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A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis

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ABSTRACT

Building energy use is expected to grow by more than 40% in the next 20 years. Electricity remains the largest energy source consumed by buildings, and that demand is growing. To mitigate the impact of the growing demand, strategies are needed to improve buildings' energy efficiency. In residential buildings home appliances, water, and space heating are answerable for the increase of energy use, while space heating and other miscellaneous equipment are behind the increase of energy utilization in non-residential buildings. Building energy management systems support building managers and proprietors to increase energy efficiency in modern and existing buildings, non-residential and residential buildings can benefit from building energy management system to decrease energy use. Base on the type of building, different management strategies can be used to achieve energy savings. This paper presents a review of management strategies for building energy management systems for improving energy efficiency. Different management strategies are investigated in non-residential and residential buildings. Following this, the reviewed researches are discussed in terms of the type of buildings, building systems, and management strategies. Lastly, the paper discusses future challenges for the increase of energy efficiency in building energy management system.

1. Introduction

Buildings such as residential, education, office, healthcare, and industrial are emerging as critical consumers in energy consumption. Energy consumption for buildings represents 30–45% of global energy use [1–3], with a larger part of the energy used by the building subsystems, which consist of cooling and heating systems; safety, water, lighting, and similarly combined subsystems. In this context, efforts at this time are focused on the fulfillment of the requirements for energy-efficient in buildings, by guaranteeing the operative needs with the base conceivable energy cost and environmentally friendly [4]. In many developing and developed countries, energy efficiency is viewed as the best mechanism to address and defeat ever-rising energy needs [5]. In any case, advancing the energy efficiency of these subsystems is very testing since they typically have to comply with complex working requirements, dynamic energy necessity, and comfort needs [6].

Considering the use of the building, the idea of Building Energy Management Systems (BEMS) is now being used. BEMS can be described as a combination of strategies and methods needed to improve its performance, efficiency, and energy utilization [7]. This technology permits the implementation of key energy management tasks such as automating demand response approaches, overseeing energy costs, detecting energy use anomalies, and arranging energy use information [8]. There are numerous studies and research work that are describing advanced use of BEMS either for subsystems such as, cooling and heating systems [9,10] or the whole building [11,12]. Comfort and energy management in buildings have gotten noteworthy research enthusiasm throughout the most recent decade. Commercial systems will, in general, depend on specified working timetables, depend on the occupation

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Abbreviation and nomenclature

AHU	Air Handling Unit
BEMS	Building Energy Management System
BES	Battery Energy System
CO_2	Carbon Dioxide,
DR	Demand Response
DSM	Demand Side Management
EE	Energy Efficiency
EMS	Energy Management System
ESS	Energy Storage System
FDD	Fault Detection and Diagnosis
HVAC	Heating Ventilation Air-Conditioning
IoT	Internet of Things
MPC	Model Predictive Control
PV	Photovoltaic
RO	Robust Optimization
SO	Stochastic Optimization
TES	Thermal Energy System
WSN	Wireless Sensor Network

expected at the building layout phase. It has been discovered that such timetables can vary significantly from real occupancy behavior, causing energy to squander [13].

The objective of this paper is to provide a review of energy management strategies for non-residential and residential buildings to know what are the gaps in terms of strategies and techniques used for types of buildings and the future lines to follow. The paper reviews existing studies' respect for building types, building subsystems, and used techniques. We identify the current state and future challenges in BEMS research. The structure of this paper is: Section 2 presents the methodology used in this review, Section 3 offers background information of buildings and subsystems inside a smart building, Section 4 gives a summary of existing studies on management strategies for BEMS, Section 5 discusses the previous studies, Section 6 presents future challenges in the topics of management strategies for BEMS, and Section 7 concludes this paper.

2. Methodology

The methodology for the realization of this review consisted of the following steps:

- Articles search procedure: A keyword-based search was made using Science Direct and IEEE Xplore databases. Keywords such as building energy management systems, building management systems, and building management methods were used. Furthermore, the papers were chosen by types of article, selecting research articles, and review articles. Science Direct and IEEE Xplore were selected, because both databases have a large number of high quality and innovative articles, and the search engines have multiple advanced search options that allow a more precise search.
- Articles filtering: The outcomes of the articles search procedure from both databases were imported into a reference manager to be filtered based on the title, keywords, and abstract, so articles that were not related to the topic were eliminated.
- Sub-topics selection: After having reviewed the remaining articles, a critical analysis was made based on the topics of focus, selecting which would be the sub-topics to develop and which would be to introduce, and allowing to organize in the reference manager the articles in different sub-topics.
- New articles search: Once the sub-topics were defined, new searches were made in the aforementioned databases, combining the sub-topics with the main topic using logical operators. Then again an article filtering was done, eliminating duplicate articles and articles not related to the topic.
- Analyzing the outcomes: The survey results were examined to distinguish research breaches in the field of building energy management systems and to highlight the future directions of research.

3. Smart buildings

Buildings can go about as intelligent systems that encourage the move towards an increasingly feasible energy use perspective. They can promote the quickened take-up of sustainable technologies and the decrease of carbon emissions, operational costs, productivity, wellbeing, energy consumption, and comfort [14]. Presently, there are several kinds of building depending on the design goals. For instance, there are green buildings, net-zero energy buildings, and smart buildings (**se**e Fig. 1).

Green buildings are commonly intended to be eco-friendly for the entire building cycle from plan, development, running, and activity, and upkeep to a building remodel and destruction. For net-zero energy buildings, the objective is to make the building supply its energy by protection and sustainable power source generators in the structure and accomplish net-zero energy use and consequently carbon emission on a yearly premise [15]. The concept of smart buildings includes the incorporation of technology and energy systems within buildings. This focuses on automation, resource management, occupants' comfort, and energy conservation [16]. Balancing energy use requirements and occupant comfort is the biggest issue in smart buildings. Three key considerations which determine the occupants' comfort inside a building are air quality, visual and thermal comfort [17]. In this paper, we focus attention on smart buildings that have their highest energy consumption in the operation stage of the lifecycle of a building.

