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Review

Building Energy Prediction Models and Related Uncertainties: A Review

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Abstract: Building energy usage has been an important issue in recent decades, and energy prediction models are important tools for analysing this problem. This study provides a comprehensive review of building energy prediction models and uncertainties in the models. First, this paper introduces three types of prediction methods: white-box models, black-box models, and grey-box models. The principles, strengths, shortcomings, and applications of every model are discussed systematically. Second, this paper analyses prediction model uncertainties in terms of human, building, and weather factors. Finally, the research gaps in predicting building energy consumption are summarised in order to guide the optimisation of building energy prediction methods.

Keywords: building energy consumption; building energy prediction models; white-box models; black-box models; grey-box models; uncertainty analysis

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1. Introduction

The use of large amounts of fossil energy has caused serious environmental impacts, such as global warming and frequent extreme weather [1–3]. The building industry, in particular, consumes vast amounts of energy. For example, in 2021, the building industry accounted for 39% of total energy consumption in the US, and residential buildings accounted for around 40% of all building energy consumption in the European Union [4–6]. In addition, energy consumption in the building sector will continue to grow due to increasing urbanisation in a number of countries.

With such a serious fossil energy problem in buildings, many studies have intended to find ways of decreasing building energy usage by focusing on advanced controls and renewable energy applications [7–9], and building energy prediction models are used to advance these building technologies. There are three types of models: white-box, black-box, and grey-box [10]. Building energy prediction models can broadly be defined as physics-based mathematical approaches. In the early stages of development, building energy prediction models were mostly used in building energy simulations (i.e., white-box models) [11]. With the development of machine learning algorithms, another kind of building energy prediction model began to be used more widely, namely the data-driven approach, also called the black-box approach [12]. Then, the grey-box approach, which combines elements of both white-box and black-box approaches, was developed [13].

These three building energy prediction models have advantages and shortcomings. First, the white-box models, also called the physics-based models, are based on the conservation of matter and energy. The simulation results of the white-box models are more explainable than those of the other two models [14]. However, due to the many inputs required, it is difficult to collect the required building parameters in sufficient detail [15,16]. Second, the black-box model approach is data driven. Black-box models use collections of historical data related to building energy consumption. Therefore, one of the disadvantages of the black-box model is that it requires high-quality data sets. Missing data and errors can directly reduce the accuracy of these models. However, these models also have many advantages. For example, they are highly adaptable and can be constantly updated and optimised as new data are entered [17,18]. The grey-box model is a combination of both white-box and black-box models. The grey-box models are explainable in terms of physics, simplify the calculation process, and improve prediction efficiency [19,20].

Uncertainties in existing building energy prediction models can be divided into three kinds: human, building, and weather factors. Many human factors have been studied in recent years; these consist of many varied aspects, including people's perceptions and evaluations of the environment, as well as habits and physiological condition. These factors are related to energy consumption and cannot be accurately predicted. For example, the usage frequency of heating appliances by occupants in residential buildings is decided by the occupants' physical condition, habits, and occupations. It is, therefore, difficult to develop a schedule for all building occupants [21,22]. Building factors have been analysed since the development of white-box models. These factors have the greatest impact on the overall building energy efficiency. They include the building type, orientation, and envelope parameters and the use of heating, ventilation, and air conditioning (HVAC) systems. In recent energy efficiency studies, researchers studied the effects of envelope parameters, such as wall materials, wall hygrothermal parameters, window types, window layers, and applications of HVAC systems [23,24]. Some envelope parameters change according to the temperature and relative humidity, so there are some uncertainties when modelling without taking such changes into account [25]. As HVAC systems are, to some degree, affected by occupant activities, there are also uncertainties regarding HVAC systems [26]. Because of the changeable nature of the weather, it cannot be accurately predicted and therefore causes uncertainties around energy use in buildings [27].

The goal of this study is to provide a comprehensive review of the three kinds of building energy prediction models and the uncertainties that influence their effectiveness. Section 2 will introduce the white-box models and compare various commonly used simulation tools. Section 3 will study the black-box models, and the grey-box models will be introduced in Section 4. Prediction uncertainties and possible optimisation strategies for each prediction model will be presented in Section 5, and the conclusions will be drawn in Section 6.

2. White-Box Models

White-box models are also called physics-based approaches or engineering approaches. The calculation of white-box models is based on the principles of heat transfer. In other words, white-box models can estimate energy usage in the building sector without requiring any previous data. Instead, the application of white-box models requires an awareness of the overall physical properties of buildings. Many factors affect the thermal performance of a building, including indoor and outdoor temperatures, relative humidity, thermal resistance, and surface area. In particular, a building's thermal performance is influenced by the thermal inertia effect of the building materials used in its construction, which leads to thermal hysteresis [28]. In general, developing white-box models requires adequate information, such as meteorological, building, and occupant parameters [11]. Nevertheless, white-box models are still the most commonly used building energy prediction models due to the popularity of the related software packages and their ease of use [29]. Published studies related to white-box models are summarised in Table 1.

Table 1. Studies related to white-box building energy prediction models.

Year	Tool	Building Type	Purpose of Prediction	Reference
2012	TRNSYS	Residential	Building energy consumption	[30]
2012	IDA ICE	All types	Heating and cooling loads	[31]
2013	EnergyPlus	Office	Energy demands and potential savings	[32]

Table 1. *Cont.*

Year	Tool	Building Type	Purpose of Prediction	Reference
2013	IDA ICE	Residential	Energy performance of low-temperature hydronic heating system	[33]
2014	EnergyPlus	Buildings with double-skin façades	Thermal simulation	[34]
2015	EnergyPlus	All types	Building energy use in several climate conditions	[35]
2015	TRNSYS	All types	Building energy consumption	[36]
2015	IDA ICE	All types	Energy use in the highly glazed spaces	[37]
2015	IDA ICE	Commercial	Building energy consumption	[38]
2016	TRNSYS	Educational	Heating and cooling loads	[39]
2017	EnergyPlus	Buildings with vertical greenery systems	Building energy consumption	[40]
2017	EnergyPlus	Office	Energy demand for cooling systems	[41]
2017	IDA ICE	All types	Energy demand for heating systems	[42]
2017	TRNSYS	All types	Building energy consumption	[43]
2018	EnergyPlus	Residential	Energy-use intensity	[44]
2018	EnergyPlus, IDA ICE, TRNSYS, Dymola	All types	Comparing the accuracy of different tools	[45]
2019	EnergyPlus	Residential and commercial	Energy consumption of HVAC systems	[46]
2019	EnergyPlus	Office	Energy consumption of HVAC systems	[47]
2019	IDA ICE	Residential	Building energy consumption	[48]
2019	Dymola	Office	Building electricity flexibility	[49]
2020	EnergyPlus, IDA ICE, TRNSYS	All types	Comparing the accuracy of different tools	[16]
2020	EnergyPlus	All types	Energy use of buildings with semi-transparent photovoltaic modules	[50]
2020	EnergyPlus	Buildings with adaptive facades	Energy implications of adaptive facades	[51]
2020	TRNSYS	Solar greenhouse	Transient heating requirement	[52]
2020	IDA ICE	Residential	Building energy consumption	[53]
2021	EnergyPlus	Commercial	Energy consumption of HVAC systems	[54]
2021	EnergyPlus	All types	Building energy consumption	[55]
2021	EnergyPlus	Residential	Building energy consumption	[56]
2021	TRNSYS	Residential	Energy use of near-to-net-zero energy buildings in a hot and dry climate	[57]
2021	TRNSYS	Public	Energy demand for heating systems	[58]
2021	TRNSYS	Street canyon	Building energy demand	[59]
2021	IDA ICE	Hotel	Building energy consumption	[60]
2022	EnergyPlus	Office	Energy demands of ventilation systems	[15]
2022	EnergyPlus, IDA ICE, TRNSYS	Urban building cluster	Urban-scale energy analysis	[61]
2022	TRNSYS	Residential	Building energy consumption	[62]
2022	TRNSYS	Residential	Energy use of domestic hot water systems	[63]
2022	IES VE	Residential	Building energy consumption	[64]

