Intelligent Systems for Building Energy and Occupant Comfort Optimization: A State of the Art Review and Recommendations

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Abstract: Today, buildings consume more than 40% of primary energy in and produce more than 36% of CO_2. So, an intelligent controller applied to the buildings for energy and comfort management could achieve significant reduction in energy consumption while improving occupant's comfort. Conventional on/off controllers were only able to automate the tasks in building and were not well suited for energy optimization tasks. Therefore, building energy management has become a focal point in recent years, promising the development of various technologies for various scenarios. This paper deals with a state of the art review on recent developments in building energy management system (BEMS) and occupants comfort, focusing on three model types: white box, black box, and gray box models. Through a comparative study, this paper presents pros and cons of each model.

Keywords: intelligent buildings; building energy management systems; comfort management; energy optimisation; white box models; black box models; gray box models

1. Introduction

Currently, buildings are responsible for preeminent amount of world's energy consumption and CO_2 emission. According to the European Energy Efficiency Commission (EEEC), buildings in the EU represent 40% of total primary energy consumption [1] and nearly 36% of CO_2 emission [2]. The energy generated from fossil fuels contributes considerable CO_2 emission and causes global warming. Consequently, the government authorities, regulators and policy makers have been influencing people in the direction of sustainable buildings by introducing energy efficiency policies. The International Energy Agency (IEA) specifies: "Globally, the wide deployment of best available technologies and energy efficiency policies could yield annual savings in buildings final energy use of roughly 53 exajoules (EJ) by 2050" [3]. This amount is equivalent to cumulative energy consumption by buildings in China, France, Germany, Russia, the United Kingdom and the United States in 2012 [4]. Therefore, optimization of energy consumption is crucial for healthy environment and sustainable development. Integration of renewable energies [5] and intelligent systems [6] to the buildings could achieve the estimated savings in energy consumption. However, efficient building energy consumption optimization is still a challenging task because of various parameters that affecting building energy consumption. These influential factors can be divided into major five types:

1. Building physical and thermal properties (thermal conductivity, specific heat, thickness, density, etc.) [7].
2. Occupancy behaviour (occupancy activities, interaction with the building, etc.) [8].
3. Building sector type and building energy policies (type of building, location, respective regional policies, etc.) [9].
4. Population size (number of occupants presence, indoor activities) [10].
5. Climatic conditions (outdoor dry bulb temperature, wind speed, outdoor relative humidity, solar radiation, etc.) [3].

Among these five influential factors, building physical properties, climatic conditions and occupancy behaviour have a direct impact on energy consumption. At the same time other parameters represents slightly minimal effect on the energy consumption. A study conducted on university buildings to evaluate the relationship between energy consumption and population size, user activities, and demand profiles reveals population size have a minimal impact on electrical energy consumption as compared to other parameters [10]. Generally, people spend 90% of their life in buildings [11], hence the maintenance of comfortable environment is important to assure occupants' health and productivity. The quality of occupants' living is determined by three comfort parameters: thermal comfort, indoor air quality and visual comfort. These three comforts are achievable by exploiting Heating, Ventilation and Air-Conditioning (HVAC) controller and lighting systems with natural resources (day lighting, outside temperature, etc.).

A Building Energy Management System (BEMS) is required to improve energy performance meanwhile ensuring improved occupants' comfort. Conversely, realisation of indoor comfort environments draws more energy to achieve and maintain the optimal comfort. Therefore a proper trade-off is required between energy and indoor comfort [12]. In this context, recent developments in the BEMS are focusing on smart technologies to address the gap between energy consumption and occupants' comfort.

1.1. Building Modelling Approach

Three main approaches have been used for building energy management systems: white box models, black box models and gray box models. White box models [13,14] are a physical modelling approach relying on thermodynamic and/or mathematical equations and engineering methods for energy modelling, analysis and control. White box-based modelling approach examples are the building energy analysis simulation software such as: EnergyPlus [15], Transient System Simulation Tool (TRNSYS) [16], eQuest [17], etc. These software tools basically are used during building planning and designing phases, prior to the building construction. They calculate overall energy consumption [18], HVAC design [19], operation scheduling, lighting information [20], etc., based on the detailed building physical properties [21], occupancy schedule, geographical conditions, and type of building and climatic parameters. However, availability of such precise data for the simulation is troublesome and in some cases impossible to obtain. Also, due to the non-linear behaviour of building parameters, white box models are suitable for simple models and as when applied to complex buildings, the model tends to be thermodynamically complex.

Black box models are data driven building energy models, which are built on data basis [22–26] often considered as easy to model over physics-based white box models. Generally, black box models are applied for prediction of energy consumption [25], HVAC operation scheduling [27], and adaptive control systems [28]. Black box models methods examples are Artificial Neural Networks (ANNs), Support Vector Machine (SVM), Genetic Algorithms (GAs), Reinforcement Learning (RL), deep machine learning [29], etc. Aside from the ease to apply, black box models require large input data to train the model [30]. This data may not be available in buildings in which sensors are not installed, thereby limiting their application to the few buildings with installed sensors.

To overcome white box and black box models drawbacks, hybrid models were introduced [31]. Hybrid models (gray box models) are combination of physics-based models (white box models) and statistical methods (black box models). Gray box modelling is found out as robust and accurate for building systems modelling and in building performance improvement [31].

1.2. Indoor Comfort Parameters

People spend most of their time in buildings. Maintenance of indoor comfort parameters is therefore significant to improve occupants productivity, health, and comfort feeling [32]. Thermal comfort in indoor environment is the principal component for ensuring indoor environment quality. Thermal comfort is generally expressed as the satisfaction of thermal environment, usually referred as psychological sensation of thermal environment [33]. Visual comfort is another parameter affecting the indoor environment quality. Basically, proper illumination level is essential for commercial, institutional, and industrial buildings to preserve inhabitants working efficiency.

1.3. Objectives and Motivation

Several literature reviews have been previously published in building energy and comfort management context. Dounis and Caraiscos [34], reviewed advanced control systems for energy and comfort optimization covering various control strategies, whereas Lombard et al. [35] detailed building energy consumption by building types and HVAC systems. Zhao and Magoulès [36] summarized various building energy consumption prediction methods based on classification; engineering model, statistical model, neural networks, support vector machines, and gray models. Amasayli and El-Gohary [37] elaborated data driven prediction methods and in addition, Wei et al. [38] discussed classification of building energy consumption. Previous literature studies have discussed various building energy management systems, prediction of energy consumption, and occupancy relation with buildings. However, a clear gap is observed for the consideration of recent developments in control strategies for optimal energy and comfort management in buildings. In this state of the art paper, the recent developments in BEMS methods along with indoor comfort conditions were discussed in detail and critically reviewed. Besides, the review papers are selected from the year 2013 onwards (around 80% papers) for clearly focus on recent developments. An elementary related research was conducted by using search engine and scientific websites: Google scholar, Science Direct and IEE explore digital library. The keywords 'building energy management', 'building comfort management', 'intelligent systems for buildings', and 'building control' were used for filtering papers to perform the review process. Papers were only selected from top international journals and indexed conference proceedings. Based on the selection criteria, 90 papers were further considered for this state of the art review.

The content of the paper is organised as follows: Section 2 reviews studies of recent developments in building energy management systems based on their model type, Section 3 details and discusses the literature review observations. Main conclusions and future investigations are described in Section 4.

2. Building Energy Management Systems—BEMS

BEMS are generally installed in buildings to monitor and control indoor comfort conditions and energy consumption [18]. These systems are mainly based on sensors, actuators, software, and hardware networks [6,39]. Normally, buildings with few occupants (residential, and office buildings) may permit to interact with BEMS technologies via a human machine interface (HMI) [40] to control electrical appliances and HVAC system operation. These interactions could be restricted in institutional, commercial, and industrial buildings because of the large number of occupants, where each may posses a unique set point, resulting in higher energy consumption. Hence, HVAC system operating values are set to a standard range to maintain indoor comfort in such buildings. However, heterogeneous parameters affecting building energy and comfort hinder the performance of BEMS models.

2.1. White Box Models

White box models are thermal dynamics modelling, which are based on fundamental laws of physics, thermodynamics, and heat transfer. Generally this approach can be roughly classified into two types: physics-based models using simulation tools such as: TRNSYS, EnergyPlus, etc., and physics governing laws-based thermal dynamics state-space equation or lumped capacitance model [41].

