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Review

Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management

Joey Li [a], Munur Sacit Herdem [b,d], Jatin Nathwani [b,c], John Z. Wen [a,*]

[a] Department of Mechanical & Mechatronics Engineering, University of Waterloo, 200 University Avenue West, Waterloo, N2L 3G1, ON, Canada
[b] Waterloo Institute for Sustainable Energy, EVO Unit 100, 200 University Avenue West, Waterloo, ON Canada, N2L 3G1
[c] Department of Management Science, University of Waterloo, 200 University Avenue West, Waterloo, N2L 3G1, ON, Canada
[d] Department of Mechanical Engineering, Adiyaman University, 02040, Adiyaman, Turkey

HIGHLIGHTS

- Artificial Intelligence is moving towards hybrid models made of multiple algorithms.
- Data analytics can enhance Artificial Intelligence and energy management.
- Cryptocurrency can be given physical meaning by representing a quantity of energy.
- A computing platform is needed to use Artificial Intelligence and data analytics.
- Patents for energy management are similar to academic literature.

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ABSTRACT

Information technologies involving artificial Intelligence, big data, Internet of Things devices and blockchain have been developed and implemented in many engineering fields worldwide. Existing review articles focus on developments and characteristics of individual topics and the associated deployment in the energy sector. These technologies, all based on communication, information, and data analysis, are naturally coherent and integrable. This article reviews the literature and patents in four closely related fields and aims to provide a holistic view of how they are related and their integrability in relation to smart energy management strategies. Artificial intelligence models forecast energy use and load profiles as well as schedule resources to ensure reliable performance and effective utilization of energy resources. Training artificial intelligence models requires immense volumes of data. Utilizing big data systems and data mining enables the discovery of new functions and relationships, which determines the performance of artificial intelligence. Data mining also refines the information; thus, artificial intelligence is trained iteratively with more accurate data. Smart energy management can be further enhanced through advanced digital technologies like Internet of Things and blockchain. An Internet of Things platform containing edge, fog and cloud layers helps connect artificial intelligence to other hardware and software devices and systems. Furthermore, an Internet of Things platform efficiently transmits and stores data, improving access and availability to stakeholders for data mining. Emerging technologies such as blockchain and cryptocurrency facilitate energy trading and can be designed in the cloud layer of an Internet of Things platform to supplement data storage. Providing an efficient and seamless integration of artificial intelligence, big data, and advanced digital technologies will be an important factor in the emerging transition of the energy sector to a lower-carbon system.

1. Introduction

Global renewable energy consumption is expected to grow by 147% in the next 30 years [1]. In 2019, new global investments in clean energy were nearly ten times the amount invested in 2004 [2]. Furthermore, the share of renewable power in global energy generation has increased from 5.2% in 2007 to 13.4% in 2019 [2]. Among all sources of renewable energy, the role of electricity has increased by a factor of two to

* Corresponding author.
E-mail address: john.wen@uwaterloo.ca (J.Z. Wen).

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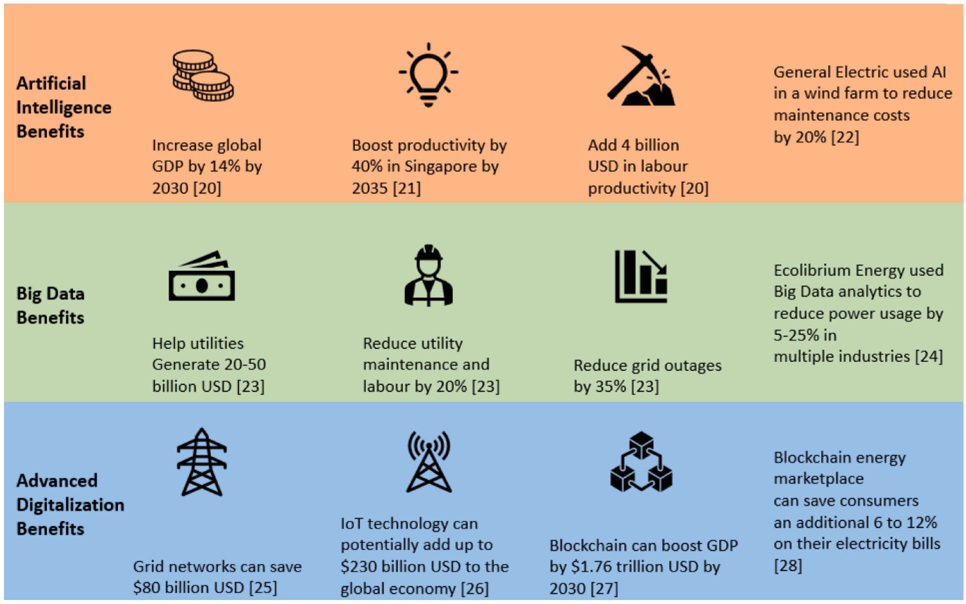

Fig. 1. The quantitative benefits of AI, BD, and ADT [20–28].

three from historic levels, and this means that all electrical system resources should be optimized in order to benefit society. To address these problems, smart energy management (SEM), using Information and Communication Technology (ICT), is needed to monitor and co-ordinate the needs and capabilities of all resources and suppliers, energy transformers, infrastructure operators, end users and energy market stakeholders [3]. Based on the requirements for an ICT platform [4], SEM should aim to achieve the following functionalities: (i) monitor, forecast and schedule usage of site energy resources and loads; (ii) maintain bidirectional communication with the wider grid and local energy resources and loads; (iii) facilitate energy trading between the grid and other sites; and (iv) store, process and communicate relevant data to stakeholders (e.g., site owner, utilities, grid operators, etc.). Efficient scheduling of resources reduces monetary costs, while real time monitoring allows for a quick response to equipment faults. Bi-directional communication is vital because grid operators need to know how much energy is being consumed and how much is available. Without real time data, grid imbalances can result in system disturbances, and in extreme scenarios, blackouts. Furthermore, communication is vital to enable energy trading between multiple sites. If the grid is constrained and if a user's own supply is not adequate, the flexibility to choose and source supply locally from a neighbour's energy resources supports a robust and resilient system. Lastly, all produced or collected information should be made available to help utilities understand consumption/supply patterns, help users adjust their energy usage, and more. These benefits are some of the reasons why energy management systems (EMSs) are important for the future of energy. Nevertheless, implementing SEM requires a combination of research and development in multiple engineering fields.

Artificial intelligence (AI), big data (BD), and advanced digital technologies (ADT) will be valuable and useful to our society in the foreseeable future, just as oil was of such great value and importance in the past. Indeed, at this point, we cannot claim that BD, AI, and ADTs will be perfect solutions for the energy sector; however, the importance of these fields will increase substantially in relation to renewable energy sources. In this review paper, we conduct a literature review on BD, AI, and ADTs to investigate their relationships and to reveal their potential integration in the design and implementation of smart energy management systems (SEMS). There have been multiple published reports and review papers dealing with various perspectives of BD, AI, and ADTs in SEM. These papers supplement our work by providing more detailed descriptions and performance of individual technologies, while this work focuses more on their interactions.

In the context of smart energy management, artificial intelligence can be used for energy generation forecasting [5–7]; demand forecasting [8, 7]; demand side management (DSM) [9]; optimised energy storage operation [7]; energy theft detection [8]; predictive maintenance and control [8]; energy pricing prediction [7]; predicting weather phenomena related to energy predictions [7]; and building energy management [10]. Some of the challenges in using AI include ensuring data security [5], understanding the principles of AI technology [5], ensuring cybersecurity [11], refitting existing systems [11], and quantifying the relationship between AI integration and economic benefits [11]. AI models can be used in all types of renewable energy including wind energy, solar energy, geothermal energy, hydro energy, ocean energy, bioenergy, hydrogen energy and hybrid energy [12]. Some of the types of AI models are Artificial Neural Networks (ANNs), Wavelet Neural Networks (WNNs), Support Vector Machine (SVM), Decision Trees, Hybrid, and Ensemble. Hybrid ML models are generally faster, more accurate, and easier to use [7]. Training these models requires vast volumes of data; thus, BD techniques are required.

Research topics in big data include energy asset and operations management [13], DSM [13], fault detection[13], predictive maintenance and monitoring for equipment[13], power quality analysis [13], energy and load forecasting [13, 14], parallel processing [14], and cloud data mining [13,14]. As observed, there are some mutual areas of research between AI and BD, thus it is even more important to understand how they can be integrated. Some of the key challenges include data uniformity, cybersecurity, and long-term planning. BD systems can be implemented through technologies such as Apache Hadoop and MapReduce, Apache Spark, and NoSQL [15]. BD solutions for the energy sector include Intelligent Network Data Enterprise (INDE) by Accenture and Active Smart Grid Analytics (ASA) by Itron-Teradata. Implementation of BD and AI requires further digitalization of the grid.

The University of Houston recently published a white paper discussing the digitalization of the energy sector [16]. AI, augmented reality, automation, blockchain cloud computing, distributed computing and data visualization were discussed. Lamagna, Groppi, Neshad, and Piras examined how the Digital Twins (DT) concept can be utilized in the energy sector [17]. A DT is a system that replicates and simulates real world scenarios; thus, system behaviour can be predicted and analyzed. DTs can help simulate DR for buildings and connected energy systems

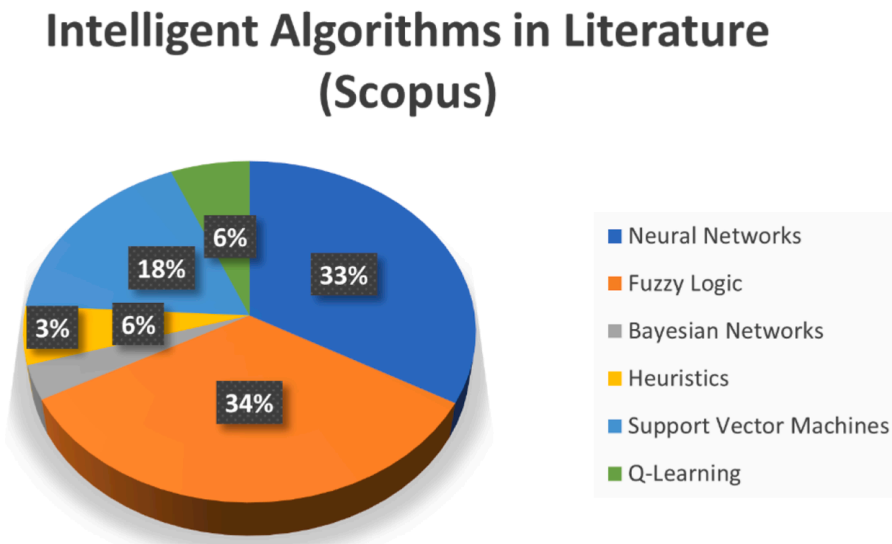

Fig. 2. The popularity of major intelligent algorithms in the literature from the Scopus database. The collected data comes from journal papers published in the years 2017–2022.

and can be utilized for transportation that relies on electricity such as electric vehicles and railways. Boretti provided perspectives on how AI can be used for integration of solar thermal and photovoltaic, wind, and battery energy storage to generate energy in NEOM city [18]. Liu and Lu discussed how to approach digitalization of the grid [19]. They stated that the primary reason for digitalization is that it can reduce costs and improve efficiency; they estimated that the electric energy industry can potentially save $80 Billion USD by 2040. Fig. 1 presents some benefits of AI, BD, and ADT.

