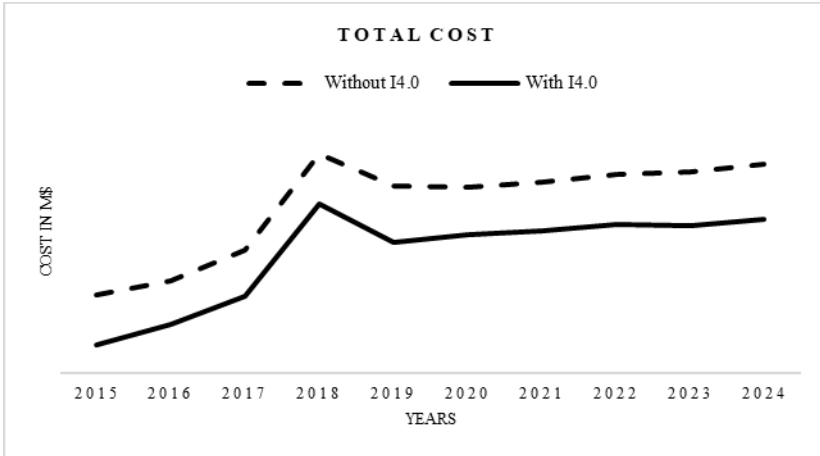

Figure 18: Comparison between Maintenance without and with I4.0 in monetary term

3.7. Discussion

The case of maintenance I4.0 focused on fuses, transformers and LV cables in the study. Furthermore, the database used takes into account only the primary volumes of outages on equipment and their causes. Had the effect of I4.0 on other equipment and volumes beyond the primary ones been considered, greater benefits would have been found. Furthermore, the benefits resulting from detecting customer/transformer mismatch, transformers not connected to at least one client could be explored in a later study. A next step resulting from this analysis would be to develop the AI algorithms required considering the potential benefits.

4. Conclusion

Firstly, the literature review reveals the link between AM and I4.0. AM includes the various maintenance policies and I4.0 will make it possible to move toward predictive maintenance. On the other hand, we note through the literature review that the IOT, Big Data analytics and Cloud Computing appear indispensable with the advent of smart grids and for their efficient operation in the current context of I4.0 and AM. Other tools that support these technologies such as AMI that form the heart of these smart grids, SCADA, GIS and Block Chain should also be considered. The literature review also allows us to distinguish 2 main types of AI which are data driven AI based on learning and symbolic AI based on reasoning

Data collection was one of the biggest tasks for the case study. Through the simulation, the relevance and benefits of matching I4.0 with AM in the EED sector have been demonstrated for customer satisfaction, resource optimization and in monetary terms. I4.0 and AM therefore become indispensable for improving life-cycle management of complex systems in EED. To the best of our knowledge, this study is the first to show the profitability of using I4.0 with AMI for an electrical grid.

References

AL-NAJJAR, B., ALGABROUN, H. & JONSSON, M. 2018. Maintenance 4.0 to fulfil the demands of Industry 4.0 and Factory of the Future. International Journal of Engineering Research and Applications, 8, 20-31.

ANITA, J. M. & RAINA, R. Review on Smart Grid Communication Technologies. 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 2019. IEEE, 215-220.

ARIF, A. & WANG, Z. Distribution Network Outage Data Analysis and Repair Time Prediction Using Deep Learning. 2018 IEEE International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 24-28 June 2018 2018. 1-6.

BENGTSSON, M. & LUNDSTRÖM, G. 2018. On the importance of combining “the new” with “the old” – One important prerequisite for maintenance in Industry 4.0. Procedia Manufacturing, 25, 118-125.

DĄBROWSKI, K. & SKRZYPEK, K. 2018. The Predictive Maintenance Concept in the Maintenance Department of the “Industry 4.0” Production Enterprise. Foundations of Management, 10, 283-292.

