A comprehensive review of artificial intelligence and machine learning applications in the energy sector

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Abstract

The energy industry worldwide is today confronted with several challenges, including heightened levels of consumption and inefficiency, volatile patterns in demand and supply, and a dearth of crucial data necessary for effective management. Developing countries face significant challenges due to the widespread occurrence of unauthorized connections to the electricity grid, resulting in substantial amounts of unmeasured and unpaid energy consumption. Nevertheless, the implementation of artificial intelligence (AI) and machine learning (ML) technologies has the potential to improve energy management, efficiency, and sustainability. Therefore, this study aims to evaluate the potential influence of AI and ML technologies on the progress of the energy industry. The present study employed the systematic literature review methodology to examine the challenges arising from frequent power outages and limited energy accessibility in various developing nations. The results of this study indicate that AI and ML possess significant potential in various domains, including predictive maintenance of turbines, optimization of energy consumption, management of power grids, prediction of energy prices, and assessment of energy demand and efficiency in residential buildings. This study concluded with a discussion of the necessary measures to enable developing nations to harness the advantages of AI and ML in the energy sector.

Keywords: Artificial intelligence; Machine learning; Deep learning; Energy; Technology

Introduction

To effectively address the obstacles connected with the integration of complicated AI technologies into smart energy systems and grids, it is important to possess a comprehensive comprehension of computational, economic, and social factors (Danish, 2023). In addition to the post-industrial society and its consequences, the pursuit of pragmatic solutions for global progress has garnered the participation of business, academia, and society in the endeavor to attain sustainable development (Raihan et al., 2018; Begum et al., 2020; Raihan et al., 2022a; Kurup et al., 2023; Raihan, 2023a). The pursuit of real answers to the global development problem involves the active participation of business, academia, and society (Raihan et al., 2019; Jaafar et al., 2020; Raihan et al., 2021b; Voumik et al., 2022; Raihan & Himu, 2023; Raihan, 2023b; Sultana et al., 2023a; Raihan, 2023c). The global energy segment is confronted with various issues, such as increasing energy use and concerns regarding efficiency, volatile patterns in supply and demand, and a lack of

adequate analytics for effective management (Raihan et al., 2022b; Benedek et al., 2023; Raihan et al., 2022c; Ghosh et al., 2023; Raihan et al., 2022d; Sultana et al., 2023b; Raihan, 2023d). The severity of these difficulties is amplified in nations characterized by expanding marketplaces, often denoted as emerging markets (Raihan et al., 2022e; Isfat & Raihan, 2022; Voumik et al., 2023a; Raihan et al., 2022f). Numerous instances of unauthorized "connections to the power grid" exist, indicating a substantial quantity of energy that remains unmeasured or unpaid. The aforementioned outcomes lead to financial losses and heightened levels of carbon dioxide emissions, hence emphasizing the significance of addressing efficiency challenges (Rao & Rao, 2019; Raihan & Said, 2022; Raihan et al., 2022g; Voumik et al., 2023b; Raihan, 2023e),

Consumers exhibit less motivation to utilize energy responsibly when it is supplied to them without any associated costs (Raihan et al., 2022h; Shi et al., 2023; Raihan, 2023f). The power business in numerous developed nations has commenced the deployment of AI and other associated technologies facilitating communication among smart grids, smart meters, and Internet of Things (IoT) devices (Raihan et al., 2023a). These advancements possess the capacity to enhance the adoption of renewable energy resources, as well as enhance power management, efficiency, and transparency (Makala & Bakovic, 2020; Raihan et al., 2022i). Ghoddusi et al. (2019) asserted that the implementation of ML is generating new prospects for innovative research in the fields of energy economics and finance. Ghoddusi et al. (2019) carried out an in-depth study of the expanding body of research on the uses of ML in the fields of energy economics and finance. It has been discovered that ML possesses a diverse array of possible applications. Ghoddusi et al. (2019) conducted an analysis that revealed diverse applications across various sectors. These applications encompassed the evaluation of macro and energy trends, the prediction of demand, the mitigation of risk, the formulation of trading strategies, and the manipulation of data. Crude oil, natural gas, and power are three forms of energy whose prices serve as illustrative instances that can be projected. Furthermore, Chen et al. (2020) put forth the notion that the utilization of ML is swiftly transforming the domains of physics and chemistry, along with several other disciplines.

According to Chen et al. (2020), AI and ML have the potential to facilitate the establishment of material connections, enhance the understanding of material chemistry, and expedite the process of material creation. ML is presently being investigated as a novel approach to use its capacity for autonomously performing intricate tasks. AI is also being utilized in the facilitation of material linkages. The study conducted by Chen et al. (2020) demonstrated the potential application of ML techniques in diverse energy materials. The materials encompassed in this category are rechargeable alkali-ion batteries, catalysts, photovoltaics, piezoelectrics, thermoelectrics, and superconductors. According to Liu et al. (2021), the utilization of data-driven approaches in materials research has the potential to revolutionize scientific advancements and introduce novel paradigms in the realm of energy materials. This transformative potential is attributed to the advancements in AI and ML techniques. These advancements are anticipated to transpire as a result of recent enhancements in technology. As a result of this development, there exists a heightened potential for data-driven materials science to exert a substantial influence on research outcomes. Liu et al. (2021) argue that the application of ML technology in data-driven materials engineering has the potential to streamline the process of designing and developing advanced energy materials. Additionally, ML can enhance the efficiency of discovering and implementing these materials.

The residential and commercial sectors are estimated to contribute around 40 percent of the overall world energy consumption (Nabavi et al., 2020; Raihan & Tuspekova, 2022a; Raihan, 2023g). Nabavi et al. (2020) conducted a study that employed three separate ML algorithms to forecast the future energy demands in both residential and commercial sectors in Iran. Several methods, including multiple linear regression, logarithmic multiple linear regression, and nonlinear autoregressive with exogenous input artificial neural networks, were utilized in these approaches. The study effectively anticipated the energy demands of Iran. Accordingly, Nabavi et al. (2020) posited that the anticipation of energy demand in the residential and commercial sectors would enable

governments to effectively provide energy sources and formulate sustainable energy strategies. Several examples of these designs involve harnessing both renewable and non-renewable energy resources to establish a secure and ecologically sustainable energy infrastructure. According to Nabavi et al. (2020), an argument is put up on the significance of modeling energy consumption in residential and commercial sectors as a means to identify the essential economic, social, and technological factors that contribute to achieving a reliable energy supply. The basis of this argument is the discovery that by identifying the significant economic, social, and technological factors, it becomes possible to create a model for predicting energy use in both residential and commercial sectors. The subject matter was addressed within the framework employed to simulate the energy consumption of residential and commercial buildings. Furthermore, Xu et al. (2019) argued that precise forecasts of corporate bankruptcy within the Chinese energy industry have a dual role in stimulating ongoing enhancements in state power generation and promoting sustainable investments in the energy sector. The findings were deliberated with stakeholders from the Chinese energy industry. Moreover, Xu et al. (2019) introduced a new integrated model (NIM) for predicting business failure in the Chinese energy industry, which incorporates both textual and numerical data. Based on the findings of Xu et al. (2019), it can be inferred that the utilization of AI and ML holds significant potential in the energy segment, specifically in emerging economies, for energy production and consumption.

