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DISTRICT HEAT DEMAND PREDICTION USING ARTIFICIAL NEURAL NETWORK WITH DATA OF SAMPLE BUILDINGS

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ABSTRACT

The prediction of building heat demand using engineering models will take unbearable long simulation time when they are applied to large energy networks. To deal with this problem, this paper uses the artificial neural network (ANN) to replace the engineering model in predicting the heat demand of buildings in a district heating network. To train the ANN with efficient learning process, the key data, such as the weather profiles, building fabrications, heating times, and customer heat demand, is collected from the simulation results of sample buildings in engineering models. The ANN trained with data from sample buildings is finally used to predict the heat demand of buildings in a district. In addition, different number of sample buildings for data collection and different percentage of data for training are achieved to balance prediction performance and training speed. The result shows that the ANN-based statistical model has a strong capability to accurately predict the heat demand of buildings with different types of operational functions in a district-level energy network.

Keywords: building heat demand prediction, artificial neural network, statistical modelling

1. INTRODUCTION

Recently, the depletion of fossil fuel and environmental issues have compelled many countries to focus on the reduction of the world's energy consumption and greenhouse gas emission [1]. Building energy consumption has steadily increased and become an important sector globally in current and future energy landscapes [2-4]. In Europe, buildings account for nearly 40% of the total energy use and more than 1/3 of CO2 emission [5]. In the building sector, heat demand is much higher than in other sectors and constitutes 40% of the household energy consumption [6]. Building energy efficiency improvement can be achieved by accurate prediction of the building's heat demand [7].

The methodologies of modelling the building heat demand can be categorised into engineering methods, data-driven approaches, and their hybrids. Engineering methods are developed as building energy simulators, which use bottom-up models to simulate the energy behaviour of a building based on the physical principles of heat transfer and engineering expertise [8]. However, these simulation tools would require detailed model to account for the end-use heat demand [9]. It will take unbearable long simulation time when they are applied to large or complex energy networks. Besides, their accuracy drops dramatically when the required information is incomplete. Thus, the statistical methods can become an alternative modelling type to analyse the historical data of heat demand from end-users.

The data-driven models are constructed based on a data group of factors that affect building energy. These factors are normally divided into environmental parameters and artificial designing parameters [10]. The environmental parameters include temperature, solar radiation, humidity, wind speed and atmosphere pressure. The artificial designing parameters include the percent area of windows, thermal properties of the wall, building orientation. The recent research indicates that the heating timing correlated to both the indoor temperature and, therefore, the time series data is also an important input variable to improve the accuracy of the data-driven model in heat demand prediction [3]. Comparing with the conventional statistical methods, artificial intelligent (AI) techniques are verified to be more reliable and efficient in the building energy prediction [9]. The most popular AI techniques include the genetic algorithm, decision tree, support vector

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machine-based learning algorithm and artificial neural networks (ANN) [11]. ANN has become one of the most important class in empirical nonlinear modelling and widely used in many engineering fields [10, 12]. The previous researches focused on predicting the building energy with the ANN model trained by its historical data. The impact of different building features is not considered and used to train the ANN in predicting the energy consumption of end-users.

This paper deals with the training of ANN using data from a smaller number of sample buildings to predict the heat demand of large amount of buildings in a district. The simulated data from building models is used to train the ANN model for the prediction of the heat demand of buildings with different building feature and parameters.

2. ARTIFICIAL NEURAL NETWORK USED IN BUILDING HEAT PREDICTION

2.1 Artificial Neural Network Model

Neural network is a nonlinear computational model that typically includes the input layer, the hidden layer, and the output layer [11], as shown in Fig 1. The number of hidden layers can be one or more depending on the complexity of the data used for training. Every single neuron is connected to all the neurons of a previous layer through adaptable synaptic weights [13]. In the normal ANN model, there is one input layer, one hidden layer and one output layer. The normal ANN model uses 26 input neurons for ANN training corresponding to the input parameters shown in Table 1, and 20 hidden neurons for internal relation of ANN model.

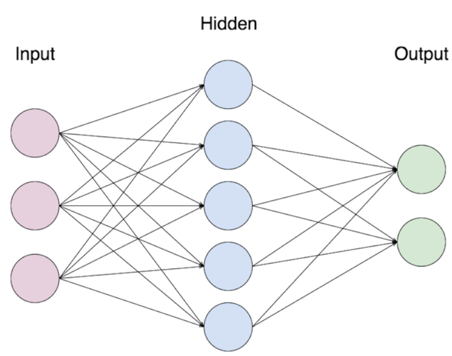

Fig 1 Structure of neural network

The training of ANN uses a group of input and output patterns in data mapping and produces the dependent variables for the corresponding input [14]. In ANN data mapping process, the neurons in the input layer are multiplied by the weight of corresponding neurons in the hidden layer. Then they are summed up with bias to the neurons in the output layers [12]. As an example, the input features (e.g., dry-bulb temperature) are multiplied by the weight of the corresponding neuron and summed up with bias for the output activation, which is determined for the heat demand prediction. The predicted results are compared with the historical data, and their error is used to update the neuron's weights by suitable adaptation [11].