Due to the diversified and heterogeneous behaviour of building parameters, complexity of hardware network (sensors, and actuators), and occupants interaction with buildings, it is difficult to carry out full scale experiments. Hence, software tools are affordable and ease-to-use platforms that can be used for building dynamics evaluation and analysis. Numerous software tools have been developed over the last few decades for the analysis of energy consumption, HVAC design, operation scheduling, lighting information, renewable energies, etc., Regular up-gradation is performed on these simulation tools to improve the performance efficiency and decreasing computational cost. The list of US Department of Energy (DOE) organisation approved building simulation tools is available in [42].

EnergyPlus is a building energy performance analysis simulation software and console-based program that reads inputs and writes outputs in text files, developed based on DOE-2 [43] and the Building Loads Analysis and System Thermodynamics (BLAST) by National Renewable Energy Laboratory(NREL) and U.S. DOE Building Technologies Office (BTO) [15]. Zhao et al. [44] used EnergyPlus to procure raw data for commercial building to perform overall energy performance and dynamic pricing by using Cyber Physical Systems (CPS)—enabled BEMS [45]. Furthermore, a fuzzy logic controller (FLC) is initially designed based on the data probation from EnergyPlus and a GA method applied to FLC for evolution of improved member functions population for improved comfort control energy optimization of a food service center. The results were compared with stand-alone EnergyPlus output and investigated that the GA-FLC-based method resulted notable decrease in energy consumption during both cooling and heating [46]. This shows that EnergyPlus lacks interactive control optimization techniques and would be coupled with other dynamic computational software (Matlab, Modelica [47]) via co-simulation software building controls virtual test bed (BCVTB). Kim et al. [19] used EnergyPlus for training ANNs and coupled GA for optimization of integrated daylighting and HVAC systems. This was performed to ensure large database available for training ANNs in less time, otherwise 3 months would have been needed to procure data from sensors. A multi-objective optimization strategy is validated using non-dominated sorting genetic algorithm (NSGA), implemented in the GenOpt [48] optimization engine through the Java genetic algorithms package, to instruct the EnergyPlus simulation tool [12]. Meanwhile, Huh et al. [49] developed a system to generate predicted real-time weather data for 24 h duration using EnergyPlus coupled with GenOpt through BCVTB [50]. This approach improves the building energy control optimization based on real time prediction control.

TRNSYS (Transient systems simulation program) is a dynamic computational software for building energy performance analysis [16]. It is incorporated with Matlab for database generation to train 2 ANNs used for predictive and adaptive approach applied to hotel building. The developed model efficiently improved thermal comfort and building energy optimization during summer season resulting in 18–38% energy savings over the simulation period [28]. TRNSYS was used for determining building cooling load needed from the chiller plant, Later, these data were fed to Matlab for performing optimization analysis [51].

BCVTB is used for coupling various simulation tools for co-simulation and co-simulation to hardware. Refs. [13,46,52] used BCVTB to ease the simulation process by coupling EnergyPlus, Matlab in their model for building energy performance analysis. Meanwhile, BCVTB was coupled with EnergyPlus to generate real-time weather data file for energy consumption prediction in one day [49]. Figure 1 shows the process of generating a weather data file based on the forecasted weather using BCVTB as a coupling platform between EnergyPlus and other tools. The weather elements from weather forecast by national weather station, calculated weather parameters, measured

weather elements, and default parameters are coupled together in BCVTB platform for generating weather forecast.
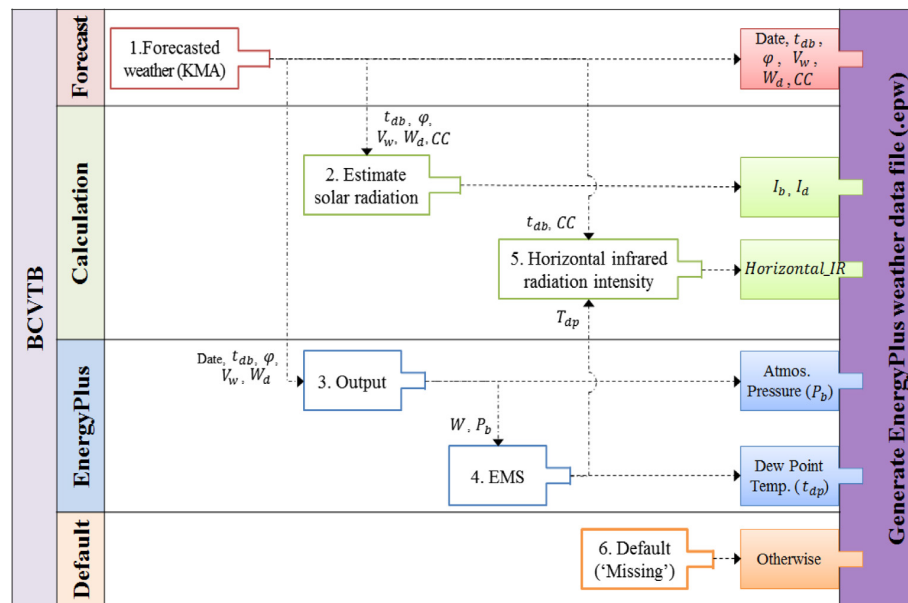

Figure 1. Process of generating a weather data file based on the forecasted weather [49].

Although simulation tools are the first choice for building energy performance analysis because of accuracy and effectiveness, they require proper data of building, weather parameters, and physical properties. However, collecting appropriate data is always difficult and in some cases these data are not available. This is the major challenge in retrofitting existing buildings. In addition, these tools lack controller development flexibility and absence of high performance controller systems in their libraries yields difficulty to develop and integrate in practical application/implementation [53].

2.2. Black Box Models

These are also known as data-driven models and are developed based on statistical models by quantifying historical data parameters and correlating between building performance and data to find optimal pattern. Data-driven model approach is often considered as less complex with high accuracy and low computational cost. However, the inner process is mostly unknown, leading to reduced control flexibility of the overall process. The primary requirement of black box models are pre-collected data. These can be obtained from following sources:

- Real data collected from existing building through sensors, smart meters, and other smart systems [54].
- Simulated data collected from the simulation tools such as EnergyPlus, BCVTB, etc., [30].
- Standard data available in public benchmark datasets such as ASHRAE's data [23].

Black box models are known for prediction techniques and gained huge consideration over last decade. Commonly, these models are used in prediction of building energy consumption [23,25,55], indoor temperature [54,56], heating/cooling load demand [24], HVAC parameters, occupancy [57,58], and energy generation from RES. Some major algorithms of these models are ANNs [59], SVM [60], GAs [61], decision trees [62], and other statistical machine learning methods.

Indoor comforts are influenced by various parameters, especially weather conditions (e.g., wind speed, air temperature, and humidity) that are volatile in nature. In such conditions, indoor thermal comfort can be rapidly affected and could cause excessive energy consumption to maintain temperature range. To maintain indoor thermal comfort under a given range despite of rapid changes in influential parameters, a prediction model and temperature controller is introduced by