Energy has a pivotal role in global economic and social growth (Raihan & Tuspekova, 2022b; Raihan et al., 2023b). In recent decades, there has been a substantial increase in global energy demand, exhibiting exponential growth (Raihan & Tuspekova, 2022c; Raihan et al., 2023c). As a result, many governments have expressed significant concern regarding the precise forecasting of energy consumption (Raihan & Tuspekova, 2022d; Raihan et al., 2023d). Nevertheless, the implementation of AI and other related technologies has the potential to improve power management, efficiency, and transparency (Ahmad et al., 2022). Furthermore, the utilization of ML is creating novel opportunities for pioneering research in the domains of energy economics and finance (Danish, 2023). However, there is a research gap in the existing literature evaluating the implications of AI and ML in the energy segment. Therefore, the aforementioned factors motivated this study to fill up the research gap by examining the challenges stemming from the prevalent absence of electricity and the persistent incidence of load-shedding. The objective of this study is to assess the potential impacts of AI and ML on the energy industry, with a specific focus on their role in improving energy generation in developing areas. The current investigation examined the growing body of literature concerning the application of ML techniques in the fields of energy economics and finance. This review additionally presents an original contribution by examining the potential consequences for future research in the domain of smart cities and identifying potential areas for further investigation. This study makes a valuable contribution to the current body of research by examining the potential implications, challenges, as well as future prospects of AI and ML in the context of smart energy and sustainability. The novelty of this research is the emergence of unique opportunities for harnessing the potential advantages of AI and ML in the energy sector of emerging nations. The results of this study serve as a valuable basis for future research endeavors that aim to explore the potential impact of AI and ML on the energy sector, with a specific focus on improving energy efficiency in developing countries.

The subsequent sections of this article are structured in the following manner: the initial section introduces the theoretical and empirical viewpoints of AI, ML, and deep learning (DL). Subsequently, the study delved into the technique employed and explored the potential contributions of AI and ML in the energy sector of developing nations. The "Literature Review" section is followed by the "Methodology" section where the methods of conducting this study are described. The "Results and Discussion" section demonstrates various implications of AI and ML technologies in energy production as well as provides recommendations for emerging energy markets

to maximize the integration of AI and ML technologies. Finally, the "Conclusion" section summarizes the study findings with concluding remarks, challenges, limitations, and future research directions.

Theoretical and Empirical Perceptions of AI, ML, and DL

The historical narrative of AI extends beyond the mere replication or substitution of human cognitive abilities by computers. It encompasses the evolution of our understanding and perception of intelligence over time (Bharadiya, 2023). Consequently, it can be argued that AI should not be considered a mere invention, contrary to the prevailing narrative. Instead, it is deeply rooted in broader historical contexts that encompass the fundamental components of intelligence and AI. According to McCarthy (2007), AI can be described as the field of study and application that encompasses the scientific and engineering principles involved in developing intelligent devices, with a specific focus on intelligent computer programs. AI is associated with the same domain of utilizing computer systems to comprehend human intelligence. Nevertheless, AI is not restricted to solely employing physiologically observable methodologies. Conversely, it pertains to the endeavor of employing computational systems to grasp the intricacies of human intelligence (Sutton, 2020). Alternatively, intelligence can be defined as the ability to acquire and employ efficient problem-solving techniques and achieve desired objectives, taking into account the unique circumstances of a dynamic and unpredictable world. According to Hua et al. (2023), a manufacturing robot that is fully pre-programmed exhibits versatility, accuracy, and reliability, although it is devoid of any form of intelligence.

The inception of discourse on AI was established by Alan Turing's seminal work, "Computing Machinery and Intelligence," published in 1950. This occurred several decades before the emergence of this notion. In this particular written work, Turing, widely recognized as the pioneer of computer science, raises the inquiry of whether machines possess the capability to engage in cognitive thought. Subsequently, he put out a proposed examination that would subsequently gain widespread recognition as the Turing Exam. In the conducted experiment, an individual acting as an interrogator would endeavor to discern between a written response generated by a machine and one produced by a human (IBM, 2023). The question test has undergone extensive examination since its initial publication, rendering it a significant component of both the AI field's historical narrative and an enduring topic within the realm of philosophy. This is due to its utilization of language concepts. Subsequently, Stuart Russell and Peter Norvig proceeded to author a seminal publication titled "Artificial Intelligence: A Modern Approach," which has since garnered significant recognition as a very influential textbook within the realm of AI research. The article discusses four distinct objectives or conceptualizations of AI, which categorize computer systems according to their capacity for logical reasoning and cognitive processes as opposed to practical applications. In alternative terms, a comparison is made between the two. Figure 1 illustrates the diverse conceptions of AI. Alan Turing's notion of AI would have encompassed systems that exhibit behavior similar to that of humans. AI can be described as an interdisciplinary field that integrates computer science with large datasets to facilitate problem-solving. Furthermore, it encompasses the subfields of ML and DL, which are frequently cited within the realm of AI. These domains consist of AI algorithms that aim to develop advanced systems capable of making predictions or classifications based on the available data (IBM, 2023).

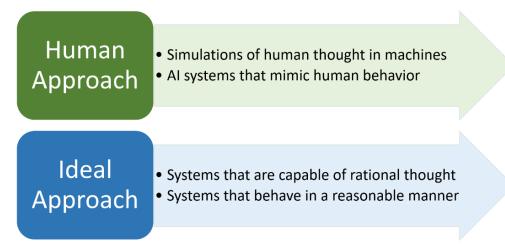


Figure 1. Definition of AI.