Evident by the review articles in the literature, separate studies have been published related to various applications of BD and AI such as: to improve energy management, to manage supply and demand control, and to forecast energy generation from renewable sources and energy usage of buildings. However, most of the papers reviewed AI, BD, and ADTs in pairs or separately. They either provided a list of applications, or just focused on one specific application. The main effort of our work is to describe how the research in the three fields can be combined into a SEMS.

The specific goals of this paper, through gaining a holistic view of BD, AI, and ADT in the context of energy management, are: (1) describing applications of AI, BD, and ADT research with respect to energy management, (2) identifying the relationship between AI, BD, and ADT, and (3) outlining the key components, when these three technologies are considered, for a SEMS. This review will cover literature documents from Scopus and Web of Science, and patents from Depatisnet and Google Patents. Depatisnet is an online patent document archive created by the German Patent and Trademark Office (DPMA) [29]. This article is organized as follows: Section 2 outlines AI applications and techniques for energy management, Section 3 describes BD and data mining for energy management, Section 4 outlines how ADTs can be used to implement EMSs, Section 5 reviews patents for AI, BD, ADT, and energy management, Section 6 provides some perspectives towards integration of different technologies, and finally, the conclusions will summarize the key findings of the paper.

2. Artificial Intelligence

This section discusses methods and techniques used to implement artificial intelligence for energy management systems. Section 2.1 discusses popular intelligent algorithms, which are used to create AIs; this section focuses on the theoretical methods and techniques. While Section 2.2 briefly discusses how AIs can be implemented in hardware and software; this section focuses on the practical implementation of AI for energy management.

2.1. Intelligent algorithms

In this paper, an "Intelligent Algorithm" will be regarded as one that can autonomously provide the best output based on varying inputs. Without the intelligent algorithms, the SEMS would have to rely on fixed mathematical formulas with a well-defined process. The AI gains its adaptive abilities from multiple intelligent algorithms working together. There is no fixed formula that it relies upon. As will be explained, some of these algorithms rely on training and can be updated to improve their performance unlike a set mathematical formula, while others can variably adjust their actions based on inputs and outputs, thus making them more widely applicable. Algorithms such as deep learning and machine learning algorithms fall under this category.

Fig. 2 visualizes the popular intelligent algorithms or models in the literature. The data was extracted from VOSviewer and consists of 581 journal papers published in the years 2017–2022. Furthermore, these algorithms encompass many subtypes. Thus, the chosen algorithms were deemed to be the most representative and current ones in the literature. The most prevalent algorithms appear to be Fuzzy Logic (FL) and Neural Networks. Each intelligent algorithm in Fig. 2 will be discussed in this section. The discussion will start with Fuzzy Logic. The popularity of FL can be primarily attributed to its technical adaptability and wide range of applications.

Based on the literature, Fuzzy Logic (FL) is used as the central control algorithm for energy resources or loads. Kofinas, Dounis, and Vouros use a hybrid Fuzzy Q-learning model in a multi-agent system (MAS) to manage a microgrid [30]. Every agent control one load or resource. The overall idea is that each agent needs to balance its consumption or supply with the other agents. Alfaverh, Denai, and Sun combine Reinforcement Learning and Fuzzy Logic in a home energy management system for residential demand response [31]. The aim of the system is to minimize the power consumption. It will shift the operation of appliances from peak hours to low demand hours. Al-Sakkaf, Kassas, Khalid, and Abido use Fuzzy Logic in a central energy management system to control supply and consumption in a microgrid [32]. The inputs and outputs of the FL algorithm are scaled by an Ant Bee Colony Optimization (ABCO) algorithm to compensate for errors in the estimation of power needed. Nikolovski, Baghaee, and Mlakic developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast solar PV power

Table 1
Summary of key intelligent algorithms that use a neural network or support vector machine to help with forecasting.

Intelligent forecasting algorithm	Inputs	Objective	Target environment	Optimization	Reference
Efficient Deep Convolution NN (EDCNN)	• Dew point temperature • Dry bulb temperature • Wind speed • Wind power (current hour-24) • Wind power (current hour-25) • Wavelet Decomposed wind power • Time of the day	Predicted Wind power (MW) at each hour for the next 24 h	900 MW Wind Farm in Maine, New England		[34]
Hybrid Model (Long Short Term Memory (LSTM) + Convolutional NN (CNN))	• temperature • humidity • holiday status • day of the week • season	Predicted power demand (GW) for the next 7 days	Daily power demand in South Korea		[38]
Attention Long Short Term Memory (ALSTM) NN	• PV power • PV module temperature • Day of year (1–365) • Time step (7.5, 15, 30, 60 min intervals)	Predicted power demand (kW) at each time step (7.5, 15, 30, 60 min intervals) for each day	20 kW rooftop PV power station in Shaoxing city, Zhejiang Province, China		[36]
Elman NN	Solar irradiation from 5 weather stations which is then transformed by Discrete Fourier Transform	Predict solar irradiation for the next 24 h for a given city	Qingdao, Shandong Province, China		[37]
Hybrid Model (two Recurrent NN s+ Backpropagation NN + autoregressive moving average model + improved complete ensemble empirical mode decomposition)	• Maximum wind speed • Minimum wind speed • Mean wind speed • Standard deviation	Forecast wind speed at 15-min intervals	Wind turbine farm		[35]
Hybrid feed-forward particle swarm artificial NN model	• Energy demand • Environmental Temperature • Carbon Dioxide • Carbon Monoxide (%) • Methane gas (%) • Hydrogen gas (%) • Nitrogen gas (%) • Active Power • Power factor • Generator frequency • Lower heating value • Airflow to internal combustion engine	Predict the required Biomass flow (kg/h), Syngas flow, and gasification plant airflow to meet the energy demand	Biomass Gasification plant	Particle Swarm Optimization	[39]
Hybrid Model (Wavelet Transform + Particle Swarm Optimization + Support Vector Machine)	• Solar radiation intensity • Temperature • Cloud cover • Humidity • Pressure • Wind speed	Forecast power generation of a PV power system every hour	480 kW PV power system with six arrays in Beijing, China	Particle Swarm Optimization	[40]
Support Vector Machine	Wind speed (m/s) measured by wind turbines	Predict the wind speed in a wind farm location every 10 min	1500 kW wind Farm in Penglai, Shandong Province, China	Cuckoo Search Algorithm	[41]
Support Vector Machine	• Historical load data • Ambient temperature • Weather data (unspecified)	Predict the power consumption of a microgrid every 40 min	Offshore oilfield microgrid	Dragonfly Algorithm	[42]
Hybrid Model (Support Vector Regression+ LSTM)	• Number of Household • High-Income households • Medium-Income households • Low-Income households • Number of Water Pumping • Number of Milling Operations • Number of Small Shops • Number of Schools • Number of Clinics • Number of streetlights	Predict the hourly power consumption of a microgrid containing residential and commercial loads	Rural microgrid in South Africa		[43]

production and power demand [33]. Then an FL algorithm is trained using the outputs from the ANFIS; its objective is to curtail the loads based on the power production.

In general, the actions of the Fuzzy Logic system should choose when to supply the load or grid with the energy resources, to charge or discharge energy storage, and to turn loads on or off. To choose the correct action, an FL model requires information such as the power demand (kW), electricity price ($/kWh), State of Charge (SoC,%), and power output from the site energy resources (kW). What should be noted is that FL can use measured real time data or forecasted data. The average hourly data will not be known until the hour is over. Thus, in the meantime, FL can perform its actions based on the forecasts. As the real time data rolls in, it can update its actions and policy. Even if the FL algorithm updates itself based on 15 min time horizons, calculated estimates can provide the basis for its actions.

From these papers in the literature, a pattern starts to emerge that explains the popularity of FL; namely its versatility. FL is mathematically flexible, as it has been combined with Markov Decision Processes, Q-learning, and Neural Networks. Furthermore, it is adaptable to different applications like demand response and energy balancing. Its flexibility

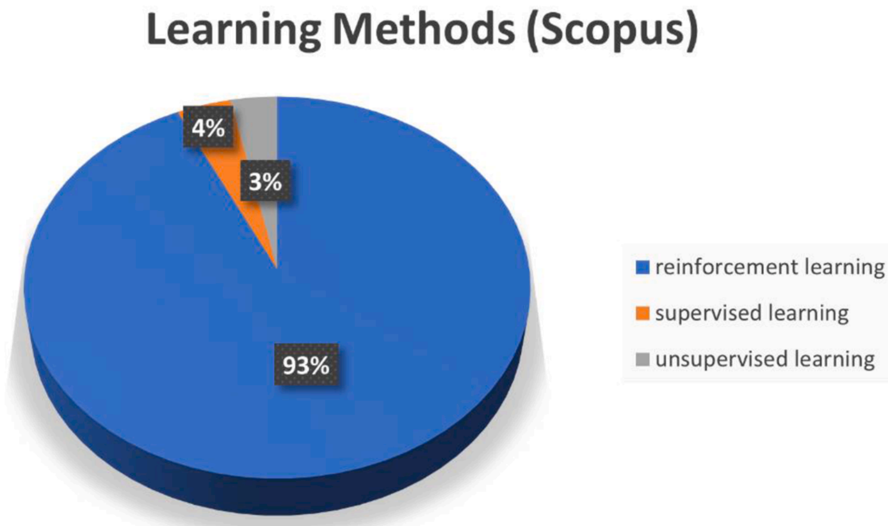

Fig. 3. Popularity of the three major learning methods from Scopus. The collected data comes from journal papers published in the years 2017–2022.

can be partially owed to its simplicity; if it was a complex algorithm with too many factors to consider, then it would not be as widely combined. FL is based on an action and reward system, thus it is suitable for applications that involve controlling an observable state, like charging and discharging energy resources. However, it would not be as suitable for applications like energy forecasting, which focuses on numerical analysis of relationships and reducing numerical errors on the output result. Fortunately, there are other algorithms that can fill the gap.

It is observed from Fig. 2 that Neural Networks and Support Vector Machines are also widely used in the literature in energy forecasting. As seen in Table 1, a Neural Network (NN) can be used for predicting wind turbine energy production [34], wind speed [35], solar panel energy production [36], solar irradiance [37], and power demand [38].

