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Data Analytics and Information Technologies for Smart Energy Storage Systems: A State-of-the-Art Review

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ABSTRACT

This article provides a state-of-the-art review on emerging applications of smart tools such as data analytics and smart technologies such as internet-of-things in case of design, management and control of energy storage systems. In particular, we have established a classification of the types and targets of various predictive analytics for estimation of load, energy prices, renewable energy inputs, state of the charge, fault diagnosis, etc. In addition, the applications of information technologies, and in particular, use of cloud, internet-of-things, building management systems and building information modeling and their contributions to management of energy storage systems will be reviewed in details. The paper concludes by highlighting the emerging issues in smart energy storage systems and providing directions for future research.

1. Introduction

Demand for reliable electricity with constant voltage and frequency is increasing worldwide due to the economic growth, population rise, and considerable changes in quality of life. Demand could have significant variation at different times due to unexpected behavior of the users (Akbari and Haghighat 2021), at certain times, leading to its imbalance with electricity production (AL Shaqsi et al., 2020). Therefore, to ensure maintaining the balance between demand and supply and avoid economic losses, shortages as well as damages caused by such instabilities between demand and supply, use of energy storage systems (ESS) has emerged as a solution. The importance of energy storage systems rises further when all or part of the energy source on the supply side comes from renewable resources due to the high intermittent characteristic of renewable energies such as solar or winds (Shirzadi et al., 2021) and their varying potentials in offsetting carbon emissions (Rezaei, et al., 2021). In addition, energy storage systems are used a peak-shaving tool when there are time-of-use tariffs and highly varied behavior of the users and seasonality creating risk of shortage during the peak times (Sun et al., 2018b).

Although there are several ways to classify the energy storage systems, based on storage duration or response time (Chen et al., 2009; Luo et al., 2015), the most common method in categorizing the ESS technologies identifies four main classes: mechanical, thermal, chemical, and electrical (Rahman et al., 2012; Yoon et al., 2018) as presented in Fig. 1. Mechanical storage systems store the energy in two different forms, potential and kinetic (Evans et al., 2012). Examples of potential energy storage are compressed energy storage (CAES) and pumped hydro, while flywheels could be also considered for storing kinetic energy. Thermal energy storage systems are grouped based on their temperature mode: high or low (Gomez et al., 2011). An example of a low-temperature method used for electricity generation is cryogenic energy storage (Wen et al., 2006). On the other hand, sensible or latent heat storages are two types of low-temperature energy storage (Gil et al., 2010; Bastani et al., 2014).

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Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modeling
BMS	Building Management System
CAES	Compressed Air Energy Storage
CES	Cloud Energy Storage
CNN	Convolutional Neural Network
DES	Distributed Energy Storage
DNN	Deep Neural Network
ESS	Energy storage system
EV	Electric Vehicle
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
LSTM	Long Short-term Memory
MCFC	Molten Carbonate Fuel Cells
PEMFC	Proton Exchange Membrane Fuel Cells
RES	Renewable Energy System
RNN	Recurrent Neural Network
RUL	Remaining Useful Lifetime
SOC	State of Charge
SOFC	Solid Oxide Fuel Cells
SOH	State of Health
SVM	Support Vector Machines
V2H	Vehicle-to-Home
V2G	Vehicle-to-Grid
WSN	Wireless Sensor Network

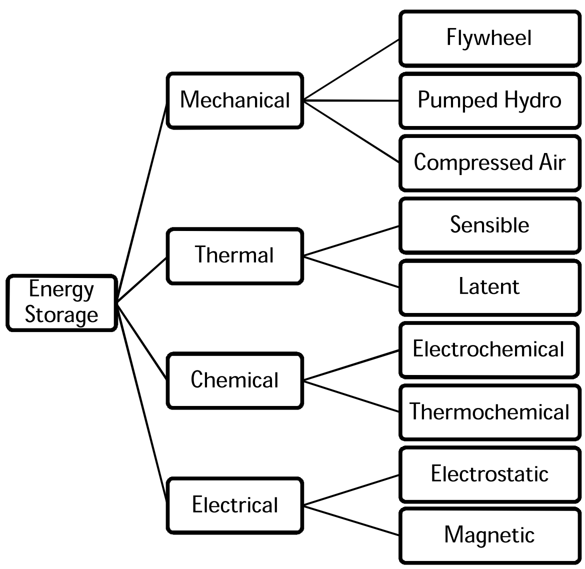

Fig. 1. A taxonomy of energy storage technologies (Rahman et al., 2012; Yoon et al., 2018).

Chemical energy storage comprises regular batteries such as lithium-ion, lead-acid, and flow batteries (such as vanadium redox and metal-air batteries). There are other forms of chemical storage that are called electrochemical storages and thermochemical storages. Fuel cells such as proton exchange membrane fuel cells (PEMFC), molten carbonate fuel cells (MCFC), and solid oxide fuel cells (SOFC) are considered as other forms of electrochemical storage while solar hydrogen and solar ammonia are two examples of thermochemical storage.

Electrical energy storage consists of two main types of storage, electrostatic and magnetic. Capacitors and ultra-capacitors are two main types of the electrostatic energy storage (Fang et al., 2011) while superconducting magnetic energy storage is an example of the magnetic method of energy storage (Boudia et al., 2021).

Energy storage systems are to play a vital role in integration of renewable energy systems with direct impact on the cost, reliability, and resilience of energy supply. This role is even more magnified in distributed generation systems where buildings act as prosumers. Storage systems could reduce the cost by decreasing the operational cost (in comparison with energy supplied from the conventional grid), storing the low price energy during off-peak, and using it during peak, reducing the indirect costs associated with power outages and saving money by participating in demand response programs. Acting as a backup in power outages situations and providing uninterrupted power can decrease the risk of power supply loss and increase the reliability of energy systems. Furthermore, adding an energy storage system could improve the system's ability to withstand the disturbances (in case of disruptions or shortages) and quickly return to a normal state (Mehrjerdi, 2021); therefore, increasing the system's resilience.

In the light of the above benefits, it shall be mentioned that the high intermittent nature of renewable energies and fluctuations in building occupants' energy consumption, while using energy storage, could still lead to operational safety and power quality issues (Ali et al., 2020). One of the major solutions to deal with this issue is to ensure a data-driven (predictive) control of the energy storage systems by implementing artificial intelligence (AI) techniques to anticipate and incorporate the intermittency of renewable sources. AI could be implemented as a predictive tool for demand, supply, and storage stages. For example, the state of charge of the battery could be estimated using the reinforcement learning method (Kim et al., 2018a), while the uncertainties related to the unexpected fluctuations of the load demand could be addressed by employing machine learning prediction techniques (Shirzadi et al., 2021). Moreover, AI could be used to predict wind speed and solar irradiance to diminish the supply side inaccuracies in establishing optimal control solutions (Hu et al., 2021; Wang et al., 2016a). Furthermore, the recent development in Internet of Things (IoT), advancement of the digital twin concept, and cloud battery management have had a considerable impact on improving the storage systems' reliability, safety, and durability (Li et al., 2020).