The next generation of smart buildings must not only contemplate features such as weather conditions and predicted occupancy, but it should also be sufficiently adaptable to maximize the use of schedule consumption around low energy price periods, local renewable resources and energy storage [18]. The structure of a smart building includes generation, energy storage, demand management, and control and communication, all of which are controlled by BEMS (see Fig. 2). The different components of smart buildings are described in the following sections.

3.1. Generation

These days, traditional generation systems are being rebuilt and transformed into intelligent grids to increase the dependability and effectiveness of the generation systems that bring about collective, financial, and environmental advantages. An intelligent grid is an electrical energy network that utilizes innovative knowledge to

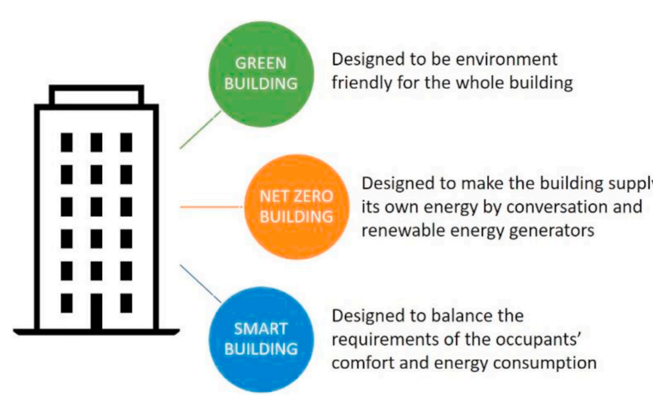

Fig. 1. Types of buildings concepts based on design goals.

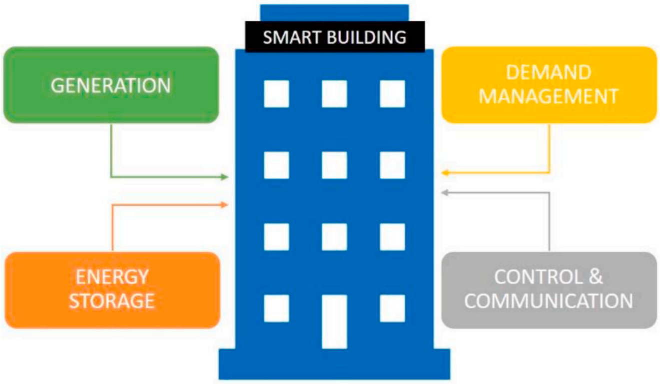

Fig. 2. General description of related systems inside Smart Buildings.

supervise and control the energy production from all sources to fulfill the fluctuating energy needs of end-clients [19]. A microgrid is a small section of the intelligent grid. A microgrid can be controlled as a separate generation system for small-scale areas as well as a dispatchable load of the typical generation system. The basic idea of a small-sized microgrid has been utilized in industrial plants, commercial buildings, and homes [20]. Photovoltaic (PV) based microgrids are progressively turning into a key energy source, particularly among residential energy consumers. In recent years, huge development on the incorporation of PV systems to the utility grid has been made [21].

An intelligent building can be view as an energy-efficient structure that can be additionally seen as a building with an integrated microgrid. It can assume a key part in the renovation of electrical energy grids and fill in as an important component in guaranteeing grid trustworthiness. This can be accomplished by changing the conduct of the building from an unresponsive to a dynamic provider [22]. For this reason, smart buildings and smart homes have an important function, because they are the final point in the distribution network [23].

3.2. Energy storage

Providing a storage capacity to assist the changing nature of wind and solar resources is one clear solution [24]. Storage gadgets, for example, water tanks, heat/ice storage units, and batteries perform a crucial task in lowering energy costs in building energy systems since they can assist to use time-of-use electricity prices and renewable energy resources [25]. End-users with dispatchable energy generators and storage gadgets provide an exceptional opportunity to raise the percentage of controllable loads [26]. For encouraging the progression of numerous types of resources in the building, two distinctive types of storages are used: Battery Energy Storage (BES) and Thermal Energy Storage (TES). BES is a high energy storage gadget that goes about as a cushion to store additional energy and help system operation when needed. TES depends on the common rule of ESS and is controlled by the movement of thermal power constrained by the restrictions of energy storage [27]. Electrical or Thermal storage is much of the time employed as regulators of demand during the day or energy buffers [28].

TES is seen as an answer for the issues of peak load shaving and power fluctuation in thermal loads, such as air conditioner or water heater which contributes to a significant part of the total energy consumption in buildings [29]. BES is the most popular hybrid energy source in buildings. Through appropriate charging and discharging timetable, the storage ability of BES components is used for peak demand shaving, frequency regulation, and load balancing [30].

3.3. Demand management

Demand Management has been characterized to be a lot of the wide scope of arranging, execution, and supervising of utility activities to impact users' behavior to create wanted changes in utility's load shape [31]. It is essential for demand to be increasingly adaptable and to urge the user to take an interest effectively in the energy market [32]. Leaders from numerous nations have begun to concentrate on policies connected with improving the quota of renewable energy sources and encouraging the application of demand management methods [33]. Demand management strategies impact the conduct of consumers for energy use. Truth be told, it depends on coordinating present age values with demand by regulating the energy use of electrical devices and enhancing their function at the user side [34].

Consumption planning is one of the significant basic ways to deal with demand management. It is accomplished by modifying the typical energy use behavior of end consumers after some time [35]. In buildings, a significant part is played by consumers because the diminution of energy use can be gotten by just giving the utilization profile of electrical devices to the users and as needs be assisting them to alter their conduct. To propel consumers to efficiently utilize energy, monetary incentives are offered to the consumers with the goal that they intentionally use energy optimally and avoid energy waste. This approach gives harmony between supply and demand [36].

3.4. Control & communication

Building automation is worried about communication and control networks in buildings; the systems consist of processing units, actuators, sensors, and communication [37]. The field of building automatic technology is not new; be that as it may, as detecting, processing, and activating technologies have built up the extent of control has extended. The utilization of progressively broad sensor/actuator systems has made it more viable for automatic technology to take control instead of tenant, considering agreeable conditions to be kept up without inefficient practices from tenants [38]. A cozy environment with high energy efficiency is the essential target of building management [39]. Sensors were utilized for the adjustment of the temperature. To prevent recurrent adjustments among the two conditions of a sensor, sensors with a Deadband were established and utilized. In any case, overshoots in the regulated temperature were not prevented, which enhanced energy use. To tackle the issue, Proportional-Integrate-Derivative controllers were used. Although these controllers improved energy use, an incorrect configuration in the controller could make the entire system unbalanced [40].