2.1. Existing Tools

Several commercial and open-source software tools are available for modelling building energy consumption using white-box models. These tools all follow physical heat transfer rules but have some subtle differences. Some of the tools are nodal-approach software packages, such as EnergyPlus and TRNSYS. EnergyPlus uses a one-dimensional nodal approach [12]. A node can represent multiple architectural elements, including figurative and abstract architectural elements. Figurative building elements include rooms and corridors. Abstract building elements include air conditioning loads and heat dissipated by occupants. The principle of TRNSYS is also based on the nodal approach. However, TRNSYS uses graphs to simulate heat transfer and is mostly used to predict thermal and electrical energy usage. TRNSYS consists of two parts: the engine and the component library. The engine processes the input parameters for the calculation. The component library provides approximately 150 models, such as multizone buildings, weather data processors, and basic HVAC equipment. In a different approach from EnergyPlus and TRNSYS, the IDA Indoor Climate and Energy (IDA ICE) software focuses directly on mathematical equations instead of using FORTRAN, C subroutines, block diagrams, or spreadsheets. By using a combination of intelligent computer algebra and numerical methods, models based on symbolic equations can be solved with comparable performance to special-purpose simulators.

In terms of accuracy, there are some differences in white-box tools regarding particular details in building energy simulations [65]. For example, when simulating glazing surface temperatures, IDA ICE has a higher rate of accuracy than other white-box tools, such as EnergyPlus, TRNSYS, and IES. However, IDA ICE has a lower accuracy rate when simulating glazing surface heat flux. When simulating air gap temperatures, TRNSYS and IDA ICE are more accurate than EnergyPlus. These subtle variations may be due to differences in the tools' methods to calculate convective heat transfer correlations. EnergyPlus uses an adaptive convection algorithm; IDA ICE uses a ventilated window model; and TRNSYS uses an internal calculation method.

In terms of the scope of application, all white-box tools can simulate the energy consumption of one or several buildings of different types, including office, residential, and commercial buildings. Boyano explored the energy-saving potential of office buildings using EnergyPlus, and the results confirmed that the building orientation is closely related to energy usage [32]. Eddib chose a property in Tangier to evaluate a flat's energy consumption using TRNSYS 16 software. The results were then used to predict the energy usage of both heating systems in winter and cooling systems in summer [43]. Chen presented a method for quantifying the flexibility of electricity supply and demand in office buildings using the Dymola platform. The results revealed that, to a substantial extent, the flexibility of an electricity supply and demand in a typical office building originates from both HVAC systems and occupant behaviour [49]. Both EnergyPlus and TRNSYS are also suitable for evaluating urban-scale building energy consumption. Single building models are simplified on the urban scale but still give reliable results [61]. Martin used EnergyPlus to compare the accuracy of simplified and detailed models. The results showed that the detailed model was more accurate in different urban microclimates [41]. Adnane created an integrated method using TRNSYS and completed a case study in a street canyon in Tangier, Morocco. The findings revealed that in street canyons, the external walls of buildings absorb more radiation, which causes higher cooling demands and lower heating demands [59]. Moreover, it is worth noting that EnergyPlus has been used to simulate energy consumption over long time scales, such as a month or year [66]. For example, Shabunko used EnergyPlus to simulate the annual energy usage of 400 residential buildings in Brunei. The maximum value of annual energy usage was 62.4 kWh/m^2, and the minimum value was 48.9 kWh/m^2 [44].

According to existing studies, compared with both EnergyPlus and TRNSYS, the simulation results from IDA ICE are more reliable when simulated objects include phase change materials [16]. It has been shown that IDA ICE can be applied in the modelling of glazed spaces. When accurate information about the windows is entered, IDA ICE can calculate relatively accurate results. Hilliaho measured data from a bedroom and a living room in Tampere, Finland. Then, IDA ICE was used to develop models with a series of necessary parameters that included the thermal conductivity of the wall materials, the window sizes, the window material parameters, and the window opening times. The simulated results were determined to be close to the measured data [37].

2.2. Advantages and Shortcomings of White-Box Models

White-box building energy prediction models have four advantages: interpretability, high accuracy, universality, and no requirement for historical data. First, all white-box models are based on the principles of physics, so the relationship between inputs and outputs can be explained. Second, white-box prediction models can be very accurate as long as all important parameters have first been collected. Third, white-box models have universality. Most white-box modelling tools are suitable for various buildings and even on an urban scale. Finally, these building energy simulations have the advantage of not requiring the collection of historical data as a basis for modelling. For example, in EnergyPlus, a virtual building can be simulated as long as the building information is known (including space dimensions and building material parameters).

However, there are three drawbacks to consider. First, gathering building information is challenging. More data must be collected if many structures are to be simulated at the same time. Not only does it take a lot of time to collect the data, but it becomes unrealistic to acquire complete information on all buildings through field studies. Although remote sensing techniques can offer comprehensive geometric building information and allow for the visualisation of building distribution, it is not possible to add occupant characteristics data [67]. Second, due to occupant behaviour, prediction errors are difficult to avoid. The use of a timetable to define occupant behaviour is common. However, the actual schedule of residential behaviour is frequently unpredictable and haphazard. The energy consumption of occupants is influenced by elements such as thermal comfort requirements, weather, building area, occupant density, and economic considerations. As a result, there is a discrepancy between the actual and the theoretical energy usage [68]. Third, it is difficult to add precise meteorological parameters due to the randomness of the weather. Many types of meteorological parameters, such as the test reference year, are currently employed in model development. Meanwhile, the micro-weather environment has a stronger influence on regional building energy usage. Micro-weather changes can be caused by a variety of variables, including changes in urban greenery and waterscapes. As a result, utilising focused meteorological factors to forecast the energy use of different buildings in an area or city will result in a degree of deviation [69].

