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Optimizing AMI Control Centres through Machine Learning: A Review

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ABSTRACT

Modernizing electrical grids requires advanced metering infrastructure (AMI), which gives users and suppliers energy usage data and boosts grid efficiency. Utility smart meter operation centres monitor and analyse these benefits to maintain them. However, the massive data quantities make manual data management impractical. This paper discusses how data analytics and machine learning (ML) can automate and optimize this process to improve control centre decision-making. Our research examines global smart meter implementation and how ML helps operators with identifying problems, preventive maintenance, network selection and cybersecurity. These applications decrease manual labour, enhance accuracy and boost productivity. We also discuss recent AMI trends to help utilities, governments and regulators plan energy. This article shows ML's disruptive potential in smart meter management by focusing on network dependability, operational safety, maintenance optimization and cybersecurity. Our findings show how ML permits utilities to provide a seamless, robust and customer-centred experience, bolstering AMI as a modern electric grid basis.

1. Introduction

The implementation of Advanced Metering Infrastructure (AMI) has helped to increase the efficiencies of electricity providers around the world. AMI as one of the key enablers of grid modernization has allowed utilities to understand better their consumers' electricity consumption through the data collected via smart meter. The two-way communication between smart meter and data centres allows utilities to collect data and send commands such as on demand read (ODR) when required. As for the customer, they are now able to monitor their daily consumptions and send a request which will be processed on the same day by the utilities. This has greatly increased the

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confidence of the customers to the utilities. In addition to that, consumers and prosumers are also able to enjoy other offerings with the implementation of AMI such as auto-billing, daily consumption data monitoring, net metering, energize and de-energization notification, power failure and storage notification, demand response [1] and also increase their awareness on the contributed carbon foot print from their daily electricity consumption. As for the utilities, the benefits gained from the implementation are lower metering and billing expenses, decreased outage costs and consumer discomfort, improved safety and fewer capital expenditures [2].

Since the early adoption of the technology, utilities and customers have benefited significantly from AMI. Consequently, more utilities worldwide are now supporting its use. This is demonstrated by the increasing number of AMI, where 1.06 billion smart meters consisting of electricity, gas and water smart meters are reported to be placed by the end of 2023 [3]. The most mature AMI implementation is available in North America [4] where 77% electricity meters are replaced with smart meters. Followed by Asia Pacific region with 60% smart meter installed in the area by 2023 [3]. Not falling far behind, with 80% penetration rate are the European countries such as Sweden [5], Denmark, Finland and Estonia [6], Spain [7], Norway and Luxembourg [8], Latvia and Italy [9], France [10], Malta [11], Slovenia and the Netherlands [12]. As for Portugal, Austria and Great Britain [13] and Ireland [14] have continued with the current roll outs and targeting to reach 80% by 2024 [15]. However, not all European countries are progressing well with the AMI technology, where Bulgaria, Cyprus, Czechia and Romania [16], Germany [17] and Greece [18] have very few smart meters. And as for Belgium, Croatia and Poland [19], Slovakia, Lithuania and Hungary are yet to start the AMI implementation [15]. Compared to the Asia Pacific region, China led the penetration as the country has completed their rollout in 2020 and will be followed closely by Japan and South Korea within the next few years. Other countries in Asia Pacific that have embark in AMI journey are such as Vietnam [20], Australia [21], Malaysia [22], Indonesia [23], Taiwan [24], Singapore [25], Philippines [26] and Thailand [27]. With almost 11 million smart meters installed in Saudi Arabia [28] by end of 2025 and 1.6 million in the United Arab Emirates [29] which expected to complete by 2029, the Middle Eastern is not falling far behind in the race to modernize its grid. This can be seen with other Middle Eastern countries following the initiative such as Iran [30], Lebanon [31] and Kuwait [32]. In South American, Brazil [33] as the region's largest and most advanced market, is expected to increase the smart meter installation from 5.6% in 2023 to 18.8% in 2029. The number of increasing smart meter installed worldwide shows the grid modernization is inevitable. Despite due to the aging infrastructure, it is also to ensure the increasing demand of electricity will be distributed successfully. AMI is also the enabler to environment sustainability in reducing greenhouse gas emission. With the data collected from the smart meter, utilities, authorities and government agencies are able to plan better by optimizing energy usage, reduce losses and support decarbonization of energy sector. Total number of smart meters installed in selected country is summarize in Table 1.

Table 1
Number of smart meters installed in selected countries

No.	Country	Number of smart meters deployed	Updated Year	Reference
1.	US	119,000,000	2022	[4]
2.	Italy	36,700,000	2019	[9]
3.	France	35,000,000	2022	[10]
4.	United Kingdom	32,000,000	2023	[13]
5.	Spain	12,600,000	2023	[7]
6.	Saudi Arabia	10,000,000	2022	[28]
7.	Sweden	5,400,000	2018	[5]
8.	Vietnam	4,000,000	2020	[20]
9.	Australia	3,300,000	2019	[21]

10.	Netherlands	3,000,000	2016	[34]
11.	Malaysia	2,300,000	2022	[22]
12.	Mexico	2,000,000	2018	[35]
13.	United Arab Emirates	2,000,000	2021	[29]
14.	Ireland	1,627,000	2024	[14]
15.	Poland	1,300,000	2019	[19]
16.	Indonesia	1,200,000	2023	[23]
17.	Taiwan	1,170,000	2023	[24]
18.	Iran	1,000,000	2022	[30]
19.	Singapore	650,000	2022	[25]
20.	Estonia	625,000	2017	[6]
21.	Greece	500,000	2023	[18]
22.	Brazil	500,000	2023	[33]
23.	Romania	320,000	2020	[16]
24.	Luxembourg	300,000	2020	[8]
25.	Malta	270,000	2014	[11]
26.	Lebanon	200,000	2019	[31]
27.	Germany	160,000	2021	[17]
28.	Philippines	140,000	2023	[26]
29.	Kuwait	120,000	2022	[32]
30.	Thailand	116,000	2021	[27]