The expression of a world in which objects, and not only individuals, will always be associated and ready to collaborate through the Internet is known as the Internet of Things (IoT) [41]. IoT defines the capacity to associate and control gadgets through the system in intelligent buildings [42]. Numerous conceivable sensor networks speak to various applications and typically include hybrid devices, these devices can have wired or remote access. They can be working to supervise and control [43]. To avoid the difficulties involved in connecting devices through wired routes in large scale networks, wireless communications are the most utilized in present-day [44]. Novel technologies such a Wireless Sensor Network (WSN) were evolved consequently to IoT advancements [45]. With the advance of WSN technology, it is presently simpler than at any other time to supervise and control industrial buildings, offices, and houses. WSN is the foundation of a huge assortment of building applications in healthcare, environmental monitoring, industrial, and security areas, among others, because of the adaptable dispersion of WSN gadgets [46].

4. Energy management strategies for BEMS

The essential idea of energy management is the consistent, methodical, and efficient review of energy use, focusing on energy cost optimization concerning user characteristics, financing ability, energy demands, funding opportunities, and emission reductions accomplished

[47]. Energy Management Systems (EMS) allow clients to achieve objectives and those of utility suppliers, based on renewable generation predictions and load demand patterns [48]. These systems could monitor and control the use of energy in industry, equipment, and building according to different developed functions or control logics [49]. In this paper, the term management strategy refers to a set of techniques used in BEMS that interact dynamically with the building to obtain results that, in this case, would be to improve energy efficiency. Also, the term BEMS is used for both non-residential buildings and residential.

BEMS is a term employed to typify various systems utilized to increase the energy efficiency of operational buildings [50] and ensure indoor comfort for building occupants [51]. BEMS are an essential piece of an intelligent grid, enables building administrators to supervise and manage the energy used in their buildings, thus cutting the demand and energy use [52]. The usage of BEMS is highly flexible in both residential buildings and non-residential.

There are two kinds of BEMS methods: active and passive. Passive methods are based on providing future strategies and improving the user's energy awareness to influence and decrease the utilization of energy in buildings indirectly. Active methods are based on the mix of the actuators and sensors' infrastructure in the building. They depend on reducing energy wastes contexts through the control of smart building actuators and gadgets [53]. Based on active approaches, we classified BEMS into four management strategies: model predictive control, demand-side management, optimization and fault detection, and diagnosis (see Fig. 3).

4.1. Model predictive control

Model Predictive Control (MPC) can foresee building response to control requests, and realizing the way to tail it can act sufficiently to accomplish the necessary operation. Forecast of building energy utilization is important for better judgment towards decreasing CO_2 emissions and energy utilization since it can help with assessing various building layout options and building operation approaches and improving requirement and supply administration [54].

Three methods have been taken for building energy use forecasts (see Fig. 4). Physics-based methods are frequently mentioned as white-box. They utilize a straightforward procedure dependent on physics calculations to explain the energy performance of buildings. Data-driven methods, regularly referred to as black-box methods, principally depend on statistical evaluations and artificial intelligence to evaluate and estimate the building energy utilization. Hybrid methods, often named grey-box methods, refer to the merge of white-box and black-box approaches [55].

There have been studies on BEMS associated with the white-box model that focused on temperature control [56], forecast energy consumption [57], predictive whole building heat and moisture [58], optimally control of cooling and heating activities [59], group of building connected to heat pumps [60], optimal Heating Ventilation Air-Conditioning (HVAC) and energy operation [61], energy flexibility

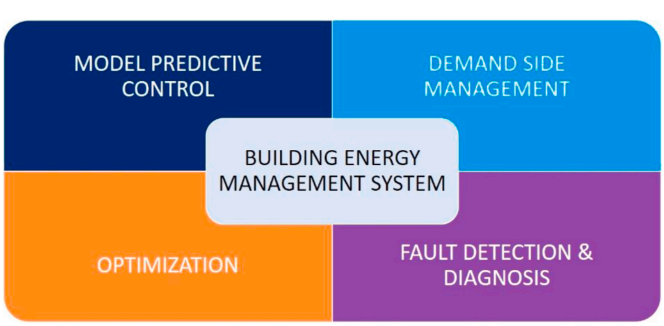

Fig. 3. BEMS management strategies.

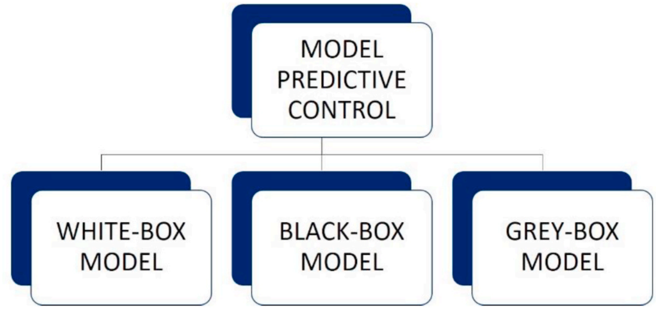

Fig. 4. MPC approaches based on building energy consumption prediction.

[62], and minimize energy consumption and the energy cost of building HVAC system with incorporated concentrated solar power system [63]. Black-box models studies have focused on predictive control for boilers [64], predictive control for HVAC system [65], peak load, thermal comfort, energy storage, and renewables [66], building energy performance models [67], and model for sustainable power source [68]. For grey-box models, studies have focused on optimizing the airflow volume and the air supply temperature setpoints [69], instant balance point temperature [70], estimate the ventilation air change rate [71], and thermal building modeling [72,73].

Based on the aforementioned studies in MPC, a summary of their contributions and limitations is present in Table 1. It is also worth noting that all models are mainly used in non-residential buildings such as offices and universities. The most researched subsystem in all models has been the HVAC system. Regarding the techniques used, a great variety of techniques are presented, but no specific technique stands out. For white-box and grey-box models, the simulation software that stands out is MATLAB, TRNSYS, and EnergyPlus. And the most used programming languages for the black-box model are Python and R.