3. Black-Box Models

Black-box models are also called data-driven models. The core aim of building a black-box model is to find the mathematical connections between independent parameters and target variables based on historical data [70]. In building energy prediction, there are three kinds of common independent parameters: (1) time-series parameters relating to occupant behaviour and equipment operation schedules; (2) weather parameters relating to air temperatures and humidity; and (3) building parameters relating to building types and materials. Common target variables are building energy consumption [71]. Because of the increasing availability of building energy consumption data sets and lower building parameter requirements, black-box models have become effective methods of predicting energy usage [72]. Some types of black-box models are popular. For example, multiple linear regression (MLR) models are the simplest and most intuitive black-box models for building energy prediction. The long development time and relative ease of learning have led to MLR models being used widely. SVMs can establish a nonlinear relationship between input and output based on a small amount of data, and artificial neural networks (ANNs) are popular for finding nonlinear relationships in big data sets, leading to many researchers choosing to use these models for building energy prediction. In this section, these three black-box model types will be introduced in detail, and other important black-box models will also be briefly described.

3.1. Multiple Linear Regression (MLR)

In 1886, Galton proposed MLR to describe the linear connection between several independent parameters and target variables, as shown in Equation (1) [73]

$$y = a_1x_1 + a_2x_2 + \ldots \cdot + a_ix_i + \cdot \ldots \cdot + a_nx_n + \varepsilon \qquad I \in [1, n] \tag{1}$$

where y represents the target variable (e.g., building energy consumption); x_i refers to the relevant independent parameters (e.g., air temperature, wind speed and direction, building operation schedules, and building materials); a_i represents the regression coefficient of the input variables; n represents the dimension of the input variables; and ε represents random errors. MLR models have been used widely because of their simplicity and good prediction performance. Ciulla built several MLR models to study the factors related to building energy usage. These thorough and calibrated dynamic models can solve the energy performance of 195 different situations [74]. Walter developed an MLR model using several parameters (e.g., operational hours, the number of pieces of HVAC equipment and occupant density) to estimate building energy consumption [75]. Mastrucci presented an MLR model based on a geographic information system (GIS) to predict building energy consumption. This model allowed for the downscaling of the measured energy usage to every building according to parameters such as space type, building area, and occupant density, and the energy usage was then distributed to different final uses. The results could provide suggestions for urban energy planning [76].

However, there are some shortcomings in MLR models. First, MLR models struggle to achieve highly accurate results, particularly in predicting the energy used by HVAC systems, as nonlinear factors such as weather and scheduling impact them [77]. Second, MLR models may overfit, leading to inaccurate results. Various MLR shrinkage strategies have been studied in order to improve the accuracy of predictions through the imposition of limits on coefficient values [78,79]. Published building energy prediction studies related to MLR models are summarised in Table 2.

Table 2. Studies related to MLR models.

Year	Purpose of Prediction	Building Type	Input Parameters	Reference
2012	Energy efficiency	Commercial	Building age, floor area, operation schedule, number of customers, occupant behaviours	[80]
2015	Energy consumption	Commercial	Seventeen parameters (related to external walls, orientation, and occupant schedules)	[81]
2017	Heating load	Rural residential	One hundred and eighty-one parameters (related to occupant information, building features, building envelope parameters, and indoor conditions)	[82]
2018	Energy consumption	Residential	Seventeen parameters (related to weather, building features, and HVAC systems)	[83]
2019	Cooling and heating load	All types	Cooling degree days, heating degree days, internal gains, window size, and façade U-values	[74]
2019	HVAC electricity use	Commercial	Outdoor temperature, relative humidity, global radiation, and operating modes	[84]

Table 2. *Cont.*

Year	Purpose of Prediction	Building Type	Input Parameters	Reference
2020	Heating load	Air-conditioned rooms	Seventeen parameters (related to thermal parameters of walls and windows and weather)	[85]
2021	Energy consumption	Educational	Location, air-conditioning capacity, building features, type of school, staff and student density, building age, and number of classrooms	[86]
2021	Energy consumption	Residential	R-values for the attic and walls, seasonal energy efficiency ratio, and heating seasonal performance factor	[87]
2021	Energy consumption	Residential	GDP, climate zone, urban density, electricity connection rate, family size, population, and building stock	[88]
2022	Building operational energy	Commercial	U-values of external walls, lighting power density, shading coefficient, building shape factor, and window-to-wall ratio	[89]
2022	Electricity use	Healthcare	Temperature, humidity, wind velocity and direction, radiation, and floor area	[90]
2022	Future weather metrics and energy demand	Office	Global horizontal radiation, cooling degree days, and heating degree days	[91]
2022	Energy consumption	Residential	Family size and building, sociodemographic, and household appliance-use characteristics	[92]

3.2. Support Vector Machine (SVM)

An SVM is a kind of machine learning method developed by Vapnik three decades ago [93]. It can analyse data for classification and regression analysis. When SVM models are used for classification, they can be called support vector classification (SVC) models. SVC models can build non-probabilistic classifiers based on the characteristics of the training examples being classified. Then, new examples can be classified. SVM models can do both nonlinear and linear classifications [94]. When SVM models are used for regression, they can be called support vector regression (SVR) models [95]. SVR models allow the data sets to be described by a specific equation, shown in Equation (2).

$$f(x_i) = < \omega,\ \varphi x_i > + b \qquad (2)$$

Where f(x) is the output; x_i is the input; φ is a parameter in the high-dimensional feature space; and <,> is a scalar product. ω and b are the adjustable factors determined by the target variables. In the SVM models related to building energy prediction, the selection of kernel functions affects the accuracy of results. The common kernel functions are linear, radial basis, and Gaussian.

SVM models are suitable for the prediction of energy usage in buildings because of their superiority in solving nonlinear problems. These models have been applied to macro perspective building energy prediction within a region or country. Ma presented an SVM model for the prediction of building energy usage in China. Ma's SVM model used a variety of inputs, including meteorological data such as annual temperature, wind direction and speed, relative humidity, and solar radiation, as well as economic parameters such as the rate of urbanisation and gross domestic product (GDP). Finally, the results of the prediction model were compared with the statistical data of 30 Chinese provinces, and the high accuracy of the model was demonstrated [96]. The SVM model can also predict the energy consumption of certain types of buildings from a micro perspective. Shao created an SVM model to study and analyse energy usage in public buildings. This model used weather parameters and HVAC system operation parameters. The results suggested potential improvements to public building usage patterns [97]. Jain built a sensor-based SVR model and applied it to a residential building in the US. The results showed that the most accurate energy predictions were achieved when the frequency of detection was once per hour per floor [98]. The published building energy prediction studies related to SVM models are summarised in Table 3.

Table 3. Studies related to SVM models.