Marvuglia et al. [54]. In this framework, outdoor temperature, air relative humidity, wind speed, and indoor temperature data are used to train artificial neural network with external inputs (NNARX) model and predicted values fed to fuzzy logic controller to maintain indoor temperature in a given range. Results show good efficiency of predictions and temperature controller. Mararulla et al. [27] implemented ANN-based predictive controller to a commercial building energy management system for operation of boilers in buildings, shown in Figure 2. This method resulted in around 20% reduction in energy required to heat the building. The ANN implementation is illustrated in Figure 2, where data obtained from the simulation tool are fed to the ANN with 10 neurons in each hidden layer and predicted results are given to BEMS for optimal operation.
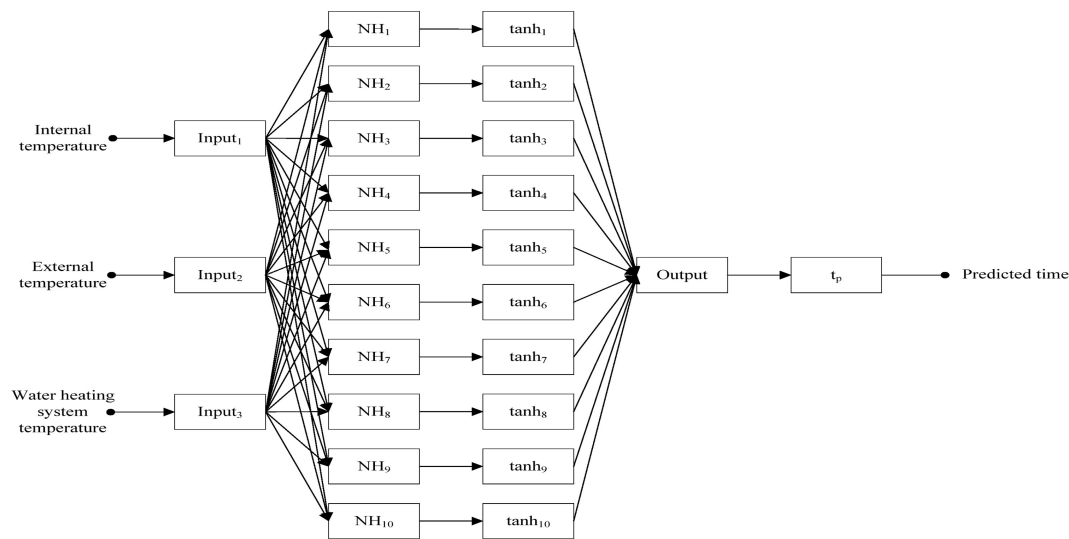

Figure 2. Artificial neural network implementation [27].

In 2016, Ascione et al. [22] used feed-forward multilayer perceptron (MLP) ANN structure to predict building energy and thermal behaviour in retrofit scenarios, which produced significant prediction values. Furthermore, the authors indicated that the number of hidden layers highly influences the ANN performance. Additionally, the importance of training data size is discussed in [30,63], both concluded that larger the training data sample is, the better the performance of ANN model.

Normally, residential buildings have non-constant occupancy and maintenance of thermal comfort for whole day leads energy wastage. Hence prediction of unoccupied hours was performed by [28] by using ANN algorithm and prediction of time required for restoration of indoor temperature to set-point temperature using another ANN model. Multi-Objective Genetic Algorithm (MOGA) controller have been efficient technologies in attaining balance between energy consumption and thermal comfort [64] and with hybrid MOGA author achieved around 31.6% energy management efficiency and 71.8% comfort index efficiency. Triple objective controller using particle swarm optimization (PSO) has been developed by [21], which achieved 19.8–33.3% decrease in annual cooling energy, while increasing in annual heating and lighting: 1.7–4.8% and 0.5–2.6% respectively. Final optimization resulted 1.6–11.3% reduction in annual electricity consumption for four climate regions in Iran. Whereas, O'Neill et al. [65] developed Bayesian networks (BNs) [66] model to predict hourly building energy performance with associated uncertainties. The BNs-based building energy performance prediction system can be applied in various scenarios: (1) Retrofitting buildings; (2) Model-based optimization systems; and (3) Energy diagnostics.

Occupancy's thermal comfort sensation of hot or cold mainly depends on subjective parameters (metabolic rate and clothing insulation) and physical ones (mean radiant temperature, air temperature, air velocity, and relative humidity) as described by Fanger's predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) model-ISO 7730. This method was developed in 1960–1970 and is

still used as a baseline model for comfort measurement. Fanger's base model advancements over the last 40 years are critically reviewed in [67]. An existing HVAC system can optimize PMV index with conventional controller, however, a fuzzy logic-based system is integrated to existing HVAC system to maintain PMV, CO_2, and energy consumption for efficient building performance [68]. This fuzzy logic's member function together with rule selection were then tuned by multi-objective evolutionary algorithms (MOEA-GA) to minimize number of rules and thus maximizing system performance. This proved to be the best combination for FLC's with reduced number of rules to maintain PMV and optimizing energy consumption. Table 1 gives the standard values for thermal sensation scale of PMV in which +3 being very hot and −3 being very cold. It is always suggested that the PMV value should be maintained within −0.5 to +0.5 to achieve better thermal comfort. The comfort classification based on relationship between PMV and PPD is shown in Table 2 [69]. Chen et al. [70] developed data-driven state-space Weiner model to evaluate the dynamic relation between dry bulb temperature variation and occupant thermal sensation. Later they compared developed model to dynamic thermal sensation (DTS). The DTS model is a reactive thermal comfort system with constantly changing its values based on the dynamic variation of weather conditions and occupant preferred thermal sensation votes delivered by an extended Kalman filer (EKF) with feedback system. Furthermore, predicted mean vote and dynamic thermal sensation models were compared by developing MPC-DTS and MPC-PMV. Results indicated that the MPC-DTS achieved better thermal comfort and energy optimisation than the MPC-PMV model, but both efficiently maintained thermal comfort compared to the baseline model using proportional integral (PI) controller. However, they assumed that there is a feedback system in BEMS, which actually is not the case. Later, Chen et al. [71] conducted the same experiment to investigate the performance difference between MPC-DTS and MPC-PMV with real time actual mean vote feedback values, in addition authors detailed the probable reasons for performance difference.

The above mentioned researches mainly focus on optimization techniques used to achieve comfort measurement. However, the accuracy of subjective and physical parameters measurement taken from sensors has a significant impact ion the PMV index evaluation. These measurement uncertainties can be evaluated using efficient tools such as: monte carlo analysis (MCA) [72], guide to the expression of uncertainty in measurement (GUM) [73], and sensitivity analysis (SA) [69]. These studies show that the proper handling of measurement uncertainties is essential in PMV index model.

Table 1. Thermal sensation scale of PMV.

PMV	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
−1	Slightly cool
−2	cool
−3	cold

Table 2. Comfort classification based on ISO-7730.

Class	Percentage of Dissatisfied (%)	Predicted Mean Vote
A	<6	$-0.20 < PMV < 0.20$
B	<10	$-0.50 < PMV < 0.50$
C	<15	$-0.70 < PMV < 0.70$
-	>15	$PMV < -0.70$ or $PMV > 0.70$

Black box models are less complex, does not need complete data of building physical parameters, efficient performance, and easy to build. Nevertheless, they require huge building operational and environmental parameter data for training in order to have efficient prediction values. These data are however difficult to obtain, while low quality data can cause huge prediction error. Even though,

these models are accurate and less complex, the lack of knowledge/explanation of the inner processes from the point of view of physics, there is some reluctance towards black box model implementation over physics-based model.

2.3. Gray Box Models

The third category of BEMS is known as gray box models. These are hybrid ones combining simplified physics-based models and data-driven ones. In a gray box model, the process is expressed in mathematical expression that may be based on the physics and/or thermodynamics laws. They consist expressions that have physical explanation (e.g., resistor capacitance network) and a part of the model may be obtained through regression from the available data.

A gray box model is a balanced model between the white box model and black box model. This combination ensures that the non-linearities in white box model can be handled using black box models and lack of laws of physics reasoning in black model can be represented through white box models, but extra effort is required to design and develop these models. However, selection of suitable gray box model structure for developing a good performance system is still a difficult task. Bacher and Madsen, ref. [7] proposed an approach to find appropriate heat dynamics of a building. Indeed, a set of different RC network models have been configured and compared using likelihood ratio tests. The study concludes that significant improvements can be obtained as the model order increases, while no further notable improvements can be expected beyond a model order of 3. Široký et al. [74] proposed an experimental analysis of a heating system using lumped capacitance network in a university building and analysis was carried out for two months. Through this approach they were able to achieve around 15% and 28% energy savings. The experimental analysis not only investigated the performance of MPC but also detailed the issues that can be encountered in its application.