4.2. Demand Side Management

Demand Side Management (DSM) is an arrangement of actions to enhance the energy system on the user side. It goes from enhancing energy efficiency by utilizing improved resources, over intelligent energy rates with motivators for certain utilization arrangements, up to modern continuous management of allocated energy resources [74]. DSM is often understood to have two approaches (see Fig. 5): demand response (DR) and energy efficiency (EE) [75,76].

By integrating technologies such as the generation of renewable resources, energy storage systems, smart devices, and smart meters, energy-efficient buildings are possible. Additionally, it establishes distributed generation, DSM, and distributed storage provisions of upcoming intelligent grids. There have been studies on BEMS associated with the energy efficiency approach that have focused on a smart meter for smart houses [77], assessment of the electrical energy behavior [78], oversee building electrical device utilization [79], load estimating of thermal demand in smart buildings [80], utilize the thermal mass in building [81], and various users with a common distribution system [82].

Performing Demand Response in non-residential buildings can assume a significant job in decreasing the peak load in the building. This increases the efficiency of power grids and mitigates costly energy and peak demand charges. There have been studies on BEMS associated with the demand response approach that have focused on decreasing the peak demand in building through end-use load control [83], decreasing costs for home energy management [84], smart home EMS for prosumers of residential buildings [85], cooling and heating systems in homerooms [86], real-time thermal EMS for intelligent homes [87], peak load diminution in a smart building [88].

Based on the aforementioned studies in DSM, a summary of their contributions and limitations is presented in Table 2. It is also worth

Table 1
Summary of previous research papers, their contributions, and limitations.

Approach	Reference	Contributions	Limitations
White-Box Model	[57]	A cost function for MPC which guarantees thermal comfort with minimal energy utilization and a linearization technique for the hydronic heating system model.	Thermal control is based on a mono-zone building model, it was viewed that climate, and inward loads forecasts were 100% solid.
	[58]	Model to foresee and evaluate energy utilization in non-residential buildings in the beginning phases.	Only one specific climate region was considered for building design parameters and shapes.
	[59]	Building a hygrothermal model dependent on a physical approach to perform optimal control.	Performance relies on upon the circumstance of a specific building system.
	[60]	Model predictive controller scheme for the cooling and heating system using prediction data for climate and inner gains.	The simulation studies did not contemplate using ventilation coils in the rooms.
	[61]	Economic MPC technique to minimize the total cost of operating the heating system for a cluster of buildings.	Do not incorporate electricity prices and climate forecasts to look at the effect of vulnerability.
	[62]	Specialized MPC technique to ideally control the HVAC system and the storage gadgets under thermal comfort and technological constraints.	No consideration was given to the active/reactive power flow in this case to guarantee the fulfillment of electrical limitations.
	[63]	Productive enhancement based MPC energy management system that is appropriate for nonlinear energy systems.	Involve non-convex constraints, making the solution optimal only locally.
	[64]	Real-time MPC framework to minimize the energy utilization and operational cost of the HVAC system with integrated micro-scale concentrated solar power.	An economical assessment and an exergy analysis of the system was not performed.
Black-Box Model	[65]	A procedure of implementing a predictive control technique based on neural network in a commercial BEMS for boilers.	Only based on the heating system temperature, internal temperature, and external temperature.
	[66]	An optimization framework for proficiently controlling HVAC systems in buildings.	Only was evaluated on one specific type of non-residential building.
	[67]	An optimal control system to synchronize HVAC, battery energy storage, and renewable generation.	Moistness and useable temperature based thermal comfort models were excluded from the control system.
	[68]	A methodology to describe and assesses building energy performance models.	The methodology was only evaluated on the HVAC system coefficient of performance.
	[69]	Neural network predictive control technique for energy management in the zero-energy building.	Only was evaluated on a residential building.
Grey-Box Model	[70]	MPC-based control framework planned for decreasing energy utilization in non-residential buildings while ensuring occupants' comfort.	The design depends on a variety of heuristic search, which can be difficult to scale up if a few factors are to be streamlined simultaneously.
	[71]	A methodology for deciding the instantaneous balance point temperature of a building.	Need to be approved on real monitored information.
	[72]	Use of a grey-box modeling approach to evaluate the ventilation air change rate.	Need further exploration in more prominent heights. Only was evaluated for rooms up to 3 m.
	[73]	A hybrid building modeling technique for the HVAC system with reduced modeling and calibration effort.	The utilization of two distinctive modeling methods requiring a different set of skills from the modeler might be an obstacle for its usage.
	[74]	A dynamic technique based on Bayesian statistics to evaluate the thermophysical properties of the building.	Estimation not considered the utilization of in-situ measurements outside the winter time frame.

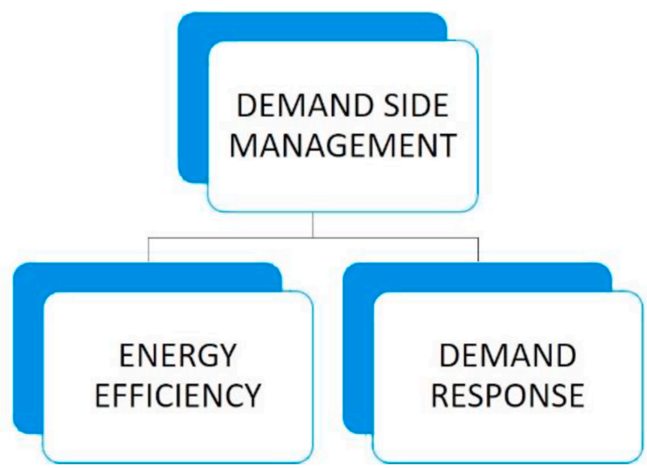

Fig. 5. DSM approaches based on utility end-user.

noting that the energy efficiency approach is mainly used in residential and non-residential buildings, while the demand response approach is used in non-residential buildings. The most researched subsystem in demand response has been the HVAC system, while the energy efficiency approach in appliance consumption and HVAC system. Regarding the techniques used, a great variety of techniques are presented, but no specific technique stands out. For both approaches, the simulation software that stands out is MATLAB.