Year	Building Type	Kernel Function Type	Input Parameters	Reference
2014	Residential	Radial basis kernel	Twenty-one parameters (related to weather and operation schedule)	[98]
2017	All types	Linear kernel	Climate conditions, building characteristics, and occupancy information	[99]
2017	Public	Radial basis kernel	Nine parameters (related to weather and operation schedule)	[100]
2018	All types	Radial basis kernel	Outdoor dry-bulb temperature, relative humidity, global solar radiation, ratio of urbanisation, gross domestic product, household consumption level, and total structure area	[96]
2018	Public	Gaussian kernel	Dew point temperature, wind direction and velocity, outdoor temperature, precipitation, relative humidity, school holiday time, and working time schedule	[101]
2019	Residential	Radial basis kernel	Barometric pressure, dry-bulb temperature, relative humidity, wind speed and direction, indoor temperature, and relative humidity	[102]
2019	All types	Radial basis kernel	Eight parameters (related to weather, economy and building area)	[103]
2020	Hotel	Radial basis kernel	Weather parameters and operating parameters of air-conditioning system	[97]
2020	Public	Gaussian kernel	Eleven parameters (related to historical energy consumption data, and weather and time-cycle factors)	[104]
2022	Residential	Radial basis kernel function	Twenty-four parameters (related to weather, building characteristics, and HVAC systems)	[105]

3.3. Artificial Neural Network (ANN)

An ANN is a nonlinear mathematical algorithm model that deals with data using a structure similar to biological neural networks. The neuron, or processing unit, is the fundamental component of an ANN. There are three interconnected layers made up of neurons in an ANN model, including input, hidden, and output layers. The hidden layers can have several sub-layers, according to the complexity of the task (as shown in Figure 1). The general formulation of an ANN is shown in Equation (3)

$$f(x_i) = \sigma\,(\omega x_i + b) \tag{3}$$

where ω and b are the weight and bias, respectively; x_i is the independent input; $f(x_i)$ is the neuron output; and σ is the activation function. The advantages of ANN models include less data being required and less time being consumed to obtain reliable prediction results. In particular, ANN models have a great advantage in predicting nonlinear relationships. However, the information in the hidden layers is difficult to interpret using the principles of physics. It is also difficult to determine the effects of every variable on energy usage totals.

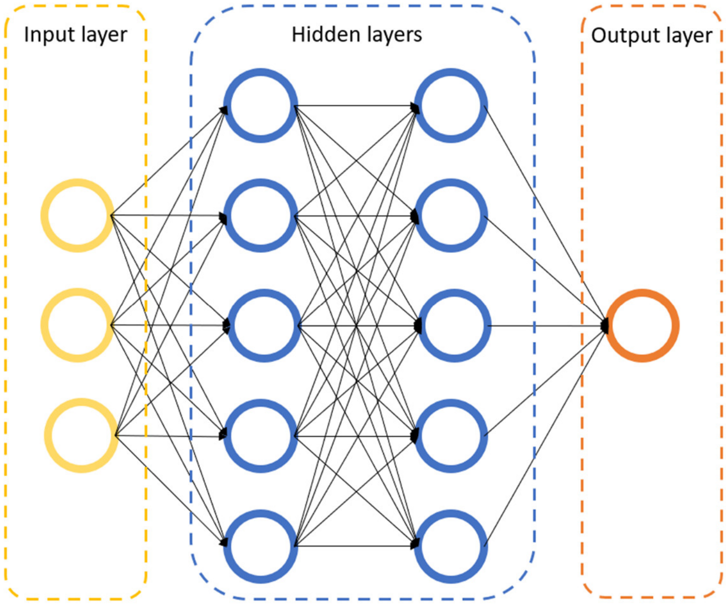

Figure 1. The ANN structure.

ANN models have been applied in building energy prediction from the 1990s onwards. Elbeltagi created an ANN model to enhance the prediction of energy usage in residential buildings before construction. This ANN model was developed using a data set generated by simulating several building design solutions [106]. To find a balance between energy consumption and the environment, D'Amico proposed ANN models based on a data set of building complexes. The data set included 29 independent parameters (13 energy parameters and 16 environmental parameters) and seven outputs (one for energy demand and six for building life cycle assessment metrics). The result of each output demonstrated high accuracy, with an average absolute error of less than 5% [107]. Deb used a variety of black-box models to predict the energy-saving potential of office buildings. The data were obtained from 56 office buildings, and the results showed that the ANN model was the most accurate, with an average absolute error of 14.8% [108]. Published building energy prediction studies related to ANN models are summarised in Table 4.

Table 4. Studies related to ANN models.

Year	Building Type	Model Characteristics	Input Parameters	Reference
2005	All types	Feedback ANN	Outdoor temperature, schedule of work, occupation level, and environmental variables	[109]
2005	All types	Adaptive ANN	Outdoor dry-bulb temperature, outdoor wet-bulb temperature, the temperature of the water leaving the chiller, and chiller electricity demand	[110]
2009	All types	Backpropagation neural network	Building transparency ratio, insulation thickness, and orientation	[111]
2018	Educational	ANN and teaching learning-based optimisation algorithm	Wind speed, solar radiation, humidity ratio, outdoor dry-bulb temperature, and operational hours	[112]
2018	Office	ANN with appropriate variables	Fourteen parameters (related to building area, air-conditioning energy consumption, operational hours, and chiller plant efficiency)	[108]

Table 4. *Cont.*

Year	Building Type	Model Characteristics	Input Parameters	Reference
2019	All types	ANN and hybrid particle swarm optimisation models	Weather, photovoltaic/thermal systems, and building parameters	[113]
2019	Office	Multi-layer perceptron neural network	Twenty-nine parameters (related to energy and environment)	[107]
2020	Office	ANN and genetic algorithm	Wall U-values, equipment load rate, lighting density, infiltration rate, number of people, and roof U-values	[114]
2020	Residential	ANN and electromagnetism-based firefly algorithm	Relative compactness, surface area, wall area, roof area, overall height, orientation, and glazing area and distribution	[115]
2021	Office	Zone-level ANN	Outdoor and indoor temperature of thermal zones, the temperature difference between inlet and outlet at the ground source side of ground source heat pumps and occupancy status	[116]
2021	Residential	ANN and metaheuristic algorithm	Location, weather, air conditioning conditions, and building envelope parameters	[117]
2021	Residential	Backpropagation neural network	Seventeen parameters (related to weather, building characteristics and HVAC systems)	[106]
2022	All types	Elastic weight consolidation-based ANN	Time variables (hour, month, and day types), outdoor air temperature, and outdoor air relative humidity	[118]
2022	Residential	Multi-layer perceptron neural network	Relative compactness, surface area, roof area, wall area, orientation, overall height, glazing area, frame, and sash	[119]

3.4. Other Black-Box Models

Some other black-box models, such as random forests (RF), extreme gradient boosting (XGBoost), and recurrent neural networks (RNN), are suitable methods for building energy prediction models as well. These three models will be introduced in this section. RF is a black-box model that is based on decision tree models. The prediction results of RF are based on the average prediction results of several decision tree models. Each decision tree model is developed based on a random sample of the data that have been collected. To some extent, this modelling approach reduces overfitting and has been used to investigate the optimal thermal parameter values for the external walls of buildings in cold regions. The results showed that the U-values of external walls and the window-to-wall ratio were the factors that had the greatest impact on building energy usage [120]. XGBoost was developed relatively late and has been used less in predicting building energy usage. Different from the RF model, in which several decision tree models are not sequential, XGBoost adds predictors in a certain order. Yan used the XGBoost model to study the energy performance of public buildings in temperate areas. The energy prediction results achieved an accuracy of 0.77 [121]. RNNs are important types of ANNs that are built on time-ordered data sets. In RNNs, current input data can influence the future input and output data. Therefore, RNNs are suitable for building energy predictions over time. Li proposed an RNN-based building energy prediction system using data sets gathered from a commercial building. Compared to other ANNs, the RNN model showed a certain degree of interpretability and a high degree of accuracy [122]. Published building energy prediction studies related to these three black-box models are summarised in Table 5.