The terms "deep learning" and "machine learning" are occasionally employed interchangeably; nonetheless, it is crucial to establish clear boundaries between the two. DL is a specialized domain within the broader science of ML, which itself falls under the umbrella of AI. Both ML and DL are considered sub-disciplines within the broader topic of AI. Figure 2 illustrates the interrelationships of AI, ML, and DL. Neural networks serve as the foundational components of DL methodologies. According to IBM (2023), a DL algorithm can be characterized by the inclusion of more than three layers in a neural network, encompassing both the input and output layers. The term "deep" in the context of "deep learning" pertains to the significant number of layers included in the neural network architecture (LeCun et al., 2015).

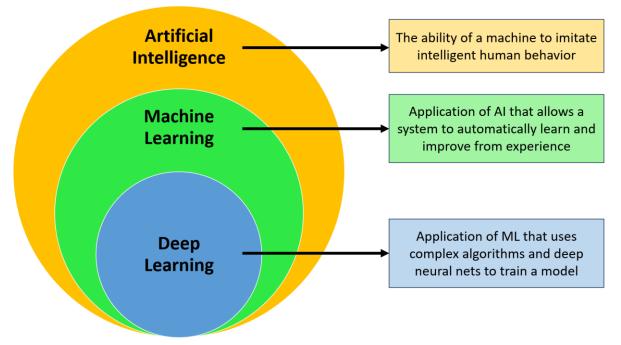


Figure 2. The connections between AI, ML, and DL.

Figure 3 provides a visual representation of the knowledge acquisition process employed by individual algorithms, specifically DL and ML, for comparative purposes. DL can automate a substantial proportion of the feature extraction stage in the process. Consequently, a reduction in the necessary manual human involvement can be achieved, thereby enabling the utilization of larger data sets (Budd et al., 2021). Contrary to ML, DL can operate without the necessity of a labeled dataset, as highlighted by Attri et al. (2023). Supervised learning, also referred to as ML, is a term used to describe a specific category of algorithms within the field of AI. The system possesses the capacity to process unstructured data in its original state, encompassing both textual and visual content. Additionally, it is capable of autonomously discerning the hierarchical structure of qualities that distinguish distinct data kinds. Unlike ML, human interaction is not necessary for the processing of data. Consequently, the potential for further advancements in ML can be extended in a more stimulating manner (Sun & Scanlon, 2019).

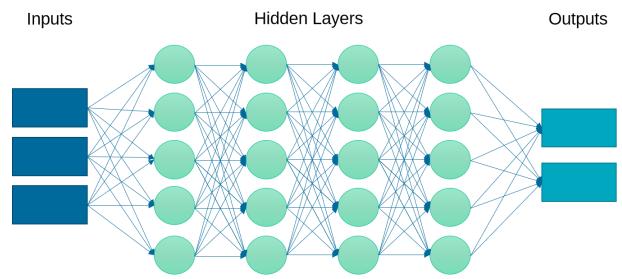


Figure 3. Deep learning neural network.

The sub-discipline of AI, sometimes referred to as ML, is concerned with the development and application of algorithms designed to facilitate data-driven prediction, classification, and optimization systems. The study of ML encompasses three primary subfields, namely supervised learning, unsupervised learning, and reinforcement learning. In the domain of ML, the term "supervised learning" pertains to the procedure of constructing algorithms that enable prediction or classification tasks by utilizing data that has been appropriately labeled. According to Talukdar et al. (2023), these algorithms must have inputs (predictors) that are associated with an output (reaction). When the output variable is characterized by distinct categories, the task at hand is classification. Conversely, when the output variable is characterized by a continuous range of values, the task at hand is prediction. Supervised learning encompasses a range of methods, including linear and nonlinear regression, neural networks, random forests, and decision trees, as demonstrated by Kumar et al. (2023). Unsupervised learning encompasses the identification and analysis of patterns and trends within unlabeled data. The objective of this scenario is not to predict a certain outcome, but rather to detect shared characteristics within the data through the utilization of clustering algorithms and comparable methodologies (Cunha et al., 2023). One of the techniques that fall under consideration is the principle components analysis. Reinforcement learning involves the development and deployment of learning agents within an environment, to maximize their potential rewards (Coraci et al., 2023). There exists a necessity for the implementation of comprehensive energy resource planning at both the national level and within emerging economies (Raihan & Voumik, 2022a; Raihan & Tuspekova, 2022e; Raihan, 2023h). The utilization of ML techniques in energy systems, encompassing both energy generation and consumption, exhibits significant potential. Ahmad et al. (2022) argued that the application of ML algorithms can enhance the optimization of energy generation systems, explicitly those of wind and hydro sources.

The application of predictive maintenance systems, which employ condition monitoring techniques typically facilitated by ML and the IoT, can be extended to the maintenance of energy production systems such as stations, machinery, and power lines. In the context of consumption, energy efficiency emerges as the paramount determinant (Raihan & Voumik, 2022b; Raihan & Tuspekova, 2022f; Raihan, 2023i). ML has proven to be highly effective in optimizing consumption through the utilization of supervised learning algorithms, including neural networks and similar techniques (Wang et al., 2023). An apt demonstration of this concept can be observed in the context of a cooling system. For example, it is necessary to possess knowledge about the operational context, the functions it fulfills, the leadership dynamics, the activities conducted within its premises, and the prevailing seasonal conditions, such as winter or summer. In the given situation, ML demonstrates outstanding performance. Routine modifications to the gadget are unnecessary for an engineer, as it possesses the capability to accommodate a diverse array of input values and acquire knowledge from the data it is provided. Optimizing the usage of individual air conditioning units has the potential to yield a significant impact, given the huge volume of air conditioners supplied and installed annually, which reaches millions.