4.3. Optimization

There are a few ways to deal with the optimization in EMS and their related issues. EMS and their elements might be enhanced as for profoundly various goals and on distinct concept levels [89]. Based on data uncertainty problems, optimization has two approaches, namely robust and stochastic optimization (see Fig. 6).

Stochastic Optimization (SO) expects that the genuine prospect dissemination of dubious information must be known or assessed. On the off chance that this condition is met and the reformulation of the unsure optimization issue is computationally tractable, at that point SO is the method to take care of the questionable optimization issue within reach [90]. There have been studies on BEMS associated with a

Table 2
Summary of previous research papers, their contributions, and limitations.

Approach	Reference	Contributions	Limitations
Energy Efficiency	[78]	Power management system idea dependent on residential DC distribution with smart plugs for smart homes.	The implementation of this idea requires an initial investment to modify the distribution network of the home.
	[79]	A method for the examination of electricity conduct of buildings, utilizing clustering techniques.	The method requires an immense measure of crude information to acquire in-depth helpful data of the electricity conduct.
	[80]	A control model to manage main electric appliances in residential buildings.	The control was applied to a home with 12 different loads. The optimal setpoint for each load was not investigated.
	[81]	A short-term activity-aware thermal energy demand forecasting method.	The method did not implement production management strategies that optimize the operation of the equipment.
	[82]	An algorithm to utilize building thermal inertia to spare energy and encourage coordinated effort inside building clusters.	Activity joint effort of buildings and other factors, for example, electric vehicles and shared resources were not assessed.
	[83]	Assessment of the impact of the incorporation in a local grid of commercial clients, as apartment buildings and districts.	The assessment was validated with a building that was not fully operational.
Demand Response	[84]	An approach to get proposed reduction values for home energy management.	The usage of the approach is commonly unmistakable and issue coordinated.
	[85]	Method to decrease the building's peak electrical demand through end-use load control.	Excludes the joining of renewable generation and storage at the client-side with demand-responsive buildings.
	[86]	Algorithm for schedulable loads and battery units for prosumers of a smart home.	The algorithm is evaluated in a scenario where the cost of energy varies depending on the schedule
	[87]	An energy management scheme to decrease the overall energy utilization of HVAC units.	The scheme was developed for a decentralized HVAC system.
	[88]	A thermal energy management system in smart buildings for peak-load shifting.	The management system and simulation results were confirmed by trial tests.
	[89]	An energy management system to diminish peak load as observed by the electricity grid in a smart building.	Do not consider local appliances and HVAC system, but only electric vehicles.

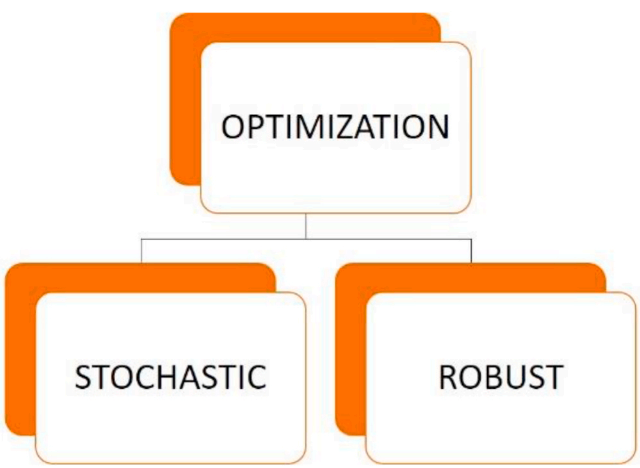

Fig. 6. Optimization approaches to deal with information ambiguity.

stochastic approach that have focused on maximizing the comfort index utilizing minimum power consumption [91], effective policy measures [92], identifying energy consumptions patterns [93], maximizing the general energy efficiency performance [94], load demand prediction of PV integrated intelligent buildings [95], and energy savings through analytics of actuators and information sources [96].

Robust Optimization (RO), does not presume that prospect disseminations are known, yet rather, it expects that the unpredictability information resides in the so-called unpredictability set. Moreover, fundamental adaptations of RO presume hard restrictions, i.e., restriction breach cannot be permitted for any understanding of the information in the unpredictability set [90]. There have been studies on BEMS associated with a robust approach that focused on optimal planning of the components of the local energy system [97], supervising multi-HVAC system [98], managing occupants' comfort and energy utilization [99], coordination of cooling system and individual fan [100], and energy use with prediction error [101,102].

Based on the aforementioned studies in optimization, a summary of their contributions and limitations is present in Table 3. It is also worth noting that the stochastic approach is mainly used in residential and non-residential buildings, while a robust approach in non-residential buildings. The most researched subsystem in a robust approach has been the HVAC system, while the stochastic approach in all building systems. Regarding the techniques used in the stochastic approach, particle swarm optimization and neural network are the most used, while in the robust approach no specific technique stands out. For both approaches, the simulation software that stands out is MATLAB.

4.3.1. *Fault detection & diagnosis*

A building could be planned and developed in an energy-efficient and green manner, a substantial fraction of energy could be lost if the EMS is not appropriately executed [103], causing an increase in the building operation costs [104]. Fault detection and diagnosis (FDD) is a programmed procedure of detecting and separating flaws in BEMS for the defense of a system from further harm. Some FDD uses in BEMS were created and studied dependent on the connections between thermodynamics, pressure, and temperature for the recognition and analysis of flaws [105]. Regarding the field of BEMS, the FDD strategy can be grouped into two techniques: knowledge driven-based and data driven-based (see Fig. 7).

Data driven-based approaches resolve FDD challenges utilizing artificial intelligence. With adequate training information, the assignment of fault detection is to decide whether the examples of supervising information are like those of the typical training information [106]. There have been studies on BEMS associated with a driven-based approach that focused on the cause of faults in the heating system [107] and recognizing irregular operation patterns [108,109]. Knowledge driven-based approaches depend on specialists to recognize and detect faults more viably and dependably than the vast majority of the current FDD approaches, particularly in the cases that analytic data is deficient and unsure. There have been studies on BEMS associated with knowledge driven-based approach that focused on analytic analysis for an air handling unit (AHU) [110], recognizing potential reasons for inconsistencies for an AHU [111], distinguishing and assess chosen faults in a cooling system [112], and distinguishing undetected flaws [113].