Table 5. Studies related to RF, XGBoost, and RNN models.

Model Type	Year	Building Type	Input Parameters	Reference
RF	2016	Residential	One hundred and seventy-one parameters (related to building, economy, education, environment, households, surroundings, and transportation)	[123]
	2017	Commercial	Thirty-six parameters (related to weather, occupant behaviours, and HVAC systems)	[124]
	2017	Hotel	Ten parameters (related to weather, time, the number of guests, and rooms booked)	[125]
	2018	Educational	Eleven parameters (related to meteorology, occupancy, and time)	[126]
	2018	All types	Eighteen parameters (related to heating, cooling, and shading systems)	[127]
	2021	Educational	Heat transfer coefficient and solar radiation absorption coefficient of exterior walls and roof, comprehensive heat transfer coefficient of windows, and window–wall ratio	[120]
	2021	Public	Forty-seven parameters (related to building construction, heating, cooling, and occupational attributes)	[128]
XGBoost	2020	Residential	Ten parameters (related to weather and HVAC systems)	[129]
	2020	Intake tower	Twelve parameters (related to time and building)	[130]
	2020	Healthcare	Ten parameters (related to weather, occupant, time, and air conditioning systems)	[131]
	2020	Residential	Eleven parameters (related to settings by occupants, indoor environment, time, and energy-use modes)	[132]
	2021	Residential	Twelve parameters (related to weather and building age)	[133]
	2021	Public	Forty-three parameters (related to weather, basic building features, building envelope, building services and energy systems, operation and maintenance, occupants, and indoor thermal environment)	[134]
	2022	Office	Sixteen parameters (related to weather and building)	[121]

Table 5. *Cont.*

Model Type	Year	Building Type	Input Parameters	Reference
RNN	2018	Public	Dew point temperature, wind direction and velocity, outdoor temperature, precipitation intensity and quantity, relative humidity, school holiday time, and working time schedule	[101]
	2019	Educational	Time parameters, outdoor environment, and operating conditions of chiller plants	[135]
	2019	Exhibition hall	Indoor environment and visitor numbers	[136]
	2020	Solar house	Outdoor temperature, relative humidity, irradiance, indoor CO_2 level, indoor temperature, and reference temperature set by user	[137]
	2021	Commercial	Solar radiation, relative humidity, outdoor dry-bulb temperature, and type of day	[122]
	2021	Public	Eleven parameters (related to weather, occupants, indoor environment, and HVAC systems)	[138]
	2022	Commercial	Temperature, humidity, solar radiation, wind speed, and air conditioning load	[139]
	2022	Public	Building and weather parameters and pattern data for energy consumption	[140]
	2022	Educational	Weather conditions, occupancy behaviour, and operating schedules of lighting and air conditioning systems	[141]
	2022	Residential	Boundary conditions, chronological information, observations	[142]

3.5. Advantages and Shortcomings of Black-Box Models

Compared with white-box models, there are unique advantages to black-box models. For example, when detailed information about test buildings is not available, black-box models based on historical data are suitable solutions for analysing energy consumption [29]. According to the types of data and building operation, both linear and nonlinear models can be applied [143]. Due to black-box models being built based on actual data, stochastic factors related to building energy consumption can be considered, such as the effects of building material parameter inaccuracy and occupant behaviour randomness.

However, there are limitations to black-box models due to an over-reliance on data. There are particular requirements not only for data amounts and accuracy but also for the data types. First, it is difficult to determine which types of data are decisive in black-box models. Data types in the available data sets are limited, and some types of data that may affect building energy consumption are not in the available data sets. Moreover, the black-box models cannot be explained by the principles of physical heat transfer. In this case, if the model does not include all the key types of data, the accuracy of the model can be compromised. Secondly, due to the limited amount of data within the available data sets, the black-box models may be inaccurate when using additional data from the same study objects. Although a small part of data (such as 20%) is used to validate the model's accuracy during the modelling process, the model's validity for the additional data is still not completely certain due to the key factors that cannot be determined [144]. Third, it is difficult for black-box models to be universal. Every black-box model is based on different data sets, including different types of data. Therefore, black-box models are difficult to apply to buildings when the types of data in the available data sets are not standardised [145].

4. Grey-Box Models

The principles of white-box models are mass, energy, and momentum conservation. Because there are too many model parameters, building an accurate model is challenging. In particular, when the simulated object is a block of buildings, the process of collecting data takes a long time. Black-box models are based on data-driven techniques. In order to train the model and achieve accurate predictions under various scenarios, sufficient data and adequate algorithms are necessary. However, resources of high-quality public data sets are limited. Furthermore, black-box models are not explainable. Grey-box models have been created to tackle these shortcomings. Grey-box models are easier to understand than black-box models and simpler to calculate than white-box models.

4.1. Existing Models

According to existing studies, resistance–capacitance (RC) models are the most common grey-box models [13]. Other grey-box models have no fixed pattern or name and are developed based on specific research questions. RC models have been developed since 1985 [146], and the determination of parameters in these models can rely on either data from experiments or simulations from physical models. In order to describe the model clearly, RC models can be written as '**xRyC**', where **R** represents thermal resistance; **C** represents thermal capacity; and **x** and **y** represent the numbers of **R** and **C,** respectively. Determining the R and C values is the most significant process during the building of RC models. An RC model of a general single-pane window can be recorded as 1R0C because thermal conduction of the window is an important factor and thermal storage of the window is insignificant (as shown in Figure 2). A single-layer wall is commonly recorded as 2R1C because there is heat convection on both inner and outer wall surfaces as well as heat conduction through the wall (as shown in Figure 3) [147]. The parameters used in RC models are shown in Table 6. There are three kinds of tools that can be used to create RC models: MATLAB, Modelica, and multi-functional programming tools (e.g., Python and C++) [148].

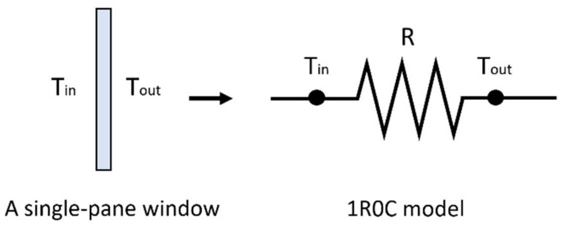

Figure 2. RC model for a general single-pane window.