Knowing the predicted power generation influences whether there will be excess energy that can be sold or stored, or if there will be insufficient energy and the load must be supplied by the grid. However, due to the intermittent nature of solar power generation, consistently accurate predictions can be difficult. This fact alone provides motivation for researching energy or weather forecasting NNs for weather forecasting. Like FL, NNs are flexible and can be combined with other algorithms, such as a FL algorithm [44] and an autoregressive moving average model (ARIMA) [35], to further improve predictions. Table 1 also shows that a Support Vector Machine (SVM) can also be used for predicting solar panel energy production [40], wind speed [41], and power demand [38, 39]. Furthermore, Table 1 also shows that SVMs can be used in hybrid models. In summary, both NNs and SVMs are ideal for energy forecasting.

Unlike FL, in NNs and SVMs, there is no inherent mechanism for defining the states and associated procedure. Furthermore, FL has a variable reward system that guides the algorithm in each action. These reasons can explain why NNs and SVMs are more popular for energy forecasting as opposed to energy control. Both NNs and SVMs have numerical parameters that can be modified. These parameters adjust their performance. However, it is not feasible to attempt to manually adjust the parameters. Using optimization algorithms such as a Particle Swarm Optimization [39, 40], a Cuckoo Search Algorithm [41], a Dragonfly Algorithm [42], and a Genetic Algorithm [45] can iteratively tune the model.

Heuristics and Bayesian Networks have also been used for energy management. Heuristic algorithms are a type of search-based algorithm that aims to find an optimal solution for a given problem [46]. In the literature, they have been used for optimizing EV charging schedules [47], trade portfolios for electricity markets [48], energy usage of cooling systems in a building [49], and usage of energy resources in a microgrid [50]. Heuristics are useful because they can give potential solutions for problems that do not have a clear answer. Things like EV scheduling and energy resource usage are dependent on factors that cannot always be controlled. Thus, Heuristics can provide a potential solution to be evaluated. It may not be as popular because of the difficulty in understanding on how to use it in an energy management AI; Heuristics search for a solution, unlike FL an RL algorithms which directly output an action that can be used immediately.

Bayesian Networks are graphs that help describe the probabilities of events occurring based on the current state [51]. In the literature, they have been used for identifying potential fluctuations in electricity markets [52], help to predict user responses to demand side management strategies [53], and accounting for uncertainties in energy consumption and solar PV energy production [54]. Bayesian Networks are useful in energy management because they can quantify the uncertainties; renewable energy generation can be intermittent and user schedules can change. Bayesian Networks may not be as popular because, like Heuristics, it is difficult to implement a Bayesian Network in an energy management AI; the Bayesian Network gives a map of probabilities, but the problem becomes how to train an AI to evaluate these probabilities.

The results from these cited papers show that the current trend in intelligent algorithms is heading towards hybrid models. These authors used various algorithms to optimize the parameters of other models to improve performance. The literature also shows that algorithms are being linked together to create multi-stage algorithms. Furthermore, it appears that FL, NNs, and SVM are all commonly used in hybrid or multistage models. In conclusion, the current trend in intelligent algorithms in energy management is headed towards hybrid and multi-stage models. Looking at the popularity of individual intelligent algorithms is one way to find research trends. However, examining the different learning methods used in intelligent algorithms can also be used to find trends.

As shown in Fig. 3, the chart visualizes three major learning approaches that describe how intelligent algorithms or models can be trained to improve their outputs, unlike Fig. 2, which describes the different implementations of algorithms or models. The data was extracted from VOSviewer and consists of 184 journal articles published in the years 2017–2022. As observed, reinforcement learning (RL) is overwhelmingly popular compared to the other two approaches in the field of SEM. Due to its popularity, the following paragraphs will focus on RL applications. Before discussing why RL is so popular, it is important to understand what each approach is and why it is chosen. Supervised learning algorithms can abstract relationships between user

Table 2
Summary of intelligent algorithms that use reinforcement learning or fuzzy logic to schedule and control energy resources.

Intelligent control algorithm	Inputs	Objective	Target environment	Reference
Adaptive Neuro-Fuzzy Inference System (ANFIS) + Fuzzy Logic	• Wind Speed (m/s) • Wind Power (MW) • Temperature (°C)	Predict the power output of the load and PV system (15 min intervals) and curtail the load to match the PV generation and remaining battery power	Distribution network with a solar PV system, battery, and load	[33]
Fuzzy Q-Learning	• Power consumption of each load • PV power production • Battery Charge or Discharge power	Each agent aims to balance supply and meet power demand of each load while minimizing usage of the diesel generator	• Sources: PV System, Fuel Cell, Diesel Generator • Loads: Electrolyzer unit, desalination plant, variable electric load	[30]
Fuzzy Q-learning	• Shiftable Appliances (with priority levels attached to each one) • Non-shiftable appliances • Numerical reward based on whether action is Bad, Good, or Very Good	Monitor, control, and optimize the energy consumption	• Household with various appliances (Washing machine, Dish Washer, TV, Laptop etc.)	[31]
FL w/ Artificial Bee Colony Optimization	• Renewable power generation (kW) • Load demand (kW) • Battery SoC • Fuel Cell power output	Meet load demand while maximizing usage from renewable energy and the battery and minimizing generation cost from the diesel generator and fuel cell	DC microgrid with a PV system, wind turbine or diesel generator, fuel cell, and battery energy storage connected to a house	[32]
LSTM	• Current SoC • PV energy generation • energy demand • time of use tariff	Generate Charge and Discharge Schedule for EVs in the building parking lot	Commercial building with PV solar system and EV charging stations	[59]
Model-free Q learning	• The bids on the market (if a load agent) • Numerical reward based on whether action increased profit (if supply) or lowered expenses (if load)	In a microgrid with an auction based energy trading system, each agent, representing a load or supply, aims to maximize their revenue (if a supply) and minimize their expenses (if a load)	A microgrid with energy storage, PV power systems, wind turbines, diesel generators, and customer loads	[56]
Batch Q-learning	• Previous actions and rewards • Battery SoC • Load • Inverter efficiency • PV energy production • Electricity price	Schedule the charge or discharge of a battery storage system (in 15 min intervals) while minimizing the energy bought from or sold to the main grid	Microgrid with a load, battery storage system, and PV power system	[57]
Deep feedforward NN + deep Q-network	• Operational cost of the distributed generator • Operational cost of the ESS • Price of selling electricity to the main grid • Cost of buying electricity from the main grid • Load	Schedule the charge and discharge of the energy storage system and local generators while minimizing the daily operating expenses and satisfying the load	Microgrid with various renewable energy generators, loads, and energy storage systems	[58]

defined inputs and outputs. This method can be used for training intelligent algorithms to predict energy production or energy forecasting. Neural Networks use supervised learning and from examining Fig. 2, it is observed that they are very popular. However, its low popularity may be simply due to lack of appropriate keyword tagging.

In Reinforcement Learning (RL), the agent aims to minimize or maximize a value. For energy management this value can be energy costs or energy usage. An RL algorithm will continually adjust its actions with respect to the feedback from the environment. This process requires the appropriate action which is dependent on the environment. This approach is very useful in managing energy resources because of the uncertainty in energy consumption and production.

Unsupervised learning (UL) techniques involve identifying key patterns in data and then clustering them based on the identified patterns. Thus, they are useful for classification problems. UL algorithms can be used for fault detection in equipment, electricity theft detection, load clustering and more. Unsupervised learning may not be as widespread because data clustering is not as easily applied to energy management. The other two types of learning approaches are more appropriate to use for applications that have a set objective: forecasting energy and minimizing energy costs or energy usage. A book by Jo discusses unsupervised learning, supervised learning, and RL in more detail [55].

In RL, the agent continually adjusts its actions with respect to the environment. This approach is very useful in managing energy resources because of the uncertainty in energy consumption and production. RL is commonly used for energy scheduling. With respect to Fig. 2, the discussed RL algorithms will be based on Q-learning. Foruzan, Soh, and Asgarpoor discuss how RL can be used for microgrid management and energy trading in a Multi-Agent system [56]. The agents were based on model-free Q-learning algorithms. Autonomous energy trading is a vital part of a SEN, and it encourages integration of renewable energy systems. Suppliers are incentivized to provide distributed renewable energy because they can make more profit, while consumers are encouraged to consume from these resources because they can save on energy expenses. Mbuwir, Ruelens, Spiessens, and Deconinck use a model free Batch RL algorithm [57]. Unlike Q-learning, which discards its history after each update, batch RL keeps its history and uses it to influence its next actions. The goal is to reduce energy bought or sold from the grid, thus maximizing the energy usage of the on-site storage. An approach that considers history is useful because there are trends in energy; for example, a person's consumption schedule, the peak solar production, or electricity prices throughout the day. Ji, Wang, Fang, and Zhang also devised an energy management algorithm that considers energy production and consumption in a microgrid [58]. However, they used a hybrid deep reinforcement learning approach called Deep Q-Network (DQN). In essence, it uses the idea of actions and rewards from Q-learning and uses it to tune an NN. This approach is interesting because it is seen how reinforcement learning can be combined with

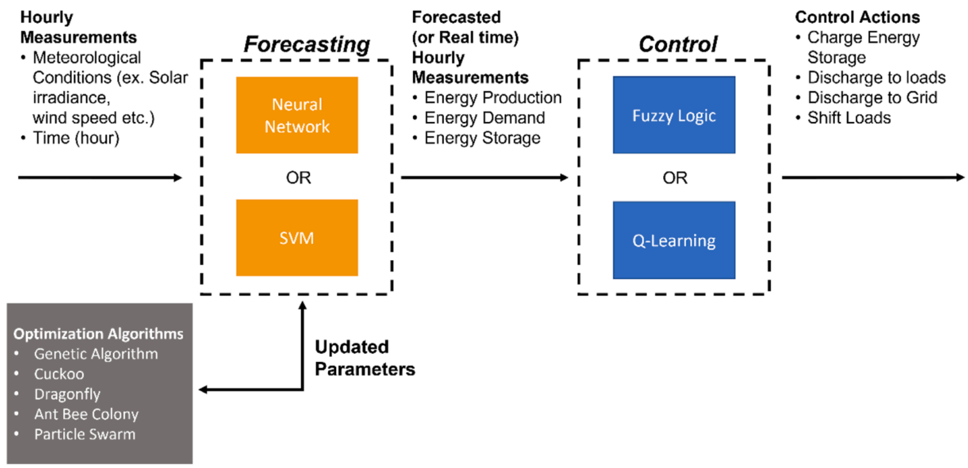

Fig. 4. High level diagram summarizing the literature and intelligent algorithms in an artificial intelligence for an SEMS.

another algorithm. Table 2 summarizes the intelligent algorithms that can be used for energy control.