The heating, ventilation, and air conditioning (HVAC) systems within a building are tasked with the responsibility of regulating and sustaining optimal temperature and humidity levels (Raut et al., 2023). Woods et al. (2022) asserted that HVAC systems contribute to over 50% of the overall energy usage within a building and consume approximately 10% of the global electrical supply. The optimization of HVAC systems is a significant potential for us to effectively achieve our sustainability objectives by reducing energy consumption and mitigating carbon dioxide emissions (Ahmad et al., 2022; Raihan & Tuspekova, 2023a; Raihan, 2023j). ML and AI have been extensively utilized in the domain of fossil fuel energy source exploration and drilling (Okoroafor et al., 2022). An example of collaboration between academic and industrial entities is the partnership between the Massachusetts Institute of Technology (MIT) and Exxon Mobil. This collaboration aims to build autonomous underwater robots with ML capabilities. The primary objective of these robots is to explore the ocean surface and identify suitable locations for oil and natural gas drilling operations. These autonomous robotic systems possess the capability to collect and analyze data on the oceanic bed. By integrating ML techniques, specifically reinforcement learning, these robots can acquire knowledge from their mistakes during the process of underwater exploration. However, the utilization of AI and ML systems and algorithms for grid management holds significant potential as a vital field of application in developing nations that employ smart grids. According to Ghiasi et al. (2023), smart grids facilitate bidirectional communication between electric energy producers and consumers. Smart grids refer to power grids that integrate ML, AI, and the IoT by utilizing sensors, meters, and other alerting devices to gather and provide data to users (Slama, 2022). This feature allows individuals to observe and enhance their energy usage. Smart grids, alternatively referred to as intelligent grids, are a recognized term in the field. In the realm of manufacturing, smart grids offer producers the ability to effectively monitor energy use and mitigate the occurrence of unauthorized power connections. These issues are particularly prevalent in emerging nations, as highlighted by Kataray et al. (2023). Smart grids have the potential to facilitate the monitoring of energy use by producers and reduce the occurrence of unauthorized power connections.

Empirical Literature Review

The utilization of data systems is of paramount importance in the attainment of climate targets within the energy industry (Das et al., 2023; Raihan & Tuspekova, 2023b). The proliferation of digital technology in the energy industry and the abundance of data have led to the emergence of data-driven ML strategies as viable approaches (Strielkowski et al., 2023). To now, scholars have primarily directed their attention toward enhancing the predicted accuracy of ML algorithms (Lee et al., 2023). According to Ghoddusi et al. (2019), the field of ML is facilitating novel avenues for research in the domains of energy economics and finance. In their study, Ghoddusi et al. (2019) presented many illustrations of practical implementations, encompassing the projection of energy prices for commodities such as crude oil, natural gas, and power. Additionally, the authors discussed the application of these projections in anticipating demand, managing risk, constructing trading strategies, processing data, and assessing macro and energy trends. According to the findings of Ghoddusi et al. (2019), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Genetic Algorithms (GAs) are among the predominant methodologies employed in the investigation of energy economics. The study concluded by emphasizing specific areas of limited understanding and providing recommendations for further investigation. To establish a correlation between dimensionless characteristics and power-law-like associations, Lin et al. (2022) proposed the utilization of a novel neural network framework known as DimNet. The study conducted by Lin et al. (2022) demonstrated the potential of transforming DimNet into an explicit algebraic piecewise power-law-like function. This transformation enhances the interpretability of DimNet, distinguishing it from traditional neural networks that are commonly regarded as opaque or "black boxes". The ease of modification of DimNet played a crucial role in enabling this finding. Lin et al. (2022) have devised a data-driven, empirical model employing DimNet to approximate the pre-dry out heat transfer coefficient in flow boiling within micro fin tubes. The main objective of this model is to forecast the flow boiling heat transfer coefficient before the onset of drying. The model created by DimNet underwent fine-tuning through the comparison of multiple sets of prominent dimensionless properties. Additionally, the network design was modified after training on a comprehensive database consisting of 7349 experimental data points for 16 distinct refrigerants. The model proposed by Lin et al. (2022) is both statistically robust and incorporates trends in the heat transfer coefficient that are determined by a specific set of factors.

The high level of accuracy in predicting outcomes attained by the model can be attributed to DimNet's capacity to autonomously categorize the data into optimal regions while concurrently establishing correlations among the variables within each region. According to the findings of Lin et al. (2022), the DimNet design demonstrates a high level of suitability for effectively modeling heat transfer and flow problems that involve many physical domains. In the context of convective heat transfer, the search for a power-law-like input-output relationship is particularly relevant. Zhou et al. (2021) also asserted the significance of short-term forecasting models in predicting photovoltaic (PV) energy generation. The utilization of these models is imperative in the context of AI-driven IoT modeling for smart cities, as they play a crucial role in ensuring the stability of power integration between PV systems and the smart grid. According to Zhou et al. (2021), recent developments in AI and IoT technology have facilitated the application of DL techniques to enhance the accuracy of energy generation forecasts for PV systems. This proposition is viable as the conventional approach for predicting PV energy production encounters challenges in including external factors, such as seasonality, in its calculations.

Zhou et al. (2021) proposed a hybrid DL strategy for forecasting PV energy generation by incorporating clustering algorithms, a convolutional neural network (CNN), a long short-term memory (LSTM), and an attention mechanism into a wireless sensor network. The aforementioned plan was formulated to augment previous endeavors aimed at resolving the matter. Zhou et al. (2021) propose a system that is founded upon three

independent procedures: clustering, training, and forecasting. The study conducted by Zhou et al. (2021) involved a comparison of experimental outcomes with those achieved through conventional systems, including traditional artificial neural networks, long short-term memory neural networks, and an algorithm that combines long short-term memory neural networks with an attention mechanism. The results indicated notably improved prediction accuracy rates across all time intervals. According to Arumugam et al. (2022), ML encompasses a diverse range of methodologies aimed at developing a predictive model only based on past data, with the ability to forecast future data. Zhou et al. (2021) elucidate that the development of a prediction model through ML entails the assessment of data samples to discern patterns and the establishment of decision rules. In addition, Zhou et al. (2021) posited that the predictive capabilities of ML algorithms have the potential to facilitate intelligent agricultural practices and enhance wind speed forecasting, both of which play a pivotal role in augmenting energy generation.

According to Zhou et al. (2021), a critical concern in the field of electrical engineering research is the enhancement of accuracy in forecasting power demand and pricing. Zhou et al. (2021) argued that the utilization of ML algorithms is highly advantageous in tackling the complex issues encountered in the field of energy and power engineering, owing to their remarkable predictive capabilities. Energy has a significant role in the economic and social development of a nation (Raihan & Tuspekova, 2022g; Raihan, 2023k). The demand for energy on a global scale has seen exponential growth in recent decades (Raihan & Tuspekova, 2022h; Raihan, 2023l). The issue of energy demand forecasting has been a significant focus in an increasing number of countries (Raihan & Tuspekova, 2022i; Raihan, 2023m). If governments possess the ability to anticipate the energy requirements in the residential and commercial sectors, they will be more effectively equipped to provide energy resources and formulate strategies for the establishment of sustainable energy production (Raihan & Tuspekova, 2022j; Raihan, 2023n). The implementation of these techniques may entail harnessing both renewable and nonrenewable energy sources to establish a dependable and environmentally sustainable power network (Raihan & Tuspekova, 2022k; Raihan, 2023o).