This paper aims at providing a state-of-the-art review of smart energy storage concepts and its integration into energy management practices. In doing so, we will provide a review of the applications of AI and information technologies (as organized in Fig. 2) in establishing smart energy storage systems.

Despite a parallel approach in conduct of the literature review (as presented in Fig. 2), this review highlights the interconnections and integration of these smart tools and technologies in management of ESS, including data analytics (energy supply and demand predictions), IoT (monitoring and tracking of ESS), and BMS/BIM (operation and control of ESS).

The review of articles cited in this paper is also done to identify the advantages and usefulness as well as the limitations of adopting "smart" tools and technologies in management of energy storage systems. The remainder of the paper is classified into four main sections. Section 2 represents a review of data analytics and AI techniques used for storage energy management. Section 3 describes smart technologies such as IoT, building management systems (BMS), and building information modeling (BIM). Finally, a conclusion providing a summary of the article and suggestions for future research is discussed in section 4.

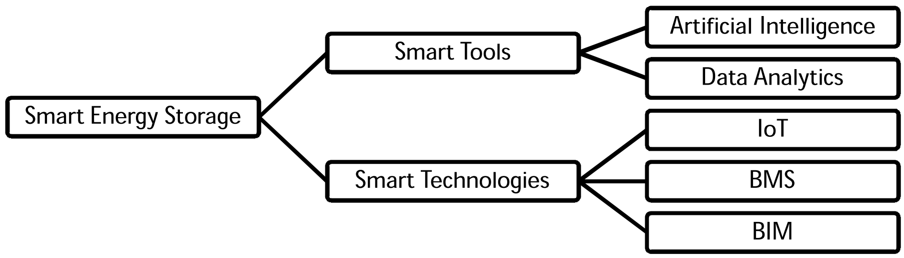

Fig. 2. Structure of the literature review

2. Smart Energy Storage Systems: Data Analytics

ESSs are nowadays recognized as an important element that can improve the energy management of buildings, districts, and communities. Their use becomes essential when renewable energy sources (RESs) are involved due to the volatile nature of these sources. In order to design an accurate model of the system and to select effective control strategies for the ESSs deployment, accurate data analytics tools are necessary. Data analytics is the use of data and predictive techniques to estimate or predict future outcomes. Fig. 3 shows a classification of data analytics applications in energy storage systems, which will be discussed in the following sections.

2.1. Renewable energy production, load demand, and energy price estimation

The successful deployment of ESSs is mainly based on the effectiveness of the employed operational control approaches. In fact, for an effective and efficient ESS management system, it is crucial to adjust the charging and discharging operation based on the estimated needs, while maximizing the corresponding performance, i.e., maximizing profits, minimizing operational costs, and prolonging the predicted device's lifetime (Al-Ghandoor et al. 2009). This should be done in accordance with the expected RESs energy production, energy demand, and energy price. These three features are usually referred to together as energy forecasting.

As for RESs, their key characteristics are the limited controllability, scarce predictability, and power output variability, as they completely rely upon environmental factors like solar irradiance, temperature, humidity, and wind speed (Scarabaggio et al. 2021). Large fluctuations in RESs production introduce several challenges, including voltage regulations as well as reserve power flow problems and power distribution issues (Nowotarski et al. 2018). Similarly, the demand side exhibits intermittent behavior of energy consumers due to various factors, that can be classified in economic, time/seasonal factors, and weather effects. Indeed, the economic framework has a clear effect on demand patterns, while seasonal effects, weekly daily cycle, legal, religious and holiday periods play an important role in influencing load consumption. Also in the case of load forecasting, meteorological conditions are responsible for significant variations, since several loads - such as heating, air conditioning, and agricultural irrigation - are weather-sensitive. For a long time, the energy industry has been considered by economists as a standard commodity; conversely, energy is indeed different from most other commodities, and the energy market has its own peculiar complexities. As matter of fact, energy cannot be appreciably stored, and the power system stability requires constant balance between supply and demand. Hence, the energy price may change hour by hour and these changes typically reflect the variations in the availability of generation resources, fuel costs, and demand curve.

It is worthwhile noting that, on the one hand, accurate forecasting methods are necessary to meet generation and demand in an effective and safe way (Khalid et al. 2018). On the other hand, it is apparent that RESs production, load consumption, and energy prices forecasting are intrinsically correlated, even though they require different adjustments and assumptions to be made. There is a large number of publications in this area (Hong et al. 2020); in particular, we can classify forecasting methods into probabilistic, data-based, ensemble and hierarchical approaches.

Due to the inherent stochastic yet recurrent or cyclic nature of loads and RESs, the simplest approach is to analyse these patterns and define the underlying probability distribution to predict future behaviours (Scarabaggio et al. 2021). Probabilistic approaches are deeply used for load (Gan et al. 2018; Xie and Hong 2016, 2017) and RES prediction (Chen et al. 2018; Gallego-Castillo et al. 2016; Scarabaggio et al. 2021; Yuan et al. 2018) due to their straightforwardness. Compared to the probabilistic RESs and load forecasting that leverage on the

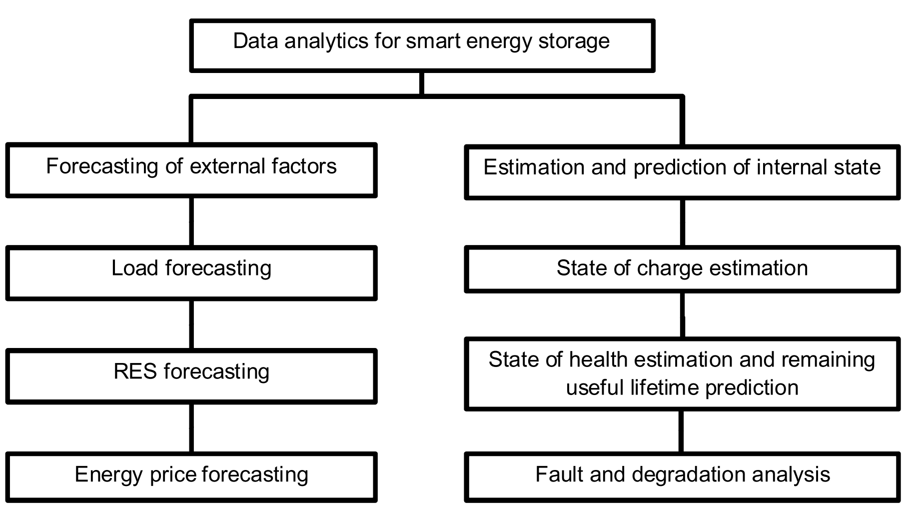

Fig. 3. Classification of data analytics for smart energy storage.

well-established meteorological forecasting, the literature on probabilistic energy price forecasting is relatively scarce (Nowotarski et al. 2018; He et al. 2014; Ziel et al. 2018).