Figure 3 illustrates the basic principle of MPC model structure [74], the inputs of the systems are time varying parameters: energy price can be taken from energy market, comfort conditions set by the occupants, occupancy prediction, and environmental parameters. The MPC system formulates the optimization of an objective function by using building dynamic model, a cost-function and constraints. After each time sample formulation, feedback from occupants and weather conditions are fed back to MPC for the formulation of next time sample, which ensures that unanticipated disturbances are taken in consideration through feedback loop.
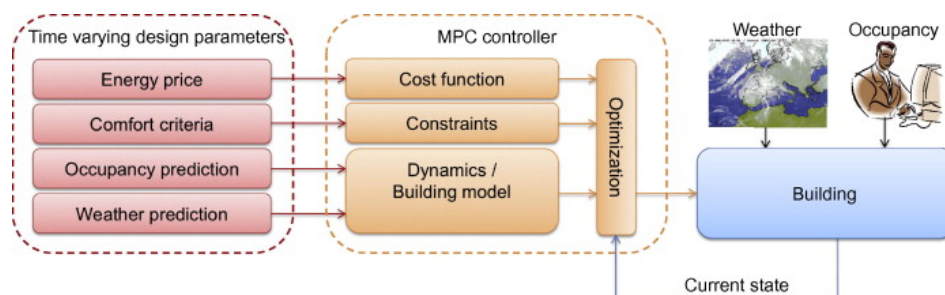

Figure 3. Basic principle of model predictive control for buildings [74].

A simplified low order gray box modelling has been introduced in [75]. The study considered a whole building as single zone building (Figure 4) neglecting the inter-zone heat exchange. Most of the studies in literature did not take account of inter-zone thermal interactions as it increases the complexity of the model and includes numerous uncertainties. In addition, the model perform-ability declines with the increase of the number of zone. However, Cai and Braun [76] proposed a resistance capacitance thermal network model for multi-zone buildings (Figure 5) with a unique three-step estimation approach to reduce the complexity of the model and thus improving the performance of BEMS system, through:

- De-grouping weakly linked zones and grouping strongly linked zones.

- Sensitivity analysis to identify and eliminate non-influential variables.
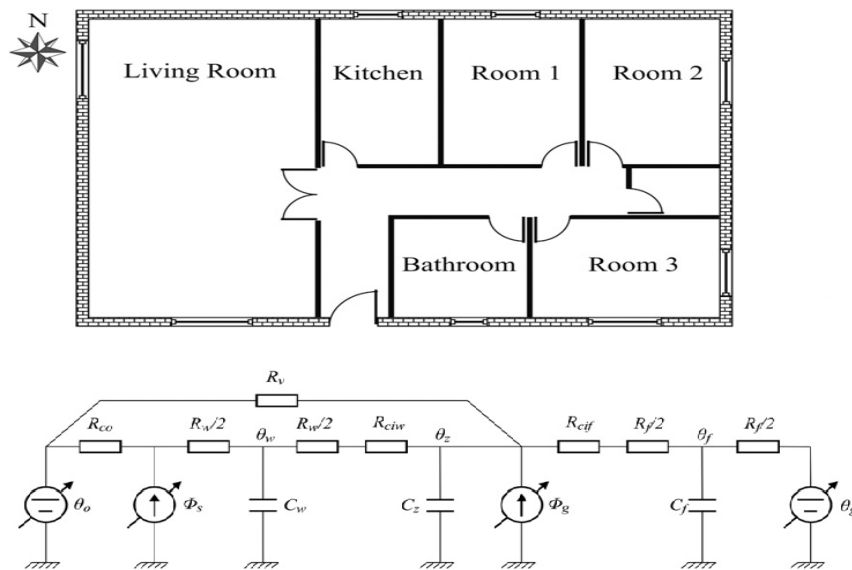- Correlation analysis to eliminate Non-correlated variables.

Figure 4. RC thermal network for single zone building [75].

Performance of BEMS system is significantly increased because of the above-considered three steps, which have simplified the estimation problem by eliminating non-influential parameters.
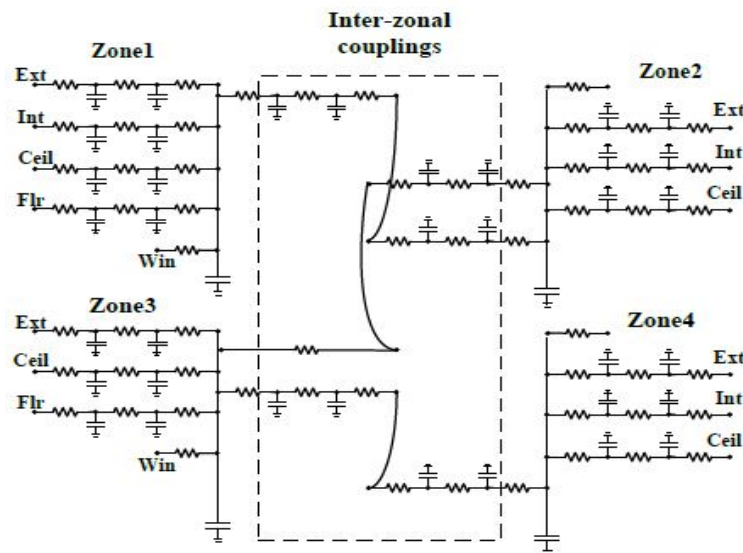
Figure 5. Resistor capacitance thermal network for multi-zone building [76].

In general, gray box models can be used for predictions of energy consumption, thermal comfort conditions, occupancy, and heating/cooling load of buildings. These applications leads to use gray box modelling to building in smart Grid context for dynamic load management and energy storage. The reduced order gray box model for buildings connected to smart Grid was investigated in [31], where it is applied on two buildings types (insulated and uninsulated). Furthermore, Sharma et al. [77] presented a study of MPC controller implementation for buildings in centralized energy management system framework (CEMS). In addition, The insulated buildings opens the possibilities of enabling

demand-side management (DSM) by exploiting heat capacity flexibility in building thermal wall mass. Harb et al. [78] developed gray-box models for forecasting the building thermal response. The analysis was conducted on four gray box models and data from three building. Building areas varied from 3000 to 30,000 m^2 and data duration from 39 to 110 days. To determine thermal behaviour of the building, three forcing functions were used in this paper:

- Radiative building environment is expressed as the solar irradiation.
- Building thermal environment is represented by the outdoor air dry temperature.
- Various heat sources consists of heating elements.

From the above a three-function input vector is constructed:

$$\mathbf{U} = [T_a Q_{irrad} \phi_h]^T \qquad (1)$$

where T_a—outdoor dry bulb temperature, Q_{irrad}—global solar radiation on horizontal surface, and ϕ_h—Building thermal consumption.

Four gray box model structures were developed in this paper: (1) 1R1C—the simplest structure characterizes the whole building into a single parameter (Figure 6); (2) 3R2C—consists of three resistors and two capacitors. Three resistors indicate convective and radiative heat exchange, and heat exchange between interior to environment, two capacitor indicates interior and exterior thermal mass (Figure 6); (3) 4R2C—extension of the 3R2C structure with additional indoor node (Figure 7); and (4) 8R3C-extension of the 4R2C considering all type of heat exchanges between interior, exterior, heating elements, and indoor air (Figure 7).
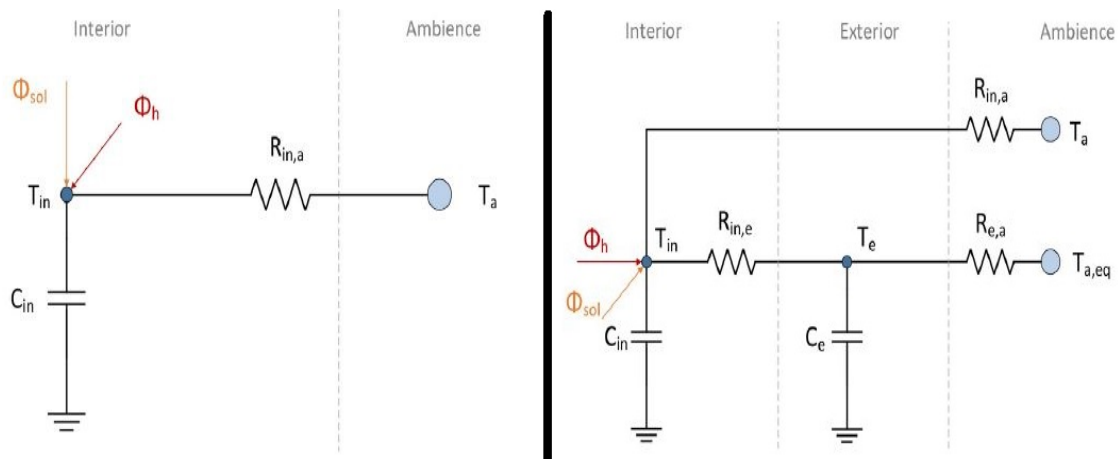