Frequently, consultancy firms with industry interests provide reports on the number of smart meters installed globally. However, accessing these reports can be challenging for researchers due to costly subscription fees. Compiling this information offers a clearer view of AMI adoption and market penetration in each region, enabling benchmarking, comparative analysis and insights into best practices, challenges and emerging technologies. To the best of the authors' knowledge, no article has yet reviewed the application of ML for the benefit of smart meter operators as shown in Table 2. This paper aims to address this gap by offering a comprehensive review of smart meter installations, focusing on operational challenges in AMI data management and the role of AI in enhancing decision-making for smart meter operation centre.

The key contributions of this paper are:

i. A comprehensive review of the current global status of smart meter deployment, highlighting associated challenges.
ii. An analysis of ML applications in AMI and their potential to support operators in control centres with daily tasks.
iii. Insights into the latest trends in AMI, aiding stakeholders like utility companies, governments and regulators in planning future energy roadmaps.
iv. Identification of four critical areas for smart meter operators, where ML can enhance efficiency and decision-making.

Despite its introduction in the early 2000s, AMI deployment is still expanding, especially in regions like the Middle East and Asia, demonstrating its benefits to utilities and consumers, while indicating room for further improvements.

The rest of the paper is organized as follow: Section 2 discusses on the challenges in managing AMI data in a large-scale deployment. Section 3 talks about the application of ML in AMI focusing on the area of fault detection, preventive maintenance, network selection and detection of cybersecurity threats. Section 4 reviews on the challenges in the implementation of ML in AMI ecosystem. Followed by Section 5 that explains on the future works and lastly, discussion and conclusions in Section 6.

Table 2
List of review paper on AMI

Paper Title	Author, Ref	Summary	Ref
AMI Standard and Communication Technologies	Garcia-Hernandez	Discussed on the most relevant communication technology strategies to implement AMI.	[36]
AMI Analytics-A Case Study	Jha *et al.,*	Study on analytics developed based on smart meter data based on Puducherry Smart Grid Pilot Project.	[37]
A game Theory Model for Electricity Theft Detection and Privacy-Aware Control in AMI systems	Cárdenas *et al.,*	The paper shares a model to address two main issues in AMI which are detection of electricity theft and preserving consumer privacy.	[38]
Analysis of AMI, Smart Metering Deployment and Big Data Management Challenges	Saleh *et al.,*	Focusing in the Gulf Cooperation Council region, the author discussed on the challenges of cybersecurity, data management and consumer adoption in AMI.	[39]
Review of Cyber Physical Attacks and Counter Defence Mechanisms for AMI in Smart Grid	Wei *et al.,*	The paper reviews on cyber-physical attacks involving smart meters such as False Data Injection Attacks (FDIA), Denial of Service (DoS) Attacks and Replay Attacks. The paper also discussed on the counter mechanisms for such attacks by enforcing encryption, authentication protocols and intrusion detection system (IDS).	[40]
Leveraging AI of Things for Anomaly Detection in AMI	Ogu *et al.,*	The application of Artificial Intelligence to analyse data at the edge of the network of AMI systems.	[41]
AMI – Towards a Reliable Network	Kornatka *et al.,*	The importance of AMI in improving low-voltage power grids is discussed in the paper. The capability of AMI to monitor and detect faults, optimize investment and enhance energy efficiency is discussed in the paper. The author highlights the need for further development and integration with smart grid technologies.	[42]

2. Challenges in AMI

Before the implementation of AMI, collection of energy consumption from electricity consumers requires electric meter, meter readers and an enterprise billing system. Meter readers have to be present physically at the customer premise to read the electric meter and once they have completed collecting meter reads at the assigned area, only then they will come back to their office to key in all the collected meter reads [43]. Among the limitations of the traditional approach is that it is prone to human error as data collection and data entry are being done manually. On top of that, if a meter failed to be read on scheduled date, it will be estimated and this will directly impact to the collection revenue to the utilities. And because the data collection is being done monthly, very limited products and services can be offered to the customers. With the conventional electric meter, it takes longer time to complete basic processes such as new connection and disconnection. Often, the customer will face with frustration when there is a spike or dispute in their electricity bills as it only provided to them once a month. The utilities also face difficulties in explaining to them on what is happening to their energy usage as limited data is available for analysis and scrutinization.

Utilities are driven to improve their customer experience and among of the early initiative adopted by them is the introduction of Advanced Meter Reading or AMR. AMR was first introduced in 1985, but the official roll out of AMR was in 2011 [44]. AMR technology allows utilities to retrieve meter readings by physically approaching the meters with a portable device or by driving past them in a vehicle to remotely capture the consumption data gathered by the meter [45]. This has enabled utilities to introduced customized tariff structured and more advanced billing structures to the customers. While AMR has increased the frequency of meter data collection, the dependency on meter readers is still very high. Hence issues such as missed or incorrect reading still occurs. Then AMR-Plus technology was introduced [46]. With AMR-plus, meter reader is no longer required to collect meter data. Instead, a one-way communication network is installed in the meter which allows utilities to perform weekly, monthly or on demand data collection from the meter to the data centre. Nevertheless, this still unable to improve the customer experience as limited applications and analytics can be performed. Therefore, the development of AMI surface to the industry in the early 2000s where United States and some European countries start with small scale pilot project in 2011 [47].

