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A review of the research of data-driven technology in the built environment

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Abstract
Data driven technology is widely used in different research fields and has achieved great results, but also has an important impact on our daily life. This paper reviews the application of data-driven technology in the study of built environment from the following three perspectives: (1) energy consumption prediction; (2) Air conditioning system control optimization control; (3) Inhabitant behavior prediction. The application methods and advantages of data-driven technology in related fields are reviewed and suggestions for further research are provided.
Keywords: *Data-driven technology; Built environment; Energy prediction; System control; Occupancy*

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I. INTRODUCTION

According to the International Energy Agency, the building and construction sector directly or indirectly accounts for 30% of global final energy consumption. At the same time, CO2 emissions from building operations account for about 28% of global carbon emissions [1]. The world's energy consumption is expected to increase by more than 50% by 2030 [2]. From 2010 to 2020, carbon emissions from building operations continue to grow at a rate of 1% per year. Continued decarbonisation has slowed emissions, but is still off track to achieve carbon neutrality by 2050. To achieve this carbon neutral goal, all new buildings and 20% of existing buildings need to be zero-carbon by 2030 [3]. Therefore, it is very important to improve the energy efficiency of buildings and reduce the carbon emissions of buildings. Among the most important are the need for accurate energy consumption prediction, efficient air conditioning system control and the judgment of occupants' behavior.

The prediction of building energy consumption is an important part of energy planning, energy management and energy conservation [4]. A data-driven approach is considered the best way to produce the desired results in a prediction task [5]. The most commonly used data-driven methods for building energy consumption prediction are machine learning, deep learning and statistical analysis model [6].

In terms of HVAC control methods, Abdul Afram[7] et al reviewed major HVAC control methods and pointed out the research gap in model predictive control. Wang et al. [8] also summarized some control strategies of low-energy buildings from 2006 to 2016, pointing out that the best control strategy is proportional integral differential control model predictive control (PID-MPC). June Young Park[9] et al., in studying the relationship between thermal comfort and building control, pointed out that building control is mainly concerned with energy saving, and identified the potential research direction of thermal comfort. In recent years, data-driven control methods have been applied. Qiming Fu et al. [10] reviewed the application of reinforcement learning in building energy consumption control. Mirza discussed the application of deep learning in predictive maintenance of facilities management and emphasized its importance [11].

The behavior of occupants will have an impact on building energy consumption, and the assessment finds that occupants have an energy saving potential between 10%-25% and 5%-30% in residential buildings and commercial buildings [12]. Shuo Chen[13] divided occupants' behaviors into three main categories, namely residence, interaction and behavioral efficiency, and proposed that it is an effective and economical method to change occupants' behaviors. From a complex perspective, occupant behavior can be defined as occupation, equipment operation and window/shade operation. Francesca Stazi[14] et al. analyzed some driving factors of occupant behavior and evaluated these factors. Aya Nabil Sayed et al. [15] evaluated the application of transfer learning and deep learning in building occupancy, and pointed out that combining it with sensors can help achieve better prediction, thus improving the behavior of occupants can effectively help save building energy consumption.

At present, the direction of big data analysis tends to focus on only one direction, and there is a lack of a research review that combines energy consumption prediction, air conditioning system control and occupants. In the aspect of energy consumption forecasting, there is a lack of research and analysis in the direction of big data on long and short term forecasting time scale at present. There are relatively few researches on the control optimization of air conditioning system in the direction of big data. There are also few reviews of data-driven resident behavior. Therefore, this paper reviews the latest research on energy consumption prediction, air conditioning system control and occupant behavior.

II. Energy consumption forecast

Short-term (for example, sub-hourly, hourly or daily) and long-term (for example, annual) energy consumption forecasts are very important for the operation and development of buildings and equipment. In addition, different building types and features have different impacts on building energy consumption [16]. This part divides them into long-term and short-term building load forecasts based on different time scales. The influence of different research methods on building energy consumption under the same time scale is studied.

2.1 Annual projections of building energy consumption

In the annual prediction of building energy consumption, neural network is the most commonly used tool. Razak Olu-Ajayi[5] compared DNN with other eight different mathematical models to predict the annual building energy consumption of large residential buildings, and measured the performance of each model with a performance measurement value of 0.99, and concluded that deep neural network is the best prediction model. At the same time, ANN is slightly superior to building simulation software for its simplicity and fast speed in constructing models to deal with nonlinear parameters [17, 18]. It can easily and quickly model complex problems by ignoring some parameters (such as outdoor temperature, solar radiation, optical and thermal physical properties of materials, etc.) [19], which also helps to improve energy performance efficiency. Improved prediction of building energy use in the early design phase [20].