From these cited papers, there are a couple of key points to note. Like FL, RL is versatile in a formulaic sense and for applications. RL based algorithms can consider history (Batch RL) or be integrated with an NN (DQN). In terms of applications, RL can be applied on a macro scale, where it is used to coordinate actions between multiple agents, or on a smaller scale, to help optimize energy costs for home appliances. It also can be applied in the middle level and be used to manage a single site. In conclusion, the popularity of Reinforcement Learning can be attributed to its flexibility in applications and algorithm creation. It is also important to note that RL-based algorithms such as Q-learning are "model free". This means that they do not require a priori information on the environment. Thus, the same model can be applied to multiple different systems in different locations.

After examination of both the popular intelligent algorithms and learning approaches, there are a couple overarching trends that can be noted. First and foremost, the versatility is a prime factor in the current research for artificial intelligence in energy management. Algorithms must be easily integrated or linked with other ones. No single approach will be perfect, so combining them enables a more well-rounded system. Fig. 4 shows the process and possible architecture for the AI in a SEMS. However, while the algorithms and concepts are useful, it is important to understand how an AI system can be implemented.

2.2. Artificial Intelligence system

The AI would likely be located on a device at the plant or site. It would need to acquire specific information from the site (e.g., load demand, energy production etc.) and directly control the energy flow. Therefore, the most effective way would be for the AI to be locally connected to the plant. Another term for this would be 'Edge Intelligence' [60]. That article mentions four modes for edge intelligence: Edge-Based Mode, Device-Based Mode, Edge-Device Mode, and Edge-Cloud Mode. For a Smart Energy Management System, the edge intelligence would be in the Device-Based Mode [60]. The edge device contains the AI model and performs the inferencing using the edge device resources. Thus, the output is reliable because there should be no miscommunication errors; however, it uses significant resources. An example is the microgrid intelligent management (μGIM) platform [61]. The edge device was a Raspberry Pi. The μGIM agent was programmed using Java 8 and was loaded onto this device. It was responsible for trading energy and forecasting energy production and demand. The system used SVMs for the forecasting. Each Raspberry Pi also featured its

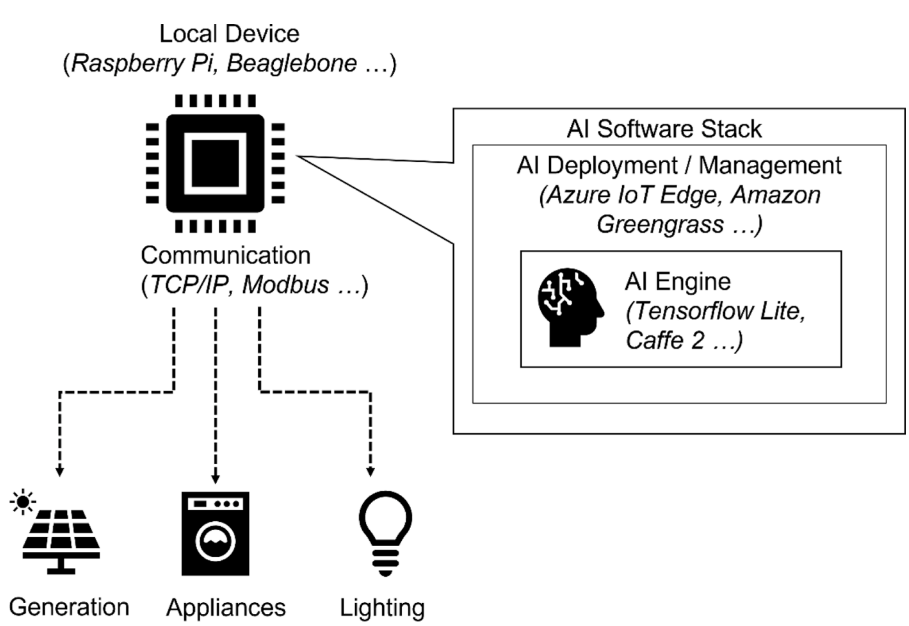

Fig. 5. Diagram showing the potential hardware and software components in an AI system.

own internal storage so it could access data for processing and store collected data. The device was integrated into the plant and communicated with the electrical resources in the plant using the ModBus or TCP/IP protocols.

Due to resource constraints, special frameworks such as Tensorflow Lite and Caffe 2 have been developed to program an AI Engine on edge devices. Additionally, there are service providers that provide services to help deploy and manage edge intelligence: Amazon Greengrass, Google Cloud IoT Edge, and Microsoft Azure IoT Edge [60]. These services can run the programmed AI Engine, use it to make predictions and upload the results to off-site data servers where it can be further processed. Fig. 5 shows a diagram of how an AI can be implemented for smart energy management.

In summary, utilizing hybrid and multi-stage intelligent algorithms for energy forecasting and energy resource control are the current and foreseeable future trends in energy management. While intelligent algorithms and automated analysis are vital to energy management, they are nothing without data. Based on the reviewed literature, there are various types of data that can be used. Moreover, to effectively train these algorithms, large volumes of data are needed. Therefore, data mining is a vital step that needs to be performed before training.

3. Big Data

3.1. Data mining for Artificial Intelligence

Data mining, in the context of energy management, involves data collection, preparation and analysis [62]. The purpose of data mining is to extract new information and relationships from existing raw data. The collection may be from repositories or measured data. The preparation involves filtering outliers in the data set, filling in missing data, or transforming the data. For analysis, a model or algorithm is used to abstract trends or relationships in the data and provide a desired output. This section will focus on how data mining methods can be used to enhance artificial intelligence models.

As reviewed in Section 3.2.1, intelligent algorithms have been used for load predictions and energy storage optimization in energy management. However, these types of models are especially reliant on proper data preparation. Ku and Jeong utilized data mining methods to help with the energy storage charging and discharging schedule for a building [63]. Their paper considers 4 unique loads: lighting, office equipment, fans, and a cooling coil. For the data preparation phase, they used a Self-Organizing Map (SOM) to determine which weather factors have the largest impact on the energy usage. SOM is an unsupervised NN model that non-linearly maps high dimensional data onto a low dimensional map space [63]. They used SOM to generate maps for each load and 25 weather factors. The colouration between the load and weather factor maps was used to determine their correlation. They complemented the SOM results using the Analysis of Variance (ANOVA) method which quantifies the impact of certain factors on the variance of other variables. In their paper, it was used to determine the impact of the weather factors on the variance of total building energy usage. This paper is interesting while two data mining methods were tested to complement and verify each other. Furthermore, it used a visual method, SOM, to prepare the data; data mining does not need to be mathematically rigorous. In this paper it is seen how data mining was used to clearly identify what weather factors have the high impact on the load. A factor with a significant impact on the output should be used as an input feature. Thus, for large and complex data sets, researchers can start by using data mining to identify the most impactful ones.

Dou, Zheng, Yue, Zhang, and Ma also used data mining to help in forecasting energy consumption, but also extended it to predict energy production [64]. The goal is to accurately predict wind power generation (WPG), PV power generation, and loads. The output data for predicting energy consumption and energy production is the historical load and generation, respectively. The data is first processed. WPG and PV power generation is intermittent and random; thus, creating inconsistencies in the data. Therefore, it is difficult to use the raw data. However, in this paper the authors used K-means clustering to select the viable data. They started by choosing the features that would be clustered. For predicting WPG, they chose wind speed and temperature. For predicting PV power, they chose humidity and cloud cover. The data is then grouped by using K-means clustering. The clusters are organized base on their mean values. These clusters are the potential candidates to be used as training data. Next the authors calculate the correlation between the clusters and the target data. The clusters with correlation higher than 0.8 are chosen. Finally, variational mode decomposition is used to reconstruct the original data points of each cluster. The data is then used by a NN to predict energy consumption. In this paper, data mining is used to quantify the relationship between the input data and the output; the results of this analysis were used to select the best data for training. This method is very useful in cases where there is substantial data available, but quality of the data varies. However, sometimes bad data can get through and reduce the model accuracy.

Another paper combines data mining algorithms with a neural network to help identify erroneous data in microgrid measurements [65]. The paper presented a Robust Extreme Learning Machine (R-ELM) combined with a density-based spatial clustering of application with noise (DBSCAN) algorithm. An Extreme Learning Machine (ELM) is a single layer neural network that can be trained very quickly. The authors improved on the ELM and created the R-ELM. The ELM is enhanced by combining it with two data mining methods; iteratively reweighted least-squares (IRLS) algorithm and existing complete orthogonal decomposition (ECOD) algorithm. IRLS helps to iteratively decrease the impact of outliers during training. While ECOD is used to help stabilize and correct the IRLS solution; it prevents the weight decrease from causing an inaccurate solution. Next, DBSCAN is a method for clustering data based on the density of the formed clusters. DBSCAN is more resilient to outliers and noise compared to others, such as K-means clustering. The R-ELM constructs an error filtering map that compares the current data to historical data. Then DBSCAN is used on this map to identify the erroneous data. There will be inaccurate entries in the training data and sometimes they cannot be completely scrubbed out. Furthermore, in real time operation, inaccurate data can still slip through. Therefore, it is important to make intelligent algorithm models robust to bad data. In this paper it is seen how data mining algorithms are used to directly enhance the ELM's resistance to outliers.

The importance of data mining for AI cannot be understated. The data mining can enhance artificial intelligence models by choosing the most impactful features to be used, choosing the best quality training data, and making the AI more resistant to bad data. If the training or inputted data is not prepared or selected properly, then it may not be able to bring out the full potential of intelligent algorithms. Even if a control algorithm has perfect accuracy, if the data has biases or errors, then the result will be inaccurate. In essence, the use of intelligent algorithms should be combined with proper data mining. While data mining can enhance energy management for a particular site, it is also valuable for higher level energy management.

3.2. Data mining for high level energy management

In the context of this paper, high-level energy management is regarded as managing multiple sites and understanding their impact on the wider grid. Low level energy management is managing energy resources or loads within a site. The people involved in high level energy management are typically utilities or grid operators. The data mining algorithms in this section help to process and summarize energy related information for sites. The summarized information can be used to help grid operators or utilities understand how much power is needed at specific periods.