As the technology of network communication evolved, the advancement of electric meter also changed. A common architecture of smart meter may consist of smart meter, communication network [48], a head-end system [49], meter data management systems (MDMS) [50] and enterprises systems [48]. The enterprises system may include data mining [51], data analytics [52], customer systems [53] for billing as well as mobile apps for customer to remotely communicate with the service provider. With smart meters, additional information is made available to the utilities as well as for the consumer such as daily interval energy consumption, meter health, potential of tampered events and alarm [54]. Since smart meters are integrated with bidirectional communication technology, allowing all meter-recorded information to be sent to utilities in near real-time. Having a near real-time information has increase the quality of utilities to communicate with their customers. Among of the features that now available to the utilities are remote connect or disconnection, outage reporting, voltage monitoring, tamper detection, over-the-air firmware upgrade, ODR and smart meter last gasp.

With the large-scale deployment of smart meters across the country, utilities are now facing new challenges in managing the massive volumes of data generated by these devices. Typically, register reads, load profiles, events and alarms are collected from the meters and these data types may vary from one utility to another depending on their specific requirements [55]. According to industry estimates, the data generated by smart meters is expected to grow exponentially, with some utilities projecting an increase in data volumes within the next five years [56]. Prior to meter installation, utilities must carefully consider data growth projections and ensure that their data storage solutions are scalable to accommodate the anticipated surge in data. Since smart meter installations can happen rapidly, it is critical that data storage capacity can be swiftly expanded to avoid potential bottlenecks or data loss [57]. Data storage is a costly and growing need, making proper planning and investment in scalable solutions crucial for utilities.

Another significant challenge in managing smart meter data is the integration across various applications within the AMI ecosystem. Naturally, the AMI architecture consists of smart meters, communication protocols and equipment, a head-end system, a meter data management system and utility enterprise systems such as customer billing, asset management, workforce management and mobile applications. Seamless integration between all these systems needs to be established, thoroughly tested and verified to ensure the accuracy and consistency of information shared across the ecosystem [58]. Data integrity across all systems and applications is paramount, as it ensures interoperability across the entire AMI ecosystem [4]. A lack of integration can severely impact future analysis, new feature development and the operations and maintenance teams, potentially leading to customer complaints and dissatisfaction.

Furthermore, the other main concern regarding smart meter data is the heightened risk of cybersecurity threats [59]. With customer data now available online and smart meters serving as potential entry points for unauthorized individuals, utilities must exercise utmost vigilance to protect their databases and infrastructure. Cybersecurity breaches can result in severe consequences, including data theft, service disruptions, financial losses [60] and reputational damage. To mitigate these risks, utilities must impose robust security measures throughout their end-to-end AMI architecture, such as quarterly cybersecurity assessments, controlled access, threat monitoring and data encryption for all data transfers when using third-party networks.

Once all these challenges are adequately addressed, utilities can confidently plan and implement new features and applications that leverage the rich data provided by smart meters, ultimately benefiting both customers and the utilities themselves.

2.1 Smart Meter Operation Centre

One of the key areas in ensuring the success of AMI implementation is the establishment of Smart Meter Operation Centre (SMOC). SMOC is a centralized facility that manages and monitors the communication networks and data flow between smart meters and utility companies. SMOCs are crucial for utilities because they facilitate efficient operation and management of smart grid systems. Their importance lies in operational efficiency by automating meter reading and enabling remote disconnections, data analytics that provide insights into energy consumption patterns, grid reliability through monitoring communication networks and customer engagement by providing detailed energy usage information [3]. Many utilities globally have implemented SMOCs, such as Pacific Gas and Electric Company (PG&E) in California with over 9 million smart meters [61], Enel SpA's centre in Rome for its European smart meter rollout [62] and Hydro One Networks Inc.'s centre in Ontario managing over 1.3 million smart meters [63].

SMOCs collect and process large volumes of meter data, store it and analyse it to optimize energy distribution, implement demand management strategies and improve customer service. They monitor the communication networks connecting smart meters to ensure reliable, secure data transmission and faster outage detection and response [64]. By reducing operational costs through automation and providing customer consumption data, SMOCs play a vital role in utilities' smart grid initiatives aimed at enhancing efficiency, reliability and customer engagement [48].

Currently, most operators working in SMOC uses data analytics [65] to help them in monitoring and decision making. While it has reduced time tremendously as compared to by using excel for their analysis, the action taken are reactive. SMOC operators will act as and when the events or alarm has triggered. Due to the this, the time taken to solve an issue is longer and customer experience is disrupted. Therefore, SMOC operators are in dire need for and automation and intelligence in assisting them in early detection and decision making. With more countries implementing AMI, the trend and interest towards having ML as part of the monitoring tool and decision assistance has increased. The addition of these tool as part of the operator’s assistance is crucial in ensuring AMI is working at optimum level. Therefore, in this paper, a comprehensive review on the academic proposals and engineering practice in ML application in the area of fault detection, preventive maintenance, network selection and detection of cyber security threats in AMI is conducted.