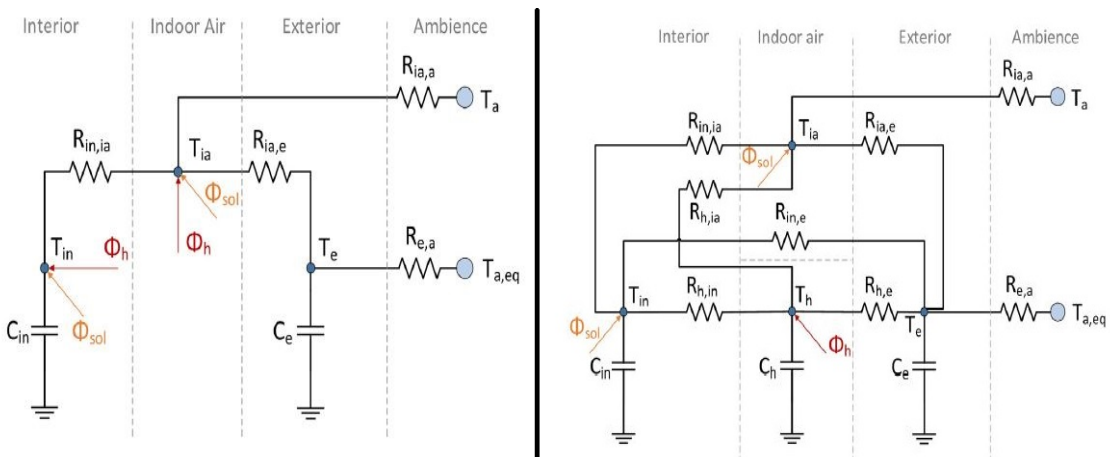**Figure 6.** Building thermal structures—1R1C and 3R2C [78].

Figure 7. Building thermal structures—4R2C and 8R3C [78].

The achieved results show that the 1R1C model produced more harmonics in the prediction values due to its simple structure, the 3R2C have produced similar disturbances in indoor air temperature prediction, due to the lack of consideration of heat exchange between indoor and outdoor air temperature. The 4R2C produced accurate prediction in daily indoor temperature prediction, due to the consideration of heat exchange between various parameters. The 8R3C produced similar accurate prediction values with no significant improvements in the results despite the detailed model. The 4R2C model can thus be considered as the suitable structure for implementation because of its accuracy and low complexity. From the achieved results it can be concluded that the addition of indoor air temperature node (4R2C and 8R3C) provides stable prediction values compared to model without indoor air temperature node (1R1C and 3R2C).

Meanwhile, application of MPC systems for building energy and comfort management has gained larger attention, Sturzenegger et al. [79] applied MPC strategy on commercial building of 6000 m^2 area for energy and comfort control. The results are later compared with existing rule-based control systems. The analysis of MPC implementation proved that energy savings were around 17% with an improved comfort level.

The above-described studies have shown that gray box models are robust, accurate, and applicable to complex buildings. However, these models posses high computational cost making them only profitable in applications for commercial buildings. Further investigations are needed to ensure adaptability and application for small buildings.

3. Observations and Discussion

This paper mainly focused on review of recent development in intelligent controller systems applied to building energy and comfort management. Several papers have been reviewed in this paper and around 80% of the papers are from the year 2013 onwards. The reviewed papers are arranged in descending chronological order in Table 3, which highlights the carried out review. The listed papers does not consider the total number of reviewed papers. Indeed, these ones have different control strategies, methods, objective parameters, and applications. Some assumptions are made for this literature review's observations:

- Buildings in the context of smart-grid are considered as residential ones.
- Apartments with large commercial space are considered as non-residential buildings.
- Grid is considered to be a supply source for papers without specific indication on the supply source.
- Demand side management and load shifting are considered as dynamic pricing.

Based on the above-given assumptions, the following observations have been made. The carried out review shows that research majority is conducted on non-residential buildings, around 66%, and residential ones, being 34% (Figure 8). Non-residential buildings include: institutional, public, office, swimming pool, hospital, and hotel buildings. This lack of research may be due to the unavailability of data or controller systems. Figure 9 illustrates control strategies applied for both building types, where black box models are dominating with 74% and 67% of the overall applied controllers for residential and non-residential buildings, respectively. Significant researches have therefore been conducted on black box models due to their ease of application. Around 21% and 27% gray box models were applied to residential and non-residential building, respectively, while gray box models were less used in residential cases compared to non-residential ones mainly because of their high computational and design costs. Simulation tools combined with other control strategies are used for building energy performance analysis but the standalone use is low because of their complexity and high data acquisition cost.

Table 3. Literature review survey.

Ref.	Year	Techniques Used	Building Type	Comfort Conditions				Energy	Dynamic Pricing	Supply Source	Simulation Tool	Data Duration	Result
				Th	Lt	AQ	RH						
[80]	2007	Decision support model	Office building	Yes	Yes	Yes	Yes	Yes	No	Grid	CLIPS with visual basics language	1 year	10% annual energy reduction
[33]	2011	PID and FLC	Residential	Yes	No	No	No	Yes	No	Grid and RES	-	30 days	Developed strategy can be implemented on already in use PID controller
[8]	2011	Cluster analysis	Residential	n/a	n/a	n/a	n/a	n/a	n/a	n/a	WEKA [81]	1 year	Investigated the relation between occupancy behaviour and energy consumption
[82]	2012	CPS based PID controller	Residential	Yes	No	No	No	Yes	No	Grid	Matlab	8 h	Designed a system which connects PID controller to CPS for real time weather forecasting to enhance performance of installed temperature controller
[56]	2012	MBPC, ANN, and GA	Institutional	Yes	No	No	Yes	Yes	No	-	-	Training: 15, 8 days, and testing 1 day	Estimation of 50% and above energy savings
[83]	2012	Stochastic Markov models	Commercial and Dwellings	No	Yes	No	No	Yes	No	-	-	-	Prediction of energy consumption through learning from occupancy behaviour and also indicates the unnecessary energy consumption areas
[68]	2012	FLC and GA	Office building	Yes	No	Yes	No	Yes	No	-	-	-	Comparison of various evolutionary algorithms and conventional controller. Result shows multi-objective evolutionary algorithm can achieve 30.4% and 50.3% higher efficiency in energy and stability optimization, respectively
[44]	2013	CEBEMS	Commercial Building (Food Service Center)	Yes	Yes	No	No	Yes	Yes	PV, CHP and Grid	EnergyPlus	1 day	Developed MAS for CEBEMS have shown better electrical and thermal energy consumption optimization in comparison with BCHP model
[54]	2013	ANN and FLC	Office building	Yes	No	No	No	Yes	No	-	Matlab	7 months	Prediction and control of indoor temperature
[84]	2013	MPC	Commercial building	Yes	No	No	No	Yes	No	Grid	Matlab and GenOpt	6 days	Reduction in energy consumption for the simulation period 75.7% without and 85.5% with shading is achieved
[85]	2013	PSO	Commercial building	Yes	No	No	No	Yes	Yes	RES	-	1 day	Applied PSO shows high comfort level achievement during shortage in energy supply
[86]	2013	MPC and Gray box model	Institutional building	Yes	No	No	No	Yes	Yes	Grid	Matlab and CPLEX	50 days	Energy cost saving considering customers preferences using developed MPC-based appliance scheduling technique
[39]	2013	GMBA-BEMS	Institutional building	Yes	No	No	No	Yes	Yes	Grid and RES	Matlab/Simbad	1 day	Cost saving 1.2 $ per day
[87]	2014	FLC, GA, and ANN	Hospital building	Yes	No	No	-	Yes	No	Grid	Matlab and TRNSYS	Training : 2 months and testing : 1 day	36% annual energy consumption reduction