Zhang, Wang, Farhangi, and Palizban devised a system that aims to cluster loads (e.g., appliances) in each area based on their power factors

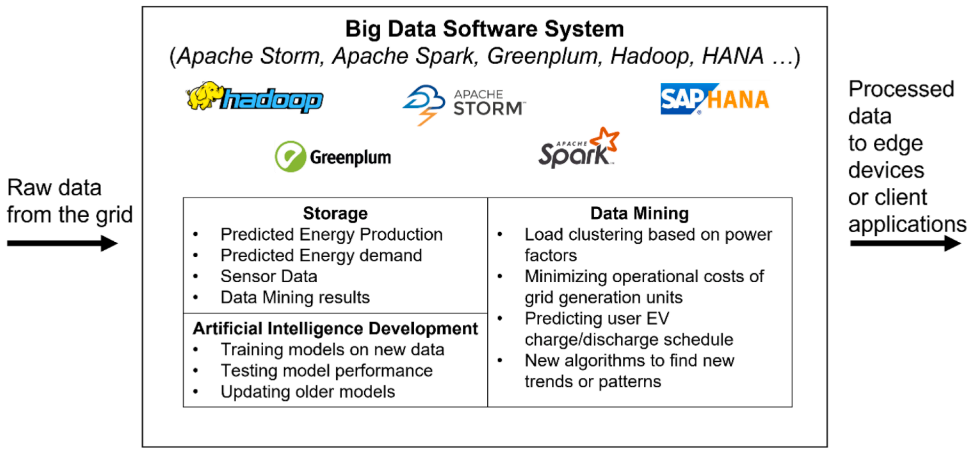

Fig. 6. High level diagram of the functions and potential software platforms in a big data system.

[66]. Hourly data was collected from multiple smart meters in an area and aggregated. Certain appliances have unique P and Q values. The algorithm then aims to determine "signatures" or identifiers of load clusters based on the hourly P and Q values. A genetic algorithm was applied to the cluster to iteratively optimize the solution to find a feasible power factor for the cluster. Then they applied a PF filter, an addition filter, and statistics to find the upper limit of active power for each cluster. This allowed them to achieve ranges for low, medium, and high PF clusters. Then they classified in which time periods the power factor (PF) category matched the load cluster. For example, between 2 and 3 PM is considered a low PF interval and clusters A and B fall into that range. Certain appliances may exhibit "low PF" characteristics, like A/C. Lastly, the disaggregation algorithm used the weighted least squares (WLS) method to finalize the classification of each load cluster into the high, medium, and low power factor categories. The benefit here is that now utilities have an idea of which areas use certain kinds of loads during certain time periods. In terms of high-level energy management, it helps utilities balance the active and reactive power for various areas.

For demand response, DBSCAN can be used to determine which loads in a smart home can be shifted [67]. As discussed in Section 3.1, DBSCAN is a method for clustering data based on the density of the formed clusters. The paper claims that their approach does not require data from sensors. The clustering determines at which time intervals, which appliances are considered non-essential and can be shifted. The clustering method is performed periodically, with updated load information, to update its calculation. Although user energy usage should generally obey a pattern, unexpected lifestyle changes may lead to changes in energy usage. Therefore, it is valuable to periodically understand and analyze energy usage patterns to gain the most accurate schedule. The clustering is used to help understand certain subjects. In this paper, the clustering helps understand which loads can be shifted. If information on a subject is unknown or unobtainable, then data mining can be used to get this information. Thus, this can benefit utilities and grid operators by helping to generalize which types of loads are shiftable. This data can be used to generate demand response policies for an area or region.

Marino and Marufuzzaman developed a big data system to perform real time data mining to minimize the operational costs of multiple power generation units within a microgrid, while still meeting the microgrid energy demand [68]. Their data mining algorithm is a sample average approximation method that solves a two-stage stochastic programming optimization model. The first stage attempts to minimize the startup, shutdown, and no-load cost of a generation unit. The second stage optimization occurs after a stochastic event. The algorithm then attempts to minimize the total energy cost by considering the operational costs, purchasing costs from the grid, and the revenue from the sale of energy from the microgrid. Essentially, the algorithm will optimize first, wait to see how the system reacts, then perform a second stage optimization after that. The algorithm outputs three policies that outline power generation unit commitment, as well as which generators should be online and when they should be online. The constraints for each policy are for the entire day, for a range of hours, and for one hour. Each policy has a different cost and risk level associated with them. Thus, microgrid operators can examine these policies and use them to help manage demand and energy resources for multiple microgrids. While data mining can be applied for static resources in energy management, it is also important to consider how they can be used for electric vehicle (EV) integration.

EVs are both mobile energy sources and loads. Furthermore, these are pre-made vehicles, thus it would be difficult to retrofit them with an edge device. Therefore, the data must be processed elsewhere. Considering there may be tens of thousands of vehicles charging or discharging, a big data system with data mining will be needed. Xiong, Wang, Chu, and Gadh present a method to coordinate EV charging and discharging across multiple parking lots while accounting for demand response from utilities and grid operators [69]. The authors used an algorithm called Clustering Latent Sematic Analysis (CSLA) that classifies users into four numbered groups based on their charging and discharging behaviour. Group 1 has a highly predictable charging behaviour, while group 4 is unpredictable. Groups 2 and 3 exhibit behaviours in between groups 1 and 4. Next, a mixture user model is built for each user. This model considers the charging and discharging rates of each user's EV model and their plug-in behaviour from the CSLA. The mixture user model provides an upper and lower bound for time availability and the net consumption of each user's EV.

From these models, optimization was performed using day-ahead wholesale electricity prices to create a charging schedule for all EVs for the day ahead. The day ahead prices were generated from an energy demand forecast; thus, peak times will be more expensive. The goal of the optimization was to minimize the charging cost, thus minimizing the load impact on the grid. With this optimization, a load profile accounting for all the EVs in the area can be generated. Then a control algorithm attempts to match the generated load profile by adjusting the charging times of the EVs. This system was tested for a smart charging network, consisting of roughly 200 EV charging stations, in a region within Los Angeles. However, even from this area, it can be observed that there were three data processing stages required before the charging control can even begin. Now imagine this system being scaled for a whole city or country. Thus, to handle all these multi-stage optimizations, a big data system is needed.

Table 3
Data mining algorithms that have been categorized according to their manipulation of data.

Data selection / Extraction	Categorization
• Pearson Correlation • Relief Method • Correlation-based feature selection (CFS) method • Analysis of Variance • Self-Organizing Map • Variational mode decomposition • Weighted Least Squares • Sample Average Approximation	• Density-based spatial clustering of application with noise (DBSCAN) • K-means clustering • Clustering Latent Sematic Analysis (CLSA)

3.3. Big Data system for data mining

When developing a big data system, it is important to understand the type of analytics it will perform [70]. There is real time, offline, memory level, business intelligence level, and massive level [70]. In the case of smart energy management, the big data system should perform real time analytics. The stakeholders need to see sensor data, predictions from the AI, and any problems as soon as possible. This way they can take appropriate action based on the information. Furthermore, it will help them understand the performance of the system more quickly so adjustments can be made. Software tools like Greenplum Database, SAP HANA cloud, Apache Storm [70], and Apache Spark [68] can be used for real time big data analytics.

Examining the work by Choi, Kim, and Yoon can help to further understand the role of a big data system [71]. The authors developed a big data system to help with demand-side energy management. Their system analyzed data from commercial, industrial, and residential buildings. Based on the analysis, it output energy saving actions such as load shifting and can make suggestions for selling excess energy. The actual big data system was implemented using a Hadoop Ecosystem. Essentially, the big data system was composed of multiple computers, called nodes, which make up a cluster. The cluster can perform parallel processing on data by distributing the work among nodes, thus reducing the processing time. There are Data Collection servers which upload information to the big data System, as well as Service Servers that interact with the big data system by forwarding information to and from the client applications. Now, with a better understanding of big data systems, a diagram can be constructed detailing the architecture and inputs and outputs. Based on these references, an approximate outline of a big data system can be developed. Fig. 6 shows a high-level diagram of a big data system with its inputs and outputs, and Table 3 summarizes the reviewed data mining algorithms. The results from data mining are valuable to stakeholders. The refined data used can be displayed on the client application. For example, the load clusters from the DBSCAN method can be shown as categories to help utilities quickly understand the high demand times.

For smart energy management to effectively utilize the concept of big data, it is vital to understand the dimensions of big data and data mining. The first step is to use the dimensions of big data to analyze and understand the data properties. Then, with a deep understanding of the data, researchers can choose an effective data mining approach that will complement its properties. For example, the veracity of the data may be questionable; thus, the data mining approach should involve steps to improve it. Garcia, Luengo, and Herrera review and evaluate the performance of several popular data mining algorithms [72]. The authors compared the performance of a classifier on an unprocessed dataset to several pre-processed datasets. The unprocessed dataset contained missing values and noise. The data mining methods were able to improve the classifier's accuracy by approximately 5%. Furthermore, quantification of the dimensions may be required to truly understand improvements. It is important to note that some of the dimensions, like velocity, influence the implementation of said data mining approach. Thus, in those cases, researchers must start to look at the intersectionality between data mining and digital technologies. Therefore, a digital infrastructure also needs to be considered. This topic falls under the scope of digital technology, and the next section will discuss how digital technology can be used to enable artificial intelligence and data mining.

4. Advanced digitalization for smart energy management

4.1. IoT computing

In a SEN there will be many devices connected that stream real time data; thus, a data processing infrastructure is needed to handle this volume of information. It is observed that most of the initial data is physical data. The data measures phenomena in the real world; for example, an outdoor temperature sensor. This can be regarded as the "edge". The edge layer concept has already been partially explored in Section 2 with AI. The information is then sent to an off-site data centre for mass storage and processing. Almassalkhi, Frolik, and Hines discuss the usage of Packetized Energy Management (PEM) to communicate and coordinate with multiple devices on the site [73]. Each load can make a request to use a 'packet' of energy. This message is sent to the local PEM coordinator, which can either reject or accept the request. The decision is based on the microgrid or grid conditions: electricity pricing, current local generation output, Battery SoC, and more. The PEM performs some data processing and decisions on site. This is done to reduce the traffic and computational burden at the cloud. This is known as fog computing. The PEM needs to be connected to the wider digital infrastructure to obtain information on the grid conditions. The data mining takes place at an off-site data center. This is called cloud computing. The data can be sent back to the edge or fog for analysis by AI or to client applications. edge/fog/cloud computing paradigms fall under the concept of the "Internet of Things". Thus, a system that utilizes these paradigms can be regarded as an Internet of Things (IoT) Platform. The basic components of an IoT platform are:

1 **Collection**: Devices that gather the data and a framework to transmit said data. A common semantic structure is needed to ensure ease-of-maintenance and compatibility across all parts of the grid.
2 **Storage**: The gathered information must be held in a data storage center to be organized and processed.
3 **Processing**: Raw data needs to be processed before being used in applications. Therefore, there needs to be a component that handles this processing. This may be performed by any of the computing paradigms.
4 **Visualization**: The data needs to be displayed to stakeholders to allow them to understand how much power they are using, equipment conditions and more.

To perform data collection, it should be known what type of data the system needs. Examples include load demand, power produced, meteorological data and more. Then the data collection devices can be determined. For example, a PV system may need a temperature sensor mounted near the panel surface to detect the surface temperature, as the temperature of a PV panel affects its power output. Technologies such as sensors and smart meters belong in the edge layer of IoT computing.