Based on the aforementioned studies in fault detection and diagnosis, a summary of their contributions and limitations is presented in Table 4. It is also worth noting that both approaches are mainly used in non-residential buildings. The most researched subsystem in knowledge driven-based approach has been the HVAC system, while data driven-

Table 3
Summary of previous research papers, their contributions, and limitations.

Approach	Reference	Contributions	Limitations
Stochastic	[92]	A building indoor energy and comfort management model dependent on data combination.	Did not incorporate electric vehicles into the smart building system.
	[93]	A model that combines energy-balance requirements with detailed modeling of regular HVAC systems.	The application of the model was in a single zone rather than in multiple zones.
	[94]	An optimization methodology for foreseeing real-time building energy utilization.	Did not considere optimize energy utilization based on usage patterns.
	[95]	A choice help strategy that distinguishes an ideal arrangement of retrofit intercessions in building stock.	The technique requires the meaning of criteria weights, which implies the user has to be able to give his global cardinal scale of values.
	[96]	An ensemble forecasting system for PV coordinated bioclimatic buildings.	The system was applied only in the load demand forecast.
	[97]	A cloud-based BEMS that integrates an enhanced sensor network with advanced analytics.	Need to show the arrangement's replicability across different buildings.
Robust	[98]	A method which decides the ideal scheduling of the components of the local energy system.	The method was tested on an emulated medium-size hotel.
	[99]	An architecture to oversee multi-HVAC systems in buildings.	The architecture excludes indoor humidity and indoor air quality index.
	[100]	A method for a smart building to manage energy utilization and the overall comfort value.	No proper function indicating the human activities was incorporated into the energy utilization calculations.
	[101]	An algorithm for the coordination between air conditioning, mechanical ventilation, and personal fan.	The models of room energy dynamics were obtained dependent on a simplified model with the measured information.
	[102]	An approach based on the probabilistic data of subintervals of the outside temperature to plan the energy utilization of HVAC.	The energy utilization model can be applied to the HVAC system with just on-off control activity.
	[103]	An algorithm, which can be performed by the consumers to look for the ideal working state, energy supply, and cost.	Consider a system consisting of an energy provider and consumers who have independent HVAC systems.

based approach in all building systems. Regarding the techniques used in both approaches, no specific technique stands out. For data driven-based approach, the simulation software that stands out is MATLAB, while in knowledge driven-based, no specific software stands out.

5. Discussion

Based on the review of previous research work, a categorization based on building energy management strategies is present in Table 5. About 71,74% of the reviewed research efforts concentrated on developing building energy management strategies for non-residential, 21,74% focused on residential buildings, and only 6,52% on non-residential/residential buildings (see Fig. 8).

About 56,52% of the reviewed studies in non-residential focused on an HVAC system, could be because the comfort inside a building depends normally on three components: air-quality comfort, thermal comfort, and visual comfort. Since two of the three factors depend on the HVAC system and the most significant building energy use occurs from cooling and heating systems, it is important to improve the utilization [114]. On the other hand, for residential buildings, only 4,35% focused on the HVAC system. Instead, the studies focused on the entire building or electrical device use (see Fig. 9), this could be due to electrical device

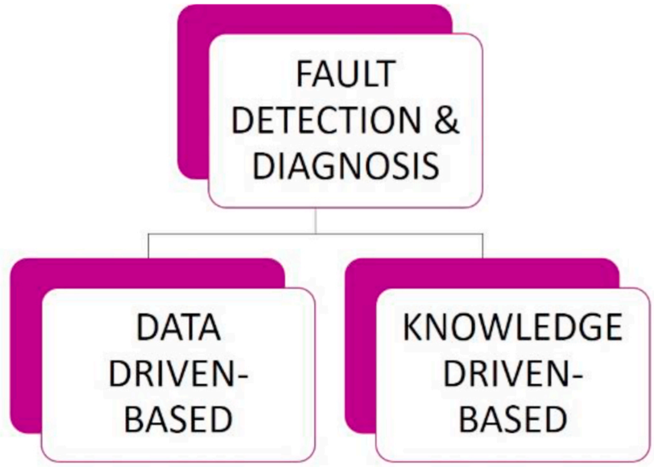

Fig. 7. Fault detection techniques in the field of BEMS.

Table 4
Summary of previous research papers, their contributions, and limitations.

Approach	Reference	Contributions	Limitations
Data driven-based	[108]	A methodology to detect functional sensor shortcomings in the hydronic heating system.	Exclude the water pressure, balance model.
	[109]	A methodology for the characterization of energy time-series in buildings and the distinguishing proof of rare and unforeseen energy patterns.	Just working days were considered, and days with a low standard deviation of the energy demand were rejected.
	[110]	Two techniques to produce named information for irregular energy utilization for both short-range and long-range information.	The techniques depend on the size of the accessible dataset.
Knowledge driven-based	[111]	A diagnostic methodology for an air handling unit.	The methodology is appropriate for finding particular and sudden changes however no for distinguishing slow degradations and gradual faults.
	[112]	A diagnostic model for an air handling unit.	The model was tested using a series of simulation experiments injecting different fault scenarios.
	[113]	An FDD approach that is non-intrusive and requires insignificant information assortment for AHU.	The FDD approach is first constrained by the requirement for models that describe hardware behavior.
	[114]	The technique to distinguish concealed faults by utilizing the likenesses between known faults and unknown faults.	The reliability of the technique depends on how well the expert knowledge can describe the fault categories at a high level.

Table 5
Summary of research papers based on building typology, building subsystems, and management strategies.

