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Review article

Physical energy and data-driven models in building energy prediction: A review

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ABSTRACT

The difficulty in balancing energy supply and demand is increasing due to the growth of diversified and flexible building energy resources, particularly the rapid development of intermittent renewable energy being added into the power grid. The accuracy of building energy consumption prediction is of top priority for the electricity market management to ensure grid safety and reduce financial risks. The accuracy and speed of load prediction are fundamental prerequisites for different objectives such as long-term planning and short-term optimization of energy systems in buildings and the power grid. The past few decades have seen the impressive development of time series load forecasting models focusing on different domains and objectives. This paper presents an in-depth review and discussion of building energy prediction models. Three widely used prediction approaches, namely, building physical energy models (i.e., white box), data-driven models (i.e., black box), and hybrid models (i.e., grey box), were classified and introduced. The principles, advantages, limitations, and practical applications of each model were investigated. Based on this review, the research priorities and future directions in the domain of building energy prediction are highlighted. The conclusions drawn in this review could guide the future development of building energy prediction, and therefore facilitate the energy management and efficiency of buildings.

Contents

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Nomenclature

AC	Air conditioning
ANN	Artificial neural networks
BIM	Building information model
CV	Coefficient of variation
CV-RMSE	Coefficient of variation of root mean square error
DNN	Deep neural networks
DR	Demand response
ELM	Extreme learning machine
LTLF	Long-term load forecasting
EMS	Energy management system
ENMIM	Evolutionary neural machine inference model
GMM	Gaussian mixture model
GPR	Gaussian process regression
GRU	Gated recurrent unit
HVAC	Heating, ventilation, and air-conditioning
kNN	k-nearest neighbors
LMSR	Linear model using stepwise regression
LR	Linear regression
LS-SVM	Least-square support vector machine
LSTM	Long short-term memory
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MARS	Multivariate adaptive regression splines
MLP	Multilayer layer perceptron
NARM	Nonlinear autoregressive model
RC	Resistance capacitance
RF	Random forest
RNN	Recurrent neural networks
STLF	Short-term load forecasting
SVM	Support vector machine
SVR	Support vector regression
XGBoost	Extreme gradient boosting

1. Introduction

1.1. Literature reviews

The building sector is a major energy consumer in the world, accounting for 39% of the world's total energy consumption according to statistics study (Somu et al., 2020). To reduce building energy consumption, improve energy efficiency, and increase the proportion of renewable energy utilization, building energy prediction plays a critical role not only in building energy systems planning and optimization (Zhou and Zheng, 2020; Fan et al., 2017) but also in building renewable energy penetration (Salkuti, 2019; Ahmad et al., 2020). As we know, buildings can be energy consumers and producers simultaneously. In this situation, the main challenge is to match the intermittent renewable energies with energy supply and demand management in place and time. Accurate and fast energy consumption prediction can help to achieve the goals of evaluating new building design alternatives and optimizing energy systems. For instance, in the design phase, the forecasting of building load is the basis of energy system selection, for example, the selection of the size and type of air conditioning (AC). In addition, with the rapid development of renewable energy, the application of energy management strategies such as demand response (DR) has been deemed to be a promising way to balance the power supply and demand in the grid (Chen et al., 2018, 2019). In the domain of building DR, a fair and accurate load baseline that commonly predicts the hour-ahead load of DR is the key factor for the stakeholders to determine whether to implement the DR program.

With the different needs in practical building programs, there are two types of common prediction models. One is short-term load forecasting (STLF) and the other is long-term load forecasting (LTLF). STLF aims to estimate the load of the next seconds up to the next two weeks, while LTLF focuses on months and longer periods (Hong and Fan, 2016). Fig. 1 shows the applications of STLF and LTLF. Commonly, DR and system operational optimization require fast computational iterations in the control algorithms; hence, STLF is suitable. For system planning and energy policy-making, energy supply and demand conditions in the future should also be considered, and thus, LTLF is usually implemented.

Regardless of the STLF or LTLF method, many efforts have been made in recent decades by numerous scientists and engineers to develop energy consumption prediction approaches. These efforts can be categorized into three types. First, the building physical energy model, also called "white box", is based on detailed building parameters and heat balance equations. Commonly used building physical energy simulation tools such as EnergyPlus (U.S. Department of Energy, 2021), Dymola (Anon, 2021b,c), and TRNSYS (Anon, 2021d) are introduced in this paper. Second, the data-driven model called "black box" is based on historical operational big data and machine learning algorithms which refer to support vector regression (SVR) (Chen et al., 2017), random forest (RF) (Dudek, 2015), extreme gradient boosting (XGBoost) (Butch, 2020), artificial neural networks (ANN) (Abu-Et-Magd and Findla, 2003), among other techniques. Lastly, the hybrid model called "grey box" is a model that combines building physical information with historical data sources (Somu et al., 2020; Dong et al., 2016).

In the domain of the physical model, the zonal and nodal approaches have been reviewed by Foucquier et al. (2013) and we recommend the readers to refer to their paper. Hence, in this study, we mainly focused on the advantages and disadvantages of other aspects of the simulation tools. Usually, the prediction accuracy of the physical models is higher compared with the statistical models (Mazzeo et al., 2020). However, developing detailed physical energy models for each building is a tiresome task. Therefore, a data-driven model is an alternative owing to the rapid development of big data technologies such as sub-metering and smart buildings, and it has gained increasing popularity in

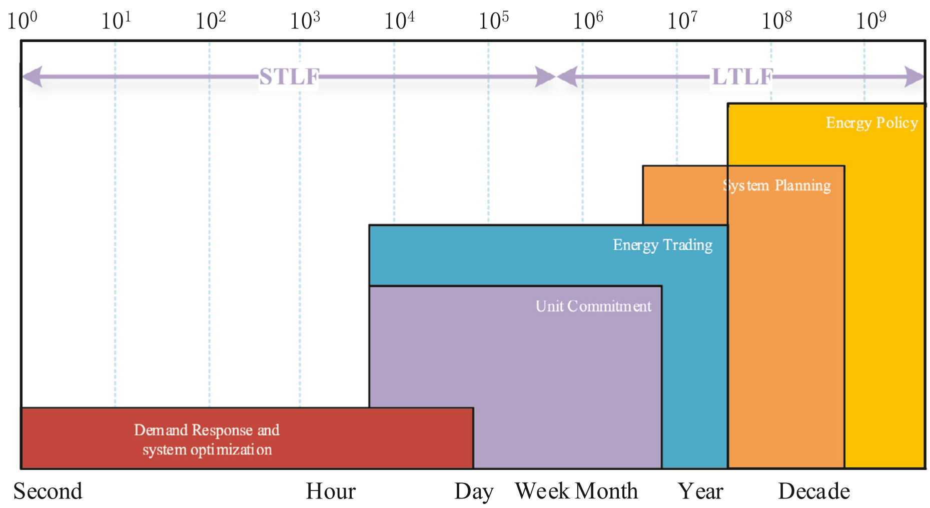

Fig. 1. Classification and applications of STLF and LTLF.

recent years. Deep learning is an example of particularly successful (Sun et al., 2020; Gassar et al., 2019). In the data-driven model domain, two main factors, i.e., feature importance and algorithm selection, were considered in the previous literature. The input feature variables, including external and internal factors, are the key elements for the prediction performance of the algorithms (Zhang and Wen, 2019a; Luo et al., 2020). Although the data-driven model has the merit of requiring less building information to develop the model, the prediction performance is unstable, especially when the model is applied to other building cases. In addition, hybrid models have been developed simultaneously to improve the prediction performance by integrating the advantages of physical and data-driven models.

There are several review papers about building energy prediction (Foucquier et al., 2013; Wang and Srinivasan, 2017a; Amasyali and El-Gohary, 2018). However, there are still two research gaps. First, most of the review papers focused on data-driven models using machine learning algorithms (i.e., "black box" model). Despite the importance of these review efforts, physical and hybrid models are also important and well-developed that they should be included and further discussed. Second, review studies that cover overall building energy consumption prediction research in terms of different prediction spans (i.e., STLF and LTLF) are still insufficient. Such a review is essential for building owners to select an appropriate prediction model. Distinguishing from the published review papers, the novelty of this paper is to elaborate on building energy prediction models based on prediction span. In the field of building energy prediction, the prediction span is diverse according to practical engineering needs. Different models have different performances in manifold tasks of various prediction spans. In this review study, three types of methods in different prediction spans (i.e., STLF and LTLF) were investigated. The principle, advantages, limitations, and practical applications of each method were investigated. In summary, this paper paves the way for a better understanding of the methodology for building energy prediction.