In addition to ANN, XGBoost is also a commonly used method in building energy consumption. Ehsan Kamel[21] uses a data-driven model and machine learning algorithm to predict the energy consumption of residential buildings in heating and cooling days. By comparing different algorithms, it is found that XGBoost achieves high-precision minimum number of input features. It shows that data model driven can provide higher precision for load prediction. Gradient lifting is also commonly used to estimate the energy consumption of commercial buildings, which can have higher prediction accuracy than random forest and other models [22], which can use a limited number of features to achieve better performance, and can analyze the potential impact of future climate scenarios and alternative models of urban growth [23, 24].

ANN has good results in predicting large and small data, is relatively simple, and has high computing speed in limited data sets. Compared with other methods, ANN requires relatively less professional knowledge to solve problems, and can be used to improve the energy usage in the early design stage. However, when the data set is relatively large, the regression model requires a lot of time and energy. This method is insufficient to support the model; In addition, gradient lifting is also the most commonly used algorithm for annual prediction of building energy consumption. It has high-precision and minimum number of input features, which can bridge the gap between the poor availability of residential and commercial data sets and help people make decisions [24]. Table 1 provides long-term energy consumption prediction and the summary of corresponding accuracy.

Table 1: Long-term energy consumption.

Building type	method	conclusion	precision	literatrue
residence	ANN、GB、DNN、RF、Stacking、KNN、SVM、DT 和 LR	DNN is the best predictive model	R^2=0.95	[5]
residence	ANN and building energy simulation tools	The ANN is consistent with the simulation software results	MAE= 5.06%，R^2=0.977	[17]
residence	ANN	ANN improves the prediction of residential building energy use in the early design phase	The lowest MAPE was 5.36%, and the highest R2 was 0.98	[20]
residence	ANN、GM（1,1）、DGM（2,1）、Polynomial model	ANN is the best predictive model	The lowest MAPE= 0.09%	[25]
school	ANN	ANN has good potential for analyzing the determinants of energy use in buildings	MAPE =0.34	[26]
/	ANN、MATLAB	ANN can be of great help to architectural design utilization	The deviation is 3.43%, and the prediction success rate is 94.8%-98.5%	[19]
residence	M0、M1、M2、Lasso，XGBoost、LR	Regression and XGBoost are suitable for heating and cooling loads	R^2=0.998	[21]
residence	XGBoost	XGBoost outperforms other predictive models	R^2=0.82	[23]

residence	GBM、RF、TOWT	GBM models are more accurate than TOWT and RF models	/	[22]

2.2 Short-term forecast of building load

The accuracy obtained at the ultra-short time interval is often high, which can promote the optimization and decision-making of the system [27]. The retrieved articles mainly use data-driven models to forecast the heating and cooling load, power demand, etc. Neural network is a good forecasting model on this time scale. It can accurately predict the meter power [28, 29], load [30] and heating demand energy consumption [31] within 15 minutes. The regression method is the most commonly used method for the hourly time interval prediction of the load. Multiple linear regression analysis and quadratic regression analysis are adopted to show that the residential energy consumption prediction is developing in the direction of a single model developed for each family [32]. In the analysis of the SVR model, the optimal time granularity occurs by floor at an hourly interval [33]. In addition, the least square method in regression eliminates all correlations with climate variables in heating load prediction [34]. Richard E. Edwards[35] evaluated seven different machine learning algorithms in the new residential data set, and the verification results showed that, The least square support vector machine has the best effect in predicting the energy consumption of residential buildings in the next hour. On the hourly time scale of the study, backpropagation neural network model and support vector regression model are adopted to show that in the comparison of hourly correlation analysis and non-hourly correlation analysis, the heat load prediction method based on hourly correlation analysis can keep the rate unchanged while maintaining the prediction accuracy of the model [36]. In terms of cold load prediction, The prediction accuracy of SVM is higher than that of ANN [37], compared with SVM, there are fewer free parameters to optimize. In terms of daily scale prediction, the best method is ANN, which can achieve more accurate prediction in terms of load power consumption. Alberto Hernandez Neto compared Energyplus and ANN to predict building energy consumption, and the average error of the former was ± 13%, while the latter was only 10% [38]. S.L. Wong also pointed out that its efficiency coefficients of 0.994, 0.940, 0.993 and 0.996 in cooling, heating, electric lighting and total building electricity consumption respectively proved its excellent forecasting ability [39].

ANN is the most commonly used data-driven method in the short-term prediction scale of 15 minutes and every day, and SVR is the most commonly used method in the hourly time prediction scale, whose main forecast objects include heating and cooling load and power demand. Table 2 provides the summary of the short-term energy consumption prediction time scale and accuracy.

Table 2: Short-term load.