Table 3. *Cont.*

Ref.	Year	Techniques Used	Building Type	Comfort Conditions				Energy	Dynamic Pricing	Supply Source	Simulation Tool	Data Duration	Result
				Th	Lt	AQ	RH						
[46]	2014	GA and FLC	Commercial building	Yes	No	No	No	Yes	No	-	Matlab, BCVTB and EnergyPlus	1 month	16.8% and 18.1% decrease in cooling and heating load, respectively over the simulation period
[88]	2014	ANN and FLC	Commercial building	Yes	No	No	No	Yes	Yes (gas)	Grid and gas	-	111 days	Developed model is applied to the complex building to control and optimize gas consumption using real time data from the gas market
[55]	2014	ANN-BPA and MLP	Swimming pool	-	-	-	-	-	-	Co-generation plants and solar thermal panels	Matlab	1 year	Prediction of thermal energy consumption, electrical energy consumption, and PMV
[53]	2014	Gray box model	Residential houses	-	-	-	-	-	-	-	LabView and Matlab/Simulink	60 days	Prediction of indoor temperature and GSHP in/out temperature for optimization process
[89]	2014	MPC and PAB	Office room	-	-	-	-	-	-	-	Matlab	14 days	Prediction of indoor temperature and energy consumption considering model uncertainties
[57]	2014	Decision support model	Office buildings	-	-	-	-	-	-	-	Rapidminer and EnergyPlus	2 years	90.3% accuracy rate in prediction of occupancy
[14]	2014	MPC	Commercial building	Yes	No	No	No	Yes	Yes	Grid	-	1 day	Management of uncertainties in prediction of indoor temperature and energy consumption
[58]	2014	Probabilistic and non-probabilistic methods	Institutional building	-	-	-	-	-	-	-	-	Training: 9 months and testing: 28 days	Occupancy pattern prediction
[31]	2014	Gray box model	Single zone building	Yes	No	No	No	Yes	-	Grid	Modelica and CTSM in R	7 days to 100 days	Model reduction method for buildings in a smart grid context
[9]	2014	Smart BEMS	2 Institutional buildings	Yes	No	No	No	Yes	Yes	Grid and RES	Matlab	1 day	Different outputs for different variables
[10]	2014	-	University building	-	-	-	-	-	-	-	-	5 months	Energy consumption and occupancy pattern analysis shows that occupancy has least significance on building energy consumption
[76]	2014	MPC and Gray box model	Commercial building	Yes	No	No	No	Yes	No	Grid	-	Training: 7 days and testing: 30 days	Model reduction method for multi-zone models
[90]	2015	Online BEMS	University building	No	Yes	No	No	Yes	No	Grid	-	2 years	Reduction in energy consumption of 1% per annum
[91]	2015	FLC	Residential building	Yes	No	No	No	Yes	No	Grid	LabView	30 days	The developed fuzzy-based advanced hydronic radiant floor heating controller produced better control characteristics over conventional controller
[23]	2015	iPSO-ANN	Library building	-	-	-	-	-	-	-	-	6 months	Hourly prediction of electrical energy consumption
[63]	2015	ANN	Office building	Yes	Yes	Yes	Yes	Yes	No	-	-	23 months	————
[24]	2015	FFNN, RBFN, and ANFIS	University building	-	-	-	-	-	-	-	Matlab	Traning: 3 years and testing: 1 year	Hourly prediction of heating energy

Table 3. *Cont.*

Ref.	Year	Techniques Used	Building Type	Comfort Conditions				Energy	Dynamic Pricing	Supply Source	Simulation Tool	Data Duration	Result
				Th	Lt	AQ	RH						
[25]	2015	CBR and ANN	University building	-	-	-	-	-	-	-	-	15 months	Hourly prediction of electricity consumption
[19]	2015	ANN and GA	Office room	Yes	Yes	Yes	Yes	Yes	No	-	Matlab and EnergyPlus	Training: 3 months and testing: 8 days	13.7% energy savings over the simulation period
[30]	2015	ANN	Office building	-	-	-	-	-	-	-	Matlab	612 days	————
[92]	2015	ANN	Airport building	Yes	No	No	No	Yes	No	-			10% energy saving per month
[93]	2015	GPM, GMM, and ANN	Office building	-	-	-	-	-	-	-	-	Training: 50, 340 days and test: 23, 180 days	Prediction of daily and hourly hot water energy rate
[65]	2015	BNs	Office building	-	-	-	-	-	-	-	GeNie	Training: 55 days and testing: 23 days	Prediction of HVAC hot water consumption with uncertainties
[51]	2015	GA	nZEB buildings	-	-	-	-	-	-	Grid and RES	TRNSYS and Matlab	-	————
[94]	2015	MPC and Gray box model	Office building	Yes	No	No	No	Yes	Yes	Grid	Modelica	2 months	30% energy savings with better thermal comfort
[52]	2015	ABM	Office building	Yes	No	No	No	Yes	No	-	HABIT, Matlab, EnergyPlus, and BCVTB	2 months	28% reduction in HVAC energy per month
[70]	2015	Weinar model	Single zone building	-	-	-	-	-	-	-	Matlab	48 h	Prediction of occupancy comfort based on real time feedback data
[95]	2015	MPC	Single zone	Yes	No	No	Yes	Yes	No	-	Matlab	6 days	Prediction of indoor temperature and PMV
[13]	2015	MPC	Commercial building	Yes	No	No	No	Yes	No	Grid	Matlab, EnergyPlus, and BCVTB	1 day	0.5% energy savings per day
[96]	2015	MLP	Institutional building	Yes	-	Yes	-	-	Yes	-	-	1 h	Prediction of thermal comfort parameters and faults (unplanned events)
[64]	2015	MOGA and HMOGA	-	Yes	-	-	-	Yes	DR	RES	-	-	31.6% energy and 8.1% comfort improvement over the simulation period
[71]	2015	Weinar model	Single zone	Yes	No	No	No	Yes	No	Grid	EnergyPlus and Matlab	36 h	————
[97]	2015	RBM	Residential, commercial, and industrial buildings	Yes	No	No	Yes	Yes	Yes	Grid and RES	EnergyPlus	51 days	12–22% improvements in building performance
[12]	2015	NSGA-II and GA	Residential building	Yes	No	No	No	Yes	No	-	GenOpt and EnergyPlus	25 days	————
[98]	2015	White box model	nZEB buildings	Yes	No	No	No	Yes	No	Grid and RES	Modelica and EnergyPlus	-	Developed model can produce solution 2200 times faster than the conventional method
[99]	2015	RBM	Dwellings	Yes	No	No	No	Yes	Yes	Grid	CPLEX	-	Developed RTP model can lead to better optimization compared to existing models
[64]	2016	MOGA	-	Yes	Yes	Yes	Yes	Yes	No	DRES	Matlab	1 day	multi-objective controller presented better trade-off between comfort and energy management
[100]	2016	AFLC	Residence building	Yes	No	No	No	Yes	Yes	Grid	Matlab	90 days	21.3% reduction in energy consumption