1.2. Objectives and structure of the review

The goal of this paper is to provide a comprehensive review of building energy prediction approaches. The goals of this paper are fourfold: (1) presenting a systematic review (including physics-based, data-driven, and hybrid approaches) to facilitate the development of energy prediction models; (2) describing the key processes and tactics of each approach; (3) paving a way for building owner to select a suitable model in practical engineering (4) summarizing the widely used models at present and pointing out future direction of building energy prediction models. The paper is organized as follows. Section 2 elaborates on the physical building energy models by introducing and comparing different commonly used simulation tools. Section 3 studies the data-driven energy prediction models, and the hybrid methods are introduced in Section 4. The advantages and disadvantages of each approach are presented in Section 5, and the conclusions are drawn in Section 6.

2. Building physical energy models – "white box"

Building physical energy models, also called physical models, are based on heat and mass balance equations, which present the dynamic thermal behavior of buildings. Three heat transfer models (i.e., conduction, convection and radiation) between building envelop and its surroundings are considered in the heat balance analysis of physical energy models. Various commercial or open-source software products such as EnergyPlus, Dymola, TRNSYS, DOE-2, and Matlab are available for building energy modeling to construct and solve these equations conveniently (Harish and Kumar, 2016), though the cooling and heating load can be calculated manually. The description of heat and mass balance equations and detailed steps to calculate the building heating and cooling loads was introduced in this paper (Hensen and Lamberts, 2012). Understanding the overall physical characteristics of buildings is important for using these building simulation tools. The heat flow through the building envelope is determined not only by the temperature difference, thermal resistance, and surface area, but also by the thermal inertia effect of the thermal mass, which results in heat lag. In general, detailed building information is required to develop such models. Building envelope parameters, HVAC systems setting, internal heat gains, equipment and occupancy schedules, thermal zones, location, and weather data are essential to construct a physical building energy model (Crawley et al., 2001). Zonal (Inard et al., 1996) and nodal (Zhai et al., 2011) approaches are two common methods for developing a physical model. These approaches are a fast and simple way to estimate the heat behavior of buildings (Foucquier et al., 2013). The rest of this section describes the modeling process, advantages and limitations, and applications of the commonly used software.

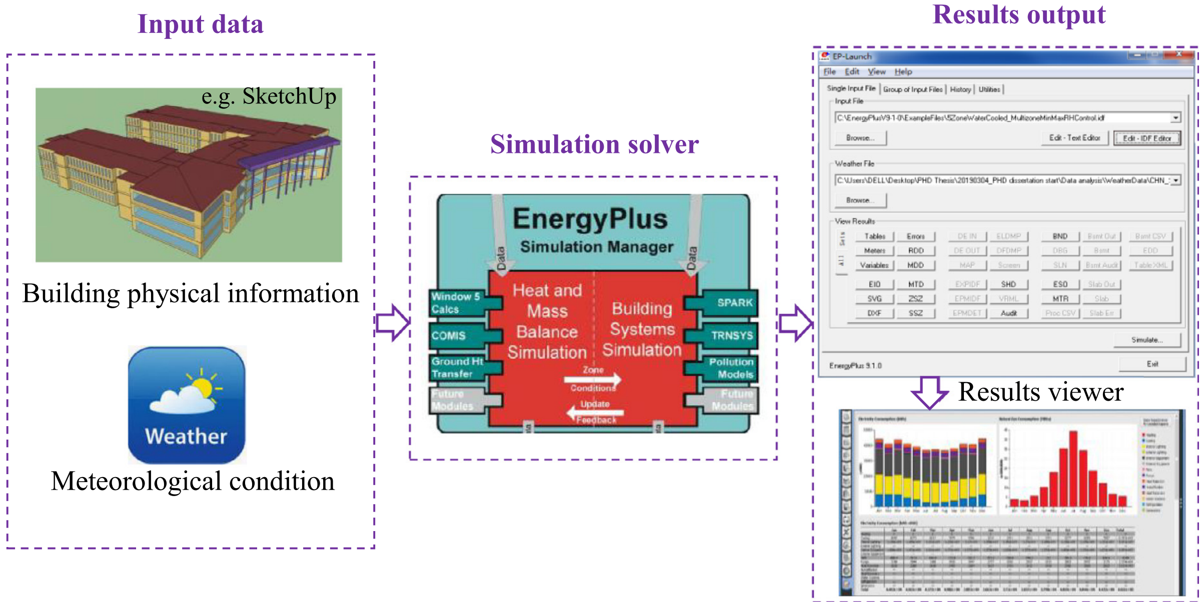

Fig. 2. Modeling flow chart of EnergyPlus.

2.1. EnergyPlus

EnergyPlus has been under development since 1997 and was first released in 2001 (Crawley et al., 2001). It is an open-source program (U.S. Department of Energy, 2021) and has been considered as a widespread and powerful energy simulation tool in buildings (Anon, 2006). Based on the Building Energy Software Tools Directory, EnergyPlus is introduced as a recommended tool for energy simulation, building performance, heat and mass balance analysis, etc. (Anon, 2021e). EnergyPlus is a typical nodal approach software. The conduction transfer function and finite-difference algorithm are the two main methods used for the nodal approach, which can be regarded as a one-dimensional method. The main advantage of this nodal approach that it can solve the heat function of a large time scale of building thermal performance within a short computation time. The modeling flow chart of EnergyPlus is shown in Fig. 2.

Owing to the merits of fast simulation speed and precise energy consumption estimation, EnergyPlus is a popular tool for calculating and analyzing the energy consumption of various buildings and energy systems, particularly at large time scales such as annual and monthly simulations (Trcka and Hensen, 2010). Westphal and Lamberts (2005) presented a case study showing that the annual electricity consumption prediction was only 1% lower than the actual value. Neto and Fiorelli (2008) conducted a comparison between EnergyPlus and an artificial neural network (ANN) for predicting building energy consumption. EnergyPlus presented a prediction error range of ±13%, while the ANN algorithm showed a prediction result of ±10%. They also concluded that the schedules of lighting, equipment, and occupancy are the major sources of uncertainties in prediction. As the literature study has shown, the prediction errors were reportedly hugely different for specific cases. To improve the stability of this method, historical operational data from existing buildings are readily used. Fumo et al. (2010) used EnergyPlus benchmark models to estimate building energy consumption. In their study, a series of predetermined coefficients determined by electrical and fuel utility bills were considered.

In the modeling process, heating, ventilation, and air-conditioning (HVAC) systems are the most complicated and time-consuming components. To evaluate the energy consumption of HVAC systems, EnergyPlus has an energy management system (EMS) module, which can be used to control energy-related systems. Cetin et al. (2019) developed an EMS program to improve the simulation performance at a short-time step (minute-level) of residential and small commercial direct expansion (DX) HVAC systems' on/off control in EnergyPlus. More realistic results representing the on/off nature of the HVAC systems could be obtained. It is worth noting that EnergyPlus was originally developed for building envelope simulation, and therefore, establishing HVAC systems is troublesome and may cause problems in EnergyPlus (Anon, 2021f).

2.2. TRNSYS

Transient system simulation (TRNSYS) was developed by the Solar Energy Laboratory at the University of Wisconsin-Madison (Anon, 2021d). TRNSYS is a transient system simulation tool with a modular structure that is characterized as a flexible tool in specific components or types for many applications such as solar systems, buildings and HVAC systems, renewable energy systems, fuel cells, and cogeneration. TRNSYS is an application with a graphical user interface and has the extreme flexibility to develop personal components or types (Wetter and Christoph, 2006).

TRNSYS is reportedly regarded as a widely used tool for building energy systems modeling, particularly for solar energy systems and heat pumps. Chargui et al. (2012) investigated the heat performance of a geothermal heat pump system using the TRNSYS model. A dual-source heat pump (Type 20) was used to study the thermodynamic properties. Quesada et al. (2011) presented a dynamic model of a grid-connected photovoltaic (PV) system on TRNSYS. The results show that an accurate prediction of long-term energy performance can be realized. A comparison of TRNSYS, EnergyPlus, and IDA indoor climate and energy (IDA ICE) was conducted by Mazzeo et al. (2020). The results showed that EnergyPlus and IDA ICE are better than TRNSYS in predicting thermal behavior in the presence of phase change materials (PCM). However, in the absence of PCM, TRNSYS showed the highest prediction accuracy in the warm period, whereas IDA ICE achieved the best performance in the cooling period. TRNSYS can not only forecast energy consumption but also facilitate energy system design for energy optimization. Magnier and Haghighat

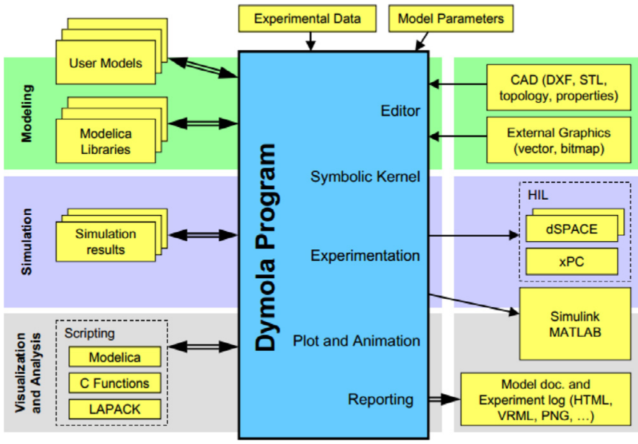

Fig. 3. Architecture of Dymola software (Dynamic Modeling Laboratory User Manual Volume 1, Dassault Systèmes A.B., 2017).