If the data collection devices do not have built in wireless capability, a Wi-Fi gateway device can be used. This gateway serves as a link to the internet. For example, an Arduino Controller was used to monitor the incoming power from the inverter and grid [74]. It transmitted the collected data to an ESP8266, serving as the Wi-Fi gateway, which forwarded the data to a cloud server. The Wi-Fi gateway fits into the fog layer.

Energy resources can cover wide areas; therefore, devices may communicate via wireless protocols. Thus, a local area network (LAN) can be used to transmit data from the edge devices to a central controller. The data communication protocols should be low power to

Table 4
A comparison of Zigbee, Bluetooth low energy, and Wi-Fi 5.*.

Protocol	Zigbee	Bluetooth low energy (BLE)	Wi-Fi 5 (
Maximum Data Rate (Megabytes/second)	0.250 [75]	2 [76]	1300 [77]
Communication Range (Meters)	0–50 [78]	0–78 [79]	0–80 [80]
Transmit Power Consumption (Milliwatts)	29.7 – 247.5 [81,82]*	4.44 – 71.46 [83]*	1266 - 4336 [84] **

* The power usage will vary depending on the electronic module and packet size.
** The power usage was measured from an Access Point. Furthermore, it will vary depending on the electronic module, packet size, frequency, and signal strength in dBm.

minimize the impact on the site's energy consumption. If the components are powered by batteries, it is vital to ensure they can last a long time before needing replacement. Table 4 gives a comparison of wireless communication protocols that can be used for a LAN. Once the data is collected it needs to be stored and processed.

For custom solutions, parallel processing and distributed computing is recommended. A suitable system for big data is the Hadoop Distributed File System (HDFS). HDFS allows computations to be spread across multiple computers: a database that can parallel process the data. The parallel processing allows multiple requests to be handled simultaneously, thus reducing the time it takes to get the needed information. One of the big advantages of HDFS is that it is part of the Apache Hadoop ecosystem. The ecosystem has other software that can help process data and transmit data to a HDFS. As an example, Hashim and Ramli used HDFS store and process smart meter data for a smart building in Malaysia [85]. They combined it with Apache Spark, which was to preprocess the sensor data. While Apache Flume is used to help aggregate and move the data to the HDFS. Examining the work of Gupta, Al-Ali, Zualkernan, and Das will help to further understand the advantage of HDFS [86]. The authors built a distributed computing system using HDFS. It is designed to store and process data from energy management systems across a region for multiple stakeholders: governments, utilities, consumers, etc. Their system outperformed the traditional monolithic relational database management system by 20X in terms of data processing speed.

In Section 2, it was discussed how the AI system would operate on an 'edge' device. However, given the new information, it would be appropriate to label it as a fog device because it serves as a data processor and gateway to connect to the cloud. This distinction compartmentalizes the roles of each component in the system. The fog layer is a vital component for IoT computing because it reduces the overall traffic volume heading to the cloud layer and shoulders some of the computational burden of processing the data. Researchers can use IoT computing to help determine and limit the functionality of each device in the overall system. Furthermore, using these layers can help build an organized interconnected web of systems.

Fig. 7 shows the high-level architecture of an IoT system. It is assumed that there is equipment that measures the energy storage and production. Firstly, energy usage, consumption and other physical data need to be collected from sensors and other equipment. The collected information should be sent to a fog device, the energy management system, with an AI to optimize energy usage, trade energy, and perform demand response. The EMS serves as a gateway for the microgrid to communicate with other microgrids or the cloud data center. Furthermore, the crux of the EMS is the AI. The controller can also serve as the internet gateway since it will aggregate the data and contain the outputs from the AI. The central controller can be a microcontroller such as Raspberry Pi, NVIDIA Jetson series, Beaglebone and more. The advantages of a microcontroller over a desktop computer are its small size and cheaper pricing. For example, the Raspberry Pi 4B measures 85 mm x 56 mm [87] and can be bought off the shelf for 35 USD'[88]. Then each site sends the processed information to a cloud server. The cloud server should have storage and is connected to multiple sites. However, there will not be one cloud server, but rather multiple servers for a specific region or area.

Notably, when reading these papers and others, it was observed that there was no semantic IoT framework, and there was little discussion on the actual implementation of the computing infrastructure. To advance research in this field, an IoT framework needs to be discussed. Therefore, Table 5 presents some IoT platforms in the industry that can be used for edge, fog, and cloud computing in energy management. The scale and sensitivity of data in a SEN means that the IoT platforms should be hosted by reputable companies with many resources. Google Cloud, Amazon Web Services, and Microsoft Azure platforms offer many services. Table 5 summarizes the services of each platform and their purpose.

A key part of any IoT platform is a customer facing application. This

Table 5
Cloud services for IoT computing and data mining.

Service	*Google cloud*	*AWS*	*Azure*
Data aggregation and streaming	Google IoT Core	Amazon Managed Streaming for Apache Kafka, AWS Glue	Azure Stream Analytics
Device management	Google IoT Core	AWS IoT Core	Azure IoT Edge
Data storage and processing	Google BigQuery	Amazon S3, Amazon Elastic Kubernetes Service	Azure SQL
Applications	Google App Engine	Amazon Elastic Kubernetes Service	Azure App Service

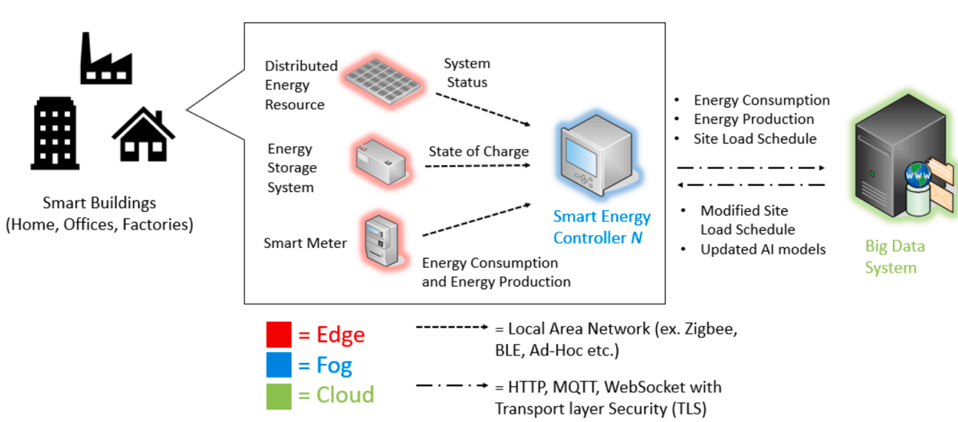

Fig.7. A high level diagram depicting an IoT architecture for smart energy management.

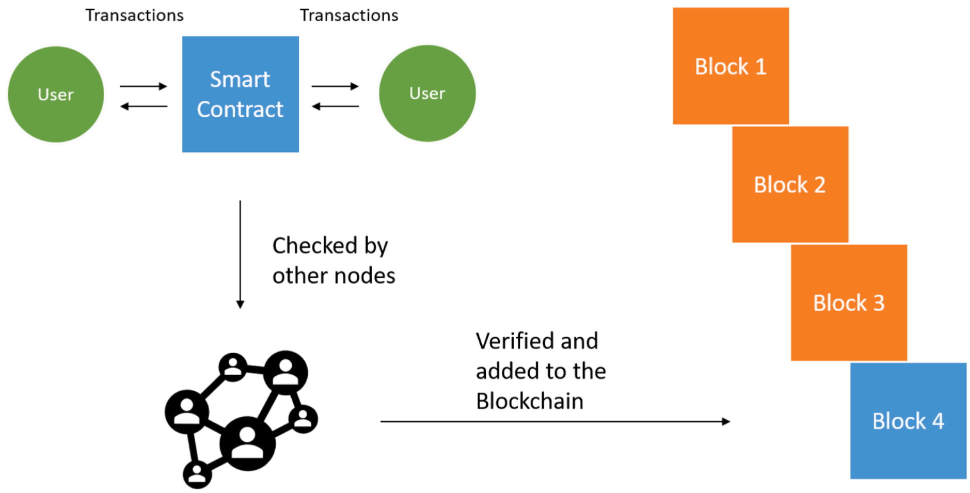

Fig. 8. A simple diagram showing the basic steps of a smart contract and how it is added to the blockchain.

component is needed to communicate key data to stakeholders. For example, utilities need to know how much energy may be generated and consumed in the next hour so they can ensure there is sufficient supply, while customers may want to see which loads are being shifted for demand response. Each application must be designed differently for each stakeholder. Regardless, the information generated from an EMS needs to be readily available. This concern raises an important caveat, being that the actual hardware and related software development still needs to be handled by the designer. As seen from the literature, the hardware design really depends on how the system operates conceptually. An IoT platform can provide connectivity for energy systems and stakeholders. However, to facilitate energy trading, another type of system can be used.

4.2. Blockchain and cryptocurrency

Blockchain technology is a secure decentralized database, or ledger, in a Peer-2-Peer (P2P) network [89]. The buyer and seller interact directly with each other; hence, the P2P, through a smart contract. This contract is a single block within the ledger. This ledger van be viewed by any user or node in the system. For transactions in this system, a buyer can use cryptocurrency as the medium of payment, and deposit it into the smart contract block. cryptocurrency (CC) is a digital payment system that is used in blockchain. Unlike fiat currency, CC allows the user to remain anonymous and is not connected to a country. Examples of CC include Ethereum, Bitcoin, Nanocoin and more. It is important to note that cryptocurrency uses blockchain as the basis for transactions [90]. Each successful transaction is added as a block to the chain.

The traditional centralized system that has all user and power information is stored in utility databases. Thus, this creates a single point of failure. If the utility databases are attacked, then it can bring down all the connected systems. If it is hacked, then the information of all users is accessible. However, in blockchain, if one node is hacked or attacked, then the malicious agent can only change or affect data at that node. In essence, each user or node is isolated from each other. Another security feature of blockchain is that every time a transaction or message occurs, each participating node will verify the integrity of the block. Thus, if the block has been modified by a malicious entity, the nodes will know. This idea allows blockchain to be applied to transactive energy. Prosumers (**Pro**ducers and Con**sumers**) can buy and sell electricity to others through a blockchain platform [89]. Smart contracts will contain the details of the sale, for example the amount (kWh), the source of the energy (wind farm, PV farm, natural gas, etc.), the amount to pay, etc. Since this contract is recorded in a block, the users can access a secure history of the transactions or messages. This concept is shown in Fig. 8.