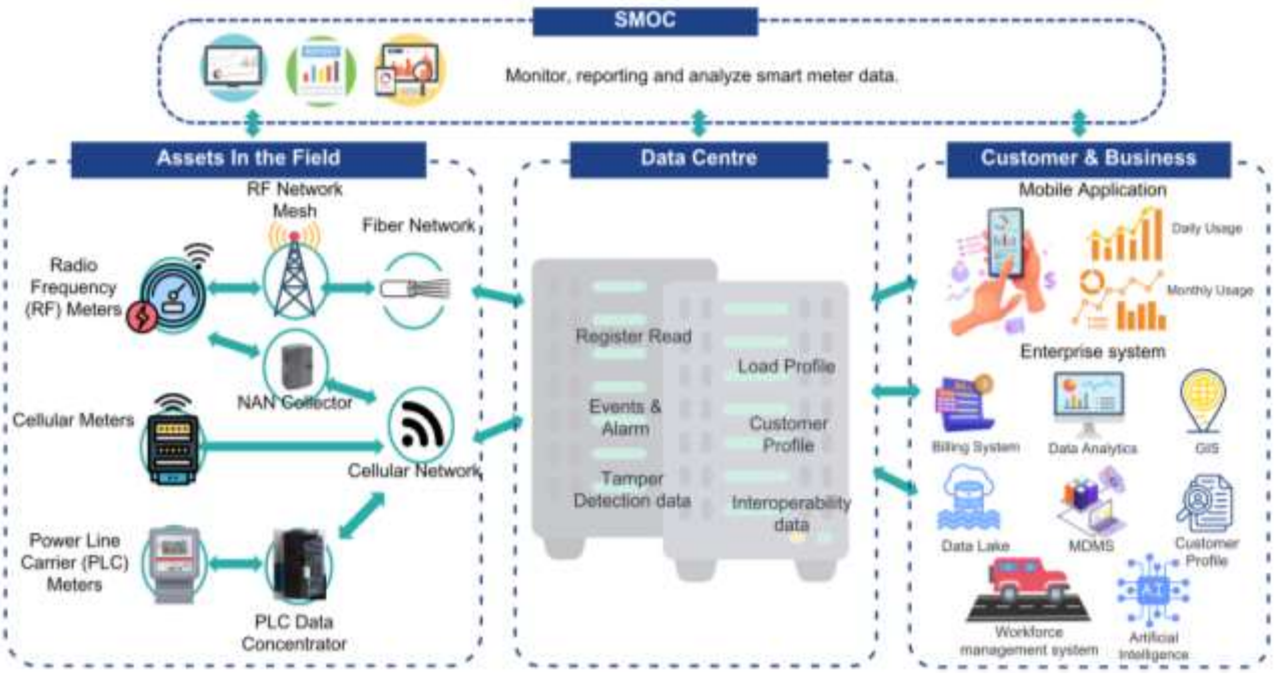

Fig. 1. Smart meter operation centre scope of work

3. ML in Advanced Metering Infrastructure

As AMI deployment always involved with large number of smart meters, dwelling with big data is expected. These large data are impossible for human to process without the help of a tool. Currently, many utilities and AMI control centres are implementing data analytics [38] to assists their operators in monitoring and decision making. However, as the number of data are growing and customers are demanding for better service quality, it is insufficient to rely on data analytics only. This is because data analytics only analyse information that has already occurred and due to the large volume, report generation may take time [54]. Which given the operators to act reactively to the incident or problem. Due to that, utilities are now exploring on the ML technology in assisting their operators for a faster and intervene the incident before it occurs.

ML and deep learning have shown encouraging advances in various areas such as data mining [55], medical imaging [56], communication, multimedia [57], aviation [58], geoscience [59], remote sensing classification, preventive maintenance [60], real-time object tracking and computer vision-based fault detection. In the context of smart grid, research and application on ML and deep learning are focusing on the comprehensive perception of the underlying systems, intelligent decision making and real-time or near real-time operations [61]. Some examples of the research and applications are on the predictions of load and price [66], cascading failure prediction [67], power generation, life cycle analysis [68], fault detection and diagnosis, demand side management and detection of cyberspace attacks. However, for the paper, the focus is on the ML and deep learning application for AMI. The area of interest will be on preventive maintenance, network selection and cyber security threats detection.

3.1 ML in Fault/Anomaly Detection

In general, anomaly is when something unusual from what is considered standard. Anomaly detection is a process of finding pattern that depart from typical behaviour [69]. This process can be achieved by using data analysis. In data analysis, outliers or irregular patterns that deviates from the normal behaviour of a dataset is identified. By using smart meter data, anomalies in energy usage can be detected where it can indicate issued with measurement errors, equipment malfunction, potential of theft and changes in customer behaviour [70]. The ability to detect anomalies within the smart meter infrastructure give the advantage to the utilities in reducing equipment failures, enhances operational efficiency and subsequently increase customer satisfaction through accurate billing.

With the implementation of AMI, utilities can identify anomaly remotely. Previously with conventional meters, faulty meters were only identified when the field crew or meter reader visited the premises. Now, with smart meter, data is collected and analysis is performed. Using ML, complex patterns are learned and presented to the operators in clearer picture for a better decision making. In Erfani *et al.,* [71], a hybrid model of unsupervised deep belief networks (DBNs) and one-class support vector machine (SVM) is used for high dimensional and large-scale anomaly detection. The method despite taking a longer time to complete, has overcome the challenge of classifying large dataset with multiple features. Power outages are also considered as unusual pattern that need monitoring and early detection. On the other hand, Moghaddass and Wang utilize Expectation-Maximization Algorithm [72] to analyse smart meter data to find unusual patterns that could mean there is a problem in the power grid. This helps the operators to predict power outages before it happened. Distributed anomaly in energy consumption was detected using deep learning method to increase accuracy and optimized computing process. Stacked sparse autoencoder is used to reduce the high-level representation from high volumes of smart meter data. Once the data is compress, SoftMax classifier is employed for data categorization for anomaly detection. The combination of stacked sparse autoencoder and SoftMax is deemed suitable for a real-world application with large datasets [73]. Using deep learning Convolution Neural Network, location of faults can also be identified and it has higher accuracy compared to using SVM method [74]. The study by Aligholian *et al.,* [75] compares with four different unsupervised ML models to identify unusual electricity consumption using smart meter data. From the analysis, it is observed that projection-based methods perform better for abnormalities with very high or very low magnitude.