(2010) built a building base model on TRNSYS to develop a database that was used to train the ANN for optimization.

2.3. Dymola

The dynamic modeling laboratory (Dymola) was initially designed in 1978 by Hiding Elmqvist in his doctoral dissertation to build a structured model language for large continuous systems (Elmqvist, 1978). The building energy modeling Dymola software is based on the Modelica language, which is an acausal, object-oriented, and equation-based language to conveniently model physical systems, including thermal, mechanical, electrical, and control systems (Anon, 2021c). The acausal modeling approach describes the components based on equations without allocating input and output variables; therefore, the components are easy to establish and modify. With this feature, Modelica supports hierarchical model composition, truly reusable libraries, connectors, and acausal connections, and relieves the users from manually converting equations to a block diagram or assignment statement. Dymola has a powerful graphic editor for developing and running models. Additionally, it can conveniently interact with external data. A typical architecture of Dymola is shown in Fig. 3.

Dymola is a relatively new tool in the domain of building energy simulations. Modelica buildings library developed by Lawrence Berkeley National Laboratory is an open-source and widely used library with comprehensive building components and control systems, which is sufficient for different buildings and energy systems (Anon, 2021b). The packages and components in this library have been tested and validated using benchmark models (Nouidui et al., 2012), and the calculation time is comparable with that of TRNSYS (Wetter and Christoph, 2006). AixLib from RWTH Aachen University in Germany, BuildingSystems from Udk Berlin in Germany, and IDEAS from KU Leuven in Belgium are three other core Modelica libraries for energy design and operation of buildings under the IBPSA Project (Anon, 2021g). Kim et al. (2015) developed a physical building information model (BIM) on the Dymola platform using object-based Modelica language to simulate energy consumption, and the Modelica building library was used in their study. Chen et al. (2019) built an office building model to estimate the HVAC load and total building energy consumption. In addition to describing the detailed HVAC systems, the internal thermal mass of the interior walls and furniture was taken into account; thus, the dynamic thermal balance of this system is much more realistic. Dymola, unlike EnergyPlus, can simulate a single building with an acceptable computational cost but it might not be suitable for a large block of buildings. Kim et al. (2019) established a single reduced model for assembling ten buildings on Dymola, calculating district heating and cooling demand.

2.4. Other tools

Other building energy performance simulation tools such as IDA ICE, DOE-2, and eQUEST. IDA ICE was developed at the Department of Building Sciences in Stockholm. DOE-2 was released in the early 1980s, and eQUEST is an advanced version of DOE-2. Researchers generally used eQUEST (Xing et al., 2015; Ke et al., 2013; Wang et al., 2015) and DOE-2 (Tuhus-Dubrow and Krarti, 2010; Siddharth et al., 2011) to calibrate energy consumption previously. Software co-simulation is a new trend because this approach can combine the advantages of two or more simulation tools, and it designates the best simulation performance and the most computationally efficient approach for different sub-tasks.

2.5. Discussion on building physical energy models

The main advantage of the "white box" is that the relationship between input and output is explainable. Correspondingly, the disadvantage is that it is time-consuming and labor-intensive to enter all the detailed building parameters, which might be a problem for many buildings in the design phase and some existing buildings. A brief description of the different simulation tools is presented in Table 1. When selecting a tool to estimate the building energy performance, it is important to make the trade-off between the prediction accuracy and computing time. Nageler et al. (2018) presented a comparison of four building energy simulation tools, including Dymola, EnergyPlus, IDA ICE, and TRNSYS, on a test-box. After comparing the room temperature of test-box with measured data, they found that the simulation results are relatively accurate with an average bias of −0.92, −2.18, −0.37, and −1.13 K for these respective four tools.

Model calibration is an integral step to ensure the accuracy of the energy model after it has been developed. For the purpose of making the simulation results meet the measured data well enough, the main process of building energy model is to adjust the input parameters, such as the efficiency of the chiller, the occupancy schedules, and so on (Guo et al., 2021). Manual calibration heavily relies on the user's practical experience to tune the key parameters in models. Automated calibration is based on an objective function or penalty function which is defined for matching simulation results with measured data, and the parameters setting is under search automatedly (Gaurav et al., 2016). Most of these calibrations are deterministic and neglect the inherent uncertainties of the building energy model. Therefore, the stochastic calibration methods such as the Bayesian approach have gained attention recently (Hou et al., 2021). The data source and data pre-processing methods utilized in the calibration process were comprehensively discussed in papers (Adrian et al., 2019; Murphy et al., 2021; Chong et al., 2021).

3. Data-driven models using machine learning algorithms – "black box"

Compared with physical models, data-driven models do not require building thermal balance equations; therefore, less or no building physical information is needed. Data-driven models are based on historical data to deduce the hidden relationship between output (i.e., building energy consumption) and input variables (i.e., features such as weather, building information, occupant behaviors, and equipment schedules) using mathematical

Table 1
Brief description of different simulation tools.

Software tool	Modeling approach	Advantages	Disadvantages	Representative Reference
EnergyPlus	Causal	Require small computation time; Applicable to large scale buildings; Good at envelope modeling; Friendly for beginners; Free	Require a significant amount of time, experience, and effort to enter the detailed parameters; Some required parameters are not available; Not good at HVAC systems	U.S. Department of Energy (2021), Trcka and Hensen (2010) and Fumo et al. (2010)
TRNSYS	Causal	Require small computation time; Flexibility and customization; Modular design; Good at solar energy systems; Friendly for beginners	Not good at building physical model; Chargeable	Anon (2021d), Quesada et al. (2011) and Jani et al. (2020)
Dymola	Acausal	Flexibility and customization; Modular design; Good at HVAC systems modeling; High reuse of components	Not friendly for beginners; Relatively long computation time; Chargeable	Anon (2021c), Hafner et al. (2014) and Violidakis et al. (2020)
DOE-2	Causal	Good at building physics modeling; A traditional building simulation tool	Not good at energy systems; Unfriendly user interface	Carriere et al. (1999) and Winkelmann and Selkowitz (1985)

methods. Data-driven methods are well adaptable for buildings without detailed physical parameters such as buildings in the design phase. A general process of the machine learning prediction method is shown in Fig. 4. Widely used input variables include time-series features (e.g., day type, occupancy rate and schedule, operational schedule of equipment), meteorological conditions (e.g., temperature, humidity, solar radiation), and building physical parameters (e.g., the number of floors, wall area, glazing area, wall heat transfer coefficient). The output variables are generally heating/cooling loads and electricity consumption (Do and Cetin, 2018; Guo et al., 2018). Data-driven models have gained increasing interest in building energy prediction owing to their simplicity and flexibility (Wang and Srinivasan, 2017b). This section presents the promising "black box" methods, including linear regression (LR), support vector machine (SVM), extreme gradient boosting (XGBoost), random forest (RF), recurrent neural network (RNN), and artificial neural network (ANN).