Table 3. *Cont.*

Ref.	Year	Techniques Used	Building Type	Comfort Conditions				Energy	Dynamic Pricing	Supply Source	Simulation Tool	Data Duration	Result
				Th	Lt	AQ	RH						
[20]	2016	FLC	Office room	No	Yes	No	No	Yes	No	Grid	DIALux	1 day	11.22% to 56.56% energy savings based on illumination level 350 lx to 200 lx
[28]	2016	ANN	Hotel building	Yes	No	No	No	Yes	No	-	Matlab and TRNSYS	Training: 4 months and testing: 13 days	18–38% energy savings over the simulation period with the developed algorithms
[21]	2016	PSO	Single zone	Yes	Yes	No	No	Yes	No	-	Matlab, EnergyPlus, and JEPlus	-	23.8–42.2% reduction in annual energy consumption
[101]	2016	MPC, PSO, and Gray box model	Institutional building	Yes	No	No	No	Yes	No	-	Matlab/Simulink	Training: 5 days and testing: 10 days	11.3% Energy savings over the 10 days period
[79]	2016	MPC	Commercial building	Yes	-	-	-	Yes	No	Grid	Matlab/BRCM	-	17% energy savings per year compare to the conventional model
[77]	2016	MPC and CEMS	Residential building	Yes	No	No	No	Yes	Yes	DER and Grid	CPLEX	1 day	17% energy cost and 8% energy consumption savings per day
[102]	2016	NSGA	Single zone	Yes	Yes	No	No	Yes	No	Grid	JEPlus, EnergyPlus, and Matlab	-	55.8–76.4% reduction in cooling demand compared to baseline scenario
[41]	2016	MPC	Residential buildings	Yes	No	No	Yes	Yes	No	-	Matlab and EnergyPlus	2 days	Nearly 43% energy consumption reduction compared to the conventional control method
[103]	2016	BRL	Laboratory demonstrator	Yes	No	No	No	Yes	Yes	-	-	Training: 20 days and testing: 2, 8, 12 and 16 days	———————
[49]	2016	MPC	Public building	Yes	No	No	Yes	Yes	LS	Grid and PV	BCVTB, EnergyPlus, and GenOpt	Training: 1 day and testing: 1 day	1.7% energy saving per day
[5]	2016	ICA	Residential building	No	No	No	No	Yes	Yes	Grid and RES	Matlab/Simulink	2 months	Reduction of 87.2% in the annual energy bill
[104]	2016	MAC	Residential buildings	Yes	No	No	No	Yes	No	Grid	Matlab	-	92% of the maximum energy savings compared to the baseline strategy
[21]	2016	ABC	Single room	Yes	No	No	No	Yes	No	Grid	EnergyPlus and Matlab	-	49.1–56.8% decrease in PPD compared to the traditional method
[29]	2016	EML	Residential building	Yes	No	No	No	Yes	No	-	EnergyPlus and Matlab	1 year	Prediction of energy and thermal comfort based on material thickness and insulation values
[105]	2017	FIS and ANN	Data center	Yes	No	No	No	Yes	No	-	Matlab	-	————
[106]	2017	FIS and ANN	Airport building	Yes	No	No	No	Yes	No	Grid	-	1 day	60% perfomance increase compare to conventional on/off controller
[107]	2017	CBR, k-NNA, and PSO	Residence building	Yes	Yes	No	No	Yes	No	Grid	-	-	————
[40]	2017	SVM	Dwellings	Yes	No	No	No	Yes	Yes	Grid and RES	CPLEX	2 days	82.97% performance improvement with respect to baseline strategy on weekend
[108]	2017	MAS and GA	Residential building	No	No	No	No	Yes	No	Grid and RES	JAVA	-	The developed model appears as an effective, smart and energy efficient solution to the problem of instantaneous power management in self-sufficient buildings
[109]	2017	Simulation	Hostel building	Yes	Yes	No	No	Yes	No	-	The Energy Guide II	1 year	————

Table 3. *Cont.*

Ref.	Year	Techniques Used	Building Type	Comfort Conditions				Energy	Dynamic Pricing	Supply Source	Simulation Tool	Data Duration	Result
				Th	Lt	AQ	RH						
[27]	2017	ANN and LMA	Commercial building	Yes	No	No	No	Yes	No	Gas for boiler	Matlab	6 months	20% reduction in gas consumption for given data duration
[110]	2017	MPC and LQT	Model house (Wooden)	Yes	No	No	No	-	No	-	Matlab and LabView	12 h	48% of energy savings compared to the constant temperature set-point control
[111]	2017	FRSC	Smart city	Yes	No	No	No	Yes	No	RES	-	12 months	————
[18]	2017	-	Residence building	No	No	No	No	-	Yes	Grid	GAMS	1 day	22.40% energy cost savings over the simulation period
[112]	2017	MBPETM	Office room	Yes	No	No	-	Yes	Yes	-	Matlab	2 days	PMV model is developed for indoor comfort management
[6]	2017	IoT	Commercial building	Yes	Yes	No	Yes	Yes	-	-	-	-	Investigation of IoT-based building energy management
[113]	2017	GRNN	Commercial building	-	-	-	-	-	-	-	Matlab	1 year	CO_2 emission analysis to predict future CO_2 emission in China

Th—Thermal, Lt—Lighting, AQ—Air Quality and RH—Relative Humidity.
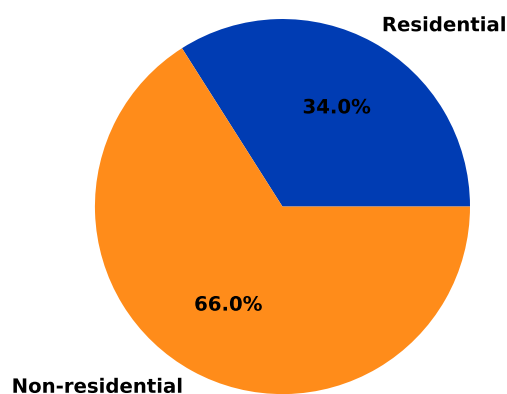
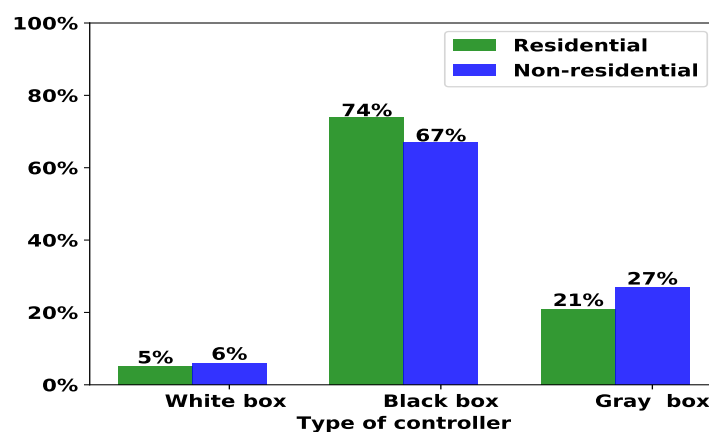**Figure 8.** Research conducted on type of building.

Figure 9. Controller application on both type of buildings.

In the context of comfort parameters, thermal comfort acquired more importance in both non-residential and residential buildings, whereas, other parameters are taken into consideration in few papers (Figure 10). This indicates the significance of thermal comfort in overall indoor comfort sensation and optimization of thermal energy leads great amount of overall energy consumption reduction in comparison to other comfort variables energy consumption optimization. There is a major lack in consideration of indoor air quality and lighting control. However, regulations and standards urge maintenance of CO_2 and luminance level in order to keep occupants good health and productivity, hence more research on this topic is necessary. Only 5% of the papers have developed controller for all four comfort parameters control. This shows the difficulties in implementation of controller for overall indoor comfort management.

Towards sustainable development, installation of renewable energies are important. This factor has also been considered in the literature review. The literature review highlights 16% and 23% renewable energies integration into non-residential and residential buildings, respectively (Figure 11). Most of RES integration is observed in smart grid and in big buildings context. The dynamic response in energy consumption by loads is an effective way of maintaining grid balance, grid durability, and cost optimization. Around 22% of non-residential and 25% of residential buildings have adopted DR. In Figure 12, it can be noticed the controller types used for DR application in both building types. Gray box modelling has higher implementation percentage because of the high flexibility for multi-objective optimization. Controllers used for RES integration are shown in Figure 13, where it should be noticed that black box models have higher percentage of implementation in residential buildings and gray box modelling in non-residential ones. This difference can be justified as follows:

(1) Gray box models are characterized by high accuracy and higher computational cost that limit their usage only for large buildings; while (2) black box models are characterized by high accuracy and lower flexibility of MIMO that limit their application to multi-objective optimization purpose. In the literature review, it had been found that black box models includes controllers such as fuzzy logic, artificial neural networks, genetic algorithms, decision trees, particle swarm optimization, reinforced learning, etc., while gray box models includes lumped capacitance model, model predictive controller, hybrid systems, etc.
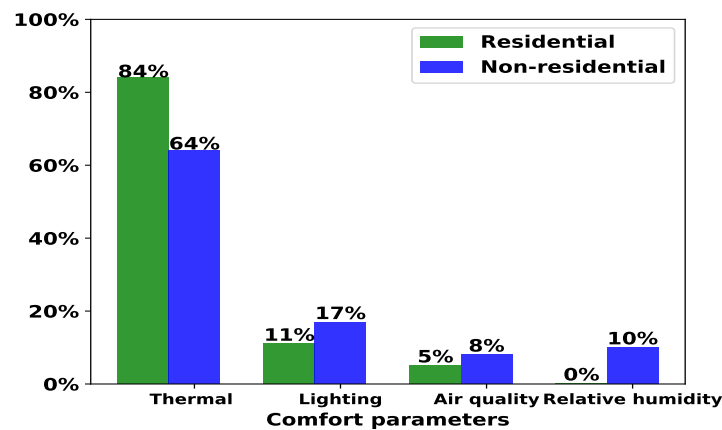
Figure 10. Controller application on comfort parameters.
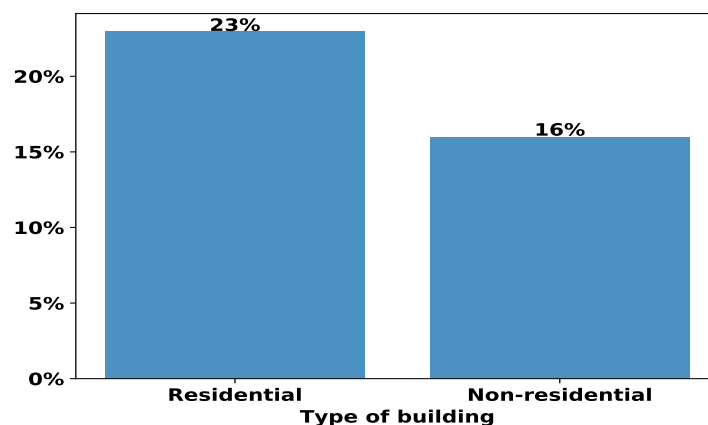
Figure 11. Renewable energy sources integration in both type of buildings.
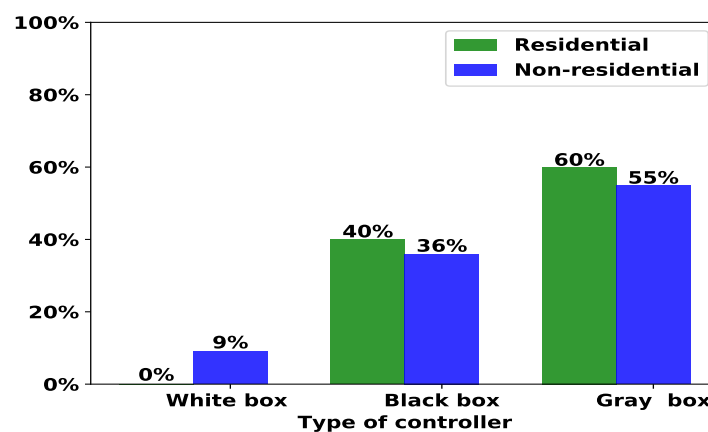

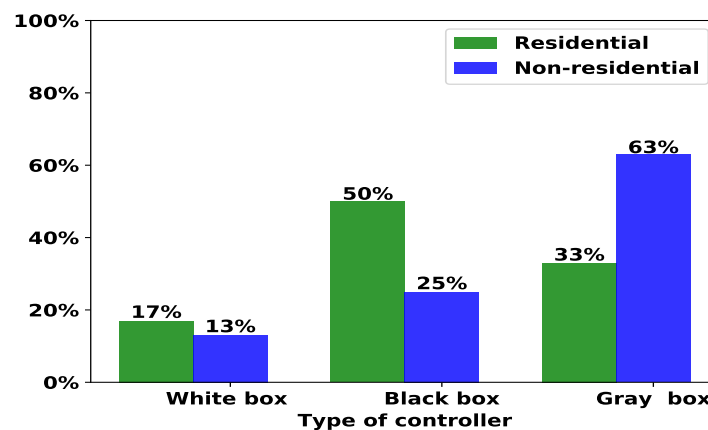**Figure 12.** Controller used for demand response application in non-residential and residential buildings.

Figure 13. Controller used for renewable energy sources integration in non-residential and residential buildings.

4. Conclusions

This paper has dealt with a state of the art review of recent developments on building energy and comfort management, and the related control. The carried out investigations includes explanation of conventional controllers and their up-gradation to the current challenging applications and new methods viz., black and gray box modelling. These models have been compared and critically reviewed on the basis of comfort conditions, RES integration, DR application, and building type. The proposed critical review will be useful for engineers and researchers in selection of suitable controller methods for BEMS model based on various conditions. In addition, the following observations, comments, and recommendations should be helpful.

- All the comfort parameters (thermal, visual, air quality, and relative humidity) need to be controlled in the building to ensure occupants' health and productivity. However, thermal comfort control remains dominant as the other parameters have a minimal impact on energy consumption. In addition, these parameters inclusion may introduce complexity in the controller model and leads to poor performance.
- White box models have been investigated as preliminary models for building energy performance analysis and were found to be used for low scale application. However, the white box application is restricted only for initial analysis and is not efficient to implementation due to its limitations.
- Black box models have high accuracy, low computational cost, and higher flexibility for building non-linearities. These models have gained significant attention in recent years. Constant developments of new algorithms ensures the improved efficiency and suitable for multi-objective applications. Nevertheless, these applications have restricted implementation due to lack of physics-laws explanation and huge amount of data is required for model training.
- Gray box models are found out to be more feasible for multi-objective optimization, predictive/adaptive, and cost-optimization applications, where design and computational time are high. This makes them not suitable for low scale applications.

Significant improvements can be noticed in intelligent controller for BEMS applications. The developments of new algorithms, and combination of various intelligent methods have ensured development of buildings towards sustainable environment. However, there is still lack of proper trade-off between energy and comfort parameters, thus further investigations in this area are still needed. The following are few future perspective points:

- Further research required on air quality and lighting parameters.
- Research efforts towards gray box models for residential buildings.

- Integration of RES into buildings still requires research efforts with feasible and uninterrupted energy supply.
- Dynamic response (dynamic pricing) for energy consumption is yet to be implemented in large scale applications.
- Development of new methods with IoT technologies will push towards more intelligent building models.
- Research efforts towards adaptive building controller models.

Author Contributions: All the authors contributed equally for elementary related research, papers selection, literature survey, discussions, and state of the art review of the paper.

Abbreviations

The following abbreviations are used in this manuscript:

ABC	Artificial Bee Colony
ABM	Agent-Based Modelling
AFLC	Adaptable Fuzzy Logic Model
ANFIS	Adaptive Neuro-Fuzzy Interference System
ANNs	Artificial Neural Networks
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BCHPs	Building Heating Cooling Power Systems
BCVTB	Building Controls Virtual Test Bed
BEMS	Building Energy Management System
BMS	Building Management System
BNs	Bayesian Networks
BPA	Back Propagation Algorithm
BRL	Batch Reinforcement Learning Model
BTO	Building TechNologies Office
CEBEMS	Cyber Physical System Enabled BEMS
CEMS	Centralised Energy Management System Framework
CEMS	Centralized Energy Management System
CPS	Cyber Physical Systems
DER	Distributed Energy Resources
DOE	Department of Energy
DR	Demand Response
DSM	Demand-Side Management
DTS	Dynamic Thermal Sensation
EEEC	European Energy Efficiency Commission
EKF	Extended Kalman Filter
EML	Extreme Machine Learning
EU	European Union
FFNNs	Feed Forward Back-propagation Neural Networks
FLC	Fuzzy Logic Controller
FRSC	Fuzzy Rough Set Controller
GAs	Genetic Algorithms
GMBA	Global Model Based Anticipative
GMM	Gaussian Mixture Regression Model
GPM	Gaussian Process Regression Model
GRNN	General Regression Neural Network
GUM	Guide to the expression of Uncertainty in Measurement
HMI	Human Machine Interface
HVAC	Heating, Ventilation and Air-Conditioning
ICA	Incremental Conductance Algorithm
IEA	International Energy Agency
IoT	Internet of Things
LMA	Levenberg-Marquardt Algorithm
LQT	Linear Quadratic Tracking
MAC	Multi-Agent Controller
MAS	Multi-Agent System
MBPC	Model-Based Predictive Control
MBPETM	Model Based Periodic Event-Triggered Mechanism
MCA	Monte Carlo Analysis
MIMO	Multi Input Multi Output
MLP	Multi Layer Perceptron

MOEA-GA	Multi-Objective Evolutionary Algorithms
MOGA	Multi-Objective Genetic Algorithm
MPC	Model Predictive Controller
NNARX	Artificial Neural Network with External Output
NREL	National Renewable Energy Laboratory
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA-II	Non-dominated Sorting Genetic Algorithm
PAB	Parameter Adaptive Building
PI	Proportional Controller
PID	Proportional Integral Derivative
PMV	Predictive Mean Vote
PPD	Predicted Percentage of Dissatisfied
PSO	Particle Swarm Optimization
RBFNs	Radial Basis Function Networks
RBM	Rule-Based Modelling
RC	Resistor Capacitor
RES	Renewable Energy Sources
RL	Reinforcement Learning
SA	Sensitivity Analysis
SVM	Support Vector Machine

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