Reference	Authors	Building Typology	Building Subsystem	Techniques	Used Software	Management Strategies
[55]	Hazyuk et al.	Tertiary	Heating	Linear Programming	MATLAB	MPC Optimization
[58]	Asadi et al.	Commercial	HVAC	Monte Carlo Simulation	DOE-2, eQuest	MPC
[59]	Salakij et al.	Residential	HVAC	Linear Quadratic Tracking	EnergyPlus	MPC
[60]	Schirrer et al.	Office	HVAC	Nonlinear Complex Model, Nonlinear Simplified Model	Modelica, MATLAB	MPC Optimization
[61]	Staino et al.	Tertiary	Heating	Cooperative Optimization	MATLAB	MPC Optimization
[62]	Bianchini et al.	Commercial	HVAC	Linear Programming, Mixed Integer Linear Programming	EnergyPlus, MATLAB	MPC Optimization
[63]	Ruusu et al.	House	Heating	Successive Linear Programming	MATLAB, TRNSYS	MPC Optimization
[64]	Toub et al.	University	HVAC	Monte Carlo Simulation	MATLAB	MPC
[65]	Macarulla et al.	University	Heating	Neural Network	MATLAB	MPC
[66]	Manjarres et al.	Office	HVAC	Random Forest Regression	Next24h Energy	MPC
[67]	Biyik et al.	University	HVAC	Unspecified	MATLAB	MPC Optimization
[68]	Fan et al.	University	HVAC	Machine Learning	CRAN	MPC
[69]	Megahed et al.	House	Overall	Neural Network	MATLAB/Simulink	MPC
[70]	Gómez-Romero et al.	Office	HVAC	Operational Plan Generator Algorithm	IES Virtual Environment	MPC
[71]	Krese et al.	Tertiary	HVAC	Cluster-based sensitivity analysis	EnergyPlus	MPC
[72]	Macarulla et al.	Office	Ventilation	Stochastic differential equations	CTSM-R	MPC
[73]	Massa Grey et al.	Office	HVAC	Gaussian Process Model	MATLAB, TRNSYS	MPC
[74]	Gori et al.	Office Residential	HVAC	Bayesian Statistics	LORD	MPC
[79]	Panapakidis et al.	University	Overall	Clustering Techniques	MATLAB	DSM
[78]	Keles et al.	Residential	Appliance Consumption	Load Shedding algorithm	MATLAB/Simulink	DSM
[80]	Fanti et al.	House	Appliance Consumption	Control algorithms	MATLAB/Simulink	DSM
[81]	Sala-Cardoso et al.	University	HVAC	Neural Network	Unspecified	DSM
[82]	Ghofrani et al.	Tertiary	HVAC	Neural Network	EnergyPlus, Building Virtual Testbed	DSM
[83]	Martirano et al.	Residential Commercial	HVAC	Load Demand Analysis	Unspecified	DSM
[85]	Faia et al.	Residential	Overall	k-Nearest Neighbors Algorithm	Unspecified	DSM
[84]	Sehar et al.	Office	Lighting, HVAC	Control algorithms	EnergyPlus	DSM
[86]	Arun et al.	Residential	Appliance Consumption	Scheduling Algorithm, Genetic Algorithm	MATLAB	DSM
[87]	Jindal et al.	University	HVAC	Mixed Integer Linear Programming	CPLEX, Gurobi	DSM
[88]	Baniasadi et al.	University	Heating	Non-convex Mixed-Integer Nonlinear Programming	LabVIEW, MATLAB	DSM
[89]	Dagdougui et al.	University	HVAC	Dual tracking control strategy	LINGO	DSM
[92]	Wang et al.	Tertiary	Overall	Particle Swarm Optimization	Unspecified	Optimization
[93]	Rocha et al.	Office Residential	HVAC	Sequential Quadratic Programming	MATLAB	Optimization
[94]	Chou et al.	Residential	Overall	Time-series prediction, Machine Learning	MATLAB	Optimization
[95]	Carli et al.	School	Overall	SAUGMECON resolution method	MATLAB	Optimization
[96]	Raza et al.	University	Overall	Particle Swarm Optimization, Neural Network, Bayesian model	MATLAB	Optimization
[97]	Howell et al.	Residential	Overall	Genetic Algorithm, Neural Network	EnergyPlus, MATLAB	Optimization
[98]	Gruber et al.	Hotel	Overall	Horizon Optimization	LabVIEW	Optimization
[99]	Aguilar et al.	Theatre Hospital	HVAC	Multi-objective Optimization	Unspecified	Optimization
[100]	Yang et al.	Unspecified	Lighting, HVAC	Multi-Objective Swarm Particle Optimization, Weighted aggregation	Unspecified	Optimization
[101]	Xu et al.	Office	HVAC	Lagrangian relaxation-based algorithm	MATLAB	Optimization
[102]	Du et al.	Unspecified	HVAC	Linear Programming	MATLAB	Optimization
[103]	Ma et al.	Unspecified	HVAC	Lagrangian dual method	MATLAB	Optimization
[108]	Djuric et al.	University	Heating	Sequential Quadratic programming	MATLAB	FDD
[109]	Capozzoli et al.	Office University	Overall	Symbolic Aggregate approXimation, Classification and Regression Tree	Unspecified	FDD
[110]	Gaur et al.	House	Overall	Statistical approach, Segmented Linear Regression	MATLAB	FDD
[111]	Pakanen et al.	College	AHU	Online Diagnostic Test	Commercial BEMS	FDD
[112]	Ploennigs et al.	Commercial	AHU	Semantic model	BEAD	FDD
[113]	Deshmukh et al.	University	AHU	Non-intrusive electric load monitoring	Unspecified	FDD
[114]	Li et al.	University	AHU	Expert knowledge-based Unseen Fault Identification	Unspecified	FDD

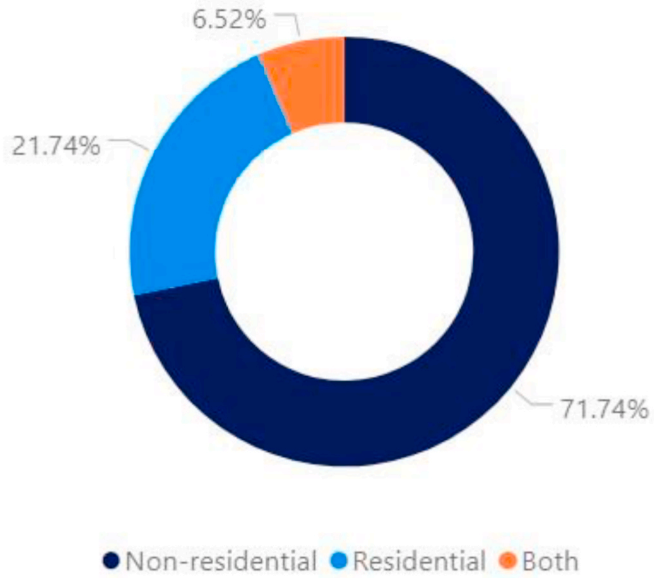

Fig. 8. Comparison of reviewed literature based on building type.

are utilized depending on the need given by users to each load regardless of the moment [115].