A more advanced class of forecasting tools are data-based approaches that can generate reliable energy forecasting from a set of input parameters. The simplest methods are linear regression, multiple linear regression, and polynomial regressions (Bissing et al., 2019; Ren et al., 2016; Yang et al., 2016). Various advanced machine learning techniques such as artificial neural network (ANN) with different setups such as single-layer network (Khodayar et al., 2017; Wu and Peng, 2017), recurrent neural network (RNN) (Kong et al., 2017; Nazaripouya et al., 2016; Shi et al., 2017), deep neural network (DNN) (Shi et al., 2017; Wang et al., 2016b), reinforcement learning (Zhang et al. 2020), and transfer learning networks (Cai et al., 2020) have been employed. Differently from probabilistic models, data-based approaches usually offer more accuracy due to their advanced data mining and feature extraction capabilities. Discovering the patterns or hidden information from historical data is the key advantage of these classes of methodologies that are therefore able to accurately forecast RES production, load consumption, and energy prices. Nevertheless, in general, the training process required by these methodologies is far more complex and time-consuming than simpler models. It is worthwhile noting that the use of these approaches requires including the physical characteristics of the involved processes, both for modeling and variable selection.

Finally, combining different forecasting approaches is being widely recognized as one of the best practices for forecasting many phenomena and systems in nature (Nowotarski et al., 2016). Hence, ensemble and hierarchical forecasting technique, which reconciles forecasts generated individually at different levels, are the most promising approaches also for the energy forecasting (Hubicka et al., 2018; Hyndman et al., 2016; Qin et al., 2019; Nowotarski et al., 2016; Wang et al. 2018).

2.2. ESS state estimation

Storage devices are complex systems with several variables whose state is most of the time unknown (Del Pero et al., 2018). Hence, accurate state estimation is necessary for effective control of the device. In particular, essential tasks are monitoring and estimating the status of the device and predicting the lifespan and remaining capacity.

2.2.1. State of charge estimation

For the effective management and control of ESSs it is crucial to estimate the state of charge (SOC), which is quantified by the ratio of the releasable capacity of an ESS over its rated capacity. This information allows estimating how long the storage can continue to supply or store energy at a given operating condition. Indeed, the SOC depends on the operating conditions, while its definition is most of the time not unambiguously defined. Moreover, different storage technologies require the measurement and estimation of different variables. From a system point of view, for any type of storage technology, the methods used for SOC estimation can be classified into look-up tables, integral, Kalman filters, and data-driven approaches (Wang et al. 2020). The look-up table approach is the simplest one, since it requires only a mapping between the ESS's SOC and the characteristic parameters, such as the internal resistance (Yao et al., 2018), open-circuit voltage (Dong et al. 2016; Zhu et al. 2015), impedance (Bao et al., 2018; Zheng et al. 2016), or temperature (Chirino et al. 2018). Nevertheless, these approaches can be therefore used only for static analysis and cannot be used in real-time applications (How et al., 2019). Another widely used approach is based on the integral counting approach of the current (Lashway and Mohammed 2016; Zhang et al. 2014). If this approach is used in an open-loop fashion it may lead to the accumulation of prediction errors (Wang et al. 2020). A better approach, is adapting the well-known Kalman filter. In fact, when a model of the ESS is available the Kalman filter can be used to reconstruct its state. The literature presents a large number of contributions employing linear Kalman filters (Lashway and Mohammed 2016; Wei et al. 2017), extended Kalman filters (Lee et al., 2017; Pan et al. 2017), and other Kalman filters (Barz et al. 2018; Pernsteiner et al 2021; Aung and Low 2015; Bi and Choe 2020; Chen et al. 2019; Jiang et al. 2019; Zhu et al. 2019). A more recent and performant class of SOC estimation are the data-driven techniques. These approaches can estimate the SOC employing all the characteristics in a self-learning algorithm. The SOC estimation within the so-called data-driven approaches is usually done with regression methods (Richardson et al. 2018; Sahinoglu et al. 2018; Hrisko et al. 2021). In addition to these approaches, ANN-based models are widely used for SOC estimation showing high accuracy in the prediction (Chemali et al. 2018; Tong et al., 2016; Zhou et al. 2020).Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used to estimate the ESS's SOC based on complex feature datasets with time-series characteristics (Shen et al. 2020; Song et al. 2019; Xiao et al., 2019; You et al., 2017).

2.2.2. State of health estimation and remaining useful lifetime prediction

Among the various available energy storage solutions, chemical energy storage systems, and in particular lithium-ion batteries, are widely regarded as promising candidates for various applications due to their advantages of high energy density and low self-discharge (Wang et al., 2021). Nevertheless, the life span of chemical energy storage systems is not unlimited. Indeed, their performance decreases with time and their operation (Liu et al., 2019).

In general, a chemical energy storage system reaches the end of its service life when its maximum capacity drops to a certain percentage of the initial value. Therefore, estimating when this will occur is a crucial and challenging problem in a battery management system. This is usually referred to as health estimations and can be done by defining several different indicators available in the literature. Nevertheless, to forecast the health conditions and provide a tool for the replacement of a device the state of health (SOH) and the remaining useful lifetime (RUL) are widely used. However, the SOH and the RUL are not uniquely defined in the related literature (Zhang et al. 2019). Usually, the SOH is defined as the ratio of the original capacity of the device and the actual one (Hu et al. 2021), while the RUL is typically quantified by the time or cycling number when the capacity or SOH decreases to a threshold value (Li et al. 2019b). Accurately predicting the SOH/RUL is critical to adjust its controlling strategy to ensure the performance, safety, and lifetime. Besides, accurate estimation and prediction, the RUL is vital in guiding device reuse or recycling. The SOH/RUL estimation methodologies can be categorized into measurement-based, Kalman filter, and data-based approaches (Sarmah et al. 2019). The measurement-based approaches aim to predict the SOH/RUL directly from specific measures. These approaches are the most straightforward; however, their accuracy is low. The inputs used in the lifetime prediction are various since they range from charging voltage curve, trend surface temperature (acquired from the infrared images), electrical information (incremental current/voltage data) (Weng et al. 2013; Zhou et al. 2017) and electrochemical impedance spectroscopy (Galeotti et al. 2014). As for the SOC estimation, the model-based approaches employing the Kalman filter have in general better results (Wassiliadis et al. 2018; Yan et al. 2018). The latter category is based on machine learning methods applied to predict the SOH/RUL starting from a set of complex input features (Tang et al. 2020). Regression algorithms are often used to estimate and predict SOH/RUL with their linear version (Severson et al. 2019), Gaussian processing regression (Liu and Chen 2019; Sahinoglu et al. 2018) or with kernel-ANN regression algorithm (Zhou, Huang, and Pecht 2020). Besides the regression approach, decision trees (Zhu, Zhao, and Sha 2019) and support vector machines (SVM) are used to predict SOH/RUL (Liu et al. 2015; Patil et al. 2015; Zhou et al. 2016). When handling dataset with complex time-series characteristics various ANN-based models are applied for SOH/RUL prediction (Pan et al. 2018; Tong, et al., 2016; Wu, et al., 2016), such as DNN (Khumprom & Yodo, 2019; Srivastava et al. 2014), RNN (You et al., 2017) and long short-term memory (LSTM) neural networks (Ma et al. 2019).

