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Artificial Intelligence and Machine Learning for Energy Consumption and Production in Emerging Markets: A Review

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Abstract: An increase in consumption and inefficiency, fluctuating trends in demand and supply, and a lack of critical analytics for successful management are just some of the problems that the energy business throughout the world is currently facing. This study set out to assess the potential contributions that AI and ML technologies could make to the expansion of energy production in developing countries, where these issues are more pronounced because of the prevalence of numerous unauthorized connections to the electricity grid, where a large amount of energy is not being measured or paid for. This study primarily aims to address issues that arise due to frequent power outages and widespread lack of access to energy in a wide range of developing countries. Findings suggest that AI and ML have the potential to make major contributions to the fields of predictive turbine maintenance, energy consumption optimization, grid management, energy price prediction, and residential building energy demand and efficiency assessment. A discussion of what has to be done so that developing nations may reap the benefits of artificial intelligence and machine learning in the energy sector concluded the paper.

Keywords: artificial intelligence; energy sector; machine learning

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1. Introduction

A multifaceted understanding of computational, economic, and social issues is required to overcome the challenges associated with the integration of complex artificial intelligence technology into smart energy systems and grids. Beyond the post-industrial society and its ramifications, the search for practical answers for the advancement of the globe has attracted the involvement of academia, business, and society in the effort to achieve sustainable development [1]. Academia, business, and society are all involved in the search for practical solutions to the global development problem. The energy sector is facing challenges on a global scale, some of which include rising consumption and efficiency concerns, fluctuating trends in supply and demand, and a deficiency in the analytics required for efficient management. The gravity of these issues is exacerbated in countries with growing markets commonly referred to as emerging markets. There are many unauthorized "connections to the power grid", which implies that a significant amount of energy is not metered or paid. This results in losses in addition to greater levels of CO_2 emissions, making efficiency difficulties an especially critical issue.

After all, consumers have less incentive to use energy responsibly when it is provided at no cost to them [2]. In many industrialized nations, the implementation of "artificial intelligence and other related technologies that enable communication between smart grids, smart meters, and Internet of Things devices" has already begun in the power industry. These developments have the potential to increase the utilization of renewable energy sources while also improving the management of power, efficiency, and transparency [2]. Ghoddusi et al. [3] state that the application of ML is producing novel opportunities for cutting-edge research in the sectors of energy economics and finance. Ghoddusi et al. [3] carried out an in-depth examination of the rising body of research on the uses of ML in the disciplines of energy economics and finance. They found that ML has a wide range of potential applications. The investigation carried out by Ghoddusi et al. [3] uncovered applications in a variety of domains, including the assessment of macro and energy trends, the forecasting of demand, the management of risk, the development of trading strategies, and the processing of data. Crude oil, natural gas, and power are three types of energy whose prices are some examples of those that can be projected. In addition, Chen et al. [4] proposed that machine learning is rapidly altering the landscapes of a variety of fields, including the fields of physics and chemistry, as well as other areas.

Chen et al. [4] found that AI and ML can help to establish material connections, comprehend the chemistry of materials, and speed up the development of new materials. ML is currently being explored as a completely new technique to use its ability to do complex tasks on its own. AI is also being used to help establish material connections. Work that was presented by Chen et al. [4] indicated how ML may be applied to a wide variety of energy materials. These materials included "rechargeable alkaliion batteries, photovoltaics, catalysts, thermoelectrics, piezoelectrics, and superconductors". Liu et al. [5] claim that data-driven materials research will transform scientific discoveries and lead to new paradigms in the production of energy materials because of developments in AI and ML. These developments are expected to occur because of recent technological improvements. Because of this, there is now a greater opportunity for data-driven materials science to significantly impact the outcomes of research. According to Liu et al. [5], recent developments in data-driven materials engineering suggest that implementing ML technology would significantly simplify the design and development of advanced energy materials, as well as improve the discovery and deployment of these materials. It was argued by Nabavi et al. [6] that "energy plays a strategic role in the economic and social development of countries. In the past few decades, energy demand has been increasing exponentially across the world, and one of the primary concerns in many countries is attempting to predict energy demand".

It is believed, as stated by Nabavi et al. [6], that the residential and commercial sectors account for around 34.7 percent of the total energy consumption on a global scale. Therefore, Nabavi et al. [6] argued that "anticipating energy demand in these sectors will help governments to supply energy sources and to develop their sustainable energy plans. Some examples of these plans include making use of renewable and non-renewable energy potentials for the development of a safe and environmentally friendly energy system". Nabavi et al. [6] also made the case that modelling energy use in the home and commercial sectors makes it possible to pinpoint the key economic, social, and technological elements that ultimately lead to a secure level of energy supply. This argument was founded on the finding that identifying the important economic, social, and technological elements allows for modelling energy consumption in the residential and commercial sectors. This was covered with the framework used to model how much energy is used by residential and commercial structures.

The work by Nabavi et al. [6], anticipated residential and commercial energy demands in Iran using three distinct machine-learning approaches. "Multiple linear regression, logarithmic multiple linear regression methods, and nonlinear autoregressive with exogenous input artificial neural networks" were some of the methods that were incorporated into these approaches. This paper was successful in predicting Iran's requirements for energy. Accurate predictions of corporate failure in the Chinese energy sector, according to Xu et al. [7], serve as both a catalyst for continuous improvement in state power generation and sustainable investment in the energy sector. These results were discussed with the Chinese energy sector. During the lecture, the backdrop for this discussion was China's energy industry. Therefore, by simultaneously considering textual data and numerical data, Xu et al. [7] proposed a novel integrated model (NIM) for business failure forecasting in the Chinese energy sector. Following the establishment of these foundations, Xu et al. [7] believe that AI and ML will be useful in the energy industry, particularly in emerging markets in the production and consumption of energy. As a result, the purpose of this study is to evaluate the possible contributions that AI and ML could make to the energy sector, particularly in the enhancement of energy generation in emerging regions. The research aims to investigate the problems that have arisen because of the widespread lack of electricity and the constant occurrence of load-shedding. The rest of the document is organized as follows: the first section introduces the theoretical and empirical perspectives on artificial intelligence, deep learning, machine learning and the empirical literature. This was followed by the methodology and the possible role that can be played by Artificial Intelligence and Machine Learning in the energy sector in emerging economies.

2. Theoretical and Empirical Perspectives

2.1. Artificial Intelligence

According to Dick [8], the history of artificial intelligence is more than just a record of machines attempting to imitate or replace human intellect; rather, it is also a record of how our conception of intelligence has developed with time. As a result, artificial intelligence (AI) is not an invention, despite what the dominant narrative would have us believe; rather, it is ingrained in far more extensive histories of what makes up intelligence and what makes up artificial intelligence. John McCarthy defines artificial intelligence (AI) as the science and engineering behind the creation of intelligent devices, particularly intelligent computer programs. It is related to the same work of using computers to understand human intelligence, but AI does not have to confine itself to physiologically observable approaches. Instead, it is related to the task of using computers to comprehend human intelligence [9]. On the other hand, intelligence may be described as the capacity to acquire and use effective strategies for problem-solving and goal-attainment, considering the specifics of the situation in a world that is inherently uncertain and constantly shifting. A factory robot that has been completely pre-programmed is versatile, accurate, and reliable, but it lacks intelligence.