DUDEK, G., GAWLAK, A., KORNATKA, M. & SZKUTNIK, J. Analysis of smart meter data for electricity consumers. 2018 15th International Conference on the European Energy Market (EEM), 2018. IEEE, 1-5.
GAHA, M., CHABANE, B., KOMLJENOVIC, D., CÔTÉ, A., HÉBERT, C., BLANCKE, O., DELAVARI, A. & ABDUL-NOUR, G. 2021. Global Methodology for Electrical Utilities Maintenance Assessment Based on Risk-Informed Decision Making. Sustainability, 13, 9091.
GERMÁN, M. O., MOLINA, J. D., ROMERO, A. A., GÓMEZ, H. D. & GARCÍA, E. Power Asset Management: Methods and experiences in Colombian power system. 2014 IEEE PES Transmission & Distribution Conference and Exposition-Latin America (PES T&D-LA), 2014. IEEE, 1-6.
JARADAT, M., JARRAH, M., BOUSSELHAM, A., JARARWEH, Y. & AL-AYYOUB, M. 2015. The Internet of Energy: Smart Sensor Networks and Big Data Management for Smart Grid. Procedia Computer Science, 56, 592-597.
KHUNTIA, S. R., RUEDA, J. L., BOUWMAN, S. & VAN DER MEIJDEN, M. A. 2016. A literature survey on Asset Management in electrical power [transmission and distribution] system. International Transactions on Electrical Energy Systems, 26, 2123-2133.
KHUNTIA, S. R., RUEDA, J. L. & VAN DER MEIJDEN, M. A. 2017. Smart Asset Management for electric utilities: Big data and future. Asset Intelligence through Integration and Interoperability and Contemporary Vibration Engineering Technologies. Springer.
KOMONEN, K., KORTELAINEN, H. & RÄIKKONEN, M. 2006. An Asset Management framework to improve longer term returns on investments in the capital intensive industries.
LIBONI, L. B., LIBONI, L. H. & CEZARINO, L. O. 2018. Electric utility 4.0: Trends and challenges towards process safety and environmental protection. Process Safety and Environmental Protection, 117, 593-605.
LUAN, W., PENG, J., MARAS, M., LO, J. & HARAPNUK, B. 2015. Smart meter data analytics for distribution network connectivity verification. IEEE Transactions on Smart Grid, 6, 1964-1971.
MATTIOLI, J., PERICO, P. & ROBIC, P. Artificial Intelligence based Asset Management. 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), 2-4 June 2020 2020. 151-156.
MOTEPE, S., HASAN, A. N. & STOPFORTH, R. 2019. Improving load forecasting process for a power distribution network using hybrid AI and deep learning algorithms. IEEE Access, 7, 82584-82598.
MUKTI, P. H., PAMUJI, F. A. & MUNIR, B. S. Implementation of artificial neural networks for determining power transfomer condition. 5th International Symposium on Advanced Control of Industrial Processes (ADCONIP2014), Hiroshima, Japan, 2014. Citeseer, 473-477.
NIETO, D., AMATTI, J. C. & MOMBELLO, E. 2017. Review of Asset Management in distribution systems of electric energy–implications in the national context and Latin America. CIRED-Open Access Proceedings Journal, 2017, 2879-2882.
OCHELLA, S. & SHAFIEE, M. Artificial intelligence in prognostic maintenance. Proc. 29th Eur. Saf. Reliab. Conf. ESREL 2019, 2019. 3424-3431.
PAU, M., PATTI, E., BARBIERATO, L., ESTEBSARI, A., PONS, E., PONCI, F. & MONTI, A. 2018. A cloud-based smart metering infrastructure for distribution grid services and automation. Sustainable Energy, Grids and Networks, 15, 14-25.
SHAH, R., MCMANN, O. & BORTHWICK, F. 2017. Challenges and prospects of applying Asset Management principles to highway maintenance: A case study of the UK. Transportation Research Part A: Policy and Practice, 97, 231-243.
SULAIMAN, S., JEYANTHY, P. A. & DEVARAJ, D. Smart Meter Data Analysis Issues: A Data Analytics Perspective. 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), 2019. IEEE, 1-5.
VAN DEN HONERT, A., SCHOEMAN, J. & VLOK, P. 2013. Correlating the content and context of PAS 55 with the ISO 55000 series. South African Journal of Industrial Engineering, 24, 24-32.
WANG, K. 2016. Intelligent predictive maintenance (IPdM) system–Industry 4.0 scenario. WIT Transactions on Engineering Sciences, 113, 259-268.
XIA, Y., LU, J., LI, H. & XU, H. A Deep Learning Based Image Recognition and Processing Model for Electric Equipment Inspection. 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), 20-22 Oct. 2018 2018. 1-6.
ŽARKOVIĆ, M. D., STOJKOVIĆ, Z. M., SHILJKUT, V., ĐORĐEVIĆ, M. & TOMAŠEVIĆ, M. POWER TRANSFORMERS ASSET MANAGEMENT BASED ON MACHINE LEARNING. The 12th Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER 2020), 9-12 Nov. 2020. 127-134.

ZINFLOU, A., TREPANIER, M., BEN SIK ALI, O., CAUCHON, L., MIRALLES, F., MAGNAN, M.-A. & RACINE, J. 2019. Deep learning techniques applied to thermal inspection of the underground distribution cables. Montreal AI Symposium / Symposium IA Montréal.
ŽIVIC, N. S., UR-REHMAN, O. & RULAND, C. Evolution of smart metering systems. 2015 23rd Telecommunications Forum Telfor (TELFOR), 2015. IEEE, 635-638.