Another research that also compares two unsupervised learning which are nested dynamic time warping (DTW) distances and Mahalanobis distance in detecting abnormal inactivity within a household is conducted [76]. Based on the comparisons, Mahalanobis distance-based model is more reliable when the lag time is longer. A combination of two models – Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) was used by Hollingsworth *et al.,* [77] for anomaly detection in smart meter energy consumption data. From the research it shows combining both models give high accuracy and able to detect specifically true anomalies compared by using ARIMA or LSTM separately. Detection anomaly in energy patterns also allows utilities to prevent potential theft. Using unsupervised method, Park *et al.,* [78] uses normal energy consumption and build an outlier detection model using k-means clustering. Consumption trend changes in home electrical appliances is being studied using time series data [79]. From the study, Prophet and LightGBM models perform better compared to the WAR models in detecting anomalies. Current trends for anomaly detection in AMI is to use federated learning instead of centralized learning. For example, Zafar *et al.,* [80] a Federated Learning-Convolutional Gated Recurrent Unit model is developed and it shows high efficacy in detecting electricity theft.

A fundamental approach in anomaly detection is by using statistical method equation, Z-score:

$$Z = (X - \mu)/\sigma \tag{1}$$

Where:
X = is the observed value
μ = is the mean of the sample
σ = is the standard deviation of the sample.

Using this equation, the baseline is established. For example, if the detection of anomaly is based on daily electric consumption, as we replace X with the electricity consumption of the day, μ with the normal or average amount and σ as the standard deviation of the daily electricity consumption sample, from there the baseline is establish. Using the baseline, a rule is established that is anything above or below than the baseline is considered as unusual. An example of algorithm to clustering load patterns in to groups is used by Jiang *et al.,* [81] as in Figure 2.

Algorithm 1: The algorithm of daily load curve clustering.

Input: n-dimensional daily load curves, X_0;
Output: load pattern, C_{center}.

Initialize $C_{reserved} = \emptyset, C_{temp} = \emptyset$;
Reduce the dimensionality of X_0 by α-level 1D DWT, generate $X_{\alpha L}$ and $X_{\alpha H}$;
Normalize $X_{\alpha L}$ by z-score normalization to gain $X'_{\alpha L}$;
for $k = 2, k \leq 10, k++$ **do**
    $A_k = K\text{-means}(X'_{\alpha L}, k), D_k = K\text{-means}(X_{\alpha H}, k)$;
    Calculate the Simplified Silhouette Width Criterion of A_k and D_k, gain S_{A_k} and S_{D_k};
$K_A = \arg\max_k \{S_{A_k}\}, A = K\text{-means}(X'_{\alpha L}, K_A)$;
$K_D = \arg\max_k \{S_{D_k}\}, D = K\text{-means}(X'_{\alpha H}, K_D)$;
for $A_i \in A(1 \leq i \leq p, p = len(A))$ **do**
    for $D_j \in D(1 \leq j \leq q, q = len(D))$ **do**
        $AD_{ij} = A_i \cap D_j$;
        if $A_i = D_j$ **then**
            $C_{reserved} = C_{reserved} \cup \{AD_{ij}\}$;
        else
            if $A_i \neq D_j$ ***and*** $A_i \cap D_j \neq \emptyset$ **then**
                $C_{temp} = C_{temp} \cup \{AD_{ij}\}$;
$l_1 = \text{len}(C_{reserved}), l_2 = \text{len}(C_{temp})$;
if $l_2 = 0$ **then**
    $C = C_{reserved}$;
else
    if $l_2 > \max\{p, q\} - l_1$ **then**
        $K_{temp} = \max\{p, q\} - l_2, C'_{temp} = K\text{-means}(C_{temp}, K_{temp})$;
    else
        $C'_{temp} = C_{temp}$;
    $C = C_{reserved} \cup C'_{temp}$;
calculate the centers of C, C_{center};
return C_{center}.

Fig. 2. Example of Z-score algorithm used in anomaly detection [81]

3.2 ML Application in Predictive Maintenance

Machines, equipment, structures, software and appliances require maintenance in order to have the best experience while also ensuring the safety of the user. Four types of maintenance exist:

i. Regular and timely maintenance
ii. Corrective maintenance
iii. Predictive maintenance (PdM)
iv. Prescriptive maintenance.

Regular and timely maintenance also helps to expand the longevity of the items or systems. Often, maintenance of an equipment can be categorized into four categories based on occurrence which are corrective, preventive, predictive and prescriptive [82]. Corrective maintenance is performed when fault is detected or there is assign of failures. Preventive maintenance is an activity performed in interval following a specific schedule. As for predictive maintenance (PdM) uses time-based information and knowledge to report possible failure avoiding downtime. And lastly, prescriptive maintenance is to improve and optimized the existing performance. Among all these four maintenances, preventive maintenance and PdM are the maintenance that frequently performed by organization to ensure continuity of service. The difference between preventive maintenance and PdM is preventive maintenance involves monitoring the actual condition of the equipment using sensors and other data collection method to assess the current states of components [83]. As compared to the PdM, the approach is proactive as it forecast equipment failures before the occurrence with the help of IoT network, AI and data analytics. With PdM, repairs and maintenance are performed when prompt [84]. This section discussed on ML model used in PdM.