However, the genesis of the artificial intelligence conversation was defined by Alan Turing's key paper, Computing Machinery, and Intelligence, which was released in 1950. This was decades before this concept. Turing, who is commonly referred to as the father of computer science, poses the question, "Can machines think?" in this piece of writing. After that, he proposes a test that would later become commonly known as the Turing Exam. In this test, a human interrogator would attempt to differentiate between a machine and a human written response [10,11]. Although this test has been subjected to a great deal of scrutiny ever since it was published, it continues to be an important part of the history of artificial intelligence as well as an ongoing concept within philosophy since it utilizes ideas revolving around linguistics [11]. After that, Stuart Russell and Peter Norvig went on to publish a book called Artificial Intelligence: A Modern Approach (link lives outside IBM), which has since become one of the most influential textbooks in the field of AI research. In it, they go into four alternative aims or definitions of AI, which divide computer systems based on logic and thinking versus action. In other words, they compare the two.

2.2. Potential Definitions of AI

The various interpretations of artificial intelligence are depicted in Figure 1 below. Systems that behave in a manner analogous to that of humans would have been included in Alan Turing's definition of artificial intelligence. To define it in its most basic terms, artificial intelligence (AI) is a discipline that enables problem-solving by combining computer science and extensive datasets. In addition to this, it incorporates the subfields of machine learning and deep learning, both of which are commonly referenced in the context of artificial intelligence. These fields are comprised of AI algorithms that strive to construct expert systems that can make predictions or classifications depending on the data that they are provided with [11].

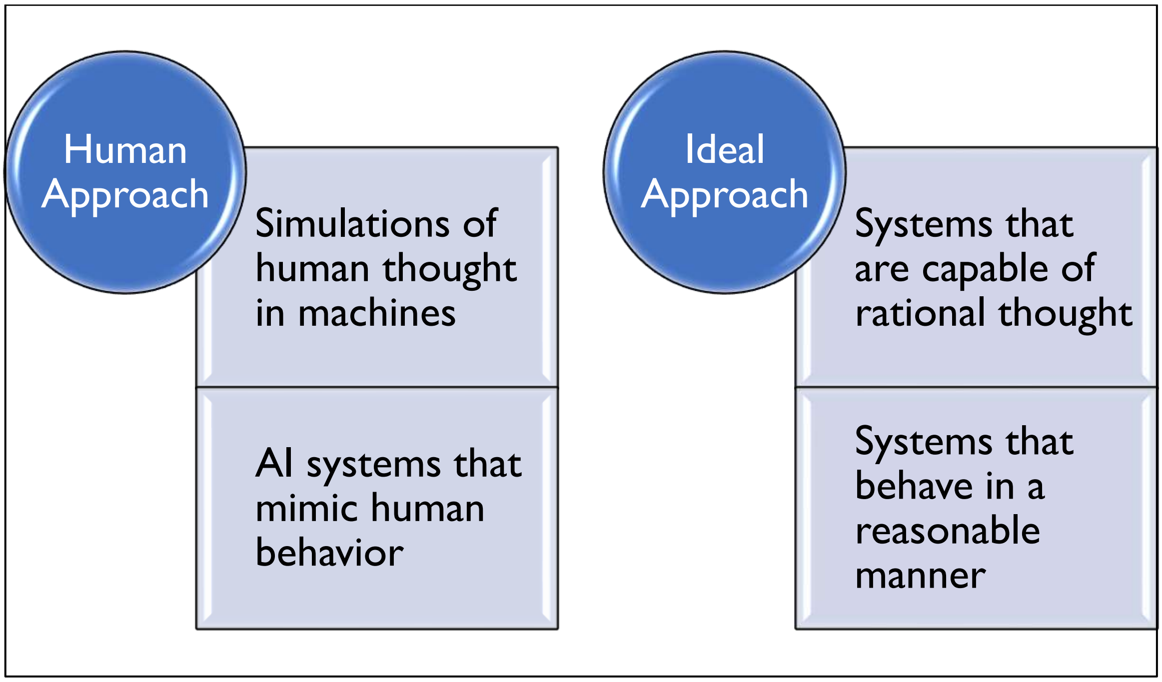

Figure 1. Potential definitions of AI.

3. Deep Learning and Machine Learning

The terms "deep learning" and "machine learning" are sometimes used interchangeably; nevertheless, there are important distinctions between the two that should be made clear. Deep learning is a sub-field of machine learning, which in turn is a sub-field of artificial intelligence (AI). Both machine learning and deep learning are sub-fields of AI as shown in Figure 2 below.

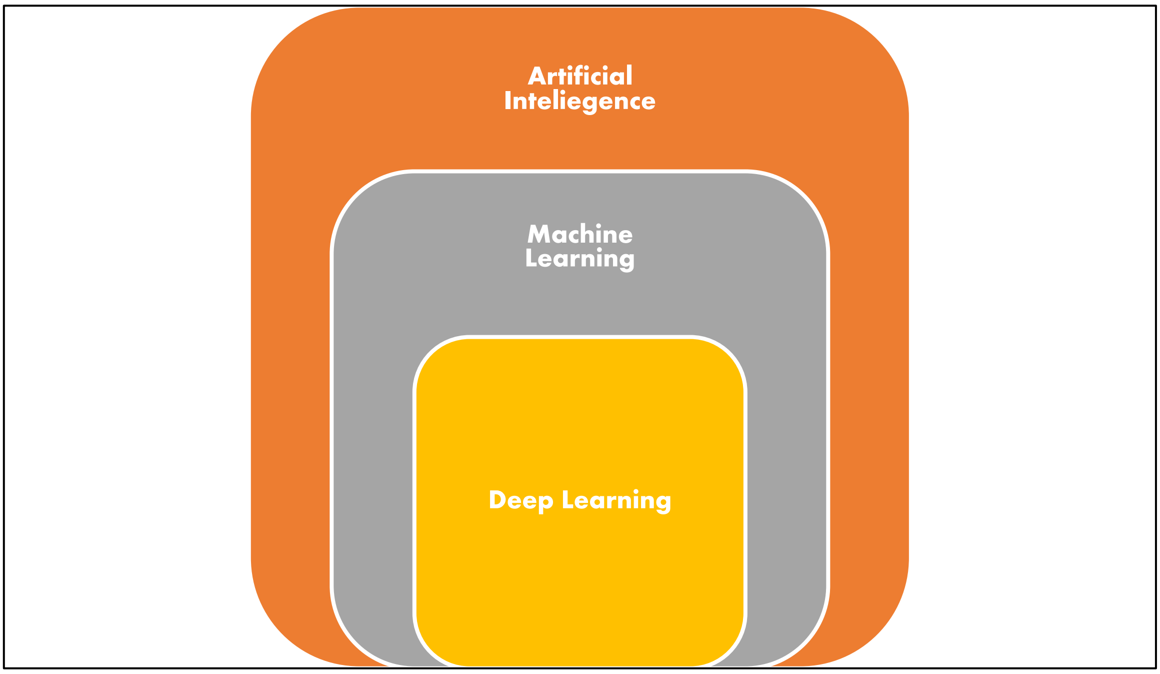

Figure 2. Machine Learning, Deep Learning and Artificial Intelligence developed from [11].