Nabavi et al. (2020) posited that the modeling of energy use in both residential and commercial sectors facilitates the recognition of significant economic, social, and technological factors, hence leading to the attainment of a reliable energy supply. The assertion made in the statement is supported by the research conducted by Raihan et al. (2023e), which demonstrates that the utilization of industrial energy may be effectively analyzed by considering the impact of economic, social, and technological factors. In their study, Nabavi et al. (2020) employed three distinct ML methodologies to forecast energy consumption patterns in both residential and commercial settings in Iran. Various methodologies, including nonlinear autoregressive with exogenous input artificial neural networks and logarithmic multiple linear regression, were employed in the study. Nabavi et al. (2020) have conducted research indicating that there would be a notable rise in both home and business energy usage within Iran over the forthcoming years. When constructing these models, various criteria are considered, including the proportion of renewable energy in total energy consumption, gross domestic product (GDP), population size, natural gas pricing, and electricity rates.

Serban and Lytras (2020) assert that the Smart Energy domain poses significant research challenges for the future of smart cities. This is primarily due to the criticality of optimization concerns, the necessity of smart and customizable networks, and the utilization of advanced analytical methods and techniques facilitated by AI and ML. According to Raihan et al. (2022f), the utilization of renewable energy is of paramount importance for the sustained expansion of the global economy, particularly in light of the challenges posed by climate change and the depletion of natural resources. To adapt to these changes in demand, the field of AI necessitates the development of novel protocols for the coordination and oversight of various tasks (Serban and Lytras, 2020). To effectively address the various challenges that may impact the growth and resilience of the energy sector, it

is imperative to improve the architecture of the energy infrastructure, as well as the deployment and production of renewable energy. In their study, Serban and Lytras (2020) proposed a technique for assessing the influence of AI on the real estate market in Europe.

Raihan (2023p) asserted that energy efficiency within the public sector holds significant importance within the framework of smart cities, given that buildings, particularly public ones such as educational, healthcare, governmental, and other public institutions with high usage rates, constitute the primary energy consumers. Furthermore, Zekić-Sušac et al. (2021) stated that there has been inadequate exploration of the new advancements in ML within the realm of big data. The objective of this essay was to address the question of integrating a Big Data platform with ML techniques to develop an intelligent system for effectively managing energy efficiency in the public sector. The concept of the smart city primarily depends on the aforementioned interoperability. Zekić-Sušac et al. (2021) employed deep neural networks, Rpart regression trees, and Random Forests, along with variable reduction approaches, to develop prediction models for the energy consumption of public sector buildings in Croatia. The study conducted by Zekić-Sušac et al. (2021) revealed that the Random Forest technique had the highest level of precision in generating the model. Additionally, a comparative analysis was conducted to assess the key predictors derived from the three distinct methodologies. The suggested MERIDA intelligent system has the potential to integrate models.

To enhance the management of energy efficiency in government buildings within a Big Data framework, this system integrates the collection of extensive data sets with predictive models that analyze energy consumption patterns for individual energy sources. The utilization of big data and the implementation of the MERIDA framework have been suggested as strategies to enhance energy efficiency within the public sector. The use of AI methodologies is progressively becoming integrated within the public and governmental domains (Wirtz et al., 2022). Power and energy enterprises exemplify such industries due to their important significance in sustaining daily existence. Nevertheless, the inclusion of reliability, accountability, and explainability as criteria poses challenges in the direct implementation of AI-based technologies in power systems (Kaur et al., 2022). This is because the economic burdens associated with catastrophic breakdowns and widespread blackouts have the potential to amount to billions of dollars. The development, implementation, and assessment of AI systems play a vital role in the energy industry. To accomplish this objective, it is necessary to employ principles from the field of physics in the analysis of power system measurements. Additionally, the development of AI algorithms is crucial for accurately predicting demand. Moreover, it is vital to construct responsible AI protocols and reliable metrics for assessing the effectiveness of the AI model. These steps are crucial for the betterment of society.

Methodology

The objective of this study is to assess the potential impact of AI and ML on the energy industry, with a specific focus on improving energy generation in developing regions. This study attempts to examine the issues that have emerged as a result of the prevalent absence of electricity and the persistent incidence of load-shedding. The present study employed the systematic literature review methodology as suggested by Raihan and Bijoy (2023). According to Benita (2021), the systematic literature review framework is considered to be a dependable approach. A preliminary review of the literature was conducted to identify pertinent articles, validate the proposed idea, avoid redundancy with previously covered issues, and ensure the availability of sufficient articles for conducting a comprehensive analysis of the significance of AI and ML in the energy sector. According to Tawfik et al. (2019), it is crucial to enhance the retrieval of results by acquiring a comprehensive understanding and familiarity with the study topic through the examination of pertinent materials and active engagement in

relevant debates. This objective can be achieved by conducting a thorough examination of pertinent literature and actively participating in pertinent academic conversations.

The present study examined various strategies aimed at mitigating the influence of prejudice. One of the methods employed was performing a systematic manual search to identify any reports that might have been missed during the original search process. This investigation, employing the methodology proposed by Vassar et al. (2016), discovered no discernible indications of bias. In the context of this investigation, a comprehensive set of five unique methodologies were employed to carry out manual searches. The methods employed encompassed many strategies, such as conducting an exhaustive literature search to identify relevant references from the studies and reviews under consideration. Additionally, efforts were made to establish direct communication with authors and industry experts. Furthermore, supplementary materials, including related papers and articles cited within reputable academic databases such as Google Scholar, Scopus, and Web of Science, were thoroughly examined. The manual search results were initially enhanced and polished through the process of examining the reference lists of the included publications. The initial stage of the process was undertaken. Subsequently, the author engaged in the practice of citation tracking, a method involving the systematic monitoring of all the scholarly works that reference each of the papers incorporated in the collection. In conjunction with the manual search, an online search of databases was also undertaken as an integral component of the comprehensive search process. This study exclusively relied on research articles that have undergone rigorous evaluation by experts in the field,

Inits study exclusively relied on research articles that have undergone rigorous evaluation by experts in the field, ensuring the reliability and validity of the findings. Both qualitative and quantitative secondary literature on the application of ML in the fields of energy economics and finance were considered. The publications were thereafter evaluated to ascertain whether their main subject matter bore a resemblance to that of the present inquiry. Priority consideration was given to papers published after the year 2000. The primary justifications for the elimination of papers are their lack of relevance, duplication, incomplete textual content, or limited presence of abstracts. The predetermined exclusion criteria were established to safeguard the researcher against potential biases that could influence their findings. Figure 4 illustrates the progression of review criteria employed for the selection of appropriate documents for analysis.