Prior to the implementation of AMI, operations rely field crew to detect faults at site and followed with fault isolation or clearing the faults [85]. With the implementation of AMI, large energy data type can be collected by utilities. The availability of large energy data allows the application of ML to take in place to advance utilities to a better state. By research, ML has shown promising output where it can reduce maintenance cost, stop of work reduction, machine fault reduction, machine life-span increases, inventory optimization [86], optimized resourced allocation and many more. A survey of conducted on predictive maintenance method and types of faults in distribution network was conducted [85]. The author described methods of predictive method that is currently being used by the distribution network operations team which are conventional and using ML. In the paper, there are four types of ML models identified used for predictive maintenance which are SVM, Artificial Neural Network (ANN), Random Forest and Recurrent Neural Network. It is important to design a highly available and reliable predictive maintenance system as poor equipment maintenance may lead to service degradation and unavailability [87]. Predictive maintenance is an important strategy to increase efficiency and gain continuous customer trust. Compared to the conventional maintenance approach, predictive maintenance is more proactive by anticipating possible equipment failures and irregularities. Omol *et al.,* [88], four prominent ML techniques are identified that commonly used for anomaly detection in smart grid and the similarities between these four ML models are they are capable to handle high dimensional data and three out of four models are unsupervised learning techniques. Unsupervised learning technique is used for unlabelled data which suitable for anomaly detection. Predictive maintenance in smart grid does not only cover low voltage, but also medium voltage. One use case of ML is predictive maintenance for medium voltage switchgear. However, the challenge in this is finding a robust and accurate sensor to measure switchgear faults and anomalies [89].

3.3 ML Application in Network Selection

A typical infrastructure of AMI usually consists of three main components which are meter, communication network technology and system applications [49]. While each of the components have its own challenges, choosing the right communication network is the most vital decision when implementing AMI. The decision must take into consideration on the availability of the present infrastructure, impact on system equipment and functional requirement and economic consideration [90]. After considering all that factors, the selected communication network must be able to have the best coverage area, best data rate , power consumption and security level [91]. To assists decision makers in making the best selection, ML is employed. A comprehensive dataset that covers criteria such as frequency, data rate, distance, bandwidth, line of sight (LoS), stability, interference, topology and terrain is used to train with five difference ML models [92]. One of the critical components in communication network for AMI is data aggregation points (DAPs). Depending on the type of chosen technology, these DAPs could be a gateway for extender bridge for radio frequency solutions (RF) or data concentrator for Power Line Carrier (PLC). Using a clustering algorithm, the maximum and minimum distance from DAPs to SM is proposed considering three different neighbourhoods which are urban, suburban and rural premises [93]. Besides distance, number of DAPs and the installation location also plays a big role in ensuring AMI communication network able to transmit data to the control centre with minimum data loss. Using unsupervised K-means clustering algorithm, placement and the best number of DAPs within Neighbourhood Area Network (NAN) is determined [94]. However, the paper does not discuss if there is an overlapping of neighbourhood area and how it will affect the number of DAPs to be installed. The position of network nodes also may be influenced by severe weather, winds or vandalism [95]. One of the preferred communication network technologies chosen for the implementation of AMI is G3-PLC. Countries like Spain, France, Italy, United Kingdom and Germany implemented G3-PLC for their smart meter installation as it allows utilities to leverage on their existing power line infrastructure. Despite having the advantage of using existing infrastructure, PLC may have it limitations such as noise interference and signal attenuation from electrical equipment. Using ML, prediction model of determining data link quality is developed and it provides better accuracy for decision makers in modulation selection [96].

3.4 ML Application Cybersecurity Threats

The two-way communication in AMI offers numerous benefits to utilities. However, it also opens opportunity to the attackers as more access points and devices are now accessible to them. Therefore, the enforcement of cybersecurity in AMI is critical to safeguard the integrity, confidentiality and availability of the infrastructure, energy and customer data. Some of the common cyber-attacks in IoT are Distributed Denial of Service (DDoS), Data Type Probing (DTP), Malicious Control (MC), Scan, Spying, and Wrong Setup (WS) [97]. Other common cyber-attack in the Smart Grid architecture are Malware infections, Man-in-the-Middle (MitM) attacks [59], False data injections attacks, De-pseudonymization Attacks, Meter Spoofing and Energy Fraud Attacks and disaggregation attacks [38,98-101]. Advanced Persistent Threats (APTs), Unauthorized access and control and cyber physical attacks. Some of the known cyber-attack on smart grid happened back in March 2018 where hackers have infiltrated power control system in the United States smart grid and causing black out in several areas [102]. Another attack, in 2015, causing Ukraine control centres not fully operational even after two hours [103]. This attacked impacted roughly 230,00 consumers in Ukraine lasted for at least 6 hours of unplanned power outages [104]. These incidents show the importance of comprehensive cybersecurity strategies in protecting AMI and Smart Grid Systems.

AMI relies heavily on the communication network that ensures all smart meter data successfully transferred to the utilities data centre. However, like any IoT technology, the automation, integration and architecture of AMI is also exposed to the potential cyber threats. It is advisable as according to U.S Energy Department's National Electric Sector Cybersecurity Organization Resource (NESCOR) for utilities to invest in enhancing their security measures against cyber-attacks [105]. Annual penetration tests need to be conducted in order to discover and enhance any weak spots, guaranteeing the installation of the newest software versions and firmware and implementing continuous monitoring to mitigate any cyber-attacks are among of the mitigation action to reduce the cyber security threats. Today, with the emerging of ML technology, potential cyber threats can be reduced. One of the most widely used ML techniques for addressing cybersecurity threats ML in AMI is anomaly detection. Often, operators are unable to differentiate between actual disturbance or an actual cyber-attack. However, using ML based anomaly detection, the actual fault due to disturbance is able to be differentiated from intelligent cyber-attack [106]. Furthermore, using a two-layered hierarchical with random forest classifier as a base model has proven distinguishing between natural and attack event is possible with 99% accuracy in detecting natural event [107]. This method is suitable for data with limited attack event.