The connections between artificial intelligence, machine learning, and deep learning are illustrated in the figure that can be found above. Neural networks are the fundamental building blocks of deep learning. A neural network with more than three layers, which would include both the inputs and the output, can be a deep learning algorithm [11,12]. The term "deep" in "deep learning" refers to this number of layers [12,13].

The process by which each algorithm acquires knowledge is illustrated in Figure 3, which compares deep learning and machine learning. Deep learning can automate a significant portion of the feature extraction portion of the process. As a result, some of the required manual human interaction can be eliminated, and bigger data sets can be utilized. Deep learning does not always require a labelled dataset, in contrast to machine learning, which can make use of labelled datasets to educate its algorithm. Supervised learning is another name for machine learning. It has the capability of ingesting unstructured data in its raw form, which includes text and images, and it can automatically determine the hierarchy of attributes that differentiate various types of data from one another. In contrast to machine learning, it does not require the involvement of humans in the processing of data. As a result, we can expand machine learning in more exciting ways.

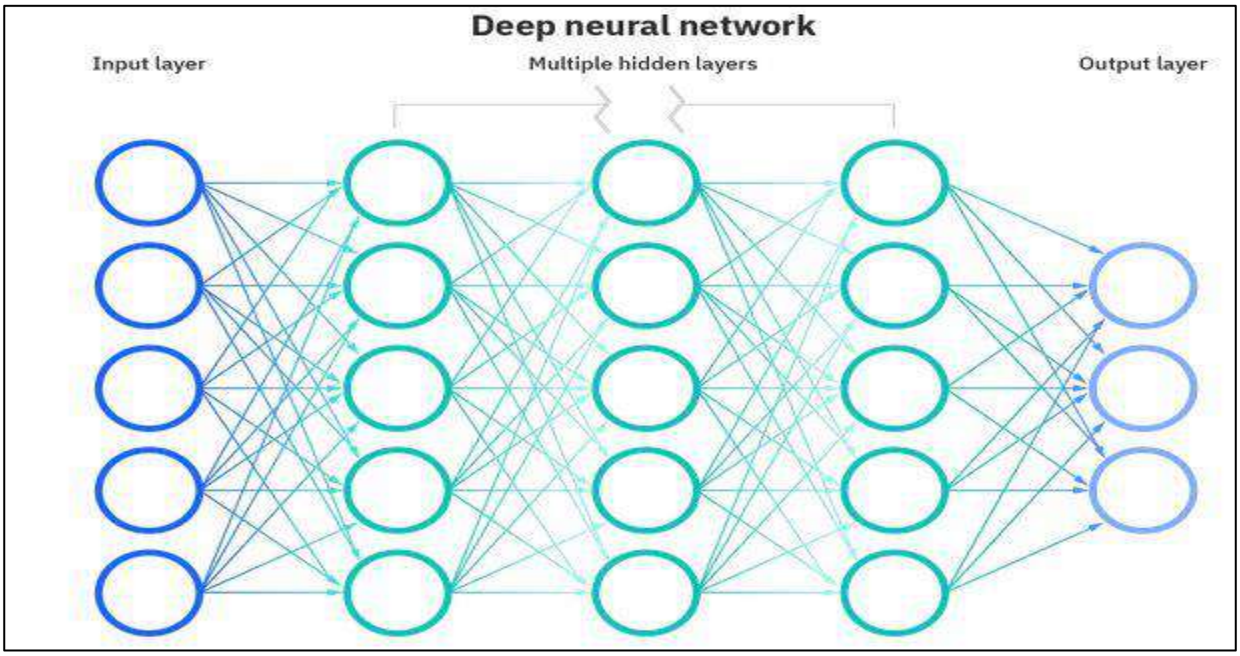

Figure 3. Deep Learning Algorithm, from [11].

Machine Learning (ML)

The "sub-field of AI" known as machine learning is "involved with the creation" and implementation of algorithms for data-driven prediction, classification, and optimization systems. "Supervised learning", "Unsupervised learning", and "Reinforcement learning" are the three main subfields that fall under the umbrella of "machine learning". In the context of machine learning, supervised learning refers to the process of developing algorithms for prediction or classification in the presence of labelled data. These algorithms require that inputs (predictors) be mapped to some output (response) [14–16]. When the output is categorical, the problem that needs to be solved is classification, but when the output is continuous, the problem that needs to be solved is prediction. Methods such as linear and nonlinear regression, random forests, neural networks, and decision trees are all examples of algorithms that can be used for supervised learning. The formation of patterns and trends in data that have not been labelled is an aspect of unsupervised learning.

In this scenario, the goal is not to anticipate an output but rather to identify common elements in the data using clustering algorithms and other similar approaches [3,15]. These include the following: principal components analysis, The process of developing and deploying learning agents in an environment for them to maximize their potential rewards is what reinforcement learning entails. There is a need for energy resource planning on a national scale, and in South Africa, this is accomplished through the Integrated Resource Plan (IRP), which is where energy supply and demand forecasts are developed. This is achieved to ensure that there is a supply of energy available to meet the requirements of the economy under a variety of potential future scenarios. Up to this point, the IRP has been formulated by the application of conventional forest management strategies, such as time series methods. It is possible that the IRP models could be improved through the utilization of ML approaches for scenario analysis and forecasting. For instance, making use of Monte Carlo methods for sensitivity analysis and Recurrent Neural Networks for demand forecasting could improve the validity of scenario analysis and the accuracy of predictions, respectively. Both techniques are currently being researched and developed further. The application of ML in energy systems, both on the side of energy generation and the side of energy consumption, shows considerable promise. Using ML algorithms, the optimization of energy generation systems such as wind, and hydro, can be improved.

Predictive maintenance systems, which involve the use of condition monitoring commonly accomplished using machine learning and the Internet of Things, can also be utilized to perform maintenance on energy production systems (stations, machinery, and power lines) (IoT). When it comes to consumption, energy efficiency is the most important factor. Through supervised learning algorithms such as neural networks and other similar methods, machine learning is effective at optimizing consumption. A nice illustration of this would be a cooling system. For instance, you should be familiar with the environment in which it operates, the role that it plays, the characteristics of individuals who are in charge, the pursuits that take place in the room in which it is situated, and whether winter or summer is currently taking place. In this context, ML performs exceptionally well. An engineer does not need to make routine adjustments to the gadget because it can accept a wide range of input values and learn from the data it receives. It is possible to make a substantial difference if you optimize how each air conditioning unit is used because the number of air conditioners that are sold and installed each year is in the millions.