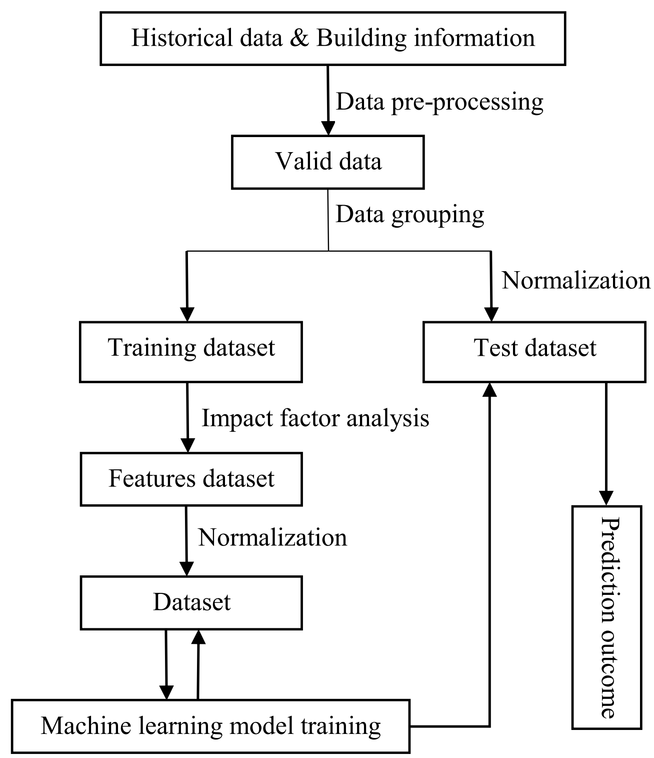

Fig. 4. Flow chart of machine learning model development and validation.

3.1. Linear regression (LR)

LR is the simplest machine learning algorithm for a data-mining beginner because no parameters need to be tuned. In addition, it requires fewer computing resources and therefore has a fast prediction speed. LR has been widely used owing to its simplicity and good prediction performance in many fields. Linear and non-linear regression are two regression methods. The principle of the regression is to establish the relationship between the output response variable $\boldsymbol{y}$ (i.e., label) and input explanatory variables $\boldsymbol{x}$ (i.e., feature variables). One of the most common regression models of LR is expressed in Eq. (1). Other types of regression models can be found in Fahrmeir et al. (2013).

$$\boldsymbol{y} = a_1\boldsymbol{x}_1 + a_2\boldsymbol{x}_2 + \cdots + a_i\boldsymbol{x}_i + \cdots + a_n\boldsymbol{x}_n + \varepsilon \qquad i \in [1, n] \quad (1)$$

where $\boldsymbol{a}$ is the regression coefficient of the explanatory variables, ε is a random deviation or error term, and n is the dimension of the explanatory variables. For example, if the predicted output $\boldsymbol{y}$ is the electricity consumption of buildings, the feature variables could be ambient temperature, solar radiation, occupancy schedules, and the total heat transfer coefficient of walls.

Because of the strong correlation between building loads and outdoor air temperature, temperature as the most common explanatory variable is chosen in many different regression models. Hagan and Behr (1989) established an LR model with time series and temperature as explanatory variables to predict the building electricity loads. According to the global energy forecasting competition (Hong et al., 2014), linear and non-linear regression models are still a popular option for energy prediction. LR models are simple and have a fast prediction speed. However, LR models can barely meet high-precision prediction requirements, especially for HVAC loads, which are influenced by non-linear and uncertain factors such as weather and schedules. The LR models have acceptable prediction performance for weather-insensitive loads such as lighting and equipment loads, but they lack the ability to accurately predict weather-sensitive loads such as HVAC loads (Chu et al., 2020).

3.2. Support vector machine (SVM)

SVM is a promising machine learning algorithm owing to its strong non-linear capabilities, capable of realizing classification and regression. SVM is commonly used for classification, while support vector regression (SVR) can be used to forecast building

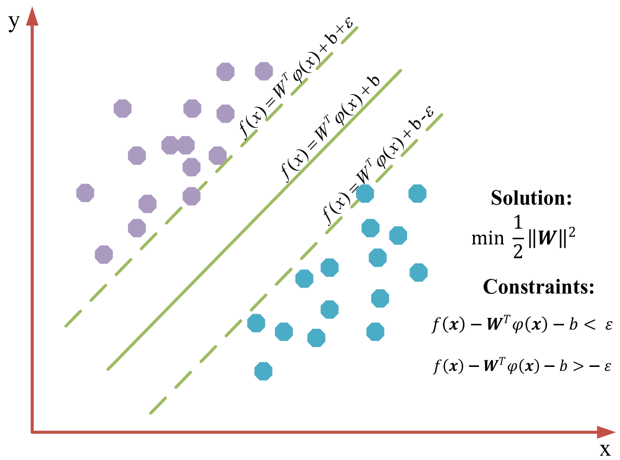

Fig. 5. Schematic of the hyperplane.

loads. The main idea of SVM in regression is to introduce a kernel function, which is capable of nonlinearly mapping the input space into a hyper-dimensional feature space that formulates an optimized hyperplane to realize LR in the feature space (Vapnik, 2013). The SVR function is expressed in Eq. (2).

$$f\left(\boldsymbol{x}\right)=\boldsymbol{W}^{T}\varphi\left(\boldsymbol{x}\right)+b \qquad (2)$$

where $f\left(\boldsymbol{x}\right)$ denotes the prediction outputs, $\boldsymbol{W}$ is the weight factor, b is the adjustable factor, and $\varphi\left(\boldsymbol{x}\right)$ is the map function of mapping the input space into a high-dimensional feature space. Fig. 5 shows the solution process of the SVR. A margin of tolerance ε is set, and the main goal is to maximize the margin to minimize prediction error.

Studies on SVM for building energy prediction have been widely reported in recent years (Chen and Tan, 2017; Son and Kim, 2015) because of the ability to solve non-linear regression problems. Chen et al. (2017) proposed a novel SVR model in which the ambient temperature of two hours ahead was chosen as the real input variable for short-term electrical load prediction. This innovation improves the prediction accuracy by reducing the weather-sensitive loads' lagging effect from building's internal thermal inertia. The input variables are the ambient temperature and time series, which are adaptively used to build cases where only the weather information is permitted. Vrablecova et al. (2018) used SVR to forecast load using smart metering data from individual households. They concluded that SVR is not the best algorithm for individual households' electricity forecasting, but it is a promising method for forecasting aggregated loads from single buildings and a cluster of buildings. SVR has been frequently reported in short-term load forecasting because of its prediction accuracy and speed in this field (Yang et al., 2019; He et al., 2017). Chen and Tan (2017) used SVR to forecast 24-h ahead hourly electric demand for a hotel and a mall. According to their study, the SVR model can complete the prediction procedure within 20 s, and the prediction errors are approximately 4.0% and 6.0% for the hotel and mall, respectively, which is applicable for real-time control of a building energy management system such as DR.

3.3. Random forest (RF)

RF is a supervised learning algorithm that uses a bagging (bootstrap aggregating) algorithm for regression. RF is based on a decision tree, and multiple trees are established to obtain average prediction results. The prediction process of the RF is shown in Fig. 6. Each decision tree is formed randomly with different features and training datasets, and they can be trained in parallel. In this way, the prediction accuracy is higher than that of a single decision tree. In addition, it overcomes the overfitting problem by establishing multiple decision trees, where each decision tree works on a random sample of the original dataset. Thus, the prediction results are less likely to be influenced by outliers, which are quite common in datasets. In the RF model, the number of trees and the depth of a tree are two key parameters that need to be tuned, and therefore RF model requires fewer parameters to be set compared with other algorithms (Dudek, 2015; Lahouar and Slama, 2015; Moon et al., 2018).

Ahmad and Chen (2019) made a comparison between a nonlinear autoregressive model (NARM), linear model using stepwise regression (LMSR), and RF for medium-term and long-term energy prediction. Ambient temperature and relative humidity ratio are the two main input variables in the models. For different seasons, they found that the RF model had a lower average error (MAPE: 2.64%) than the other two methods, i.e., LMSR (MAPE: 3.10%) and NARM (MAPE: 4.21%). In all these three models, the average MAPE was worse in summer and winter (summer: 3.97%; winter: 3.42%; spring: 3.00%; autumn: 2.87%). One reason is that AC loads are more complicated and difficult to forecast with a standalone algorithm in the summer and winter seasons. Therefore, decomposing the building loads into different types and predicting them individually is a promising way to improve the prediction performance (Wang et al., 2012; Ji et al., 2016).

In addition to the advantages of less overfitting and higher accuracy, RF can give the importance of features that are used in the training and testing process of the model. Feature importance is important for choosing the main features while skipping the weak ones to accelerate the computational process and ensure the prediction accuracy at the same time. Lahouar and Slama (2015) predicted the day-ahead building load based on the RF model. In their study, an expert feature selection strategy was adopted. The input feature variables included day type, temperature, and load of the previous day. They concluded that the order of the importance is previous day load, day type, and temperature.