4. Challenges of ML in AMI

Even though research on ML has been around for more than a decade, the implementation of ML in Smart Grid is still at entry level. This is due to the challenges of implementing ML such as reliable data for testing and training. The volume and variety of data also plays a role in ensure the accuracy of the desired outcome for implementing ML. However, managing large volume of data may become a challenge for organizations as several aspects need to be considered such as data storage, data management, data quality, resources for data monitoring and data integrity across all organization system integration. Utilities need to consider the capacity of their data storage for offline and online data. Scalability of smart grid system infrastructure need to be considered as smart grid usually consists a lot of equipment's such as millions of smart meters, sensors, network communication equipment and external data such as weather, geospatial information and customer background. Storing these data can be costly if not properly plan. As ML is considered new among organizational, ethical concerns regarding on ML application may arise during the development and application of ML in daily operations [108]. If there are hidden biases in the data, ML models will unavoidably reflect these biases because they learn directly from the data provided, including any biases present in it. These biases if not detected and corrected may impact the organization future decision as it provide in accurate data.

Furthermore, ensuring a unified and working system integration can be time consuming and costly but is essential in making ML available to the organization. ML models require a clean, accurate and complete data in order to function effectively. Lack of good quality data may lead to inaccurate decision and eventually reduce the trusts to the organization due to the bad outcome. On top of that, the cyber security aspects also need to be considered and emphasized. Hacker is looking at AMI and considered it as a new path to try and manipulate smart meter switches in order to generate load fluctuations [109]. By controlling the smart meter switches, hackers will made-up as if there is a load oscillating incident happening, triggering equipment "trip" or "shut down" and eventually causing the whole grid to blackout. Additionally, smart meter may become entrance point for hackers to access customer data available in utilities database. Leakage of customer information is also a concern as this may exposed consumers usage patterns and behaviour. To overcome this issue, utilities may need to comply with certain regulatory and standardization. The effort to comply to the standard is costly and requires sources with specific technical expertise. Which is also an issue in this industry. Many may have claimed to have the knowledge, but not all have the experience for implementation especially in a large-scale environment.

Table 3
Summary of research conducted in fault/anomaly detection, predictive maintenance, network selection and cybersecurity threats in AMI

Method	ML Techniques	Author, Year	Achievements	Ref
Anomaly/ Fault Detection	• DBN • One-Class SVM	Erfani *et al.*,	• The hybrid approach of combining DBN and One-Class SVM managed to address the complexity and scalability issues. • Up to 20% improvements are achieved. Performed 3 times faster in training and 1000 times faster in testing.	[71]
	• SVM	Moghaddass *et al.*,	• Issues of missing point and regularization is address by introducing dynamic indicator and focusing only in important predictors into the model.	[72]
	• kNN classification	Jiang *et al.*,	• A 3-phase model including load pattern extraction, consumer grouping and consumer classification is proposed in the paper. • The 3-phase method used in the proposed model shows higher accuracy of classification and provides more sufficient electricity consumer characteristics.	[81]
	• Prediction-based regression • Prediction-based neural network • Clustered based • Projection-based methods.	Alighholian *et al.*,	• Various techniques have varied capacity to identify diverse forms of abnormalities. • The performance of each model depends on the collection of attributes used for training.	[75]
	• ARIMA • LSTM	Hollingsworth *et al.*,	• Proposed model detected all true anomalies with no false detections. • Combination method has highest accuracy and specificity with lowest False Positive Rate. •	[77]
	• Anomaly Pattern Detection • Unsupervised Learning	Park *et al.*,	• The model has no dependency on historical data of the customer as it compares with other legal customer. Hence, the challenge of obtaining customer history data is eliminated.	[78]
	• Prophet • LightGBM	Malki *et al.*,	• Prophet and LightGBM is superior than vector autoregressive (VAR) model for anomaly detection. • Using weather and time, future energy consumption is predicted using the model	[79]

	• CNN • SVM	Kurup *et al.*,	• CNN have an accuracy of 96.06% when compared to the linear SVM method. • The research also proposed to install a fault detector before a three-class SVM as is lower the overall test error.	[74]
	• DTW • Mahalanobis distances	Zhou *et al.*,	• With minimal data, the research able to achieve satisfactory performance. • Both methods are practical to install in smart meter as it does not require offline training as well as parameter tuning. Thus, making non-intrusive household anomaly monitoring possible.	[76]
	• FL- ConvGRU	Zafar *et al.*,	• While maintaining data privacy, electricity theft is accurately detected using this method.	[80]
	• Recurrent Neural network • Convolutional Neural Network • Random Forest • Decision tree	Hernández *et al.*,	• Recurrent network shows highest precision in detecting peculiar activities within a household based on their daily activities such as sleeping, breakfast and lunch. • This achievement may contribute towards the development of home of assisted living.	[70]
Predictive Maintenance	• Support-Vector-Machine-Based Proactive Cascade Prediction in Smart Grid Using Probabilistic Framework	Gupta *et al.*,	• Proactive blackout prediction model that can predict as early as possible before unplanned power failure occurs which tailored to the smart grids. • The research successfully combines probabilistic framework for cascading failures and SVM to predict power failures.	[110]
	• Isolation Forest • One-Class SVM • Autoencoders • Random Forest	Omol *et al.*,	• Using a qualitative research approach this research able to shows the importance of predictive maintenance in enhancing reliability, efficiency and resilience of smart grid infrastructure.	[88]
Network Selection	• K-Medoids	Gallardo *et al.*,	• The proposed framework has better coverage areas as it is based on the real DAP and smart meters placement. • Furthermore, the algorithm also tested on urban, suburban and rural scenarios for AMI network planning.	[93]
	• Unsupervised K-means clustering	Molokomme *et al.*,	• The proposed model assists in minimizing number of DAPs deployed without compromising the network coverage for smart meters. • The model helps to reduce implementation and maintenance cost as fewer equipment is deployed at the field but with maximum coverage.	[94]