2.2.3. Fault and degradation analysis

An important issue in the management of ESSs is the detection of defects, as well as the detection of abnormal behaviours, to ensure the future availability of the device. Most of the approaches used to detect anomalies are based on machine learning techniques since faults are usually the results of a series of complex interactions between different factors. Several machine learning algorithms are applied to classify the unbalance and damage of battery cells including logistic regression ANN, kernel-SVM (Dong et al. 2016; Kim, Lee, and Cho 2012; Ortiz et al. 2019). Classical regression techniques such as the Gaussian process regression (Lucu et al. 2020) and deep learning approaches are also gaining significant attention (Li, et al. 2019b; Liu et al. 2018; Yao et al. 2020; Zhao et al. 2017). In some applications, the input to the machine learning models is in the form of images, such as the snapshots of the battery electrode microstructure. Under this circumstance, CNN, which is highly capable of extracting the features of images, can be utilized (Badmos et al. 2020; Wang et al. 2019). The estimation of the device's degradation is a very complex issue since the cycle-based degradation depends on the charge/discharge sequence and on natural factors that contribute to the degradation such as ambient temperature, humidity, and storage technology. The degradation analysis aims to predict the future SOH/RUL based on the predicted operating conditions. In fact, a vital aspect of energy storage operation is to accurately model the operational cost, which for many devices mainly comes from the loss of energy capacities under repeated cycling (Xu et al., 2017). Hence, predicting the impact of different charging/discharging processes on the ESS's health state can be useful to select the best performing control inputs (Zhou et al., 2011). Several ESSs studies include degradation models either based on battery charging/discharging power or energy throughput (Ortega-Vazquez, 2014). These degradation models are convenient to be incorporated in existing optimization problems, at a cost of losing accuracy in quantifying the actual degradation cost. The capacity fading can be properly described in terms of the fatigue process since mechanical stress plays a key role in the degradation of the device performances (Xu et al., 2017). The similarities of the storage devices' degradation with the classical approach for the ageing of mechanical systems subject to fatigue cycle loading led many papers to select this as the most appropriate model for describing the performance deterioration (Laresgoiti et al., 2015; Shi, et al. 2018; Xu et al., 2017). The battery ageing process is fundamentally described by a set of partial differential and algebraic equations, however, they are in some sense too detailed and thus semi-empirical degradation models are often used. These approaches define a relation between cycle depth and battery degradation, and the loss of battery life is the accumulation of degradation from all cycles. To count these cycles several algorithms for cycle identification in material fatigue analysis as well as for battery degradation (Muenzel et al. 2015; Shi et al. 2018; Xu et al. 2016) can be used.

The literature review on data analytics applications in ESSs highlighted a number of limitations in applications of data analytics approaches in management of energy storage systems, prompting avenues for future research. A major challenge rests in forecasting of highly uncertain (and sometimes) chaotic phenomenon such as wind speed used to predict wind energy generation potentials as a basis for energy storage scheduling. The existing probabilistic, data-driven, and even ensemble approaches models have deficiency in generating forecasts when facing such an extremely uncertain phenomenon. There exists an opportunity to integrate such a dynamism into energy storage scheduling through environment-based learning approaches (Zhou et al., 2022). In contrary to batteries, in case of mechanical energy storage systems, such as compressed air energy storage, there unsteady characteristics such as lags in charging and discharging phases (Guo et al., 2022), which needs to be incorporated into state of charge forecasting models (in particular when there are exchanges with the grid) as a delay factor. This phenomenon could be formulated through adopting a more detailed forecasting approach that resembles the physics of such mechanical processes to forecast the state of charge at any given time in future. The other emerging issue in data analytics application for energy storage systems relates to prediction of failure and degradation under extreme operational pressure. Most of the failure prediction models formulate over-time degradation of these systems with limited studies on impact of sudden changes in operational requirements due to disruptions caused by extreme events. There is an emerging trend towards combining resilience assessment models with failure prediction (Ameli et al., 2021).

3. Smart Energy Storage Systems: Smart Technologies

The integration of energy storage into energy systems could be facilitated through use of various smart technologies at the building, district, and communities scale. These technologies contribute to intelligent monitoring, operation and control of energy storage systems in line with supply and demand characteristics of energy systems.

3.1. IoT and smart energy storage

IoT addresses the needs of the energy sector to move forward towards a promoting efficient and sustainable use of natural resources. In order to achieve this, the concept of IoT proposes the development of a smart industrial platform enables to improve the efficiency and sustainability of system operations and to predictive maintenance by connecting cyber and physical systems. Therefore, IoT is the fundamental technology for realization of smart power and energy systems with energy storage. Such smart systems require bidirectional information exchange among different segments that can be provided with IoT-based technologies. IoT is not a single technology, but an interconnected network comprises of several technologies enabling communication of physical objects (Things) via the Internet in real time. The key elements of IoT technologies are, IoT devices embedded with sensors and software for collecting real-time information, IoT networks and gateways for secure transmission of sensors data and an IoT management platform with several functions such as data storage management, data analytics and application enablement (Patel et al., 2016; Presser et al., 2018). In energy sector, the advancement of IoT technologies support a wide range of applications, along with Smart Grid concept, in power generation, transmission, distribution and consumption, including smart deployment of energy storage systems in buildings, districts and communities.

3.1.1. Cloud computing and fog computing technologies

The value of IoT is in the ability to process and analyse massive data streams in real time in order to make optimized informed decisions. This necessitates advanced data processing approaches, instead of storing and processing data only on local hard drives. Cloud computing and fog computing are the two well-accepted computing platforms for IoT applications (Motlagh et al., 2020). Cloud computing platforms provide on-demand services including data storage, data processing and computation without owning the hardware systems through the Internet. This allows access to heterogeneous data shared among different sectors anywhere and anytime, while reducing the costs of hardware and maintenance and enhancing the computational power and storage capacity.

However, such a centralized computing approach cannot satisfy all IoT applications, particularly latency sensitive applications with widely geo-distributed IoT devices (Rani et al., 2021). Fog computing, also known as edge computing, is a distributed computing approach, which extends cloud computing to the edge of network. That can be using any IoT devices with storage and computing capabilities for data processing instead of sending the data to the Cloud. Fig. 4 shows the cloud and fog computing architecture for IoT applications.