The heating, ventilation, and air conditioning (HVAC) systems in a building are responsible for maintaining the appropriate temperatures and humidity levels. According to research, heating, ventilation, and air conditioning (HVAC) accounts for more than half of the total energy consumption in a structure and uses 10% of the total electricity utilized worldwide. The optimization of HVAC systems is a huge opportunity for us to meet our sustainability goals by cutting our consumption of energy and our production of carbon dioxide. Both machine learning and artificial intelligence have applications in the field of fossil fuel energy source exploration and drilling. For instance, the Massachusetts Institute of Technology (MIT) and Exxon Mobil have collaborated to develop self-learning submersible robots that are intended to investigate the ocean surface to find potential drilling sites for oil and natural gas. These robots can capture data about the ocean floor, which, when combined with machine learning (in particular, reinforcement learning), will allow the robots to learn from their errors while they are doing exploration. Despite this, the implementation of AI and ML systems and algorithms for grid management could also be a crucial area of application in South Africa using smart grids. Smart grids make it possible for electric energy producers and consumers to communicate with one another in both directions. Smart grids are power grids that combine the power of machine learning, artificial intelligence, and the internet of things through sensors, meters, and other alerting devices to collect and display data to consumers. This enables consumers to monitor and improve their energy consumption. Smart grids are also known as intelligent grids. On the production side of things, smart grids will help manufacturers monitor consumption and avoid illicit power connections, both of which are major problems in emerging markets. Smart grids will help producers monitor consumption and avoid illegal power connections.

4. Empirical Literature Review

Data systems play a crucial part in achieving the energy sector's climate targets. The increasing digitization of the energy business and the availability of relevant data have given rise to data-driven machine learning (ML) tactics as feasible solutions. Up until this moment, researchers have mostly focused on finding ways to increase ML algorithms' predictive accuracy. Machine learning (ML), as stated by Ghoddusi et al. [3], is opening new doors for innovative study in the disciplines of energy economics and finance. In this paper, we examine the rising corpus of literature on the use of machine learning in energy economics and finance. Ghoddusi et al. [3]'s summary offers examples of applications including projecting energy prices for commodities such as crude oil, natural gas, and power; forecasting demand; managing risk; establishing trading strategies; processing data; assessing macro and energy trends. Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Genetic Algorithms (GAs) appear to be some of the most extensively used approaches for researching the topic of energy economics, as shown by the results of an analysis undertaken by Ghoddusi et al. [3].

The report concludes by highlighting certain knowledge gaps and offering suggestions for future research. To connect dimensionless features to power-law-like relationships, Lin et al. [17] argue that a novel neural network architecture named DimNet should be used. Lin et al. [17]'s research shows that DimNet can be transformed into an explicit algebraic piecewise power-law-like function, making it interpretable in contrast to conventional neural networks, which are often used as "black boxes". The fact that DimNet can be easily modified facilitated this discovery. To estimate the pre-dryout heat transfer coefficient of flow boiling within microfin tubes, Lin et al. [17] developed a data-driven, empirical model using DimNet. The primary goal of this model is to predict the flow boiling heat transfer coefficient before drying. The model that DimNet generated was fine-tuned by comparing numerous sets of prominent dimensionless characteristics and by modifying the network design after training on a database including 7349 experimental data points for 16 different refrigerants. Lin et al. [17]'s model is not only statistically sound, but it also takes into consideration trends in the heat transfer coefficient that are based on a set of parameters.

The excellent degree of prediction success achieved by the model can be attributed to DimNet's ability to automatically classify the data into ideal regions while simultaneously correlating the data of each zone. Lin et al. [17] state that the DimNet architecture is well-suited for modelling multi-physical-domain heat transfer and flow problems. For issues such as convective heat transfer, where a power-law-like input–output relation is sought, and this is especially true. Short-term forecasting models for photovoltaic (PV) energy generation were also claimed to be significant by Zhou et al. [18]. These models are required for AI-driven internet-of-things (IoT) modelling of smart cities because they stabilize the power integration between the PV and the smart grid. Recent advancements in AI and IoT technology, as reported by Zhou et al. [18], have allowed deep learning approaches to produce more precise energy generation forecasting estimates for PV systems. This is feasible because the standard method for foreseeing PV energy generation has problems accounting for external feature variables such as seasonality.

By integrating clustering methods, a convolutional neural network (CNN), a long short-term memory (LSTM), and an attention mechanism with a wireless sensor network, Zhou et al. [18] suggested a hybrid deep learning approach to the PV energy generation forecasting problem. This strategy was developed to enhance prior attempts to address the issue. Three distinct procedures clustering, training, and forecasting form the basis of Zhou et al. [18]'s suggested method. The experimental results shown by Zhou et al. [18] were compared to those obtained using conventional systems, such as conventional artificial neural networks, long short-term memory neural networks, and an algorithm combining long short-term memory neural networks and attention mechanism and demonstrated significantly higher prediction accuracy rates across all time intervals. Arumugam et al. [19] state that machine learning comprises a wide variety of techniques for constructing a model that can predict future data based on historical data alone. A prediction model can be developed using machine learning by evaluating data samples to discover trends and establishing decision rules, as described by Zhou et al. [18]. Furthermore, Zhou et al. [18] argued that the predictive nature of machine learning algorithms enables smart farming and wind speed prediction, both of which are crucial to increasing the amount of energy produced.

Zhou et al. [18] state that improving the precision with which power demand and price predictions may be made is one of the most pressing issues in electrical engineering research. In their study, the authors made this claim. The predictive nature of many machine learning algorithms, according to Zhou et al. [18], makes them the best tool for addressing the challenges of energy and power engineering. In terms of a country's economic and social growth, energy is a major factor, as stated by Nabavi et al. [6]. Global energy demand has been growing exponentially over the past few decades, as reported by Nabavi et al. [6]. Energy demand forecasting has thus emerged as a central concern in a growing number of nations. Nabavi et al. [6] report that roughly 33.5% of global energy consumption comes from the residential and commercial sectors combined. If governments can foresee the need for energy in these areas, they will be better prepared to supply energy sources and build their plans for sustainable energy production. These strategies may involve tapping into both renewable and nonrenewable energy sources to build a reliable, eco-friendly grid.

Subsequently, Nabavi et al. [6] argued that modelling energy consumption in the residential and commercial sectors enables the identification of the influential economic, social, and technological aspects, which in turn results in a secure level of energy supply. This was backed up by the fact that economic, social, and technological influences on industrial energy usage may be modelled. Using three different machine learning techniques, Nabavi et al. [6] predicted energy use in Iranian homes and businesses. Methods such as nonlinear autoregressive with exogenous input artificial neural networks and logarithmic multiple linear regression were among those used. According to research by Nabavi et al. [6], residential and business energy consumption in Iran will increase in the next several years. The renewable energy share of total energy consumption, GDP, population, natural gas prices, and electricity rates are only a few of the factors taken into account when building these models.

According to Şerban and Lytras [1], the Smart Energy domain is a challenging research area for the future of smart cities because of the importance of issues such as optimization, the availability of smart, customizable networks, and advanced analytical methods and techniques made possible by artificial intelligence and machine learning. Şerban and Lytras [1] argue that RE is a crucial resource for the global economy's long-term growth considering climate change and resource depletion. To accommodate these shifts in demand, artificial intelligence (AI), according to Şerban and Lytras [1], requires the formulation of new standards for the management of activities. It is necessary to enhance the design of the energy infrastructure, as well as the deployment and production of renewable energy, to address the many issues that will affect the growth and resilience of the sector. Şerban and Lytras [1] developed a methodology to analyze AI's impact on Europe's real estate market.