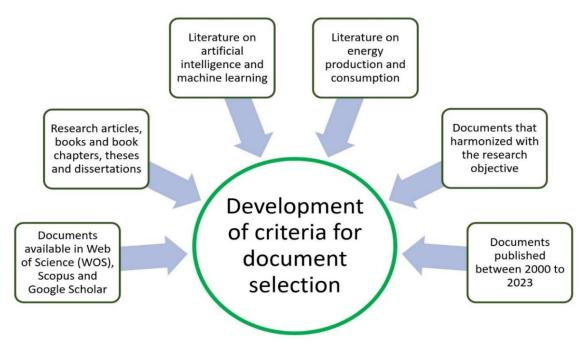


Figure 4. The development of criteria for the selection of documents.

The comprehensive literature review encompassed a total of 130 distinct scholarly articles. The present study implemented a data verification process, wherein each included article was cross-checked with its corresponding entry in an extract sheet using visual evidence in the form of photographs. This was done to identify any discrepancies or errors in the data, as suggested by Tawfik et al. (2019). These errors may arise due to the expected presence of human error and bias. It is noteworthy that of the 130 papers subjected to qualitative synthesis, only those publications containing relevant material were cited in the reference list contained in the manuscript. This implies that certain articles were not included in the reference list. Figure 5 illustrates the systematic review methodologies utilized in the current study. After the research topic was chosen, this study proceeded to find and locate relevant articles, do an analysis and synthesis of diverse literature sources, and create written materials for article review. The synthesis phase encompassed the collection of a wide range of publications, which were subsequently amalgamated into conceptual or empirical analyses that were relevant to the finalized research.

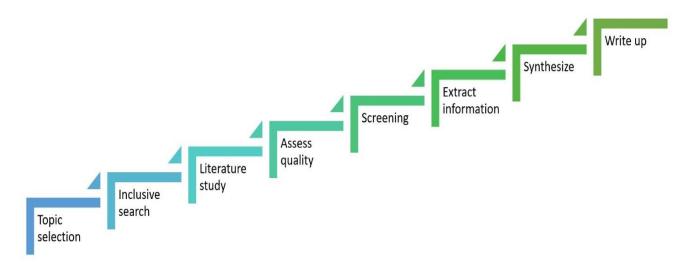


Figure 5. The procedure of systematic review conducted by the study.

Results and Discussion

AI and ML for energy production

The application of AI and ML can offer advantageous improvements in the optimization of power generation. The utilization of AI and ML in the energy industry within emerging nations holds significant potential for positive outcomes. Some potential solutions include the use of predictive maintenance techniques, exploration of alternative energy sources, effective grid management strategies, utilization of ML algorithms to address energy consumption challenges, and enhancement of energy efficiency in both residential and commercial buildings. Figure 6 provides a comprehensive overview of the significance of AI and ML in the production and utilization of energy.

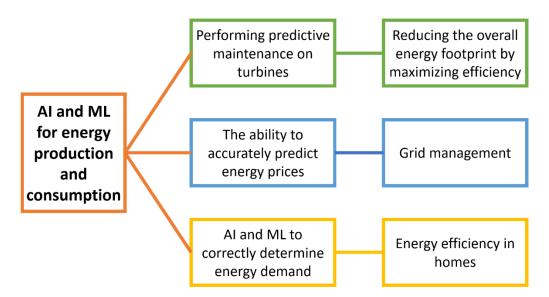


Figure 6. AI and ML for energy production.

Predictive turbine maintenance and energy optimization

The concept of "predictive maintenance" encompasses the utilization of diverse methods and strategies for data analysis, to detect anomalies in the operation of machinery and processes, as well as identifying prospective deficiencies in these components, to address these concerns before they escalate into severe failures. The approach in question was devised by IBM during the 1980s. Stetco et al. (2019) investigated the employment of ML models to monitor the status of wind turbines, specifically focusing on tasks such as blade defect detection and generator temperature monitoring. Various models are classified using standard ML procedures, which encompass data sources, feature extraction and selection, model selection (classification, regression), model validation, and decision-making. Stetco et al. (2019) asserted that the majority of models rely on simulated data. The majority of the remaining procedures rely primarily on regression analysis, while just around one-third of them incorporate categorization techniques. The predominant technologies employed in many domains are neural networks, support vector machines, and decision trees.

Furthermore, Hsu et al. (2020) conducted an analysis on a dataset of 2.8 million sensor data points obtained from 31 wind turbines located in Taiwan. These turbines were installed within the timeframe of 2015 to 2017. The primary objective of the analysis was to identify flaws in the wind turbines and predict the extent of maintenance that would be necessary. The study utilized historical data on wind turbines obtained from Taiwan's Changhua Coastal Industrial Park to examine and predict the maintenance needs of these turbines. During the period spanning from 2015 to 2017, a cohort of 31 wind turbines amassed a cumulative sum of 2,815,104 observations. By employing two distinct methodologies in ML, viz. decision trees and random forest classifications, Hsu et al. (2020) reported a noteworthy accuracy rate of over 92% in the prediction of abnormalities in wind turbines. The analysis of sensor data from wind turbines prioritized the utilization of maintenance checklist insights offered by practitioners. Besides, Hsu et al. (2020) conducted research to identify the underlying causes of wind turbine malfunctions. The study collected and analyzed data on both abnormal and normal stages of wind turbine operation and utilized a combination of data analytics and domain expertise to construct predictive models. The results of this study offer practical insights for Taipower and other wind turbine operators in the identification of turbine malfunctions and the prediction of future maintenance needs.

The topic of energy consumption has garnered significant attention from individuals in both domestic and professional settings for an extended period (Raihan, 2023q). Nevertheless, in the absence of doing a substantial quantity of manual calculations, our ability to precisely determine the specific appliances or devices that consume the highest amount of energy has been limited. The aforementioned circumstances have been disrupted due to the widespread use of IoT devices and smart meters. Non-intrusive appliance load monitoring (NIALM), alternatively referred to as disaggregation, is a technique that uses ML algorithms to examine energy usage at an individual device level. By employing this equation, it becomes straightforward to ascertain the home appliances that exhibit the most elevated monthly operational expenditures. Customers who employ this technology will have the capacity to effectively modify their consumption habits, enabling them to achieve cost savings and reduce their energy consumption. Individuals have the choice to either reduce the frequency of using costly appliances or substitute them with more energy-efficient alternatives.