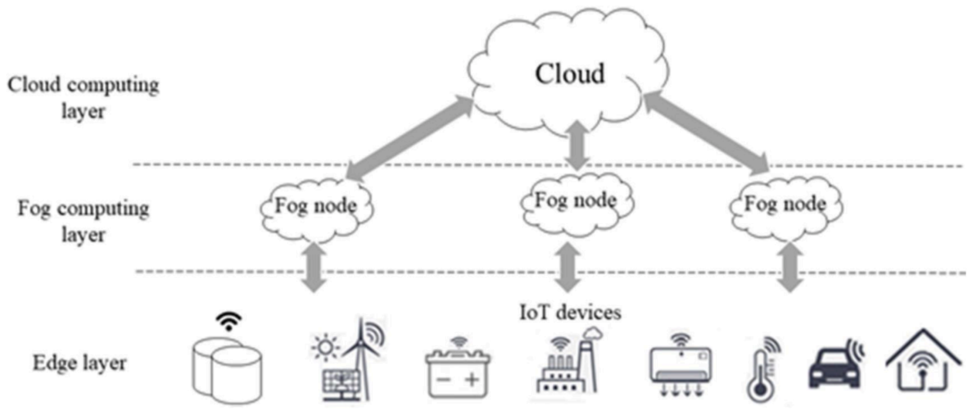

Fig. 4. Cloud and fog computing architecture

3.1.2. IoT-based energy storage systems

In industrial energy sector, relying on the IoT cyber-physical network technology, which provides a bank of information for optimized decision, an energy management platform comprising of two main layers; a "core cloud" and the "edge clouds" has been proposed by (Golpîra & Bahramara, 2020). At edge clouds, microgrid aggregators solve optimization problems to determine the energy balance of each microgrid, whereas, at the core cloud, the distribution system operator solves an optimisation problem to meet the energy balance of the distribution grid with optimal scheduling of energy storage systems. Motivated by widespread use of lithium-ion (Li-ion) batteries as grid-level energy storage systems, a battery condition monitoring platform has been proposed by (Kim et al., 2018b), which utilizes IoT devices and cloud components. The architecture consists of wireless module management systems incorporating IoT devices and a cloud battery management platform with cloud storage, analytics tools, battery algorithms, and visualization modules. Critical model parameters of the battery cells and battery conditions such as state of charge and state of health can be estimated with the proposed platform for the purpose of fault detection and predicting the remaining useful time of the battery cells.

In domestic energy sector, IoT technologies are the main driver for integration of distributed energy storage (DES) systems, e.g. battery of electric vehicles (EVs), roof top photovoltaic panels and local solar thermal storage systems in energy systems leading to a more flexible and scalable power grid (Ahmad & Zhang, 2021; Bedi et al., 2018). EVs as mobile distributed energy storage devices become an integral part of Smart Grid and smart buildings with vehicle-to-grid (V2G) and vehicle-to-home (V2H) technologies (Alsharif et al., 2021; Mehrjerdi, 2021). This has led to extensive research studies focused on optimal planning for EVs charging/discharging. For instance, based on the distributed fog computing technology, three optimization algorithms have been proposed in (Chekired et al., 2020), for an intelligent scheduling of EVs plugin. The system architecture consists of centralized cloud data centers and decentralized fog data centers for real-time information exchange, such as EVs requests for charging/discharging and energy prices. A new concept of DES system referring as cloud energy storage (CES) has been proposed in (Liu et al., 2017), which enables residential and small commercial consumers to rent a customized amount of energy storage from a so-called CES operator via the Internet, instead of using their own on-site energy storage systems. Different centralized energy storage technologies, such as flow batteries or compressed air energy storage can be provided as distributed energy services to the users, who aim to reduce their electricity bills considering volatile real-time energy prices by CES technology. Other than electricity storage systems, IoT-based thermal energy storage systems play an important role in balancing energy supply and demand in smart cities. Water storage tank for water heater or thermal mass of buildings are examples of thermal energy storage systems that can be utilized for Smart Grid services, such as load shifting, via controlling IoT enabled building systems and appliances (Sharda et al., 2021).

The use of IoT technologies enables renewable energy suppliers and utilities to efficiently design and operate their storage systems in order to tackle the intermittency of renewable resources hence, promoting the sustainability and stability of power grid. The other key advantage of IoT is the coordination of distributed energy storage systems such as batteries of EVs to enhance the reliability of grids or local generation capacities (e.g. renewables). Similar to other technologies, adoption of IoT technology presents some challenges. Several challenges have been discussed in the literature, for example in relation to network coverage and bandwidth, interoperability of the system components or data storage and security (Khatua et al., 2020).

IoT technology comprises of numerous IoT devices that consume power. Therefore, it is important to have plugged-in IoT devices with low power consumption and remote IoT devices with long battery lifetime in order to make IoT solution affordable and sustainable for energy system applications. This has led to the emergence of green IoT technologies. A comprehensive review of the techniques and strategies for enabling green IoT technologies has been provided in (Almalki et al., 2021). Energy harvesting techniques, that is converting ambient energy sources such as ambient light into electrical energy, has been studied in the literature e.g. in (Adila et al., 2018) as a technique for prolonging the battery life time of the IoT devices. High energy consumption of cloud-based data centers is also a topic of research studies related to the IoT energy consumption. For instance, a multi-objective optimization problem has been formulated in (Guo et al., 2021) for integrated planning the capacity of internet data centers and the battery energy storage systems in a coupled smart grid and communication system.

Application of IoT devices, especially in residential sector, increases the risk of privacy violations with sharing smart meters data that can be translated to behavioral patterns of smart building occupants (Zainuddin et al., 2021). Several techniques have been discussed in the literature for preserving the privacy in IoT applications, such as data anonymization which removes attribute information from the meter readings (Ren et al., 2021) or data obfuscation which distorts customer energy profile by integrating another energy source e.g. energy storage units at the customer premises (Sun et al., 2018a).

IoT technology connects thousands of physical devices, mostly via some form of wireless communication. With increasing emergence of IoT devices and new technologies, spectrum scarcity has addressed as a challenge for wireless transmission, where IoT devices are overlapping or close to each other in spectrum (Li et al., 2019). This can cause severe signal interferences, particularly in industrial environments in energy systems. (Tlake et al., 2021) reviews interference challenges for Narrowband Internet of things (NB-IoT) communication standard. An unsupervised machine learning framework applying semi-Markov chains and a Poisson-distribution arrival rate has been presented in

(Homssi et al., 2021) for modelling interference in IoT applications. Various signal processing techniques or techniques to isolate interference transmission have been proposed in the literature to manage signal interference (Li et al., 2019).

3.2. BMS and Smart Energy Storage

The energy consumed in the building sector has recently grown considerably. According to the latest reports, 40% of global energy and 25% of total electricity demand is associated with buildings (Behzadi & Arabkoohsar, 2020a). More than 84% of this energy is provided by fossil fuels leading to higher CO_2 concentrations in the atmosphere and global temperature increment (Zou et al., 2021). As a result, the need for BMS as a promising technique becomes necessary to address these challenges and makes a big step toward decarbonization (Iddianozie & Palmes, 2020). By definition, BMS is a sophisticated computer-based system providing a set of approaches to monitor and control the building's mechanical and electrical equipment. Examples of main operational subsystems monitored by the BMS are heating, ventilation, and air conditioning (HVAC) systems, energy storage units, lighting systems, power equipment, and fire systems (Salimi & Hammad, 2019). The most important features of BMS are increased energy efficiency, less environmental effects, lower energy costs, improved standards of building functioning, and efficient use of staff (see Fig. 5). Higher initial, operating, and maintenance costs and the need for an expert operator are the negative characteristics of a BMS (Dounis & Caraiscos, 2009).

A BMS is made up of four distinct components, which are as follows: a 3D office building model with a thermal cycle network consisting of all of the characteristics of the materials used in the building; a management system that satisfies the thermal comfort needs of consumers while also reducing energy consumption; and an energy simulation and comfort study. The ASHRAE Standard 55, widely acknowledged by laboratories in Europe and the United States, serves as the foundation for energy and comfort modeling simulations. Based on the simulation interface tool's recommended settings, the set zone loads per zone considers some criteria, including equipment load, infiltration rate, illumination density, the number of people, and ventilation per area/person, as shown in Fig. 6. Moreover, Fig. 6 demonstrates that occupancy, heating and cooling set points, lighting, and equipment are all included in the one-year schedule program.