Building type	method	Time scale	object	precision	literatrue
commerce	ANN	15 minutes	Electricity consumption	RMSE=10％	[28]
hospital	ANN	15 minutes	Load consumption	MAPE=7％	[29]
School	ANN	15 minutes	Electricity consumption	MAPE=4.88％	[30]
School	ANN	15 minutes	Heating demand	The energy consumption error is 0.02%	[31]
residence	LR	hourly	Power and HVAC equipment energy consumption	/	[32]
residence	SVR	hourly	Electricity consumption	CV=2.16	[33]
residence	LR、FFNN、SVR、LS-SVM、HME、LR、HME、FFNN、Fuzzy C-Means、FFNN	hourly	Electricity consumption	LS-SVM is the highest	[35]
residence	SVR、ANN、CART、CHAID、GLR、SVR +ANN	hourly	Heating and cooling load	The RMSE for SVR +ANN and SVR was 39% and 65.9%, respectively	[40]
Office building	BPNN、RBFNN、GRNN、SVM	hourly	Cooling load	GRNN and SVM are the best prediction models	[37]
Office building	BPNN、SVR	hourly	Heat load	RMSE decreased by 10.4% and 12.9%, and R^2 increased by	[36]

				11.7% and 7.9%, respectively	
Office building	ANN	daily	Electricity consumption	Average error 10%	[39]
Office building	ANN	daily	Electricity consumption	CV is 3% to 5.6%	[38]

III. Air conditioning system control optimization

Air conditioning system is a combination of multiple air conditioning individuals together, centralized cooling and heating an overall structure,System energy consumption can be better reduced by controlling parameters such as supply air temperature, humidity, pressure and carbon dioxide concentration. Jin Hou[41] et al. Adopted MLR to model supply air temperature and static pressure, and adopted particle swarm optimization to solve and calculate, which can reduce energy consumption by more than 7%. In addition to temperature and pressure, Andrew Kusiak[42] also introduced parameters such as carbon dioxide concentration to optimize the solution. The sensor is usually used to analyze the detected set point temperature, humidity and carbon dioxide concentration to realize automatic on-off control of the HVAC system, so as to realize the system detection, diagnosis, control and other processes. Problems such as excessive system pollution and diffuser condensation can be found [43, 44] ANN model is the most widely used in energy saving of the system. Ferreira[45] used model predictive control and RBF ANN model to build temperature, humidity and PMV models to predict and process the best control trajectory, achieving energy saving of more than 50%. Zakia Afroz[46] combined neural network and particle swarm optimization algorithm to build a prediction model. Compared with the previous prediction model, it took more consideration of VOC concentration, cold and hot water flow rate, etc., so as to achieve the best control of the unit temperature and pipeline static pressure set point, and reduce the energy consumption of HVAC system by 7.8%. Mariam Elnour[47] et al pointed out that compared with other machine learning models, the optimization method combined with neural network and model predictive control can achieve 46% energy-saving effect of HVAC system.

In addition to the system, the main host of the air conditioning system is usually optimized, which is mainly realized by the control of the chiller. Wuxia Zhang[48] pointed out that machine learning can build the system prediction model and real-time optimization control strategy, and the traditional use of the chilled water air conditioning system to adjust the sensible heat and latent heat load in the space will cause a certain amount of energy waste. Qinmin Yang[49] proposed a predictive control strategy based on neural network model to control indoor air temperature and humidity of chilled water air conditioning system by changing the rotational speed of compressor and fan. Compared with traditional PID control, this model has a smaller control error. Wang[50] Chan[51] et al. used neural network to model the input parameters of compressor and blower, which can help find the optimal set point of chiller, such as supply temperature, operation sequence and chilled water flow rate, and help build cop model for optimization.

The research shows that the parameters such as supply air temperature and supply air pressure are mostly optimized by particle swarm optimization algorithm, which has better optimization results. The neural network model has been widely used in the predictive control of air temperature and humidity, and has great application potential. Its prediction effect is better than the traditional PID control, which can help people better find the optimal set point of the chiller. The new HVAC system operation automatic control strategy based on real-time big data achieved by sensors can better improve indoor air quality, which is also the direction of future research. Table 3 shows the controlled objects of air conditioning system control optimization and the corresponding conclusions.

Table 3: System control optimization.

Controlled object	method	literature
Energy consumption, supply air temperature, supply air pressure and uncontrollable parameters	MLR	[41]
Static pressure and supply air temperature set points	MOPSO	[42]
Co2 concentration and set point temperature	Real-time big data analytics	[43]
Temperature, humidity and carbon dioxide concentration	Real-time big data analytics	[44]
PMV	RBF、ANN	[45]
Environmental parameter	NARX、ANN	[46]
Compressor speed and fan speed	ANN	[49]
Air conditioning system component parameters	MLP	[50]
Water supply temperature and flow	ANN	[51]

IV. Inhabitant

In the operation stage of a building, energy consumption is closely related to the behavior of occupants, and the behavior of occupants is also considered to be one of the key factors affecting the energy performance of a building [52]. In its research field, big data technology is a relatively common method, such as [53, 54], which has produced a good research effect on the occupancy rate and occupant behavior. In this paper, occupant behavior is analyzed in terms of occupancy rate, interaction with equipment and window opening.

