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An Investigation of the Applications of Artificial Intelligence and Other New Technologies in Smart Energy Infrastructure

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Abstract: ***Globally, numerous engineering domains have developed and employed information technologies that incorporate blockchain, big data, IoT devices, and artificial intelligence. Review articles that are now available concentrate on the features and advancements of specific subjects as well as their application in the energy industry. These technologies are inherently coherent and integrable since they are all dependent on information, communication, and data analysis. This review paper will address the applications of artificial intelligence and other upcoming technologies in smart energy infrastructure. In order to guarantee dependable performance and efficient use of energy resources, artificial intelligence models estimate energy demand and load profiles and plan resources. Massive amounts of data are needed to train artificial intelligence models. Artificial intelligence performance is determined by the functions and relationships that may be found via the use of big data platforms and data mining. Additionally, data mining enhances the information, allowing artificial intelligence to be trained repeatedly using increasingly precise data. Blockchain and other cutting - edge digital technologies, including the Internet of Things, can improve smart energy management even further. Artificial intelligence is made possible by an Internet of Things platform that connects other hardware and software systems and devices with edge, fog, and cloud layers. An Internet of Things platform also efficiently transfers and retains data, making it easier for stakeholders to access and available for data mining. New technologies like cryptocurrency and blockchain make it easier to trade energy, and they may be integrated into an Internet of Things platform's cloud layer to enhance data storage. Providing a smooth and effective integration of big data, artificial intelligence, and sophisticated digital technologies will play a significant role in the energy sector's impending shift to a lower - carbon system.***

Keywords: artificial intelligence, smart energy, blockchain, big data, Internet of Things

1. Introduction

Big data (BD), advanced digital technologies (ADT), and artificial intelligence (AI) will soon be just as important and useful to our civilization as oil was. The availability of renewable energy sources will greatly increase the significance of BD, AI, and ADTs, even though they aren't yet the perfect solutions for the energy sector. In this review paper, we assess the literature on BD, AI, and ADTs to find out more about how they may be included into the creation and functioning of smart energy management systems (SEMS) and to investigate the connections between them.

Artificial intelligence can be used to forecast energy generation, demand, demand side management (DSM), optimize energy storage operation, detect energy theft, perform predictive maintenance and control, forecast energy pricing, predict weather phenomena linked to energy forecasts, and manage energy use in buildings. Assuring data security, comprehending the fundamentals of AI technology, maintaining cybersecurity, updating current systems, and calculating the correlation between AI integration and financial gains are a few of the difficulties associated with applying AI. All forms of renewable energy, such as wind, solar, geothermal, hydro, oceanic, bioenergy, hydrogen, and hybrid energy, can be produced using AI models.

Artificial Neural Networks (ANNs), Wavelet Neural Networks (WNNs), Decision Trees, Support Vector Machines (SVMs), Hybrid, and Ensemble are a few examples of AI models. In general, hybrid machine learning models are easier to use, faster, and more accurate. Large amounts of data are needed to train these models, hence BD approaches are necessary.

As seen by the review papers in the literature, independent studies have been published on a range of applications of BD and AI, including managing supply and demand, forecasting energy generation from renewable sources, and improving energy management in buildings. Nonetheless, the majority of the publications examined BD, ADTs, and AI in tandem or independently. They either gave a list of applications or concentrated only on one particular one. Our work's primary goal is to outline the ways in which the three fields' respective bodies of study can be integrated into a SEMS.

Intelligent Algorithms

The SEMS would have to rely on set mathematical formulas with a clear procedure in the absence of the intelligent algorithms. The combination of several clever algorithms gives the AI its capacity for adaptation. It is not predicated on any one formula. As will be explained, some of these algorithms are more broadly applicable because they can be trained and updated to perform better than a fixed mathematical formula. On the other hand, some algorithms are more broadly applicable because they can vary their actions based on inputs and outputs. This category includes algorithms like machine learning and deep learning.