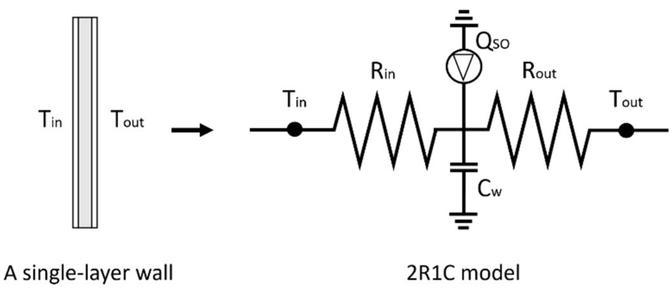

Figure 3. RC model for a single-layer wall.

Table 6. Physical parameters in RC models.

Abbreviations	Physical Parameters
T_{in}	Indoor temperature
T_{out}	Outdoor temperature
R_{in}	Thermal resistance of the inner surface
R_{out}	Thermal resistance of the outer surface
C_w	Thermal capacity of the wall
Q_{so}	Heat gain from radiation

RC models can be utilised to analyse the heat dynamics of variable building materials, including traditional and innovative building materials. Gao built a series of RC models to simulate the thermal properties of building phase change materials. Compared with other RC models, the 4R2C model required fewer parameters and was more accurate [149]. In terms of building automation and control, RC models are effective tools in this domain as well. Yang developed an indoor environmental prediction system using an RC model. The system could be used to optimise multiple objectives in real time. The automatic controller based on this system could save 19.4% of energy usage compared with a traditional ON/OFF regulation [150]. Due to their capability for fast load calculations, RC models are also used for district and urban energy modelling. For example, Bueno created an RC model for the prediction of urban building energy usage that was used to study urban thermal effects on the energy consumption of buildings [151].

Other grey-box models are a combination of both physics-based methods and data-driven methods. These grey-box models have received increased attention in recent years and have high development potential. Li developed physical models of urban building complexes and their energy supply systems. Ten machine learning models were used to predict the intensity of energy usage, and the proposed grey-box model could be applied to rapidly predict the energy consumption of building complexes [152]. To examine the influence of retrofit initiatives on multi-scale energy consumption, Nutkiewicz built a grey-box model by extending the integrated simulation and data-driven urban building energy modelling framework. Twenty-nine buildings in the US were used to validate this grey-box technique. The study found that taking the urban environment into account, the effects of retrofits on energy consumption of individual buildings could increase by 7.4% [153]. Amasyali developed a grey-box model for the prediction of energy usage based on occupant behaviour. This model included two parts: (1) the creation of machine learning models that predicted the impacts of both climate and occupant behaviour; and (2) a hybrid model that predicted building energy usage according to the results from the machine learning models. The grey-box model was tested using an actual data set obtained from a public building in the US [154]. Published studies related to grey-box models are summarised in Table 7.

Table 7. Studies related to grey-box building energy prediction models.

Year	Model Type	Research Subject	Reference
2014	RC model (6R2C)	Thermal performance of office buildings	[155]
2016	RC model (3R2C)	Modelling of building energy system	[156]
2016	RC model (3R2C)	Simplified thermal model	[157]
2016	RC model (5R1C)	Energy prediction of buildings with double-skin façades	[158]
2017	Grey-box model (based on machine learning and RC model)	Energy prediction of small-size buildings	[159]
2017	RC model (2R1C)	Thermal performance of concrete floors	[160]
2017	RC model (5R4C)	Cooling systems in residential buildings	[20]
2017	RC model (4R3C)	The thermal effects of adjacent walls on energy consumption	[161]
2018	Grey-box model (based on machine learning and RC model)	Development of grey-box models	[162]
2018	RC model (2R1C)	Energy consumption prediction of residential buildings	[163]
2018	RC model (3R2C)	Thermal physics properties estimation	[164]
2018	RC model (5R4C)	Energy consumption prediction of experimental building	[165]
2018	RC model (3R2C)	Prediction of indoor thermal comfort and energy usage	[150]
2019	Automated grey-box model (based on BIM)	Development of automated grey-box models	[19]
2019	RC model (2R2C)	Energy consumption prediction of cooling systems in commercial buildings	[166]
2019	RC model (4R2C)	Thermal performance of wall with phase change materials	[149]
2020	RC model	Uncertainty analysis of RC models	[167]
2020	Dynamic grey-box model (based on Bayesian method and RC model)	Energy consumption prediction of residential buildings	[168]
2021	Grey-box model (based on machine learning and physical model)	Energy simulation of heating and cooling systems	[152]
2021	Grey-box model (based on integrated simulation and data-driven modelling framework)	Energy consumption prediction of buildings	[153]
2021	RC model (3R2C)	Energy consumption prediction of residential buildings	[169]
2021	Nonlinear model (based on stochastic differential equations)	Energy system simulation of a school building	[148]
2021	Grey-box model (based on Bayesian neural network and RC model)	Energy consumption prediction of residential buildings	[170]
2022	Grey-box model (based on machine learning and physical method)	Energy consumption prediction of buildings	[154]
2022	Multi-zone RC model	Energy consumption in smart buildings	[171]

4.2. Advantages and Shortcomings of Grey-Box Models

Numerous studies have shown that grey-box models balance the strengths of both white-box and black-box models. RC models can calculate major physical parameters quickly, which is important for building grid integration. They can also predict based on historical data, bridging the shortcomings of physical-based methods [155]. Nevertheless, grey-box models have not been used widely due to two reasons. First, grey-box models lack widely used development software. Even though several different software tools can be used to develop grey-box models, some limitations prevent their wider adoption and use for simple procedures [160]. Second, the development methods for grey-box models are not clearly defined. Some studies have mainly utilised data-driven approaches to construct grey-box models, while other studies have mainly used physics-based approaches [172]. The benefits and shortcomings of these methods are not clear. However, grey-box models will become more common due to the advancement of building energy modelling software. This will encourage the creation and collaboration of white-box and black-box models. The advantages and shortcomings of all three building energy prediction model types are shown in Table 8.

Table 8. Advantages and shortcomings of three types of prediction models.