In the study of occupant behavior, people use various methods to capture the behavioral information of occupants. Firstly, they study the existence of occupants in rooms and buildings, and then the number of occupants in rooms and buildings at a certain period of time. In this modeling process, we call it "occupation". Data mining technology is an important tool for occupancy prediction [53]. Typical occupancy patterns can be identified by mining occupancy data, which usually adopts the pattern of obtaining occupiers by clustering [53, 55-57], and predicts occupancy scheduling according to the obtained occupancy rules. The occupancy rate includes two dimensions of time and space. Y. Wang[58] pointed out that association rule mining can reduce the total energy consumption by 26.1% in the recognition of the energy waste of the temporal change and spatial distribution of the occupancy pattern. At the present stage, there are problems such as seldom considering the difference of occupancy rate and the weak correlation between it and energy consumption. Kwonsik Song et al. [59] used k-means, artificial neural network and other methods to build a prediction model to help achieve more accurate prediction with less data.

The interaction between the occupants and the equipment has a significant impact on the energy consumption of the building, mainly from the HVAC system, lighting and domestic hot water. The combination of HVAC system control and occupancy can reduce the energy consumption of heating and cooling. Zheng Yang[60] uses the agglomeration hierarchical clustering method to save 11.5% to 14.4% of energy by reducing the diversity of occupancy at the regional level; Yuzhen Peng[61] adopted the intelligent control machine learning method, and achieved the energy saving effect of 7%-52% compared with the cooling operation; Jie Zhao[54] studied HVAC energy consumption by mining the power consumption of office equipment and found that C4.5 is a suitable algorithm for learning individual behavior and LR is a suitable algorithm for learning group behavior. In addition to HVAC systems, lighting systems and domestic hot water systems are also major consumers of building energy. Xin Zhou[62] established a random lighting model to accurately simulate the use of lighting energy, which can be used to simulate building energy and improve the simulation accuracy of real building lighting energy use. H. Kazmi[63] pointed out that the computational heuristic algorithm could optimally control the hot water supply, which achieved a 27% reduction in energy consumption within 3.5 months.

Occupants' behavior of opening or closing Windows will significantly affect building energy consumption. The driving factors of opening Windows usually include physical, psychological, physiological, environmental and social factors. However, some factors have weak or no correlation with window openings, and the influence of irrelevant variables on building energy performance can be eliminated by establishing a data mining framework. Simona D'Oca points out that the framework combining statistical analysis with clustering and association rules can be used to identify the behavior pattern of occupants opening or closing Windows. Cheng Sun[64] defined the duration of window opening by cluster analysis and determined the influencing factors of its behavior by logistic regression, pointing out that seasons and habits are the main influencing parameters when environmental parameters and behavior state change.

The behavior of occupants is mainly divided into occupancy rate, interaction with equipment and window opening behavior of occupants. The most common way to obtain the pattern of occupancy rate is clustering, and the interaction between occupants and equipment is mainly divided into HAVC, lighting and domestic hot water system. The occupancy rate is affected by the existence state, behavior pattern, space and time dimension of occupants. Data mining is a powerful tool for identifying occupancy patterns in data sets, but it is difficult to combine it with other simulation software. We should consider more differences in occupancy rates among end-user groups and analyze the correlation between occupancy and energy consumption. In the future, we should consider combining the proposed prediction model with the occupancy prediction model to obtain more accurate building energy consumption information.

V. Conclusion

In this paper, the following conclusions are drawn by reviewing the articles on energy consumption prediction, air conditioning system control and occupants in the direction of big data.

1) In the long-term energy consumption prediction, ANN and XGboost are the main prediction methods. In the short-term energy consumption prediction, ANN is the most commonly used prediction method in the 15-minute and daily prediction scale, and SVR is the most commonly used prediction method in the hourly prediction scale.

2) In the optimization of air conditioning system, the combination of real-time big data and air conditioning system has better detection and optimization effects. Particle swarm optimization algorithm is a more commonly used algorithm in the optimization of air conditioning system parameters. Compared with traditional PID control, ANN can help people find the optimal setting point of the unit more quickly and help rapid decision-making.
3) Occupant behavior is mainly divided into three aspects: occupancy, interaction with equipment and windod-opening behavior. Clustering is the most commonly used method for occupancy pattern recognition. Occupancy rate is affected by the existence state, behavior pattern, space and time dimensions of occupants.

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