3.4. Extreme gradient boosting (XGBoost) and lightGBM

XGBoost is an ensemble learning algorithm that can solve many data-mining problems in a fast and accurate manner. Released on March 27, 2014, by Tianqi Chen, XGBoost is based on a gradient boosting algorithm and dominates the field of machine learning. It is a powerful algorithm, as most Kaggle competitions reported that it was the final winner (Butch, 2020; Anon, 2021a). XGBoost was designed using a gradient boosting algorithm, converting weak learners to a strong learner. It can produce better prediction outcomes by controlling the model complexity and reducing overfitting owing to its built-in regularization. XGBoost is a relatively novel and advanced algorithm that has not been widely studied in building energy prediction (Wang et al., 2020a). Unlike the RF algorithm, in which the multiple predictors are in parallel, XGBoost adds the predictors sequentially. Nowadays, XGBoost can be easily implemented with the package in Python, R, Julia, and Scala (Anon, 2021h).

Wang et al. (2020a) studied the prediction characteristics of XGBoost on building thermal load prediction. In their models, five input variables including day of week, hour of day, holiday, temperature, and relative humidity were taken into consideration. They found that XGBoost (CV-RMSE: 21.1%) in shallow machine learning outperformed other machine learning algorithms such as SVM (CV-RMSE: 25.0%), RF (CV-RMSE: 23.7%), and LSTM (CV-RMSE: 31.9%) for long-term prediction. Because the correlation between input and output is less relevant when the prediction duration is long, algorithms such as LSTM (long-term: CV-RMSE

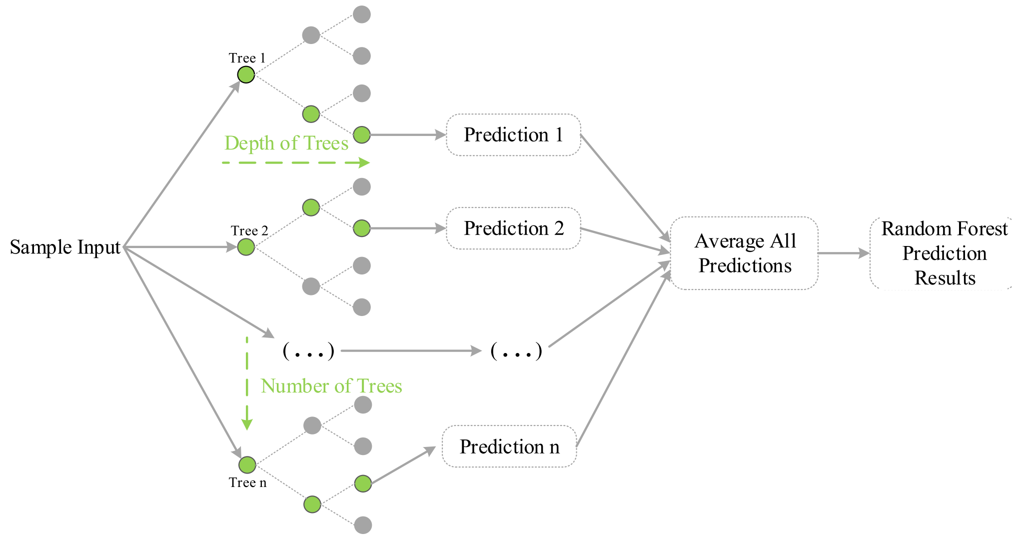

Fig. 6. Principle of RF algorithm.

31.9%; short-term: CV-RMSE 20.2%) are not good for this long-term task. XGBoost is good at long-term prediction, as other studies have found. Lu et al. (2020) proposed a novel model that combines XGBoost to predict the long-term energy consumption of an intake tower. The MAPE of the prediction results of the different methods are as follows: CEEMDAN-XGBoost: 4.85%, XGBoost: 8.06%, CEEMDAN-RF: 6.26%, and PSO-SVM: 7.92%.

In the building energy demand, the load demand of HVAC systems is the main difficulty to estimate because of its nonlinear character. Lu and Meng (2020) found that XGBoost is the best model for forecasting AC energy use in residential buildings in Chongqing. For the cooling season of AC in buildings, they found that 11 input variables have a great influence on cooling energy use. These variables mainly included outdoor air temperature, running time of the AC, and temperature differences between indoor air and set-point, whereas no building physical and thermophysical variables such as window–wall ratio and total heat transfer coefficient of the envelope were considered. The prediction performance is not well compared with the results in Wang et al. (2020a) XGBoost (CV-RMSE: 62%), RF (CV-RMSE: 64%), SVR (CV-RMSE: 64%), and ANN (CV-RMSE: 73%). Wang et al. (2019b) tested several popular models (i.e., XGBoost, RF, ANN, and SVR) to predict the heating energy consumption of a residential building in Tianjin, China. Six input features (i.e., outdoor dry bulb temperature, dew point temperature, outdoor relative humidity, wind speed, solar radiation, and hour of day) were used in their models. The CV-RMSE of the prediction results of the different models is as follows: average RF: 5.0%, XGBoost: 5.8%, SVR: 6.2%, and ANN: 7.0%.

In addition, lightGBM is a tree-based gradient boosting framework similar to XGBoost. It was first released on October 17, 2016 as a part of Microsoft's Distributed Machine Learning Toolkit project (Anon, 2021i). It was designed to be fast and distributed with the advantages of faster training speed and higher efficiency, lower memory usage, supporting parallel and GPU learning, and capable of handling large-scale data. LightGBM uses histogram-based algorithms to bucket continuous features into discrete bins so that it can reduce communication cost and memory usage (Jin and Agrawal, 2003; Ke et al., 2017). Thus, lightGBM is a promising algorithm for energy prediction in massive data sources.

3.5. Artificial neural network (ANN)

ANN is a nonlinear statistical algorithm inspired by biological neural networks. It can deduce the complicated hidden relationship between inputs and outputs. The principle of a typical one hidden layer ANN is shown in Fig. 8. A typical ANN has three interconnected layers: input, middle (i.e., hidden), and output layers. Theoretically, the hidden layer consists of many sub-layers depending on the complexity and nature of the task (Mandal et al., 2006; Kiartzis et al., 1997).

In addition to the factor of prediction accuracy, computing time is another critical factor in evaluating the performance of a model. Generally, increasing the dimension of input features can improve prediction accuracy, but this strategy may also increase the computation cost, particularly for massive data processing. Ahmad et al. (2017) compared an ANN and RF for HVAC electricity consumption prediction of a hotel. Outdoor air-dry bulb temperature, outdoor air relative humidity, day of week, hour of day, occupancy schedule, and total rooms booked were considered as input variables. They found that the ANN model's prediction results were slightly better (MAE: 9.18% vs. 9.31%) when the model used all variables (ten features) instead of only using the important variables (four features). In their study, the computation time was not provided; nevertheless, using the main input features in the model is a good way to optimize the prediction model in practice. Mena et al. (2014) predicted the short-term electricity demand of a bioclimatic building in Spain by using an ANN-based model. To avoid the use of unimportant variables in the model, input feature variable selection was implemented ahead of the data training and testing. The order of features' importance of different input variables is as follows: solar radiation, outdoor temperature, wind speed, outdoor humidity, and wind direction, and a mean error of 11.48% has been realized.

3.6. Recurrent neural network (RNN)

Elman RNN, LSTM, and gated recurrent unit (GRU) are three common RNN algorithms. LSTM was designed for handling sequential data and was first introduced by Hochreiter and Schmidhuber in 1997 (Hochreiter and Schmidhuber, 1997). Compared with the traditional neural network, LSTM can pass the information from the last steps to the next time step (i.e., backpropagation). Fig. 7 shows this memory passing process. LSTM can be considered as an integration of many traditional neural networks. Based on this feature, LSTM is an inborn network that processes sequential data such as building load. It can solve complex and long-time-lag tasks that traditional RNN algorithms can barely solve. In the study (Wang et al., 2020a), LSTM performed better for short-term load prediction compared with LR, SVM, RF, and XGBoost.

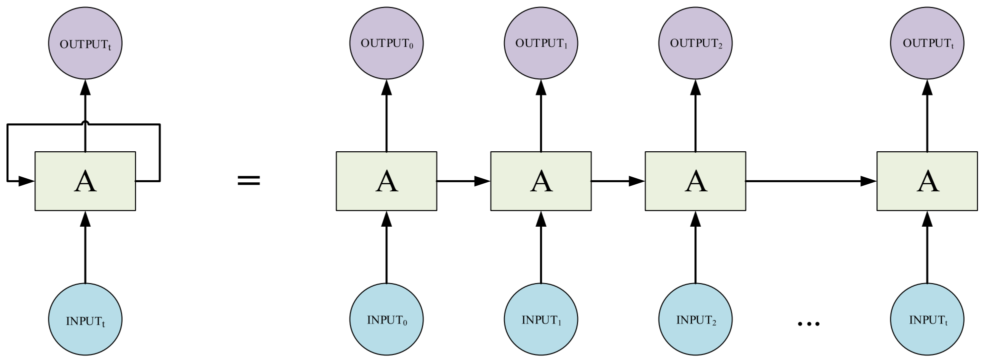

Fig. 7. Process of backpropagation approach of RNN.