Another important issue is that because the blockchain is inherently decentralized, there is no central authority to handle disputes. Any fraudulent transactions must be taken up directly with the other user in the trade. Obviously, this is a problem because the other user can deny the request with no chance of appeal. Thus, the genesis of such a platform would require a trusted central authority to start it. This is where the utilities can come in. Since they already control the distribution of electricity, it would make sense if they started and maintained the blockchain. The utilities can connect their own IT systems to the blockchain and verify that no fraudulent transactions take place. Furthermore, this means they do not have to directly facilitate transactions, thus saving them some work. However, there are still ways to ensure regulation and utility participation within a blockchain-based energy trading platform.

A consortium blockchain can be used to verify participants [91]. This method was used to verify in a P2P energy trading system for EVs. Offers and bids are fulfilled through a double auctioning system. After that, the transaction is fulfilled though a cryptocurrency deposit, recorded in a block and verified by local aggregators (LAG). The LAGs are preselected authorities whose job is to publish blocks that serve as verification of the transactions in a given time period. The LAGs use proof of work and race to complete the verification. When one LAG finishes the verification, the other LAGs then ensure that it is correct. Then the block is posted on the blockchain. This system is interesting because there is no central authority, but rather a group of verified decentralized authorities.

In another paper, a proof of reputation was proposed to verify participants for EV energy trading [92]. Identifying information such as the license plate number, ID, and business are attached to their nodes; obviously this information is encrypted. Then there are validators whose role is to allow or deny participation of nodes. Their participation is influenced by their reputation, which can be calculated. Thus, utilities can still regulate a blockchain based trading platform by assigning local aggregator or validator nodes to oversee transactions. This way consumers still get the benefits of direct trade, while having the comfort of another trusted regulatory body. The verification strategies for EV energy trading can be easily applied to individual energy sites. Instead of an EV, each agent represents the energy resources for a site.

The computing architectures discussed in Section 4.1 can still coexist with a blockchain platform because they address different parts of energy management and Smart Energy Networks as a whole. Using edge, fog, or cloud computing addresses the flow and storage of physical data, whereas the blockchain platform can store and facilitate financial transactions. Furthermore, intelligent algorithms involved in smart energy management would have two responsibilities. The first is to optimize load scheduling, charging energy storage, and discharge of energy

Table 6
Various blockchain platforms and their cryptocurrency.

Blockchain platform	Transaction method / Business model	Cryptocurrency	Locations	Reference
WePower	Auction	WPR Token	Estonia, Lithuania, Spain, Australia	[94]
Brooklyn Microgrid	Auction	N/A	New York City, New York, USA	[95]
SolarCoin (Energy Web Chain)	Injected solar power is converted to equivalent Solar coins	Solar coin = 1 MWh of electricity	International (PV power system required)	[96]
NRGCoin (Ethereum based)	Custom solutions	NRG Coin = 1 kWh of electricity	Belgium	[97,98]
POWR Ledger	Auction	POWR Token / Sparkz Token = 1 lowest denomination of local currency	Spain, Australia, USA, France, Japan, Thailand, Australia, Malaysia, India	[99]

resources. After the schedules have been confirmed, they would need to perform transactions on the blockchain via smart contracts.

To facilitate transactions on a smart contract, CC is used. The main issues with cryptocurrency are adoption and value. Also, CC itself is volatile, while fiat currency is controlled and backed by the government and the banks. For CC, there are no central authorities stabilizing it; thus, the price is very volatile. This provides a challenge to convince people to be part of system when there is a higher chance of losing money very quickly. So far, over 1000 CCs have crashed and lost value [93]. Thus, for the CC to maintain value, there must be physical meaning attached to the currency to help stabilize the value. Examples of CCs include NRGcoin, Solar Coin, and POWR tokens. Table 6 describes blockchain based energy trading systems and the associated CC.

Users can also stockpile CC, like charging, and spend them to get more energy, akin to discharging [89]. This reduces the need for larger energy storage. CC can end up saving money without taking up more space or generating more electronic waste. Thus, the strategy would be to have energy storage to supply themselves or generate tokens that can be used as a secondary storage method. In the case of NRG, their tokens are always worth 1 kWh; thus, users can confidently estimate the amount of electricity that they will have available. In the case of WePower, the contract sets how much each token is worth in terms of electricity, but users can bid for multiple tokens and still build a supply of tokens.

From the literature in this section, it is observed how various digital technologies can aid in energy management. IoT platforms can be used to connect stakeholders and devices at a site and help in scheduling EV charging. Furthermore, blockchain, and cryptocurrency can securely decentralize energy transactions, enabling users to trade energy directly, whether from a microgrid or EV. In conclusion, development and integration of digital technology is crucial to enable energy management.

5. Patents for smart energy management

So far, the paper has presented research in the literature. However, it is useful to see how such research compares with work that is more industrial. Therefore, this section will review some relevant patents in the field of energy management. The reviewed patents range from microgrid control all the way up to distribution. The reviewed literature has already shown energy management systems with forecasting, optimization, and control. However, it is still interesting to examine patents that do this primarily because they do present interesting ideas and can suggest the feasibility of EMS implementation and other technologies.

Dong, Li, and Xu describe a platform designed to facilitate demand response for a single building or multiple buildings [100]. Their system consists of an EMS in each building. Each EMS forecasts power production, forecasts energy demand, monitors the energy storage, calculates the grid energy price, and schedules energy trading with the grid. The EMS has access to data from each load and energy resource through multiple communication adapters. Their EMS architecture is interesting because it can be scaled for multiple buildings.

Belhaiza and Baroudi created a demand side management using a smart meter integrated with a controller [101]. They propose a DSM system where each smart meter is represented by an agent. The agents communicate with the utilities and a power production station to continually shift demand until a balance has been reached between all agents. The homes are connected via wireless mesh network and that a subset of these homes is connected to a data aggregator. The unique part of the system is how they used digital technologies to upgrade the smart meter to a controller. The smart meter has control software and additional data storage. It also contains a communication module for connecting to the wireless mesh network. Notably, the system uses the concepts of IoT computing; the aggregator is a fog device, while the smart meter is an edge device.

Cai and Zhang also propose a system for energy management [102]. Using the energy cost for the resources, forecasted PV power production and load, their energy management system determines how to satisfy the load demand. To aid in energy predictions, they proposed using clustering to classify whether a forecast is reliable or not. A highly reliable forecast indicates that the associated PV power prediction is more accurate, whereas a low reliability weather forecast requires a forecast from another source. It is interesting to see how the system performs an evaluation on the quality of the input data because weather forecasts are not always accurate. In summary, these patents present similar structures and ideas for forecasting energy demand and energy production. They schedule energy resource usage based on the forecasts and financial factors. These are like the ideas presented in the literature.

Hierarchal energy management strategies have also been used in patents. Farrokhabadi, Momtahan, and Paul describe a system where an AI controller manages multiple points of aggregation (POA) [103]. Each POA is an entity that can be a distribution feeder, distribution transformer, or a microgrid. These POAs may also have AIs that report to a central AI. The central AI's responsibility is to balance the active and reactive power that each POA consumes or injects. In another patent, the inventors propose a two-tier system as well [104]. The lower tier is a microgrid EMS that handles all the forecasting, scheduling, and demand response. The system can also predict the future energy costs, which is used to help scheduling. The top tier is a control system that optimizes the distribution of energy between multiple microgrids. The top tier is managed by utilities and the goals are to ensure grid stability and proper equipment operation. It can send signals to the microgrid EMSs to help balance power and voltage at the distribution level. Furthermore, it can perform energy and pricing forecasts for the utilities to help them manage the grid. Thus, having a second tier can help utilities and grid operators further manage new microgrids.

Another patent proposes a hierarchical energy hub system that can be used for residential energy management [105]. There is a micro-hub for each premise, and each micro-hub falls under a macro hub that communicates with a grid controller. The micro-hub is designed to schedule energy resource usage and optimize energy usage for the site. It can also control the loads inside the site. While the macro hub is responsible for balancing the power to and from several micro-hubs. The macro hub may make changes to the schedule set by the micro-hub. Both the micro-hub and macro hub forward collected and generate information with a cloud data centre. The system also uses IoT computing to help organize the data flow. The micro-hub is a fog device that collects data from edge devices (e.g. appliances and thermostats). While the data center is in the cloud layer and stores and process data.

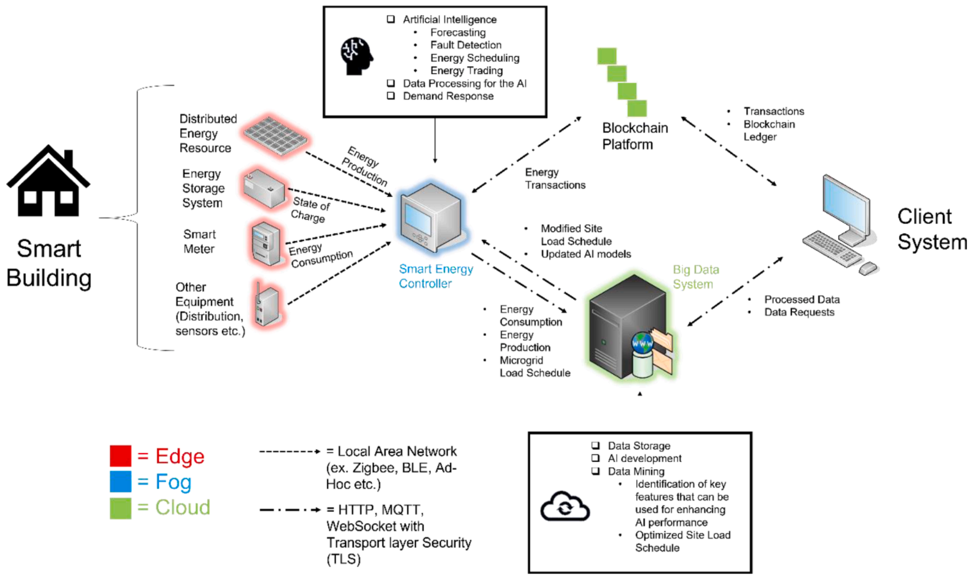

Fig. 9. A diagram showing an example architecture for an energy management system.

Operation of an energy management system is not free; thus, energy management strategies should consider financial costs. Aggoune, Albalawi, and Eisa present the idea of using an energy management system for an "energy warehouse" [106]. An energy warehouse is essentially a facility dedicated to various types of energy storage; electrochemical, chemical, thermal, mechanical, electromagnetic, and more. There is a control and monitoring system for separate energy resources. An EMS optimizes the operating cost of the energy warehouse using the data from these systems. A system developed by Anichkov considers battery degradation and financial indicators such as maintenance costs and taxes [107]. The dispatch of energy resources should consider both financial and equipment factors. Ensuring equipment longevity is important. In addition, monetary gains needs to consider equipment expenses and external assets or debts. Both patents optimize energy charge and discharge of energy storage while accounting for the equipment health.