The primary control algorithm for energy resources or loads is Fuzzy Logic (FL). A hybrid Fuzzy Q - learning model is used in a multi - agent system (MAS) by Kofinas, Dounis, and Vouros to run a microgrid. One load or resource is controlled by each agent. The general concept is that every agent must balance supply and consumption with other agents. Alfaverh, Denai, and Sun's home energy management system for residential demand response integrates Fuzzy Logic with Reinforcement Learning. The system's goal is to use as little power as possible. Appliances will start to operate during low demand hours instead of peak hours. Al - Sakkaf, Kassas, Khalid, and Abido regulate supply and demand in a microgrid using fuzzy logic in a central energy management system. An Ant Bee Colony Optimization (ABCO) method is used to scale the FL algorithm's inputs and outputs in order to account for inaccuracies in the prediction of power required. An Adaptive Neuro - Fuzzy Inference System (ANFIS) was created by Nikolovski, Baghaee, and Mlakic to predict solar PV power generation and electricity demand. The ANFIS outputs are then used to train a FL algorithm, whose goal is to limit the loads in accordance with the power production.

Generally speaking, the Fuzzy Logic system's activities should determine when to charge or discharge energy storage, turn on or off loads, and provide the load or grid with energy resources. An FL model needs data like power demand (kW), electricity pricing ($/kWh), State of Charge (SoC, %), and power output from the site energy resources (kW) in order to determine the best course of action. It is important to remember that FL can use anticipated or measured real - time data. It will not be known the average hourly statistics until the end of the hour. Therefore, FL can act in the interim based on the forecasts. It is able to adjust its policies and actions in real time as new data comes in.

Bayesian networks and heuristics have also been applied to energy management. Heuristic algorithms are a subset of search - based algorithms that are designed to locate the best answer to a certain issue. They have been applied to the optimization of trading portfolios for electricity markets, EV charging schedules, building cooling system energy consumption, and microgrid energy resource utilization in the literature. Heuristics are helpful because they can provide possible answers to issues for which there is no obvious solution. Energy resource consumption and scheduling, for example, depend on variables that are not always under our control. Heuristics can therefore offer a possible solution that can be assessed.

Using unsupervised learning (UL) techniques, data is first analyzed to find important patterns, and then the data is grouped according to these patterns. They are therefore helpful for classification issues. UL algorithms can be applied to load clustering, equipment fault detection, power theft detection, and other applications. Data clustering may not be as widely used in unsupervised learning since it is more difficult to apply to energy management. The other two categories of learning strategies are more suited for applications with predetermined goals, such as energy forecasting and energy cost or consumption minimization.

Artificial Intelligence System

Most likely, the AI would be on a machine at the facility or location. It would have to directly regulate the energy flow and obtain particular data from the location, such as load demand, energy output, etc. Thus, having a local connection between the AI and the plant would be the most efficient method. This could also be referred to as "edge intelligence" [60]. The Edge - Based Mode, Device - Based Mode, Edge - Device Mode, and Edge - Cloud Mode are the four edge intelligence modes that are discussed in that article. The device - based mode of a smart energy management system would contain the edge intelligence.

The AI model is stored on the edge device, which also uses its resources to carry out the inferencing. Because there shouldn't be any communications problems, the output is dependable; yet, it consumes a lot of resources. The microgrid intelligent management (μGIM) platform is one such. The Raspberry Pi served as the edge device. Java 8 was used to program the μGIM agent, which was then put onto this device. It was in charge of anticipating energy supply and demand as well as trading energy. SVMs were employed by the system to forecast. Additionally, each Raspberry Pi was equipped with an internal storage device, allowing it to retrieve and store data for processing. Using the ModBus or TCP/IP protocols, the device was incorporated into the plant and allowed it to interface with its electrical resources.

Owing to limited resources, specialized frameworks for programming AI engines on edge devices have been developed, such Tensorflow Lite and Caffe 2. Moreover, Amazon Greengrass, Google Cloud IoT Edge, and Microsoft Azure IoT Edge are among the service providers that offer assistance with the deployment and management of edge intelligence [60]. These services are capable of launching the preprogrammed AI Engine, using it to generate predictions, and uploading the outcomes to off - site data servers for additional processing.