The process of ANN can be described in mathematical formulas. Assume the hidden layer has m neurons. Define the neuron i with the signal of x_i (i=1, 2, …, m) and through the incoming connections with weight w_i (i=1, 2, …, m). The processed neurons are then summed up with their input signals and a bias set and then delivers to an output neuron y_l [14] as

$$y_l = f\left(\sum_{i=1}^{m} w_i x_i + b_l\right) \tag{1}$$

where f is the activation function, commonly defined as the sigmoid function [14]

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The output y_l will be delivered to the neurons in the next layer. ANN models can realise the data mapping between inputs and outputs in any nonlinear correlation without the knowledge of the mathematical equation describing the physical relationship in advance [9].

The training function of ANN includes the backpropagation (BP), general regression, radial basis function, and fuzzy inference system. The BP network is the most popular network with a strong capability in finding a nonlinear solution for data mapping. In the BP network, the errors of output are propagated to back by the derivatives [10, 15].

$$w_i(t+1) = w_i(t) + \Delta w_i = w_i(t) + \eta \epsilon y_l \tag{3}$$

$$b_l(t+1) = b_l(t) + \eta \epsilon \tag{4}$$

where η is the learning rate of the BP neural network and ϵ is the error of nodes.

Apart from the methods and algorithms of machine learning in data-driven models, the data selection with different features and sizes used for training is also a vital factor of the model performance [11].

2.2 Data Collection from Building Energy Simulator

The development of a data-driven model will normally consist of data collection and processing as well as model training and testing. The training process of ANN requires a group of datasets from historical data

Table 1: Variables and units of input parameters for ANN training

	Variables	Units	Variables	Units
Time series	Time of a day	hr	Month of a year	month
Environmental parameters	Dry-bulb temperature	°C	Wet-bulb temperature	°C
	External dew-point temp.	°C	Daily running mean temp.	°C
	Max. adaptive temp.	°C	Wind speed	m/s
	Wind direction	deg	Direct radiation	W/m²
	Diffuse radiation	W/m²	Global radiation	W/m²
	Solar altitude	deg	Solar azimuth	deg
	Cloud cover	oktas	Atmospheric pressure	Pa
	External relative humidity	%	External moisture content	kg/kg
Building information	Floor area	m²	Volume of plant	m³
	Windows area	%	Plant radiant fraction	0.0~1.0
	Time of heating	hrs/day	Room heating setpoint	°C
	Number of people	pers	DHW consumption	l/(h·pers)

records, which is used as benchmarks to cultivate the model's performance. The data used for training includes the selected environmental parameters and heat demand of each single building. However, the collection of all the required history data will take at least several months in recording data from sensors. To simplify the data collection process, the training data is collected from the simulated results of the building energy simulation in the Integrated Environmental Solutions (IES) software.

The IES is an integrated system to build bottom-up models of buildings for thermal analysis and heating load simulation using Apache engine. After setting the latitude and longitude of the target buildings, the weather profile for building energy simulation is obtained from the data of the environment recorded by the nearest airport. The building thermal behaviour is simulated depending on the variation of environmental parameters, such as change of temperature and solar radiation process, as shown in Fig 2.

Fig 2 Weather profile for building thermal behaviour in IES

In addition to the weather profile, different building characteristics will also affect their thermal behaviour. The floor area, building volume, windows area, and wall thickness are the key characteristics of a building. Apart from these, the building heat demand also depends on its type of operational function. For example, the normal working hour of an office building is from 8:00 to 18:00, whose heat demand is different with that of a restaurant

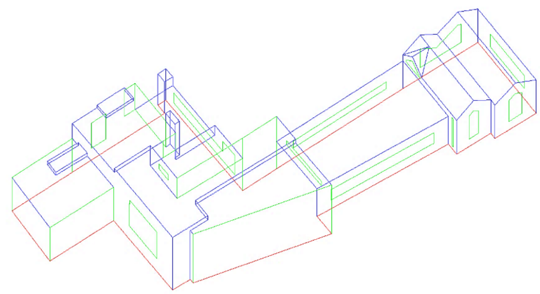

Fig 3 Building fabrication information of a sample building

opening from 12:00 to 22:00 or a library opening 24 hours. The building fabrication data of every single building is collected from IES as shown in Fig 3. All the data is collected from the IES and used to train the ANN model for the prediction of heat demand in different buildings.