Like the literature, some energy management systems used blockchain technologies to facilitate trading. Orsini proposes an EMS called TransActive Grid (TAG) that uses a blockchain network to trade energy [108]. Each entity in TAG is called a TAG element (TAGe). Smart contracts can only be fulfilled between registered TAGes. The presented blockchain system is interesting because once the contract has been fulfilled, the system will autonomously execute the contract. Thus, this reduces the involvement of people and can accelerate the process of energy trading. Despite the secure nature of a blockchain network, it is important to have redundancies.

Zhang and Xu added an AI to guard the microgrid and blockchain network [109]. Furthermore, the artificial intelligence for each microgrid may be granted permission by an administrator to modify, repair or delete nodes (users, agents) connected the blockchain. The AI can also analyze and report events. The technology used in energy management is very complex, thus it is useful to have an automated service that can process the data and constantly observe the state of both physical and virtual assets. This does not replace the decentralized management of the blockchain because it is still determined by consensus and verification through other nodes. Bindea, Bergh, Chapman, and Sawardjnes created a blockchain system with a primary control node, and this node has a duplicate of the blockchain ledger and may compare it to the ledgers stored on the smart meters attached to users' homes [110]. Obviously, if there are any differences, this may indicate that the blockchain has been compromised. This is useful as an additional security measure on top of consensus between nodes because user nodes would not have direct access to the system hosting the central node. It appears that using blockchain for financial services is the most appropriate application due to the public nature of the ledger, its immutability, and the fact that it is the basis for cryptocurrency.

With any energy management system, interoperability becomes a big concern. Energy management systems use a variety of different technologies for control or communications. As reviewed from the literature and patents thus far, energy management systems are composed of many different subsystems. However, these subsystems are not always from the same manufacturer or use the same protocols / languages. Thus, system integration becomes a critical factor in producing an energy management system. Ober, Doherty, and Crane propose a translation engine to help overcome differences in asset protocols for microgrids [111]. Essentially, the first asset sends data to a processor that translates the data to the second target asset protocol, then stores it in a database. Additionally, a label from the first data type will be translated into the second data type, to represent the relationship between the assets and their data. The assets are the renewable energy equipment or other digital technology utilized in the microgrid. Compatibility between specific technologies is not something that was previously discussed in the literature; however, for real life application, it is arguably one of the most important aspects to consider. Being able to overcome these differences in technology protocols can help accelerate the adoption of renewable energy and related systems. There have also been patents that considered integrating blockchain with other digital technologies.

As observed from these patents, the core goals of an energy system can be defined as in the introduction, and the patents' methodology falls in line with the ideas for energy management presented in the paper. The patents and literature provide a holistic view of AI, big data, and digital technology for energy management. Fig. 9 shows a sample IoT architecture synthesized from the literature and patents.

6. Perspectives

There are many components, as shown in Fig. 9 and Table 7, in a fully functioning energy management system. Proper understanding of the underlying software, hardware, concepts, and systems is vital to enable the functioning of the top-level components. In this section, the technological considerations are summarized to help the future development of smart energy management systems.

In terms of digital technology, there needs to be a semantic framework for digital technology. As provided earlier, there are available IoT

Table 7
Supplement to Fig. 9. Description of the digital entities, data, and processes in each layer.

	Digital devices / Entities	Data	Processes
Edge	• Sensors (Temperature, irradiance, anemometer etc.) • Energy Storage System (Battery, Flywheel, Thermal Storage etc.) • Smart Meter • Distributed Energy Resource Equipment (smart inverters • Smart Inverters	• Physical *(Temperature [K], Irradiance [W/m^2], Wind speed [m/s])* • Power related *(Voltage [Volts], Current [Amperes], Power Consumption [kW/h], Power Generation [kW/h])* • System Status *(Fault, OK etc.)*	N/A
Fog	• Smart Energy Management Controller • Internet Gateway	• Refined edge Data *(Physical Data and Power related)* • Generated Data *(Energy Schedule – charge / discharge of energy resources, load shifting)* • Equipment Status for each edge device and plant	• Smart Energy Management Controller contains: ◦ Artificial intelligence ◦ Data mining algorithm(s) to preprocess the data for the AI ◦ Demand response may be performed by the AI
Cloud	• Data Storage Servers • Client Application Servers • Blockchain application and platform	• Blockchain Platform contains the record of energy trading transactions and smart contracts • Data Storage Servers contain the following data from each connected SEMS: ◦ Refined edge Data *(Physical Data and Power related)* ◦ Initial and modified energy schedule ◦ Equipment Status	• The cloud computing services will: ◦ Perform data mining to reveal more relationships in data or prepare them for the client application ◦ Host the data storage and application servers

platforms made by third party companies. A common semantic framework reduces technical debt when updating software and hardware. Having a tested and well-developed existing cloud infrastructure can reduce the effort needed to create an IoT platform. When choosing a platform, researchers must consider: (1) scalability; (2) maturity of the technology, and (3) ease of integration. A practical system will have to manage vast volumes of data [112,113]; thus, it should be able to scale to the needs. Due to the sensitive nature of energy management, researchers should ensure that there are no major security issues with the tool. In the same vein as maturity, the technology should be well documented and have some proven uses. While research involves exploring new ideas, for energy systems, any errors can lead to catastrophic failures.

However, with all these components, operation of the system will be greatly affected by delays. Latency will propagate through a system, so the response of an EMS is limited by the slowest link in the system. While the hybrid and multi-stage AI models are novel and effective, the real time performance of these models is dubious and should be investigated. AI models have been tested in a closed environment; however, further analysis and work needs to be done as the AI is progressively integrated into a larger system. This leads to the crux of the issue with Energy

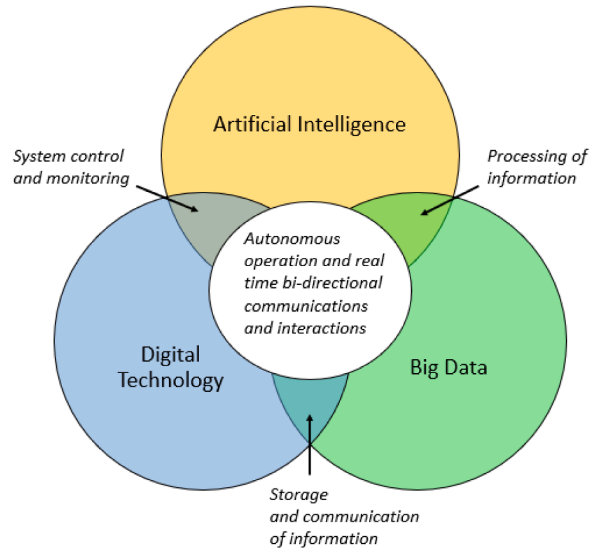

Fig. 10. A Venn diagram showing the overlap between the artificial intelligence, big data and digital technology.

Management Systems: real time operation.

Essentially, researchers should consider building mock experiments with small scale energy systems to test how effective their AI model is when considering sensors, controller software, and systems from other energy resources. Effective and simple integration of the AI can be a major novelty of the model. Proven experimental results will help guide the future of AI usage in the energy sector. The latency and response of an AI is also closely tied with the IoT Infrastructure. The AI is reliant on being connected to other digital devices and systems to perform its jobs.

While researchers do not need to divulge the exact blueprint of their system, they should note the components used: the program, software, any libraries, the sensors, the hardware controller, etc. This goes beyond just listing the tools used. Many of the papers provided theoretical background on their AI models and simulation results, but seldom presented the software or hardware used. It is vital to know what features within these programs need to be utilized; for example, GitHub repositories where users can contribute to the code base. Having more contributors can potentially increase the growth of the software. On the same note, researchers may opt to open GitHub repositories for their software to enable other users to contribute and improve their work.

To improve integration and implementation, both the literature and patents need to be reviewed. It is observed that the literature provided strong theoretical background, while patents provided practical implementations. Patents give very broad definitions and descriptions and do not always describe the theory behind their systems, while the research often failed to provide information on real life application of their methodology. This is to be expected; thus, it is suggested that researchers take the time to also file patents for their work to complement the strengths and weaknesses of both methods. Furthermore, this disseminates knowledge and allows the field to grow.

From the reviewed articles and patents, artificial intelligence, big data, Internet of Things, and blockchain all overlap and should be considered when building a Smart Energy Management System. AI is combined with data mining to provide processed data to enhance its training and performance. AI is also combined with advanced digital technologies, such as IoT computing and blockchain, to control and communicate with information systems and stakeholders. Furthermore, advanced digital technologies provide the data storage and pipelines for the processed data to flow to the AI and to the stakeholders; this fact makes it overlap with big data. Fig. 10 shows the conceptual overlap of the three fields.

7. Concluding observations

The current state of research for artificial intelligence, big data, Internet of Things, and blockchain is evolving rapidly and there is a large diversity of perspectives. Researchers should combine these research fields rather than developing them separately.

Artificial intelligence plays a major role in smart energy management automation. It is composed of multiple intelligent algorithms that enable energy prediction, energy scheduling, demand response, and energy trading. The popular algorithms for forecasting are Neural Networks and Support Vector Machines. For energy scheduling, demand response and energy trading, FL and Q-learning are the top choices. In all cases, the research is heading towards hybrid and multi-stage models to enhance the performance. To utilize the full potential of these algorithms, big data systems and data mining are needed. Data mining can be used for enhancing AI performance by performing feature selection. It can also classify and optimize data for high level energy management.

To enable the usage of artificial intelligence and big data, researchers need to consider the underlying digital technology. Designing a digital infrastructure using edge, fog, and cloud computing can enhance the flow of data and operation of the entire system. The edge is composed of sensors and data acquisition devices which are then connected to a fog device. In the context of EMS, the fog device is a central controller that is programmed with an AI and can perform demand response and basic data mining. Furthermore, the energy management system controller serves as a gateway to the wider internet and the cloud. The cloud layer is where bulk data mining is performed on data from multiple energy management systems. To handle such volumes of data, the cloud layer should utilize distributed and parallel computing to split up the work. Finally, all the data should be available to stakeholders to help them make data driven decisions. Internet of Things platforms such as Google Cloud, Amazon Web Services, and Azure can be used as common semantic frameworks for data processing.

Emerging technologies like blockchain and cryptocurrency can help facilitate transactions for energy trading and decentralize the Information Technology systems for the energy sector; this will help keep the grid up to date and more robust. Transactions can be facilitated through a smart contract that is verified by other nodes in the blockchain to ensure validity. To fully understand these fields and technologies, researchers should consider examining both the literature and patents to enhance their work or for inspiration. In conclusion, artificial intelligence, big data, Internet of Things, and blockchain are key research fields of a microgrid energy management system, and therefore their co-development and integrability are key to the future of the grid.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: John Wen reports financial support was provided by Ontario Centre of Innovation (OCI).

Data Availability

Data will be made available on request.

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