In conclusion, the present and likely future developments in energy management involve the use of hybrid and multi - stage intelligent algorithms for energy forecasting and energy resource control. Energy management relies heavily on automated analysis and clever algorithms, but these tools are useless without data. The studied literature indicates that several kinds of data can be applied. Furthermore, a lot of data is required for these algorithms to be trained effectively. As a result, data mining is an essential stage that must be completed before training.

Big Data

In the context of energy management, data mining entails gathering, preparing, and analyzing data. Extraction of new information and correlations from preexisting raw data is the aim of data mining. Measured data or repositories may be the source of the collection. Filtering outliers from the data set, adding missing information, or altering the data are all part of the preparation process. A model or algorithm is used for analysis to extract relationships or patterns from the data and get the desired result. It is impossible to overstate the significance of data mining for AI. By selecting the most useful features to employ, selecting the finest training data, and strengthening the AI's resistance to inaccurate data, data mining helps improve artificial intelligence models. The full potential of intelligent algorithms may not be realized if the training or inputted data is improperly prepared or chosen. If there are biases or flaws in the data, the control algorithm, even with perfect precision, will not produce an accurate output. Essentially, appropriate data mining should be done in conjunction with the usage of intelligent algorithms. Data mining is useful for higher level energy management even though it can improve energy management for a specific site.

Managing energy loads or resources inside a site is known as low level energy management. Utilities and grid operators are usually the ones engaged in high level energy management. This section's data mining methods aid in the processing and summarization of energy - related site data. Utilities or grid operators can utilize the condensed data to better determine how much power is required at different times.

EVs are loads and mobile energy sources. It would also be challenging to retrofit an edge device into these pre - made automobiles. As a result, another location must process the data. Considering that tens of thousands of cars might be charging or discharging, data mining and a big data infrastructure will be required. Based on how users charge and discharge, the authors employed an algorithm known as Clustering Latent Semantic Analysis (CSLA) to divide users into four numerical groups.

Day - ahead wholesale electricity rates were used to optimize these models and produce a charging plan for every EV for the upcoming day. Prices for the following day were derived using an estimate of energy usage, thus peak hours would cost more. Reducing the impact of the load on the grid by charging costs was the optimization's main objective. It is possible to construct a load profile that takes into consideration every EV in the area with this optimization. Next, a control algorithm modifies the EVs' charging schedules in an effort to align with the load profile that was established. This technology was evaluated for a smart charging network in an area of Los Angeles that included about 200 EV charging stations.

2. Conclusion

Research on big data, blockchain, Internet of Things, artificial intelligence, and other topics is currently developing quickly and from a wide range of angles. Rather than pursuing these areas of study independently, researchers ought to integrate them. An important factor in the automation of smart energy management is artificial intelligence. It is made up of several clever algorithms that allow for demand response, energy trading, energy prediction, and scheduling. Support vector machines and neural networks are two common forecasting algorithms. FL and Q - learning are the best options for energy trading, demand response, and scheduling. To improve performance, research is moving toward multi - stage and hybrid models in all circumstances. Big data technologies and data mining are required to fully realize the promise of these algorithms. By doing feature selection, data mining can be used to improve AI performance. Classifying and optimizing data for advanced energy management is another capability.

Researchers must take into account the underlying digital technologies in order to facilitate the use of big data and artificial intelligence. The data flow and overall system performance can be improved by including edge, fog, and cloud computing into the design of a digital infrastructure. Sensors and data gathering tools make up the edge, and these are connected to a fog device. The fog device, as it is known in the context of EMS, is a central controller that has an AI built into it and is capable of rudimentary data mining and demand response. Moreover, the controller of the energy management system acts as a gateway to the cloud and the rest of the internet. Bulk data mining on information from various energy management systems is done on the cloud layer.

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