For non-residential buildings, the most used strategy was MPC, the reason could be due to MPC can represent the room occupancy, weather prediction, and other data that could be of interest for ideal control of the system [116]. Analyzing occupants' interactions is fundamental for forecasting energy consumption, without such an investigation, there is a high level of vulnerability and mistake [117]. Although it should be recognized that in recent research, optimization has grown since this management strategy is not only being used in active BEMS methods but also the passive ones, such as thermal load management [118], and structural links [119]. For residential buildings, the most used strategy was DSM (see Fig. 10), the reason could be due to customers are allowed to determine their energy utilization, helping energy suppliers to reshape the load profile and decrease peak load demand. DSM in conventional EMS utilizes system-specific methods and it handles a predetermined number of manageable loads of restricted kinds [120].

Residential and non-residential buildings have a common factor that must be considered for efficient use of energy, which is the occupant behavior, which will determine how the system should work. Occupant behavior prediction is a difficult assignment in buildings since it will depend on the way the occupant thinks and the purpose of the building. Due to this, technologies such as machine learning have proven to be

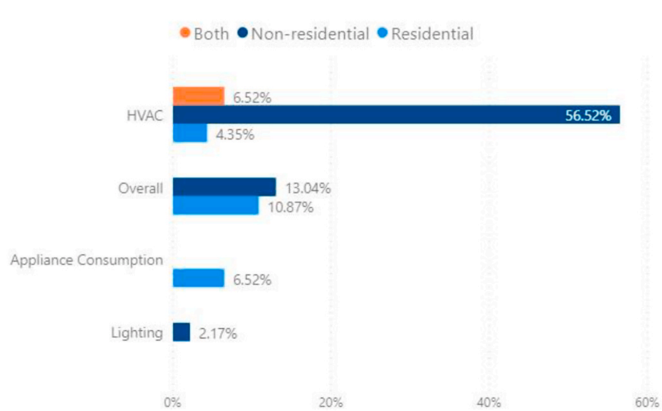

Fig. 9. Comparison of reviewed literature between building type and building system.

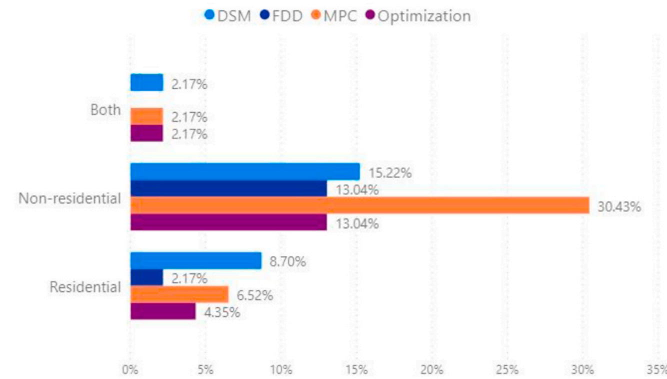

Fig. 10. Comparison of reviewed literature between management strategies on building type.

useful to predictive occupant behavior, since they are based on previous experience and model future behavior.

6. Future challenge

The energy issue in buildings has made essential a periodic change in the strategies to address building configuration/retrofit [121]. In this regard, all management strategies present future challenges that must be faced. Some are particular to each strategy while others are presented in several.

- For model-based control methods, the nature of the model that characterizes building systems and elements is fundamental to ensure acceptable execution of intelligent building control and automation [122]. Also, the accuracy and reasonableness of the information and the connections assumed from it become a basic reality [123].
- Energy needs are unequivocally connected to local climate conditions, along these lines it very well may be normal that changes in worldwide and local climate conditions will lead later on to the development of the yearly energy requirement for the current building stock [124]. Residential building demand will be affected by the environmental change because of the expansion of normal temperature, climate limits, and the ensuing change on space warming and cooling needs [125].
- Changes in the energy supply system stimulate the task of coordinating the exceptionally fluctuating and changeable sustainable energy generation with the yet firm energy demand. This prompts an expanding demand for storage and demand flexibility [126]. For that reason, energy coordination and collaboration among buildings and vehicles pulled in far-reaching intrigues these days [127].
- The life cycle of traditional buildings is normally fixed in hundreds of years, while the sensor life must be kept up in over ten years or considerably shorter [128]. Besides, techniques depend on the presumption that the sensor information is finished and solid, which is not really obvious in real practice [129].

Considering the aforementioned challenges, each of the strategies has future lines of research that should be addressed. The MPC and optimization strategies require developing improve models that have a better performance taking into account the characterization of the building systems and climatic variables so that energy savings could be achieved in systems that influence the comfort of the occupants. DSM strategies are affected by the behavior of the occupants of buildings and the devices used, it is necessary to research loads that will have a significant impact not only on the building but also on the grid, such as, electric vehicle. FDD is the most affected in terms of reliability that sensors must-have, so research that allows having a reliable communication system is increasingly required. Furthermore, the need for prediction models for specific tasks in buildings is a topic of interest for each of the management strategies.

7. Conclusion

This paper presents an overview of ongoing strategies in the area of active building energy management systems. Articles related to different management strategies for BEMS such as MPC, DSM, Optimization, and FDD in terms of residential and non-residential buildings were evaluated. The building subsystems and techniques used for each type of strategy were reviewed. Also, the software used to validate the methodologies was evaluated. This paper closes with a discussion of the outcomes found in every one of the strategies, research breach, and future research guidelines.

As found in the review, most of the studies focused on HVAC systems, prioritizing only to decrease the energy consumption of these systems but leaving aside other buildings subsystem, which may represent a higher consumption depending on the purpose of the building. The outcomes of this paper demonstrate that some research areas may require more consideration: energy consumption prediction models for different subsystems, demand management considering new loads such as electric vehicles, methods that include the behavior of the occupants based on real data and methodologies that can be applied to both residential and non-residential buildings, taking into account all subsystems. Future research directions may lead to significant improvements in these areas and beyond include machine learning techniques and occupant behavior models.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jobe.2020.101692.

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