With the development of technology, various BMS techniques have been accomplished to introduce innovative standards, designs, and web-based services to decrease energy costs, optimize energy use, and enhance the quality of living. Kaiwen et al. (2017) proposed an intelligent BMS model based on the PHP web server monitoring the comfort level and occupant behaviors working. According to their results, BMS played a critical role as a bridge between the user and smart grid, leading to 30% higher primary energy saving in a custom building. The performance of in-home BMS using a wireless sensor network (WSN) was assessed and compared against the optimization-based model by Erol-Kantarci and Mouftah (2011), concluding that WSN results in lower energy cost, peak load, and carbon emission. In a recent study, Chaouch et al. (2021) introduced a new smart BMS approach driven by fuzzy logic and machine-to-machine communication (see Fig. 6).

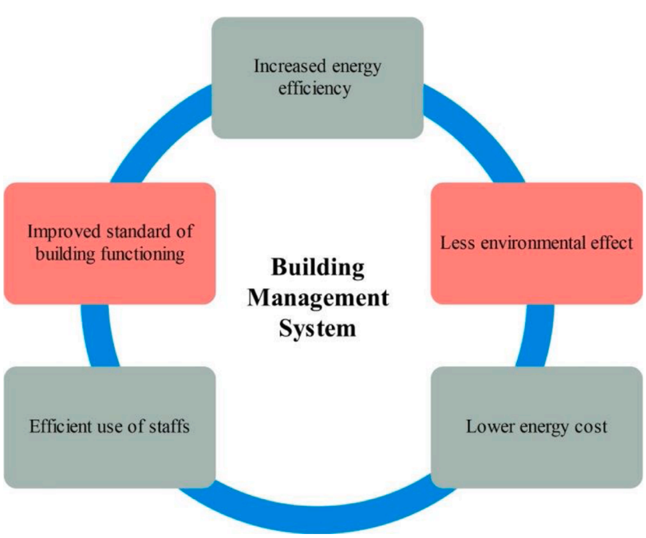

Fig. 5. The most significant features of BMS.

They revealed that the yearly energy consumption is decreased by about 16% without influencing the occupant's thermal comfort. Because keeping the occupant thermally comfortable is more complex in larger buildings, they recommend applying other artificial intelligence approaches to the smaller buildings. In this regard, a multi-model BMS supporting demand response and energy-efficient control simultaneously was proposed and validated by Griful et al. (2016). Tien et al. (2021) investigated a new vision-based BMS approach monitoring and controlling both the openable windows and HVAC system. They showed that a significantly lower heat loss and annual energy bill are attained because of their innovative BMS design. Lately, Salerno et al. (Salerno et al., 2021) presented an innovative, adaptable BMS for a house in Montreal, Canada, with no energy transfer from the nearby unit. Their results indicated that due to BMS and smart design integration, the levelized cost of heating and cooling is reduced by about 35% and 97%, respectively. Also, they showed that the energy consumption would decrease by more than 49%. They suggested that the feasibility study of the proposed smart system on a larger scale in the presence of district heating and cooling networks would be an interesting research topic for future extension of their work.

The possible mismatch between energy supply and demand and their intermittency is one of the most critical challenges of building energy systems (Behzadi & Arabkoohsar, 2020b). Hernandez et al. (Mariano--Hernández et al., 2021) showed that aside from generation, demand management, and control and communication, energy storage technology is the crucial component of smart houses controlled by BMS. In BMS, selecting the appropriate storage type is important to reduce energy consumption and improve the cost-effectiveness and utilization of renewable energy (if any). While thermal energy storage technologies are favorable to obtain lower energy costs, batteries are not economically suitable due to the high investment cost and payback period.

Various strategies, intelligent control techniques, and optimization approaches have been applied to energy storage technologies in BMS because they can reduce the energy cost while shaving the peak demand and improving the flexibility of time-of-use electricity prices. Sharifi and Maghouli (2019) implemented a novel scheduling method based on an evolutionary genetic algorithm approach to a smart BMS integrated with an energy storage device. They demonstrated that the energy bill is reduced by managing the storage unit, and the peak-to-average ratio is improved simultaneously. Luo et al. (2020) developed and validated a model-free self-control strategy for energy storage in building envelope for peak shifting and heat cost saving potential. Xu et al. (2012) studied the performance comparison of different energy storage technologies applying smart BMS. They showed that the existing uncertainties significantly influence determining the best integration and optimal operating conditions. In recent research, Aznavi et al. (2020) applied a new management strategy based on the energy price tag to smart energy storage units to neutralize the effect of unpredicted intermittency. It was concluded that the proposed framework keeps the system reliable and cost-effective due to lower energy bought from the network. In addition, they recommended that policymakers allocate more subsidies to the smart management of storage units to stimulate the building owners to adopt such systems. Yan et al. (2020) studied the feasibility of three management approaches applied to a novel energy storage system in a building. According to their results, 30% and 16% higher cooling and

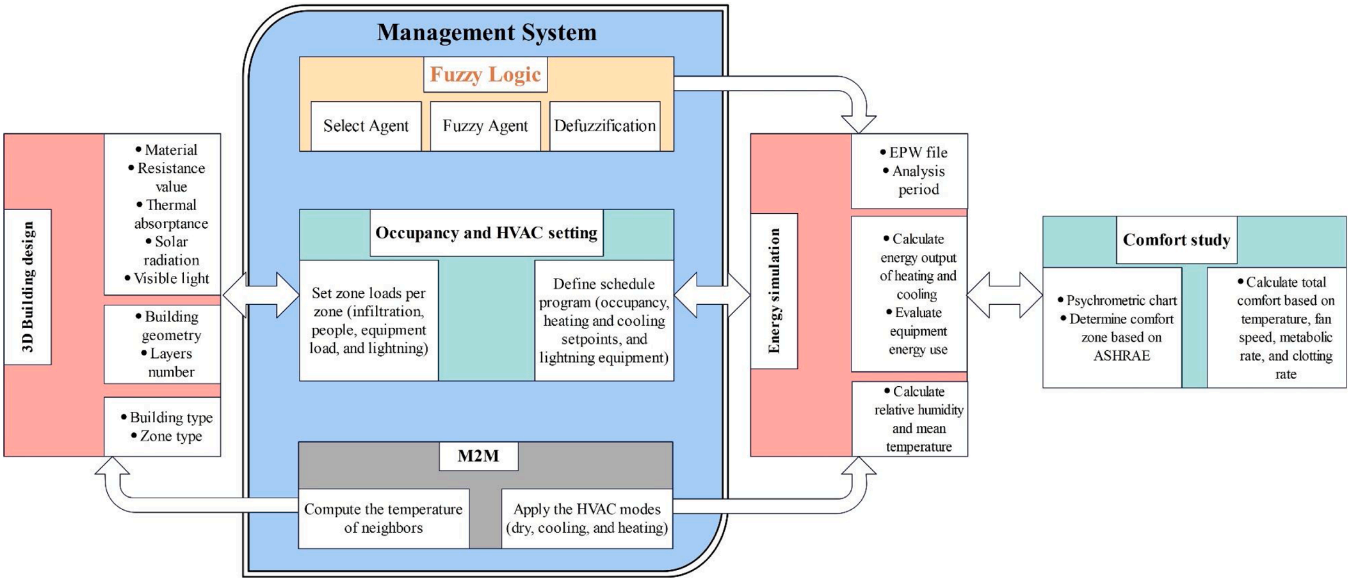

Fig. 6. Outline of BMS design (Chaouch et al., 2021).