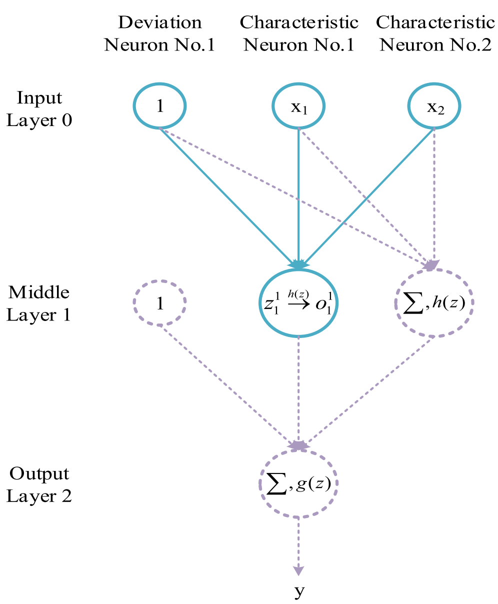

Fig. 8. Principle of typical ANN with one hidden layer.

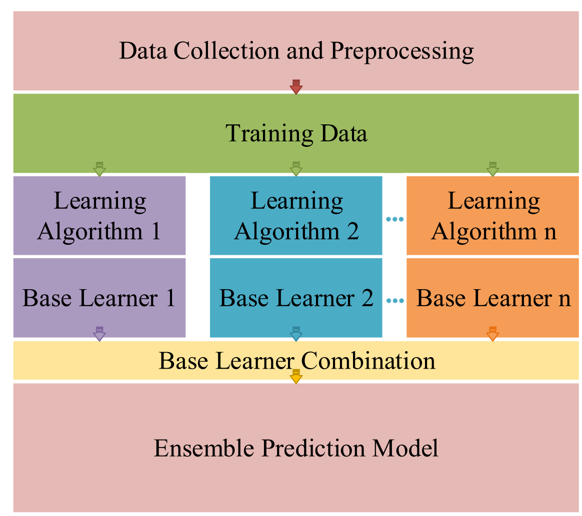

Fig. 9. Framework of an ensemble model.

3.7. Other models

In 1965, the concept of ensemble learning was introduced by Nilsson (1965). Compared with single models that use only one algorithm, the ensemble model consists of multiple algorithms. The ensemble model combines a single algorithm and takes advantage of each algorithm to improve prediction accuracy. The framework of the ensemble model is shown in Fig. 9. The goal of the ensemble model is to minimize the prediction errors; hence, the base algorithms with high prediction accuracy have higher weights.

Fan et al. (2014) developed an ensemble model integrating eight base algorithms for next-day building energy prediction. The eight base algorithms were RF, SVR, multiple LR, multilayer perceptron, boosting tree, multivariate adaptive regression splines, k-nearest neighbors, and autoregressive integrated moving average, and the weights of these algorithms were 0.404, 0.315, 0.087, 0.076, 0.066, 0.023, 0.021, and 0.008, respectively. Duc-Hoc et al. (2020) proposed a new ensemble model called an evolutionary neural machine inference model that combined SVR and radial basis function ANN. Measured data from residential buildings was used to evaluate this ensemble model. In their study, the computing time of different models was logged. The computing times of ANN, SVM, DNN, and ENMIM were 5, 7, 300, and 600 s, respectively. Zhang et al. (2020) proposed a novel ensemble deep learning method for short-term building energy forecasting. They decomposed the data into a stable and stochastic part. The stochastic part was estimated by using the ensemble model, which combines a novel deep belief network and extreme learning machine. Wang et al. (2020b) proposed a novel stacking model for building energy prediction. In their study, several widely used algorithms, including RF, XGBoost, SVR, and kNN models, were selected as the base models in the first layer. Then, the stacking method was used to ensemble each base model by cross-validation to boost the prediction performance.

Transfer learning aims to learn knowledge from one task to other similar tasks, as shown in Fig. 10. It has been successfully applied in domains such as machinery fault diagnosis (Wu et al., 2020; Chuan et al., 2020) and image classification (Swati et al., 2019). It is worth noting that data sources should have similar features to apply this method to building energy prediction. Because the building data usually meet this criterion, it is an attractive idea to use the data in well-measured buildings to predict the energy consumption of other buildings with limited data (Qian et al., 2020).

The literature reviews show that transfer learning can also be well integrated with other data-driven algorithms. Qian et al. (2020) studied the transfer learning model with SVR in short- and medium-term HVAC energy consumption. Gao et al. (2020) used the transfer learning model to predict the energy consumption of a building with poor data information. Ribeiro et al. (2018) proposed a transfer learning method for cross-building energy forecasting; the results showed that the prediction accuracy was

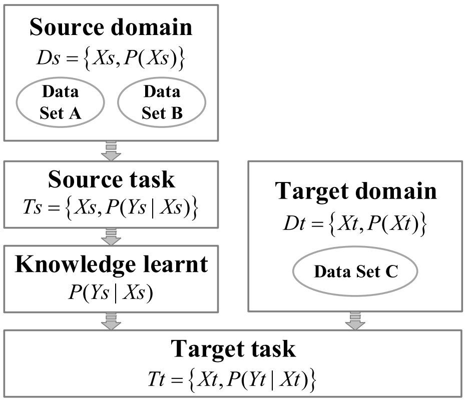

Fig. 10. Principle of transfer learning.

improved by 11.2% by using data from other buildings. A novel transfer learning-based methodology has been proposed for 24-h ahead building energy forecasting by Fan et al. (2020). Compared with standalone models, this new model could reduce prediction errors by 15% to 78%.

3.8. Discussion of data-driven models

Compared with "white box" models, although data-driven models do not require massive engineering efforts during the development process, the generalization of a well-tuned data-driven model is usually poor (Zhang and Wen, 2019a). Thus, scholars have focused on feature selection in almost all data-driven models to develop a more general model that can be used in different buildings (Luo et al., 2020). The input feature variables are commonly categorized into three types: external climate data, internal factors, and operation schedules of energy facilities (Li et al., 2009; Leung et al., 2012; Luo et al., 2019), and five mature feature selection methods were proposed in the paper (Sun et al., 2020). Considering that buildings and their energy systems are different in practice, the feature selection results are quite different from one to another. Based on a comprehensive literature review, the usage frequency of features in 25 core references is summarized in Fig. 11, and the detailed description is included in Appendix. As shown in Fig. 11, outdoor dry bulb temperature, outdoor relative humidity, solar radiation, day of week, and hour of day are the five most frequently used input features in data-driven models. In addition to external climate data, the physical information about buildings such as the number of floors, wall area, and glazing area is used to improve prediction accuracy.

According to the abovementioned data-driven models, STLF and LTLF are two common prediction requests in building energy management. Some of them are good at short-term prediction, while some perform better in the long-term. Fig. 12 shows the prediction preferences of the abovementioned algorithms for STLF and LTLF in 25 core references. As shown in Fig. 12, XGBoost is most probably used for LTLF, while RNN is commonly employed for STLF; ANN and RF could be used for both time spans.

In addition to the hard works on feature engineering and model selection, load decomposition is a promising approach to improve the prediction accuracy. There are two methods for load decomposition. First, signal decomposition and transformation are the most widely used methods, such as Fourier analysis (He et al., 2020) and wavelet analysis (Alipour et al., 2020). Chu et al. (2020) decomposed the total building loads into a basic and seasonal weather-sensitive part and obtained more accurate results. Second, sub-meter technology has been rapidly developing in recent years, which makes it possible to predict the load of HVAC systems, lighting, plugs, and other equipment separately. Fu et al. (2015) used sub-meter data to predict the electricity load of public buildings with high prediction performance. Compared with load decomposition, load clustering technology can classify homogeneous loads that have similar patterns into one group, which enhances the prediction performance by developing a single model for each cluster. An early load classification algorithm was proposed in this paper (Chen et al., 2021).

Model calibration is much easier for the data-driven models compared with the white box models mentioned above because the dataset has already obtained before model development and has been split into training and validation datasets. The commonly used split rate is 80% for training and 20% for validation (Sun et al., 2020; Liu et al., 2020). A proper validation metric is the key to evaluating a model. The widely used evaluation metrics are MAPE, MAE, and CV-RMSE (Chen et al., 2021; Zhe et al., 2020).