Grid management and energy price prediction

The field of data analytics is gaining significance in the current era of industrialization (Yeo, 2023). The electricity sector has achieved notable advancements in the adoption of data analytics methodologies. The installation of smart meters and other sensors in the smart grid has resulted in a substantial accumulation of data (Chen et al., 2023). The utilization of big data analytics is imperative to effectively handle an extensive quantity of diverse data. The integration of big data analytics and ML algorithms plays a crucial role in the functioning of the electrical transmission and distribution network. These components are essential for various tasks such as data collecting, storage, and analysis, as well as prediction for data forecasting and system maintenance (Strielkowski et al., 2023). According to Li et al. (2022), the implementation of these techniques has the potential to enhance customer service and societal welfare, as well as optimize the distribution of energy in terms of efficiency, affordability, quality, and cost.

In the realm of manufacturing, smart grids have the potential to aid firms in monitoring energy use and mitigating the prevalence of unauthorized power connections, which are notable challenges encountered in poor nations (Raza et al., 2022). One further concern pertains to the growing trend among individuals and businesses to assert their autonomy in power generation, facilitated by the increasing accessibility and affordability of personal techniques such as solar or wind power (Sun et al., 2023). Individuals possessing power generation systems can generate, utilize, and store their energy resources. The possibility of selling surplus electricity to the local power company is contingent upon the geographical location of the individual or entity in question. The determination of optimal periods for energy generation, storage, or sale can be accomplished by the application of ML techniques (Ahmad et al., 2022). According to Umar et al. (2022), in an ideal scenario, customers would engage in the use or storage of energy during periods of low costs, afterward capitalizing on the opportunity to sell it back to the system during periods of high prices. To enhance the accuracy of hourly forecasts, it is feasible to employ ML models for the analysis of historical data, consumption patterns, and meteorological predictions (Mayer et al., 2023). Individuals and businesses with personal or commercial energy-producing systems can utilize this information to inform their decision-making process on the optimal utilization of their energy resources. An example that may be cited is the Adaptive Neural Fuzzy Inference System (ANFIS), which has been utilized to predict the immediate wind patterns required for electricity generation. As a result of this phenomenon, producers can attain their maximum levels of energy production and subsequently trade this energy back into the grid during periods when prices are at their peak (Wu et al., 2023). Given the abundance of available information, it is imperative for both enterprises and governments to proactively engage in the investment of AI and ML technologies. This strategic approach will facilitate effective grid management and enable correct estimation of energy pricing.

AI and ML to accurately assess residential energy demand and efficiency

The escalating global energy demand has prompted significant apprehensions regarding potential supply constraints, depletion of energy resources, and detrimental impacts on the environment, including ozone layer depletion, global warming, and climate change (Raihan et al., 2023g; Raihan, 2023r). According to Cao et al. (2016), the energy consumption of residential and commercial structures surpasses that of other prominent industries, such as manufacturing and transportation. These structures account for approximately 20 to 40 percent of global energy consumption. The upward trajectory in energy consumption is anticipated to persist in the foreseeable future due to population growth, heightened demands for comfort and building amenities, and an increase in indoor occupancy duration (González-Torres et al., 2022). Consequently, energy policy at several levels, including regional, national, and worldwide, has prioritized the enhancement of energy efficiency within buildings. The increase in energy usage in building services, specifically attributed to HVAC systems, is a prominent observation. These systems contribute to fifty percent of the overall energy consumption in buildings and twenty percent of the total energy consumption in the United States (Cao et al., 2016).

Another important aspect to consider about AI and ML is the energy efficiency in residential buildings (Mazhar et al., 2022). The increasing popularity of smart home systems in recent years can be attributed to their ability to enhance both comfort and quality of life (Goudarzi et al., 2022). The IoT has garnered considerable attention within the electrical industry due to its emergence as a critical application for smart home technology. This development has positioned IoT as a prominent and indispensable use case for this technology. Smart lighting is a prominent platform within the realm of IoT technology, as highlighted by Yudidharma et al. (2023), particularly in the context of smart houses. The phrase "smart lighting" is frequently employed to describe lighting devices that offer enhanced functionality, such as remote dimming or on/off control, to improve user comfort and minimize energy consumption. The intelligent LED bulb can generate a diverse array of hues, with each color necessitating a specific amount of electrical power. According to a recent study conducted by Aussat et al. (2022), the utilization of smart LED bulbs inside smart lighting systems has demonstrated notable improvements in energy efficiency. A comprehensive analysis is conducted to assess the energy-saving potential of halogen, compact fluorescent lamp (CFL), light-emitting diode (LED), and smart LED technologies. The perception of minimal energy usage is only achieved when a smart LED light is both dimmed and remotely controlled. Efficiency in energy utilization within commercial buildings is a significant part of AI and ML (Khan et al., 2023). According to Robinson et al. (2017), buildings account for 40% of the total energy use in the United States.

A comprehensive comprehension of energy intensity distribution is crucial for urban planners. The use of energy within buildings is influenced by urban form factors, such as density and floor-area ratios (FAR) (Liu et al., 2023). The building sector plays a substantial role in the overall energy consumption of the country, hence giving rise to many environmental challenges that pose a threat to human sustainability (Raihan, 2023s). The utilization of energy forecasting in the context of building operations is gaining traction due to its potential to mitigate energy consumption and yield cost savings (Raihan, 2023t). In addition, the use of energy-efficient building designs will play a significant role in diminishing the aggregate energy consumption of newly constructed edifices. ML is widely recognized as a highly successful methodology for achieving desired outcomes in prediction tasks (Olu-Ajayi et al., 2022). The investigation of potential sources of energy is a significant area of study (Raihan et al., 2023u). Although the Earth's seas encompass around 71% of its surface area, there exists a

dearth of knowledge regarding the characteristics and attributes of the underlying structures inside these expansive aquatic environments. Recent advancements in marine robotics and AI have the potential to significantly reduce the enigma surrounding the ocean floor (Agarwala, 2023). The expanding number of spacecraft voyaging beyond the confines of the solar system has resulted in a growing disparity between our knowledge of outer space and our understanding of the Earth's oceans (Morrow et al., 2023). Developing nations are compelled to harness the promise offered by AI and ML. This necessitates a substantial transformation in policy within both the public and private sectors, along with the establishment of productive collaborations between the two. Given the absence of a feasible solution for the bulk storage of substantial quantities of energy, it becomes imperative for utility providers to precisely assess the energy demands of their clientele. This implies that energy must be promptly transferred and utilized following its generation. The application of ML and AI has the potential to enhance the accuracy of these projections.