This paper also makes a novel contribution by considering the implications for future research on smart cities and possible research fields. According to Zeki-Suac et al. [20], energy efficiency in the public sector is an important issue in the context of smart cities because buildings are the largest consumers of energy, especially public buildings such as educational, health, government, and other public institutions that have a large usage frequency. In addition, Zeki-Suac et al. [20] argued that the recent advances in machine learning in the context of big data have not been investigated sufficiently. This article's goal is to provide an answer to the topic of how to combine a Big Data platform with machine learning to create an intelligent system for managing the public sector's energy efficiency. The smart city concept relies heavily on this sort of interoperability. Prediction models of the energy consumption of Croatian public sector buildings were generated by Zeki-Suac et al. [20] using deep neural networks, Rpart regression trees, and Random Forests, in addition to variable reduction techniques. Research by Zeki-Suac et al. [20] found that the Random Forest method yielded the most precise model. Furthermore, a comparison was made between the significant predictors obtained by the three different approaches. Models could be incorporated into the proposed MERIDA intelligent system, according to Zeki-Suac et al. [20].

To better manage energy efficiency in government buildings in a Big Data setting, this system combines Big Data collecting with predictive models of energy usage for each energy source. Big data and MERIDA were proposed to increase public sector energy efficiency. Artificial intelligence (AI) approaches are increasingly being implemented in the public and governmental sectors, as reported by Blasch et al. [21]. Power and energy are examples of such businesses because of their central role in supporting everyday life. However, Blasch et al. [21] argue that the prerequisites of reliability, accountability and explainability make it problematic to directly apply AI-based technologies to power systems. This is since the societal costs of catastrophic failures and widespread blackouts can easily reach billions of dollars. Artificial intelligence (AI) systems in the energy sector are the focus of Blasch et al. [21]'s proposed approach for their creation, deployment, and evaluation. To do this, one must apply physics to power system measurements, create AI algorithms to foresee demand, create accountable AI procedures, and establish trustworthy metrics to evaluate the AI model's efficacy. For society's sake, these measures are vital.

5. Methodology

As a result, the purpose of this study is to evaluate the possible contributions that AI and ML could make to the energy sector, particularly in the enhancement of energy generation in emerging regions. The research aims to investigate the problems that have arisen because of the widespread lack of electricity and the constant occurrence of load-shedding. A preliminary search is recommended by Tawfik et al. [22] to locate relevant articles, establish the validity of the supplied idea, eliminate duplication of already addressed topics, and make certain that there are adequate articles for undertaking an analysis of the topic. In addition, the questions regarding the role that AI and machine learning will play in the energy industry should be the key emphasis of the themes. In addition, Tawfik et al. [22] asserted that developing a familiarity with and a profound grasp of the research subject by observing relevant films and taking part in relevant discussions is of the utmost importance for improved retrieval of results. This can be accomplished by watching relevant films and participating in relevant discussions. These precautions are essential to ensuring that we do not republish a study that has already been presented in the past and that we do not squander our time trying to solve an issue that has been solved for a large period already [22,23].

As Vassar, Atakpo, and Kash [24] proposed, the authors of this study investigated every potential avenue to lessen the impact of bias. One of these avenues included conducting an explicit hand search to retrieve reports that may have been overlooked during the initial search. Following their findings, the authors of this study found no evidence of bias. Within the scope of this inquiry, a total of five distinct strategies for conducting manual searches were implemented. These included conducting a search for references contained within the included studies and reviews, making direct contact with authors and experts working in the industry, and looking at similar papers as well as articles that were cited within Google Scholar, Scopus, and Web of Science. The manual search results were initially improved and refined by searching for the reference lists of the articles that were included. This was the first phase in the process. After that, the reviewers did something called citation tracking, which entails keeping track of all the publications that cite each of the articles that were used in the compilation. In conclusion, in addition to the manual search, an online search of databases was also conducted as part of the overall search. The last stage of the investigation consisted of examining things that were "connected to" and "similar to" other concepts.

6. Key Words Utilized in the Search

Figure 4 provides an outline of the important words that were used in the systematic literature review. These words include artificial intelligence, machine learning, energy, energy sector, energy production, energy consumption, emerging markets, and energy sector. The relevance of a study to the issues we were investigating was the major consideration in deciding whether to include it; the amount of time that had passed since the publication of the study was the secondary consideration. The papers that were published after the year 2000 were given priority consideration. Most of the reasons for eliminating papers include the fact that they are either irrelevant, duplicated, lacking complete text, or just had abstracts. These exclusion criteria were outlined in advance to protect the researcher from being influenced by any bias that they may have. The process of screening and selecting candidates is illustrated in the flow diagram that can be found below in Figure 4.

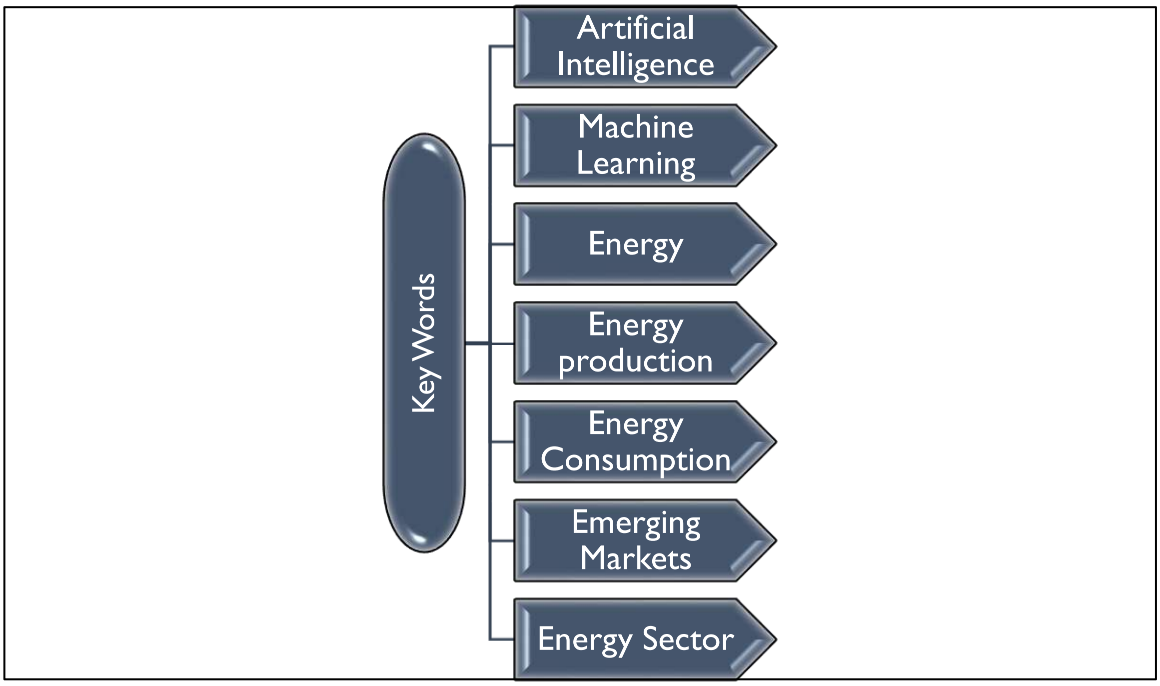

Figure 4. Keywords used in Systematic Literature review.