power load factors were obtained, indicating long-term and short-term management effectiveness. They suggested that a comprehensive analysis of the system's cost-effectiveness and encouraging policies adopted by the government are required for future studies. A smart battery-photovoltaic system handled by an innovative novel optimum management strategy was proposed by Liu et al. (2020), revealing that 48.6% higher performance efficiency and 34.7% lower carbon dioxide emissions was attained compared to the same system without smart configuration. In another work, Ahmad and Khan (2020) introduced a new algorithm based on real-time joint optimization managing smart thermal and electrical energy storage units. They concluded that using the proposed intelligent algorithm leads to 16.37% lower operating costs while satisfying the comfort requirement.

The literature review on BMS applications in ESSs highlighted a number of advantages as well as challenges in applications of BMS in management of energy storage systems. A smart design of an energy storage system controlled by BMS could increase its reliability and stability and reduce the building energy consumption and greenhouse gas emission through smart scheduling of charging and discharging of energy storage systems. The main challenge of managing ESSs through BMS rests in the uncertainties arising from unpredicted occupants' behavior and unexpected changes in the environment (affecting both energy demand as well as supply from intermittent renewable sources) requiring sophisticated control mechanisms which could add considerably to capital and operational costs of building-integrated ESSs.

3.3. BIM and Smart Energy Storage

Due to the ever increasing energy demand and environmental contamination, the need for sustainable, energy-efficient, clean, and cost-effective buildings becomes more crystal clear than ever. The last but not least significant smart technology to overcome these challenges and moves toward the green transition is the BIM used by a growing number of architecture, engineers, and contractors (Singh & Sadhu, 2019). BIM is defined as a process equipped with several tools and technologies generating and managing smart data associated with physical and functional features of geometry, components, and materials (Jalaei & Jrade, 2015).

According to Fig. 7, BIM provides numerous benefits: greater cost predictability, improved efficiency and effectiveness, fewer errors, optimized design, and a better understanding of future operating and maintenance. Lately, Yang et al. (2021) studied the benefits,

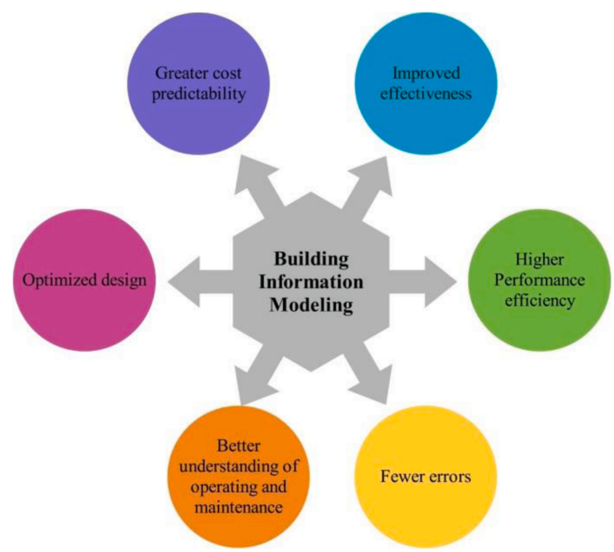

Fig. 7. The most significant advantages of BIM.

applications, and functions of BIM in smart buildings proposing a three-dimensional framework based on BIM and smart characteristics and project phases, as shown in Fig. 8.

In the literature, BIM has been extensively used to assess and improve the building's performance metrics from various aspects. Many researchers have applied BIM to a smart building for safety and equipment control analysis (Chen et al., 2020; Li et al., 2018; Riaz et al., 2014). Some scholars have studied the numerical and experimental evaluation of an intelligent green building using BIM to assess the environmental and sustainability indicators (Azhar et al., 2012; Llatas et al., 2020; Zhang et al., 2019). Some have investigated the cost and schedule estimation to enhance the project's economic benefits (Chen & Tang, 2019; Li et al., 2017; Marzouk & Hisham, 2014). Others have carried out the energy and exergy performance simulations and life cycle assessment through BIM to reduce the building energy consumption and improve the quality of energy conversion (Mellado & Lou, 2020; Rezaei et al., 2019; Wang et al., 2016b).

The depiction of energy storage size and material, the combination and visualization of energy-based information, the calculation of