According to Mariano-Hernández et al. (2020), the estimation of daily energy consumption can be facilitated by examining records of energy usage, referring to weather forecasts, and taking into account the operational status of various establishments and structures. An example of this phenomenon can be observed in the heightened energy consumption during a hot summer day occurring on a weekday when business establishments are compelled to operate their air conditioning systems at maximum capacity (Sanzana et al., 2023). During the summer season, the occurrence of rolling blackouts can be attributed to the excessive use of air conditioners. However, the implementation of preventive measures such as the utilization of weather forecasts and historical data can effectively mitigate these blackouts, provided that they are discovered promptly. When attempting to elucidate fluctuations in demand, ML algorithms seek intricate patterns within a multitude of contributing factors, encompassing variables such as the day of the week, the specific time of day, anticipated wind and solar radiation levels, significant sporting occasions, historical demand patterns, average demand levels, ambient air temperature, humidity, and atmospheric pressure, as well as wind direction (Pallonetto et al., 2022; Benti et al., 2023). ML predictions exhibit higher accuracy compared to human predictions due to the ability of ML algorithms to identify and discern subtle patterns more comprehensively. According to Arumugam et al. (2022), it is evident that there exists the potential to enhance efficiency and reduce expenses in energy procurement without necessitating excessively expensive modifications. According to Serban and Lytras (2020), in light of prospective shifts in market complexity, fluctuations in demand, the emergence of virtual clients, and other pertinent considerations, it is contended that renewable energy systems may lack dependability in the absence of adequate storage capacity. An examination of recent advancements reveals that AI has the potential to provide optimization even in situations where there is a lack of extensive long-term meteorological data.

Recommendations for emerging energy markets to maximize AI and ML

Figure 7 illustrates the significance of establishing effective and efficient partnerships between the public and private sectors when implementing AI and ML in emerging markets. Additionally, it emphasizes the necessity of government-sponsored investments in AI and ML within the energy sector. Furthermore, the development of accountable and robust AI methods, the establishment of reliable performance evaluation measures for AI models, and a comprehensive understanding of power system measurements concerning physics, design, and engineering are also crucial considerations. The utilization of AI and ML is becoming prevalent in the public and governmental domains, with a particular emphasis on its application within the electrical and energy sectors. The direct application of AI-based technology to power systems carries inherent risks, mostly stemming from the need to meet stringent standards related to reliability, accountability, and explainability. This is due to the

exorbitant expenses linked to cascading failures and extensive blackouts, which are deemed unaffordable for society.

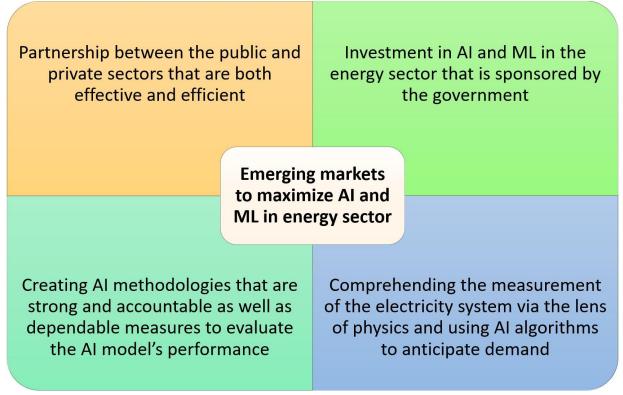


Figure 7. Effective AI and ML proposals for emerging markets.

Conclusion

Globally, the energy sector faces a diverse array of challenges, encompassing factors such as increasing energy use and the need for improved efficiency, shifting patterns in supply and demand, and a dearth of adequate analytical tools for effective management. In emerging markets, these issues manifest themselves with greater severity. The presence of numerous illicit connections to the electrical grid results in a considerable quantity of energy that remains unaccounted for and uncompensated. Therefore, the present study employed the systematic literature review methodology to examine the challenges arising from frequent power outages and limited energy accessibility. The objective of this study is to provide a comprehensive review of the potential contributions of AI and ML technologies toward the advancement of energy generation in developing countries. The findings indicate that AI and ML possess the capacity to effectively contribute to the enhancement of energy consumption optimization, grid management, accurate estimation of energy pricing, and precise determination of energy demand and efficiency in residential buildings. Furthermore, it has been determined that investments and the implementation of AI and ML techniques in the energy industry necessitate both accountability and robustness, necessitating the establishment of dependable metrics for evaluating the efficacy of AI models. Furthermore, it has been determined that a comprehensive comprehension of power system measurements within the context of quantum physics, design principles, and ML framework is crucial in the application of AI and ML in growing markets. The maintenance of a reliable energy supply is crucial for promoting the productivity of enterprises in emerging countries and facilitating the attainment of their development goals.

One of the limitations inherent in this study pertains to the exclusion of AI policies, a crucial aspect in the advancement of the energy industry and the enhancement of energy efficiency. There is significant variation in AI policy across different countries. However, despite the known trends in the utilization of AI and ML in the energy industry, further research is evidently required to determine the most effective solutions in numerous scenarios. Indeed, a significant number of the suggested solutions exhibit a deficiency in terms of testing and validation, particularly through real-life trials and research undertaken on a broad scale. Therefore, it is imperative to undertake more research endeavors, in conjunction with industrial projects and extensive experimentation, in order to facilitate the development of more precise models and AI solutions. This trajectory will facilitate the integration of AI and ML techniques into the energy sector, leading to their widespread adoption and incorporation in developing countries.

Declaration

Acknowledgment: The author would like to thank Dewan Ahmed Muhtasim (DAM) and Mostafizur Rahman for their motivation that inspired the author to write this article.

Conflict of interest: The author declares no conflict of interest.

Funding: This research received no funding

Authors contribution: Asif Raihan contributed to conceptualization, visualization, methodology, reviewing literature, extracting information, synthesize, and manuscript writing.

Data availability: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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