The screening and selection criteria are depicted in Figure 5 which may be found above. As can be seen in Figure 5 which was presented earlier, the systematic literature review covered a total of 55 different papers. We provide a data verification step, in which every incorporated article is checked with its counterpart in an extract sheet by evidence photos, to detect faults in the data as indicated by Tawfik et al. [22]. These mistakes can occur because of anticipated human error and bias. It is important to note that, out of the 55 articles that went through the qualitative synthesis, only those articles with information that was included in the manuscript were cited in the reference list. This means that some of the articles did not appear in the reference list.

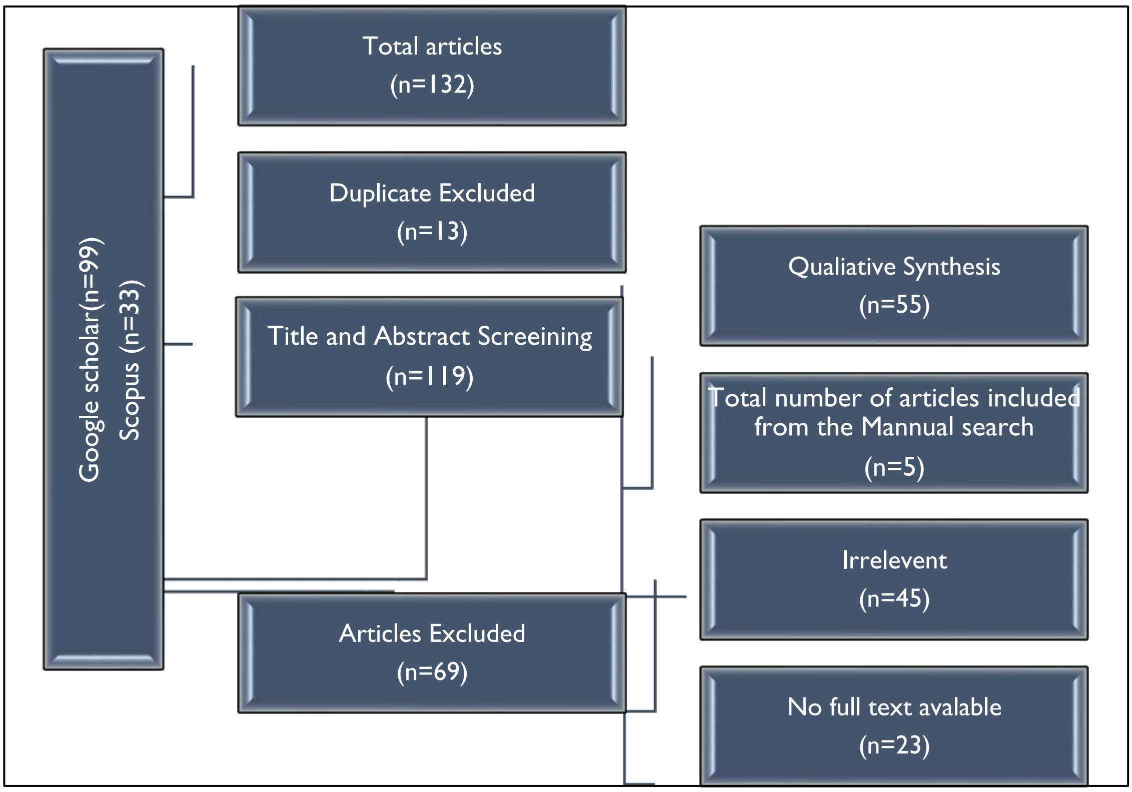

Figure 5. Flow diagram of studies' screening and selection.

7. The Importance of Artificial Intelligence and Machine Learning in the Generation and Use of Energy

The optimization of power generation can benefit from the application of AI and ML. As was just seen in the preceding Figure 1, the application of AI and ML in the energy sector in Arica can be quite beneficial. Predictive maintenance, the investigation of new energy sources, grid management, the application of machine learning to the problem of energy consumption, and the improvement of energy efficiency in residential and commercial structures are some of the solutions. Figure 6 summarizes the importance of artificial intelligence and machine learning in the generation and use of energy.

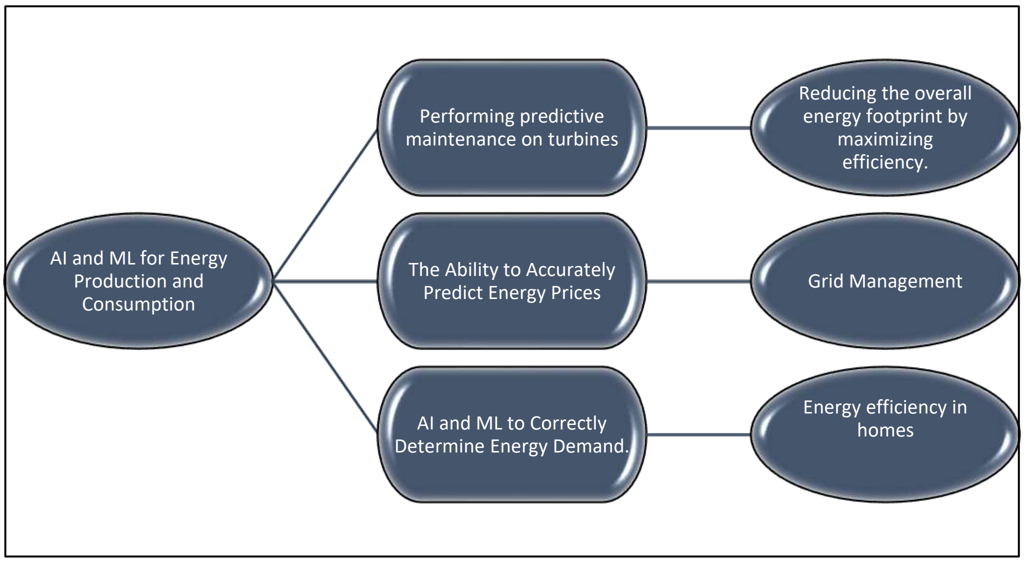

Figure 6. AI and ML for Energy Production.