	Advantages	Shortcomings	Reference
White-box models	■ Interpretability ■ High accuracy ■ No requirement for historical data ■ Universality	■ Difficulty in collecting detailed building information ■ Uncertainty from occupant behaviours ■ Inaccuracy of micrometeorological parameters	[67–69]
Black-box models	■ No requirement for detailed building information ■ Both linear and nonlinear relationships can be modelled ■ Stochastic factors can be considered	■ Unexplainable ■ Model inaccuracy due to data variation ■ Not universal	[29,143–145]
Grey-box models	■ The calculation of the construction heat transfer is simplified	■ A lack of a unified software solution for wider adoption ■ Development methods are not determined	[155,160,172]

5. Uncertainties in the Models

In terms of energy modelling and precise predictions, the built environment provides a significant problem. Many factors, including material parameters, occupant behaviours, equipment schedules, HVAC system operations, and weather, contribute to building energy usage uncertainties. According to existing studies, researchers have summarised and analysed sources of uncertainties related to building energy prediction from a variety of viewpoints. Shi focused on identifying the types of uncertainties in the white-box model software tools. Shi determined that there were two sources of uncertainty: the subjective factor created by the researchers and the objective factor caused by the building energy prediction tools [173]. Hopfe analysed the uncertainties in building energy prediction during the building design phase. Many different sources were studied and, due to different parameters, could be divided into three groups: physical, design, and scenario uncertainties [174]. Wit classified the different sources of uncertainty into four types: building specifications, building models, material parameters, and scenarios [175]. This study introduces three sources of uncertainty: human, building, and weather factors (as shown in Figure 4). The effects of these factors on the three kinds of models are shown in Table 9.

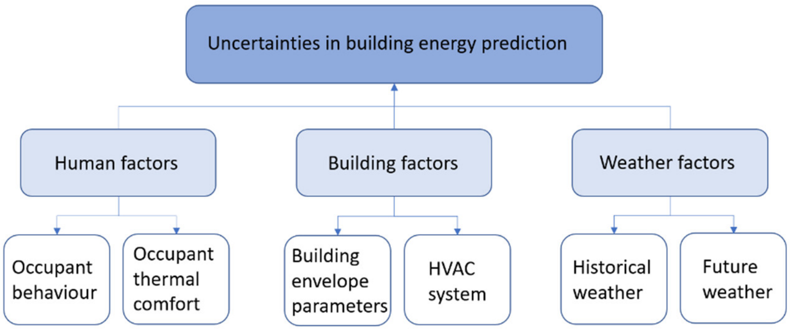

Figure 4. Three sources of building energy prediction uncertainty.

Table 9. The effects of human factors, building factors, and weather factors on the three prediction model types.

Influencing Factors		White-Box Models	Black-Box Models	Grey-Box Models	Reference
Human factors	Occupant behaviour	A large impact *	A small impact	Variable	[176–180]
	Occupant thermal comfort	A large impact	A large impact *	A large impact	[181–185]
Building factors	Building envelope parameters	A large impact	A small impact	Variable	[186–192]
	HVAC systems	A large impact	A small impact *	Variable	[193–196]
Weather factors		A large impact	A large impact	A large impact	[197–200]

* Being improved.

5.1. Human Factors

Human factor uncertainties in building energy prediction have been paid more attention to in recent years [21,22,201,202]. According to existing research, 30% of the uncertainties in building energy prediction come from human factors [203]. Even in the same building, different characteristics, behaviours, and occupant lifestyles can lead to different energy consumptions [204]. In this study, human factors will be introduced from two aspects: occupant behaviour and occupant thermal comfort.

5.1.1. Occupant Behaviour

Occupant behaviour (OB) refers to the interaction between occupants and buildings. This interaction is associated with building energy usage. OB can be indicated by the usage of equipment and systems, including lighting, shading, and HVAC systems. Two types of factors can influence OB. One type is environmental conditions (e.g., weather, indoor temperature, and indoor humidity). The other type is occupant characteristics (e.g., demographic characteristics, health status, and lifestyle habits). All of these factors have high degrees of uncertainty; for example, forecasting weather accurately is difficult, and occupants' health statuses are difficult to completely account for.

In most white-box building energy consumption models, variables related to OB can have fixed timings, such as a scheduled use of lighting or air conditioning systems. Designing such schedules is simple, but the unpredictability of how a schedule is designed does indicate the complicated randomness of human behaviour [205]. In order to reduce uncertainty from OB, occupant models are used. These are natural extensions of white-box models and are based on schedules. For example, Ward compared several occupant models, including the Dolores model, the Sun model, and the autoregressive integrated moving average model, to explore the influence of multiple internal load parameters associated with occupants in white-box models [176]. Menezes developed an occupant model based on data for individual appliances in the office. This model provided more accurate predictions than schedule-based models [177]. Brohus quantified uncertainties in building energy simulations based on stochastic differential equations. Uncertainties from multiple resident behaviours were considered [179]. Meanwhile, in the black-box models, some data sets related to OB can be used to improve prediction accuracy. Piselli developed black-box models to analyse the usage of a public building over a period of two years. Occupants participated in neurological response tests, and the results showed that taking into account subjective factors such as the occupant's emotional state, could lead to more accurate predictions [178]. Feng used a machine learning algorithm to build a stochastic model that could simulate the impact of random-usage patterns of shading systems on a building's energy consumption [180]. In grey-box building energy consumption models, the impact of OB depends on the specific model type. If grey-box models are based on fixed timetables, there will be some uncertainties.

5.1.2. Occupant Thermal Comfort

According to Standard 55 of the American Society of Heating, Refrigerating, and Air-Conditioning Engineers, occupant thermal comfort refers to the subjective feeling of temperature in an environment, which in turn relates to occupants' satisfaction with the thermal environment [182]. Occupant thermal comfort can influence occupant behaviour, which in turn influences building energy consumption. There are some uncertainties due to the subjectivity of occupant thermal comfort; for example, inhabitants of different climatic zones perceive temperatures differently.

In existing building energy prediction models, the predicted mean vote (PMV) index has been applied to analyse thermal comfort in buildings [181,183,184]. The PMV model is based on the thermodynamic equilibrium between the occupants and the thermal environment. This model is calculated based on air temperature, air velocity, humidity, average radiant temperature, clothing, and activity. Despite its widespread adoption, the PMV model has some limitations, mainly because it was developed under stable indoor conditions that did not accurately represent daily dynamic real-world conditions. In addition, the PMV model was developed using data collected from healthy adults; therefore, this model may require certain modifications when applied to environments where children, the elderly, or unhealthy people are present. Several studies have focused on adaptive building energy prediction using black-box models. For example, López-Pérez used ANN to develop a thermal comfort model that could forecast the ideal comfort temperature for people in public buildings. This model suggested that making the air conditioner operate at a higher-comfort temperature than that determined by the PMV model could reduce energy consumption and increase thermal satisfaction [185]. Though such methods are promising, they need various historical data and are potentially subjective due to the selection of occupants under study.

5.2. Building Factors

Building factors can directly influence building energy consumption. In this study, building factors were categorised into two kinds: building envelope parameters and HVAC system parameters. Some of the building factor uncertainties within building energy consumption prediction will be discussed in the following sections.

5.2.1. Building Envelope Parameters

The building envelope is closely linked to a building's energy consumption. The building envelope is the structure that separates the interior from the exterior and includes the exterior walls, roofs, windows, and doors. The building envelope plays an important role in maintaining indoor comfort over the long term. The main building envelope parameters that lead to building energy prediction uncertainties include the U-value, emissivity, absorptivity, infiltration rate, and thickness of the building materials. Each of these parameters is described below.