4. Hybrid models – "grey box"

The modeling and calibration process of "white box" software is a huge challenge for building energy stakeholders. A large number of basic input parameters are required; thus, the modeling development on a physical software platform is time-consuming, and the simulation economic cost is high. The "black box" models capture linear and nonlinear relevance between the input and output variables in an easy way. However, for such models, it usually takes enormous historical data and a long time to train the model and achieve accurate predictions under different conditions. To solve this dilemma, "grey box" has been proposed. It uses a simplified physical model and easily accessible data to simulate building energy demand, thus combining the advantages of both the white and black boxes.

4.1. resistance–capacitance (RC) thermal network

RC model is a typical grey box model which was introduced in early 1985 by Hassid (1985). He proposed two resistances and one capacitance (i.e., the 2R1C model) to represent the building envelope's thermal performance of a multi-story building. The sketch diagram of a simplified building energy RC model is shown in Fig. 13.

Ji (2016) established a new RC-S (RC-submeter) model with building submeter measured data to predict the hourly cooling load in buildings. In this model, the heat transfer through the building envelope is calculated using the traditional 3R2C model, aiming at the heat stored inside the building thermal mass. This model was verified by simulation and actual operational data, and the prediction MAE was within 9.0%. Mohammad et al. (2020) developed a second-order RC grey box representing a case building structure for building heat demand simulation with uncertainty analysis, which is crucial to ensure the validity of simulation results in a "grey box" model. Murphy et al. (2021) developed a 2R2C grey box model to predict the dynamic internal air temperature. In this grey model, internal air mass and internal thermal masses were modeled as independent capacitors; external surfaces were modeled as one resistor while walls and roofs were modeled as the other resistor. More variants of xRyC models can be found in the paper (Li et al., 2021).

4.2. Other models

A hybrid model integrated with a simulation tool and data-driven algorithm can be another option, as shown in Fig. 14. It may generate better prediction results than the "white box" and "black box". For instance, Dong et al. (2016) established a hybrid

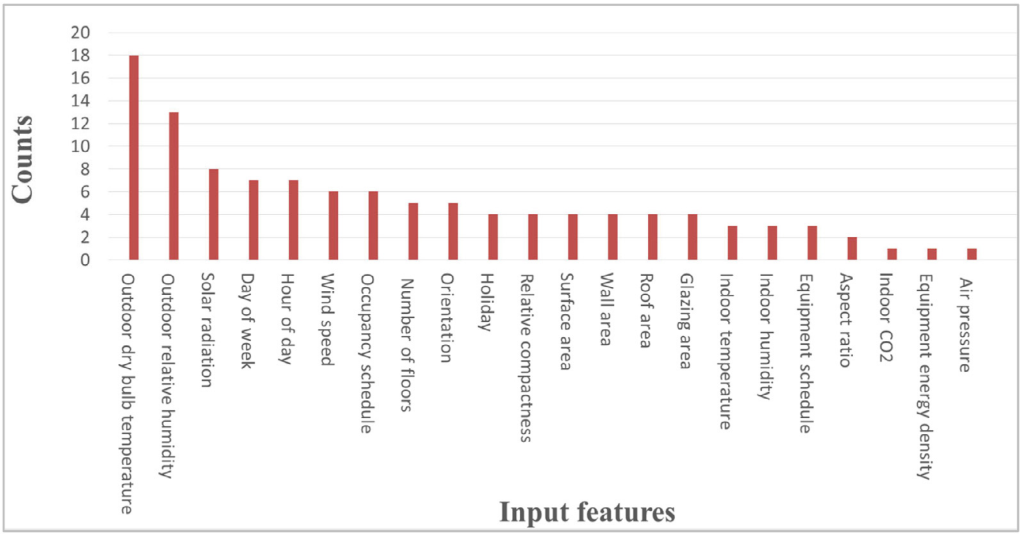

Fig. 11. Frequency of input features of data-driven models in 25 core references.

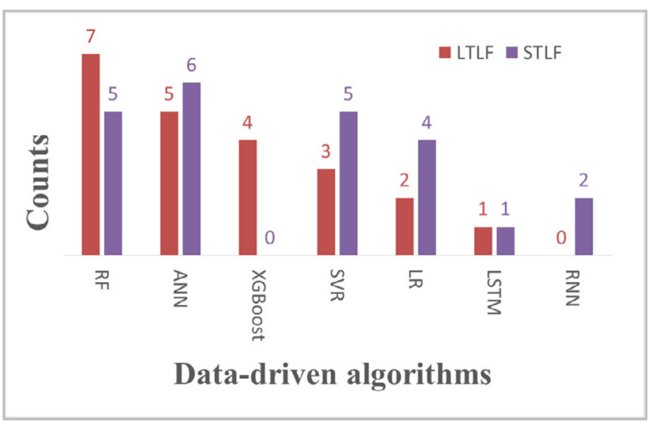

Fig. 12. Frequency of use of different algorithms for STLF and LTLF in 25 core references.

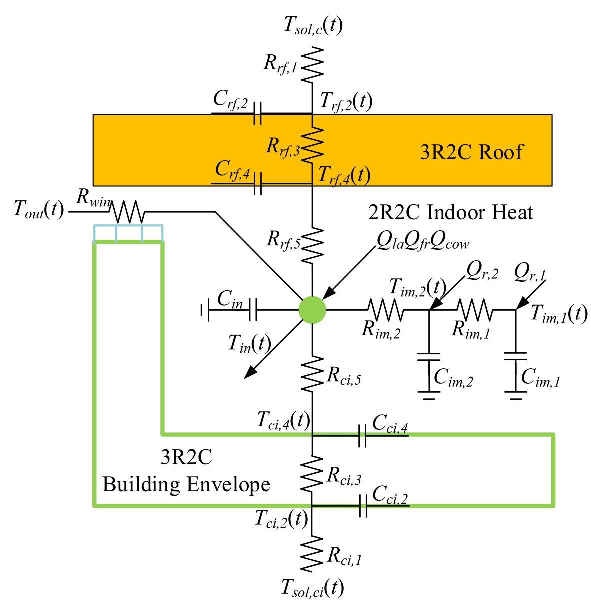

Fig. 13. An example of building RC thermal model.

model that combines data-driven and physics-based models to estimate the total energy consumption for a residential building. Compared with the other five data-driven algorithms, ANN, SVR, LS-SVM, GPR, and GMM, the 24-ahead prediction accuracy of this hybrid model is the best. Xu et al. (2012) developed a model coupling EnergyPlus with ANN to predict the energy consumption of a cluster of ten residential single-family houses. External empirical sources including experimental data and demographics were considered in the model.

4.3. Discussion of hybrid models

Through the literature review, it appears that the hybrid models simplify the description of the building heat transfer process and leverage the advantages and disadvantages of both physical and statistical methods. Thus, some of the parameters in the model are interpretable. RC model is a typical and the most popular hybrid model, and the RC model can separately represent the building physical parts and dynamic processes such as heat transfer through external envelope, zone air, zone internal mass, internal heat gains, and infiltration (Li et al., 2021). There are some applications of the hybrid model including heat dynamic analysis, building control and optimization, urban size energy modeling, and building grid integration. With the development of building energy simulation tools and cloud computing, the hybrid model could become more prevalent in the future, and promote the development and cooperation between physics-based and data-driven approaches.