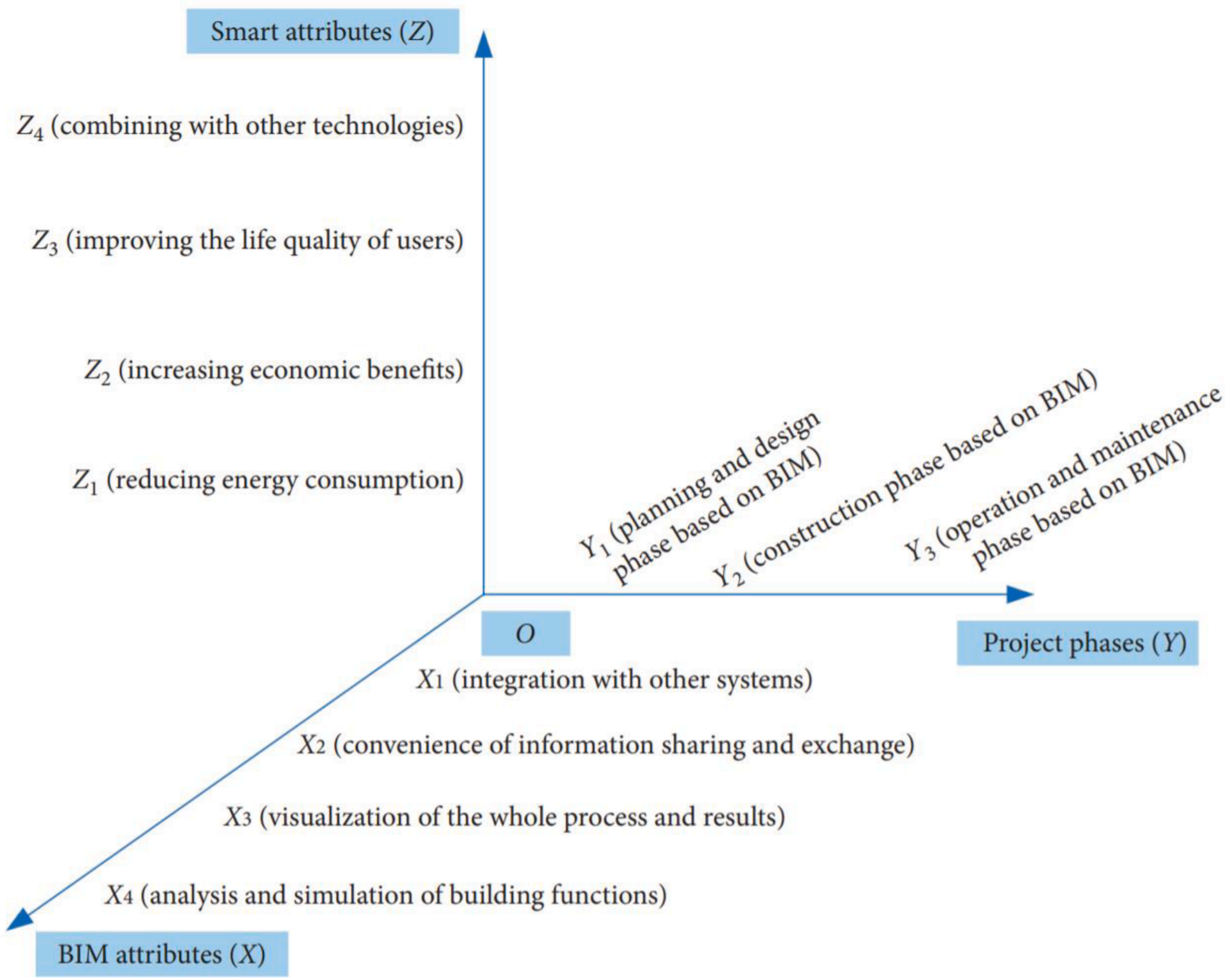

Fig. 8. A three-dimensional representational of BIM in smart buildings (Yang et al., 2021).

performance efficiency, and the optimization of energy usage are the key motivations for integrating BIM and energy storage design and analysis. In this regard, BIM can improve energy storage (operation and maintenance) by assisting building managers in scanning, analyzing, and processing data in a digital 3D environment and finding the best design parameters considering more than one objective at the same time. Such connection offers more efficient use of energy storage through a clever interaction between the supply and demand, increased cost-effectiveness, and environmental friendliness by monitoring the energy cost to establish efficient demand-side management. It also results in increased employee productivity, improved working conditions for tenants, and enhanced the level reliability of thermal comfort for users.

In a recent study, Zhuang et al. (2021) proposed a BIM framework for a school building equipped with a thermal energy storage unit optimizing energy and environmental metrics simultaneously. They demonstrated that BIM application results in a higher indoor environmental quality of 11.5% and a lower life cycle cost of 36.8%. The performance assessment and maintenance management of a real case study building located in Aveiro's University, Portugal, was studied by Matos et al. (2021) applying BIM. They concluded that the service life and operational interruptions of energy storage and HVAC technologies are improved significantly due to BIM use. Duarte et al. (2021) applied BIM software to optimize the performance efficiency of an educational building heating and cooling system in Brazil. According to their results, modeling the building information leads to 12% higher primary energy saving and 9% lower components' energy loss in addition to indoor environmental quality improvement. In another study, Wu et al. (2015) introduced an innovative BIM framework integrated with a wireless sensor network to reduce the operating cost while improving the energy efficiency of a data power center driven by electrical storage units. Schlueter and Thesseling (2009) added an advanced tool to BIM software assessing energy and exergy calculations simultaneously. They obtained that BIM not only reduces the system's payback period but also enhances the quality and reliability of thermal and electrical storage units' controls. Pishdad-Bozorgi et al. (2018) investigated the use of BIM for developing facilities management of a real project and concluded that the energy storage unit is a vital component that must be tracked in the development and planning operations phases. The combination of BIM and life cycle assessment to mitigate the greenhouse gas emission for a residential building located in China was investigated by Yang et al. (2018), showing that the physical appearance of components, including energy storage units, has a considerable contribution to reduce the carbon emission footprint.

The literature review on BIM applications in ESSs highlighted a number of benefits and challenges in applications of BIM in management of energy storage systems. Managing and modeling energy storage technology's physical and operational characteristics through BIM can create more reliability and flexibility and improves cost and energy efficiencies. The main challenge is that the digitalization of energy storage systems is data-intensive and requires advanced skills both in energy management and BIM platforms (Yang et al., 2021).

4. Conclusions

This article provided several categorizations and detailed review of the applications of smart tools (with an emphasis on data analytics) and smart technologies (focusing on BMS and BIM) in design, operation, and control of smart ESS. As energy storage systems are complex with several variables subject to a great extent of variation and uncertainty, the literature pointed to the importance of accurate estimation of their state and the trends in their input (supply side) and output (demand side) variables, and its necessity to support effective operation and control of ESS. The state of charge, i.e. the ratio of the releasable capacity of an ESS over its nominal capacity, was shown as a key estimation linking the supply and demand side variables affecting the operation of an energy storage system. In addition, forecasting the condition and SOH of ESS has emerged as a means of improving their useful lifetime through systematic detection of defects, as well as the detection of abnormal behaviours as signs of failure and availability issues.

IoT technologies were identified as the main emerging driver for integration of DES systems. In particular, the use of IoT technologies has created the capability of bringing the renewable energy suppliers and utilities to a balancing equilibrium maintained through effective design and operation of storage systems. The main advantage reported in the literature was to tackle the intermittency of renewable resources, and thus, promoting the sustainability and stability of power grid and energy security. Relying on the IoT has provided access to large amount of operational data and demand-side information that can serve as a basis for optimization of the operation of energy storage systems using data-driven training of intelligent control algorithms. However, there are still several challenges with respect to applications of IoT applications in management of ESS including their energy intensity as well as issues with respect to privacy and accessibility of information.

Integration of BMS and BIM have also been reported in the literature as means of incorporating smart design and control features for energy storage systems. An ESS controlled by BMS contributes to increasing reliability and stability while reducing building energy consumption and greenhouse gas emissions. Various strategies, intelligent control techniques, and optimization approaches have been also applied to energy storage technologies resulted in shaving the peak demand and improving the flexibility of time-of-use electricity prices. In this regard, the recent surge in applications of building information modeling in facilities management has emerged with widespread benefits; greater cost predictability, improved efficiency and effectiveness, fewer errors, optimized design, and a better understanding of future operating and maintenance conditions of buildings, occupants, and the impact on operation of ESS.

This state-of-the-art review could highlight a number of challenges pointing to avenues for future research. In smart tools category, the main challenge rests is the incorporation of uncertainties resulting from intermittent nature of renewable energies as well as varied design and operational characteristics of energy storage technologies. In this sense, a potential avenue of research would be in applications of predictive data analytics that can facilitate adapting the operation of ESSs by learning to characterize the response of ESSs to a variety of energy supply and demand profiles. In smart technologies category, incorporation of ESSs on a component-by-component basis (not as a black box system) into BMS and mapping them into BIM to establish digital twins of ESSs (to facilitate, monitor and track ESSs operation and control) remains as a major challenge due to high degrees of variations in type and scale of ESSs with indefinite choices in their design and operational characteristics. As such, establishing design and operation benchmarks and standardization for digitalization of ESSs presents itself as another main avenue for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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