8. Predictive Maintenance of Turbines and Optimize Energy Consumption

The term "predictive maintenance" refers to a method that employs a variety of tools and strategies for data analysis to identify irregularities in the functioning of machinery and processes, as well as potential flaws in those elements, to resolve issues before they become catastrophic failures. This method was developed by IBM in the 1980s. Given that a portion of the issues that have been plaguing the power provider Eskom in South Africa is the result of breakdowns brought on by ageing infrastructure, it is possible to salvage the situation by employing predictive maintenance. This is because a portion of the problems that have been plaguing Eskom are the result of the problems that have been plaguing Eskom. A recent study on "ML models that have been utilized to wind turbine status monitoring (for example, blade defect detection or generator temperature monitoring)" is investigated by Stetco et al. [25]. Standard machine learning processes, including data sources, feature extraction and selection, model selection (classification, regression), model validation, and decision-making, are utilized to classify these various models.

According to their findings, most models make use of SCADA or simulated data. The remaining methodologies are predominately dependent on regression, and just approximately a third of them make use of categorization. "Neural networks, support vector machines, and decision trees" are the technologies that are utilized most of the time. Hsu et al. [26] analyse 2.8 million sensor data from 31 wind turbines in Taiwan that were installed between 2015 and 2017 to detect wind turbine faults and anticipate the amount of maintenance that will be required. The historical information on wind turbines that was acquired at Taiwan's ChangHua Coastal Industrial Park is used in the study to investigate and forecast the maintenance requirements for wind turbines. Between the years 2015 and 2017, a total of 31 wind turbines collected a combined total of 2,815,104 observations. Using two different approaches to machine learning known as decision trees and random forest classifications, they were successful in predicting anomalies in wind turbines with an accuracy rate of more than 92%. When analyzing the sensor data from wind turbines, they focused particularly on making use of the maintenance checklist insights provided by the practitioners.

They researched to determine the causes of issues with wind turbines, segregated data on abnormal and normal states of operation for wind turbines and developed prediction models by combining data analytics with their first-hand expertise. The findings provide Taipower and other companies that operate wind turbines with realistic indications for diagnosing problems in wind turbines and estimating the amount of maintenance that will be required in the future. Consumption of energy has been at the forefront of people's minds, both at home and in the workplace, for quite some time. However, without conducting a significant number of computations by hand, we have only ever been able to obtain a general sense of how much energy is being used, without being able to identify which appliances or devices use the most. All of that has been upended because of the proliferation of the Internet of Things devices and smart meters. Non-intrusive appliance load monitoring (NIALM), which is also known as disaggregation, is a method that employs machine learning to analyze energy consumption on a device-by-device basis. Another name for this approach is non-intrusive appliance load monitoring (NIALM). Using this formula, it is simple to determine which home appliances have the highest monthly operating expenses. Customers who utilize this will be able to better adjust their consumption patterns, which will allow them to save money and cut their energy use. They have the option of either using expensive appliances less frequently or replacing them with ones that are more energy efficient.

9. Management of the Grid and the Ability to Accurately Predict Energy Prices

Data analytics is becoming an increasingly important discipline in this age of industrialization. Electricity is one of the industries that has made significant strides toward adopting data analytics practices. The smart meters and various other sensors that have been installed make for a significant quantity of data collection within the smart grid.

Processing such a massive volume of disparate data would be impossible without the assistance of big data analytics. Big data analytics and machine learning algorithms are vital components of the electrical transmission and distribution network because they are required for data collection, storage, and analysis; prediction for data forecasting; and system maintenance. These strategies can help improve customer service and social welfare while also ensuring that energy is distributed in the most efficient manner possible, at the most affordable price, of the highest possible quality, and with the lowest possible cost [27].

When it comes to manufacturing, smart grids can assist manufacturers in monitoring usage and reducing the number of unauthorized power connections, both of which are significant problems in South Africa. The second problem is that consumers and businesses are increasingly creating their power as the use of personal power generation methods such as solar or wind power becomes easier and more affordable. Individuals who have power generation systems can produce, use, and store their energy. They might even be able to sell any excess electricity to the power utility in their area; however, this will depend on where in the world they live. The most efficient times to generate, store, or sell this energy can be determined with the use of machine learning. In a perfect world, consumers would use or store energy while prices were low and then sell it back to the system when prices were high. To generate forecasts that are significantly more precise on an hourly basis, it is possible to utilize machine learning models to analyze historical data, usage trends, and weather forecasts.

People who have personal or commercial energy generation systems can use this information to help them make strategic decisions regarding what to do with their energy. One illustration of this would be the Adaptive Neural Fuzzy Inference System (ANFIS), which has been implemented to forecast the short-term wind patterns necessary to produce electrical power. Because of this, producers can achieve their highest levels of energy production and then sell that energy back into the grid at times when prices are at their highest. With all this information, it is highly helpful for businesses and governments to take it upon themselves to invest in artificial intelligence and machine learning to ensure the management of the grid and the ability to accurately estimate energy prices.

10. AI and ML to Correctly Determine Energy Demand and Energy Efficiency in Homes

Due to the rapidly increasing demand for energy around the world, there have already been some serious concerns voiced regarding potential supply problems, the exhaustion of energy resources, adverse consequences on the environment ozone layer depletion, global warming, climate change, etc. Structures are currently responsible for more energy than any other major industry, including manufacturing and transportation, and are responsible for between 20 and 40 percent of the world's total energy use. This includes both residential and commercial structures [28]. The rising trend in energy demand is expected to continue into the foreseeable future because of the development in the world's population, increased expectations for levels of comfort and building services, and an increase in the amount of time spent within buildings. As a result of this, energy policy on all three levels regional, national, and international now place a strong focus on increasing the amount of energy efficiency that can be achieved in buildings. Particularly noticeable is the rise in energy consumption among building services caused by HVAC systems, which accounts for fifty percent of total building consumption and twenty percent of total consumption in the United States [28].

The other critical issue about AI and ML is the efficiency in the use of energy in dwellings. In recent years, smart home systems have seen a meteoric rise in popularity since they increase both comfort and quality of life. Significant developments in the Internet of Things, which has emerged as one of the most vital uses for smart home technology, have captivated the electrical industry and have become one of the most important uses for this technology. One of the Internet of Things-based platforms that can be found in smart homes is smart lighting. The term "smart lighting" is commonly used to refer to lighting equipment that provides increased degrees of functionality, such as remote dimming or on/off control, to enhance the user's comfort while also reducing energy use. The purpose of this study is to investigate the effect that using smart LED bulbs in smart lighting systems has on the energy efficiency of those systems. After that, the amount of electricity required to produce each distinct colour by the smart LED bulb is determined and recorded. The intelligent LED bulb can produce a wide range of colours, each of which requires a distinct quantity of electrical power. In addition to this, three case studies are analyzed, and the energy-saving capabilities of halogen, CFL, LED, and smart LED are evaluated in detail. It is only when a smart LED bulb is dimmed and controlled remotely that it gives the impression of using the least amount of energy [29]. Another important aspect of AI and ML is efficiency in the use of energy in commercial buildings. Buildings are responsible for the use of forty percent of all the energy that is utilized in the United States, as stated by Robinson et al. [30].