5. Advantages and limitations of each prediction approach

A detailed description of each prediction approach was presented in the above sections. Physics-based, data-driven, and hybrid modes have different properties that are determined to the model preference of users. A standard to select the best approach for different scenarios was proposed in the paper (Dawn

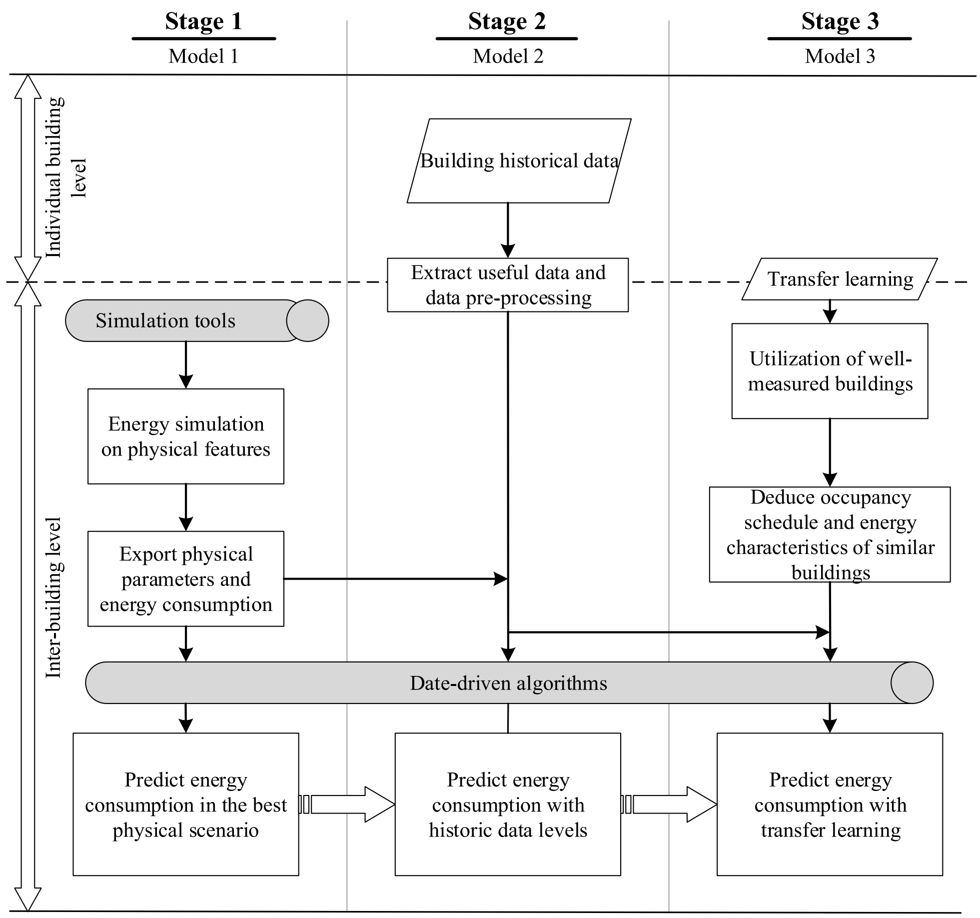

Fig. 14. Scheme of a hybrid model combining building physics with the data-driven algorithm.

Table 2
Advantages and disadvantages of different prediction approaches.

Prediction approaches	Advantages	Disadvantages
"White box" models	• The relationship between input and output is explainable • The parameters are easily modified • No historical data is required	• It requires a significant amount of efforts to input building information and parameters • Computation cost is huge • It requires previous knowledge of thermal dynamics and software
"Black box" models	• No specific expertise is required • Model development period and computational time are short • The developed model is easy to be generalized	• It requires large amounts of historical data • It is easy overfitting • It is usually no-explainable
"Grey box" models	• Less data is required • Only bounds on physical parameters are required	• It couples two distinct scientific domains • It is not easy to develop

et al., 2015). Table 2 summarizes the advantages and disadvantages of these three approaches, and it benefits engineers to select an appropriate model for their own needs.

6. Conclusion

In this paper, we presented an in-depth review of the main approaches applied to building energy prediction. These approaches were clustered into three groups including the most commonly used methods. First, the building physics-based simulation tools (i.e., white box) have been introduced. These tools can be divided into zonal and nodal approaches. Second, data-driven models (i.e., black box) have been reviewed. There are six main algorithms: linear regression (LR), support vector machine (SVM), random forest (RF), extreme gradient boosting (XGBoost), recurrent neural network (RNN), and artificial neural network (ANN). The last category is the hybrid model (i.e. grey box), which relies on both physical model and data-driven model. Through a well-rounded study of these three approaches, the following conclusions were drawn:

(1) It is better to use physical models for their reliability, interpretability and accuracy although the modeling process is time-consuming and repetitive. Data-driven models are extremely useful when owners have sufficient historic data from existing buildings, whereas there is no or insufficient information of design building. Hybrid models make a great trade-off between physical and data-driven models, and they could be a better option when the required information is insufficient for the other two models.

Table A.1

Reference	Input features	Algorithms	Prediction span
Wang et al. (2020a)	Day of week; Hour of day; Holiday; Outdoor dry bulb temperature; Outdoor relative humidity	XGBoost; RF; SVR; LSTM	LTLF
Lu and Meng (2020)	Outdoor dry bulb temperature; Equipment schedule	XGBoost; RF; SVR; ANN	LTLF
Wang et al. (2019b)	Outdoor dry bulb temperature; Outdoor relative humidity; Wind speed; Solar radiation; Hour of day	RF; SVR; ANN	LTLF
Ahmad and Chen (2019)	Outdoor dry bulb temperature; Outdoor relative humidity	XGBoost; LR; NARM	LTLF
Lahouar and Slama (2015)	Hour of day; Outdoor dry bulb temperature	RF	STLF
Ahmad et al. (2017)	Outdoor dry bulb temperature; Outdoor relative humidity; Day of week; Hour of day; Occupancy schedule	RF; ANN	STLF
Leung et al. (2012)	Outdoor dry bulb temperature; Outdoor relative humidity; Solar radiation; Wind speed; Equipment Schedule; Day of week; Holiday; Occupancy schedule	ANN	STLF
Mena et al. (2014) and Li et al. (2009)	Outdoor dry bulb temperature; Solar radiation	SVR; ANN	STLF
Chen et al. (2017)	Outdoor dry bulb temperature; Hour of day; Day of week	SVR	STLF
Kusiak et al. (2010)	Outdoor dry bulb temperature; Outdoor relative humidity	ANN	Both
Cai et al. (2019)	Outdoor dry bulb temperature; Outdoor relative humidity; Air pressure; Wind speed	RNN	STLF
Chammas et al. (2019)	Outdoor dry bulb temperature; Outdoor relative humidity; Equipment energy density; day of the week	MLP	STLF
Wei et al. (2019)	Indoor temperature; Indoor humidity; Indoor CO_2; Occupancy schedule; Solar radiation; Outdoor dry bulb temperature; Outdoor relative humidity; Wind speed	ANN	STLF
Ding et al. (2018)	Outdoor dry bulb temperature; solar radiation; wind speed; Indoor temperature; Indoor humidity; Occupancy schedule; Equipment schedule; Thermal mass	MLP; SVR	STLF
Mun et al. (2019)	Indoor temperature; Indoor humidity	LR; RF; SVR	STLF
Wang et al. (2019a)	Occupancy schedule; Day of week	LSTM	STLF
Sala-Cardoso et al. (2018)	Occupancy schedule	RNN	STLF
Fan et al. (2014)	Day of week; Hour of day; Holiday; Outdoor dry bulb temperature; Outdoor relative humidity; Solar radiation; Wind speed	Ensemble models	STLF
Seyedzadeh et al. (2019)	Relative compactness; Surface area; Wall area; Roof area; Number of floors; Orientation; Glazing area; Outdoor dry bulb temperature; Outdoor relative humidity; Solar radiation	ANN; SVM; RF; XGBoost	LTLF
Wei et al. (2016)	Aspect ratio; Window–wall ratio; Number of floors; Orientation; Building scale	RF	LTLF
Tsanas and Xifara (2012)	Relative compactness; Surface area; Wall area; Roof area; Number of floors; Orientation; Glazing area	LR; RF	Both
Kumar et al. (2018b)	Aspect ratio; Relative compactness; Glazing area; Roof area; Surface area; Wall area; Orientation; Number of floors; Glazing area	ANN; SVR; RF	Both
Kumar et al. (2018a)	Outdoor dry bulb temperature; Outdoor relative humidity; Solar radiation; Roof area; Wall area; Relative compactness; Surface area; Number of floors; Orientation; Glazing area	ELM	STLF
Zhang and Wen (2019b)	Day of week; Hour of day; Holiday; Outdoor dry bulb temperature; Outdoor relative humidity;	MARS	STLF

(2) STLF and LTLF are two different types of needs in building energy management projects. STLF is crucially important for control goals such as energy system optimization and DR, whereas LTLF is of great interest for long-term energy planning, such as system planning and energy policy formulation.

(3) Simulation tools such as TRNSYS and Dymola are good at establishing energy systems, while EnergyPlus is good at building envelop simulation. In addition, some data-driven models such as XGBoost are preferred for LTLF, while RNN is good at STLF, and ANN and RF can be used for both time spans.

(4) Feature selection is the most popular strategy for a data-driven model. Outdoor dry bulb temperature, outdoor relative humidity, solar radiation, day of week, and hour of day are the five most important and frequently used input features in data-driven models. In addition, the physical information of buildings, such as the number of floors, wall area, and glazing area, can be used to improve the prediction accuracy.

Declaration of competing interest

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

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Appendix

See Table A.1.

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