	• Naïve Bayes, • Decision Tree • Random Tree Forest • Gradient Boosted Tree • K-Nearest Neighbor	Azhar *et al.*,	• Based on seven technical criteria, Naïve Bayes ranked as the highest performing ML model in term of accuracy and execution time. • This helps to do selection of communication technology for electrical distribution substation.	[92]
	• K-Nearest Neighbors • SVR • Extra Trees • KNN • MLP	Marquez *et al.*,	• K-Nearest Neighbors model is concluded to be the most useful in determining the location of nodes for LoRaWAN network as it can detect position change within 100 meters within areas of interest.	[95]
	• LR • SVM • RFC • ANN	Razazian *et al.*,	• Using channel quality classifier, RFC model achieves 89% success rate compared to the conventional ROBO Modulation with 64% accuracy rate. • Random Forest Classifier (RFC) possesses the capability to formulate more intricate decision boundaries derived from nonlinear datasets.	[96]
CyberSecurity	• Bayesian Classifier • HMM	McLaughlin *et al.*,	• The proposed systems, AMI Intrusion Detection System (AMIDS) provide the capability of high accuracy in detecting energy theft. • The method used in AMIDS is Naïve Bayes model.	[100]
	• PCA • DBSCAN	Badrinath Krishna *et al.*,	• The combination of PCA and DBSCAN is reliable in identifying integrity attacks on smart meter data.	[101]
	• RBM • SDF • DBNs	Karimipour *et al.*,	• The proposed system in the research, which is anomaly detection tool for smart gird, achieves 99% accuracy, TPR of 98% and FPR of Less than 2%. •	[106]
	• Two-layer hierarchical random forest model	Farrukh *et al.*,	• The proposed two-layer ML model achieved 95.44% accuracy in cyberattack detection. • Outperformed deep learning models in detecting cyberattacks on smart power systems.	[107]
	• Logistic Regression • Decision Tree • Random Forest • ANN • Naïve Bayes	Mukherjee *et al.*,	• Achieved 99.4% accuracy in when considering whole dataset and 99.99% when binary values are removed. • Using the model, certain threats and anomalies occurring in smart devices and IoT solution can be prevented.	[97]

5. Future Work

Despite the challenges in implementing ML for enterprises, ML has shown promising role in AMI towards the development of smart grid. This is also inclusive of the development of smart cities, energy efficiency and energy transition:

i. Smart Cities: By using ML predictive analytics algorithms, forecasted traffic congestion, energy demand and consumption is made possible. With this information available, city authorities may have ample time to address any issues arise [111].
ii. Energy Efficiency: Real time monitoring can help to reduce and provide overview trend of energy usage through demand response [112]. Customers may enjoy incentives by participating in the demand respond programmed.
iii. Sustainability and Reliability: The reliability of microgrid in transmitting and distributing energy can be enhanced by using ML algorithms. For example, a hybrid model of SVM and Artificial Neural Network (ANN) was able to enhance the reliability of a microgrids [113].

6. Conclusions

The paper aims to address the knowledge gap by offering a thorough analysis of global smart meter implementations, operational problems in Advanced Metering Infrastructure (AMI) data handling and the revolutionary impact of artificial intelligence, specifically machine learning (ML), on improving decision-making in smart meter operation centres.

A review of smart meter installations in different countries uncovers advancements as well as ongoing difficulties. Although numerous industrialized regions have attained maturity in deployment, others like the Middle East and Asia continue in strengthening their infrastructure. These trends demonstrate the increasing significance of AMI and the variable rate of adoption, influenced by factors such as expense, regulatory preparedness and consumer receptivity.

Secondly, the article analysed the incorporation of machine learning into advanced metering infrastructure systems. Machine learning has exhibited significant potential to enhance daily operational functions in smart meter control centres, particularly in anomaly detection, predictive maintenance, network optimization and cybersecurity. These technologies enable utilities to monitor systems in real time, anticipate breakdowns, safeguard infrastructure and make proactive, data-informed decisions.

This report offers helpful recommendations for stakeholders, including utility companies, government agencies and regulators, by providing insights into recent advancements in AMI and trends in machine learning. Comprehending the transformation of data into actionable intelligence enables these companies to devise more efficient, customer-oriented and sustainable energy plans.

Ultimately, four essential operational domains were recognized in which machine learning may directly improve decision-making: anomaly detection, predictive maintenance, network selection and cyber threat mitigation. These sectors are anticipated to experience increased machine learning usage, particularly as utilities strive to navigate the scope and intricacy of contemporary Advanced Metering Infrastructure systems.

In conclusion, AMI and ML are transforming utility operations and customer service. As smart meter technology expands and machine learning technologies advance, utilities are increasingly equipped to migrate to smarter grids, enhance customer interaction and develop more resilient, future-ready energy systems.

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