City planners must have a solid understanding of the distribution of energy intensities. This is because urban form characteristics, such as density and floor-area ratios (FAR), influence the amount of energy that is consumed within buildings. The data from the Commercial Buildings Energy Consumption Survey were utilized to train machine learning models in this study's one-of-a-kind method for estimating the amount of energy consumed by commercial buildings based on a select group of physical characteristics (CBECS). The construction industry is responsible for a significant portion of the nation's total energy consumption, which in turn has resulted in several environmental problems that threaten the ability of humans to continue existing. The practice of anticipating a building's energy usage is becoming increasingly popular to reduce overall energy consumption, as well as to save money. Furthermore, the construction of buildings that consume less energy will contribute to a reduction in the overall energy consumption of newly built structures. ML, which is acknowledged as the technique, is the method that is most effective for attaining the required results in prediction tasks [31].

Exploration of potential sources of energy is another important subject. Although the oceans cover 71% of the Earth's surface, little is known about the subsurface features of these vast bodies of water. The ocean floor, on the other hand, may soon be less of a mystery thanks to developments in marine robots and artificial intelligence. As more and more spacecraft travel beyond the solar system, the gap between what we know about space and what we know about the seas widens. As a result of this discussion, South Africa is required to make use of the potential that is provided by AI and ML. Having said that, this does call for a significant shift in both public and private sector policies, as well as the formation of fruitful public-private partnerships. Because there is currently no viable option for the storage of large amounts of energy in bulk, it is essential for any utility provider to accurately estimate the energy requirements of their customers. This necessitates that energy is delivered and used practically immediately after it is generated. The precision of these forecasts may be improved with the application of ML and AI.

The amount of energy that is consumed on any given day can be partially predicted by looking at historical data on energy consumption, consulting weather forecasts, and considering the types of businesses and buildings that are open on that day. One illustration of this is how a hot summer day in the middle of the week results in increased energy consumption because commercial buildings must operate their air conditioning systems at full capacity. In the summer, rolling blackouts can be caused by air conditioners, but they can be prevented with the use of weather forecasts and historical data if they can be identified early enough. When trying to explain shifts in demand, machine learning looks for complex patterns in the many factors that play a role, including the day of the week, the time of day, the predicted wind and solar radiation, major sporting events, past demand, mean demand, air temperature, moisture and pressure, and the direction that the wind is blowing. The predictions made by machine learning are more accurate than those made by people because machine learning can uncover more intricate patterns. This indicates that it is possible to boost efficiency and minimize costs when purchasing energy without the need to make particularly costly alterations. In the context of future changes in the complexity of markets, swings in demand, virtual clients, and other factors, Şerban and Lytras [1] state that renewable energy systems may not be reliable if they do not have sufficient storage capacity. A look at recent developments demonstrates that their optimization may be supplied by AI, even in the absence of comprehensive long-term meteorological data.

11. Recommendations for Emerging Markets to Maximize AI and ML in Energy

As shown in Figure 7 below, it is very important that, when applying AI and ML in emerging markets, there are partnerships between the public and private sectors that are both effective and efficient; investments in artificial intelligence and machine learning in the energy sector that are sponsored by the government; the development of AI methods that are both accountable and robust; the creation of reliable measures to evaluate the performance of the AI model; and an understanding of the power system measurements with physics, design, and engineering. Artificial intelligence (AI) and machine learning (ML) are finding more and more uses in the public and governmental spheres, particularly in the electrical and energy industries. It is risky to directly apply AI-based technology to power systems, however, due to the criteria of reliability, accountability, and explainability. This is because the costs associated with cascading failures and widespread blackouts are simply too high for society to bear.

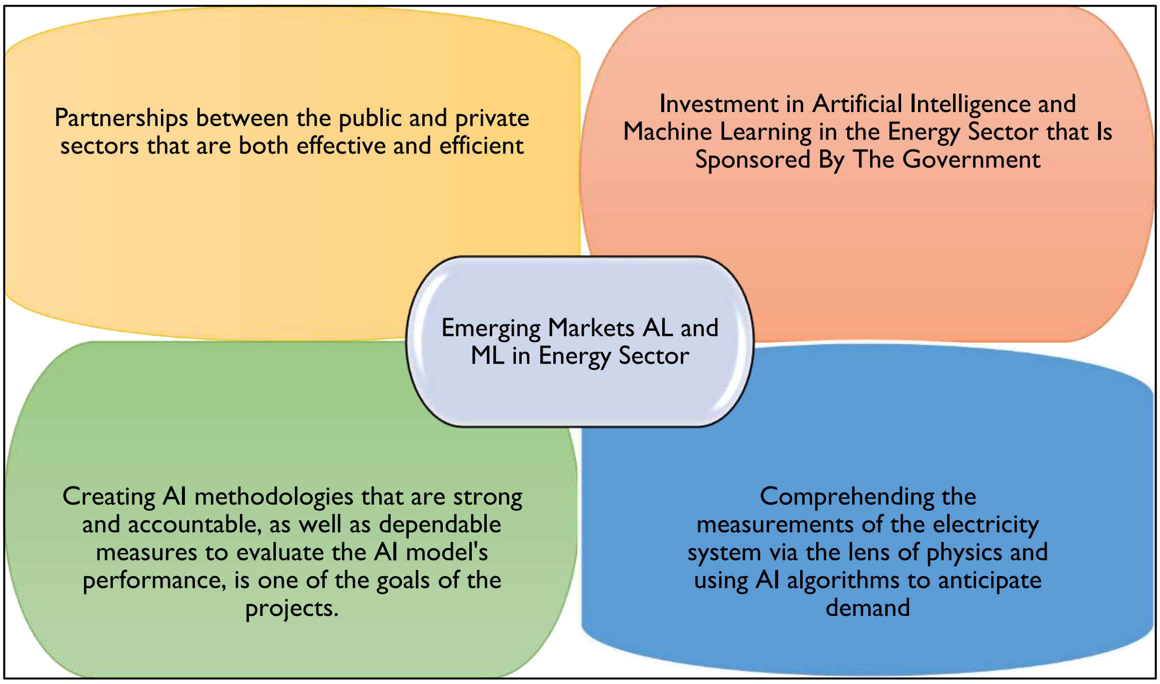

Figure 7. Proposals for AI and ML to be effective for emerging markets.

12. Conclusions and Recommendations

Around the world, the energy sector is confronted with a wide range of issues, some of which include rising consumption and efficiency, altering trends in supply and demand, and a lack of the necessary analytics for efficient management. In emerging markets, these problems show themselves more seriously. Many unlawful connections to the electrical grid mean that a significant amount of energy is not tracked or compensated. This study's goal was to assess what potential contributions AI and machine learning (ML) technologies might be able to make to the expansion of energy generation in emerging nations. The results show that AI and ML have the potential to play a significant role in the optimization of energy consumption, the management of the grid, and the ability to reliably estimate energy prices as well as correctly determine energy demand and energy efficiency in residential structures. Additionally, it was discovered that investments and the development of AI and ML methods in the energy sector should be both accountable and robust with the creation of reliable measures to evaluate the performance of the AI models. Additionally, it was discovered that an understanding of the power system measurements with quantum mechanics, design, and an ML framework is important when applying AI and ML in emerging markets. Ensuring that there is a consistent supply of energy, which in turn helps guarantee the productivity of businesses in those countries, can assist developing countries to achieve their development goals.

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