Building envelope U-values are important thermal parameters that can affect a building's energy consumption. It has been proven that U-values can vary depending on the temperature and the relative humidity [186]. Moreover, O'Hegarty investigated measured U-values of highly insulated external walls and monitored the performance of these external walls. O'Hegarty found that the measured U-values deviated from the theoretical U-values [187]. Ohlsson developed a simplified model to analyse uncertainties from the U-values of windows [192]. Ohlsson's findings suggest that if the U-value is fixed in a model, this will lead to some uncertainty. However, few researchers have focused on quantitative in-situ studies of how building material U-values vary depending on the outside environment. The emissivity and absorptivity of the building envelope are physical parameters that reflect the ability of building materials to reflect or absorb solar energy. Some studies have quantified uncertainties in the emissivity and absorptivity of building materials [188]. For example, the emissivity of common building materials is approximately 0.9–0.95, with a standard deviation of 0.02. The mean solar absorptance of light and dark bricks is 0.49 and 0.76, respectively, with a standard deviation of 0.04. The infiltration rate is related to the construction methods, building maintenance, building age, and external environment [188]. Several researchers have analysed the uncertainties related to infiltration rates using measurement data from existing buildings [189–191]. Uncertainty about the materials' thickness is mostly due to the limitations of construction technology. It is difficult to exactly match the actual building to the design specifications. Several studies have estimated the range of error in material thickness and used this range as one of the parameters affecting building energy consumption prediction [188].

In white-box models and some grey-box models (such as RC models), building envelope parameters are set, which leads to inaccuracy. Some researchers have focused on the range of parameters' uncertainties, but how to incorporate uncertainties in defined building material parameters into white-box models requires further research. Some black-box and grey-box models based on real-data sets can consider the uncertainties of parameters because the data sets can be affected by these uncertainties. However, the process cannot be explained, and this shortcoming requires more research in order to be improved.

5.2.2. HVAC Systems

HVAC systems include heating, ventilation, and air conditioning. These systems consume energy to maintain a satisfactory indoor environment in buildings. HVAC systems need to balance indoor comfort with energy efficiency. White-box models and some grey-box models (such as RC models) usually assume that HVAC systems operate in a fixed context. However, the operation of HVAC systems is influenced by their size and by the systems' maintenance frequency. In some black-box and grey-box models, uncertainties from HVAC systems are taken into account to a certain degree, as these models are based on actual energy usage data. Nevertheless, quantifying the uncertainties relating to HVAC systems is challenging.

Despite this difficulty, several studies have paid attention to quantifying HVAC system uncertainties [193–196], and an uncertainty and sensitivity analysis has been an important method. Carpino used this method to study the range of energy consumption of HVAC systems, and the results showed that uncertainties relating to HVAC systems could cause a 20% fluctuation in building energy consumption [206]. Prataviera studied urban building energy prediction using white-box models. The building heating loads predicted by analysing uncertainty and sensitivity are closer to the actual values than the original prediction [207]. Different innovative black-box methods have also been used. Shi introduced a unique assessment approach based on the exergy analysis technique that used Latin hypercube sampling and particle swarm optimisation algorithms to quantify the uncertainties of energy efficiency. Validation was carried out on an airport HVAC system in the south of China. The suggested assessment approach was more accurate than the usual evaluation method [193]. Fan suggested a more reliable cooling load forecasting technique using SVM. This model appropriately considered uncertainties in the external environment and the indoor cooling load, and the accuracy of prediction was thereby improved [195].

5.3. Weather Factors

Weather factors significantly impact building energy prediction but have a high degree of uncertainty. The most significant parameters in building energy use are air temperature, relative humidity, wind speed and direction, and solar radiation. A number of building energy consumption systems are influenced by weather factors. For example, the hours of daylight differ between winter and summer, resulting in different hours of operation for lighting systems. Heating and cooling loads in buildings may also change because of extremely cold or hot weather.

Historical weather data have been used in building energy prediction models. White-box models mainly rely on meteorological data sets that have been collected from actual weather data in many regions [197,208]. For example, Mahdy simulated the energy consumption of two residential buildings by Design Builder with typical meteorological years (TMY). The results showed that the annual energy consumption in every flat would be 1508 kWh in 2080 [198]. In some black-box and grey-box models, weather parameters are based on open-source historical weather data such as OpenWeather, which includes measured weather data and disaggregated weather description information. For example, Lin collected weather data from 2015–2018 to create weather characteristics and then applied SVM and ANN models to find days of extremely high electricity usage in different types of buildings [199]. However, there is growing concern that a single weather data set does not accurately represent sufficient weather information, and it is therefore disadvantageous for predicting energy consumption in buildings [200]. Moreover, due to global warming in recent years, historical weather data do not accurately reflect future climate characteristics, which are crucial when determining future building energy consumption.

Many studies have analysed the impact of future weather on building energy consumption [209–213]. Researchers have used the morphing approach to downscale general circulation models and analyse future weather information [214]. Based on TMY, Liu used the morphing approach to develop future weather data in China [211]. One benefit of this method is that future weather series are meteorologically matched to the best weather forecasts. The UK Weather Projections (UKCP09), published in 2009, made a significant step towards quantifying the uncertainty of future weather [215]. These projections address three sources of uncertainty: weather system complexity, natural weather variability, and differences in future greenhouse gas and aerosol emission pathways. UKCP09 projections use three scenarios to account for the uncertainty of CO_2 emissions, low, medium, and high, and give probabilistic weather forecasts for each scenario that allow for the sophistication and inherent changeability of weather systems. Future research should use UKCP09 efficiently in building energy prediction. There have also been studies quantifying uncertainties relating to future weather. Amadeh built a framework to analyse building energy demand that was influenced by the uncertainties of future weather [216]. Wang used deep learning to analyse random occurrences of different types of weather [217], and Yassaghi studied a four-step propagation process to quantify climate changes [210].

6. Conclusions

This review provided an in-depth analysis of the models used in estimating building energy consumption. These models were categorised into three groups: white-box models, black-box models, and grey-box models. First, the white-box models were presented, and related software tools and applications were introduced. Second, the black-box models were reviewed. These models use three main algorithms: MLR, SVM, and ANN. The last category presented was the grey-box models, which combine both white-box and black-box models. Then, uncertainties in these three types of building energy prediction models were analysed based on three factors: human, building, and weather factors. There are still research gaps in building energy consumption predictions:

(1) Among the many uncertainties in building energy consumption, the understanding of human factors has significant limitations. Individualised differences in occupant thermal comfort need to be better understood. For example, the relationship between occupant thermal comfort, climate zones, and demographic characteristics needs to be investigated further.

(2) The uncertainties of building parameters have not been sufficiently studied. For example, building envelope U-value variations in different climatic conditions have not been explored systematically. The impact of U-value uncertainties on building energy prediction still requires research, especially in buildings constructed from different materials.

(3) Most existing building energy consumption prediction models need to make better use of future weather forecast data, such as the hourly weather files generated by UKCP09, to reduce model uncertainties relating to weather factors and obtain more accurate predictions.

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