3. RESULT AND DISCUSSION

The simulation of ANN training and prediction is tested in two case studies based on the main campus of the University of Glasgow. The first case uses partial environmental parameters as inputs and heat demand of all buildings as output to train the ANN. This case is to test the impacts of different environmental factors as well as heating time to the heat demand of all buildings on the university campus. In addition, to train the ANN with sampled buildings for predicting the heat demand of the whole university, the second case uses the building information and number of buildings as additional factors in ANN training. To reduce the computational load and training speed of ANN, the training data are randomly sampled from the aggregate data in this case study. Both cases are simulated in MATLAB using its built-in Neural Network toolbox.

3.1 Training with partial environmental parameters

Empirically, the temperature is the main drive of the heat demand of buildings. However, the heat demand is not linear related to the ambient temperature. Due to this, the relationship from temperature to the heat demand can be found using nonlinear fitting methods. ANN is theoretically able to fit any type of function with enough training data. Thus, the ANN is trained with a large amount of simulation data to get the relationship between ambient temperature and building heat demand.

The heat demand to ambient temperature, as the only input parameter, is predicted by ANN as in Fig 4 (a). The blue points indicate the training data while the black circles indicate the predicted result points. The result verifies that the heat demand is monotonically related to the ambient temperature, the lower temperature causes higher heat demand. However, there are still lots of points distributed around the black line. This presents that heat demand depends on not only the ambient temperature but also much other weather information and human activities.

Apart from the temperature, the heat demand is probably affected by other factors as well, including other environmental factors and time series. Other environmental factors include all weather profiles that can affect heat demand, such as humidity, wind speed, solar radiation. The time series indicates specific behaviour of customer heating as a routine of time, which can include the time of a day and month of a year. In addition, the heat demand in university buildings can depend on the months, such as the summer holiday and examination month. The month in a year indicates the part impact of human activities. The fitting results of temperature as well as other input factors, such as months in a year, time in a day, humidity. Fig 4 (b) show

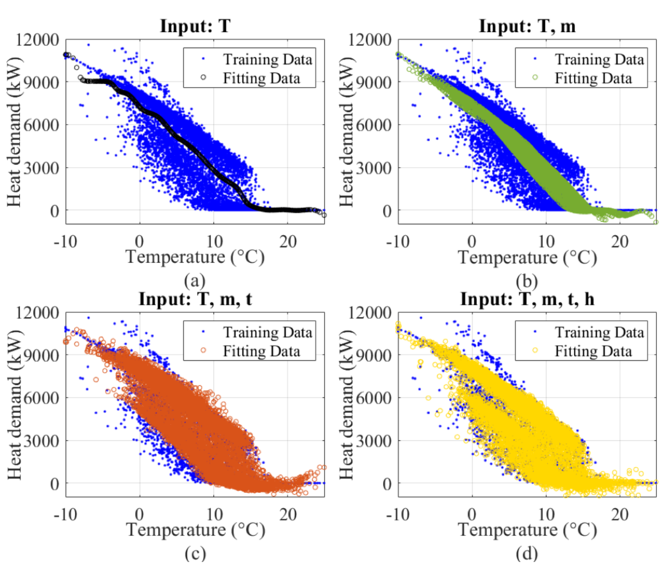

Fig 4 Heat demand prediction result of ANN after trained by different input factors

the training results of temperature and month in a year to heat demand, Fig 4 (c) shows the that of the above variables plus the time of a day, and Fig 4 (d) shows that of the above variables plus the humidity. The difference of heat demand predicted by the NN based statistical model comparing with the engineering model of building energy simulator is shown in Fig 5. The bar chart shows the results from the single input variable to the multi-input variable. From the results, the more input variables used to train the ANN, the better fitting results in finding the relationship between inputs and the heat demand and less prediction error achieved.

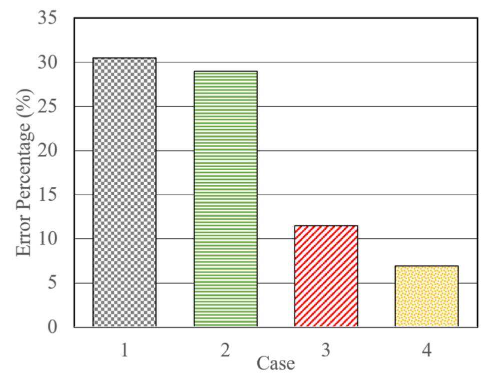

Fig 5 Error of ANN heat demand prediction with different training inputs

3.2 Training with sampled data of environmental parameters and building fabrication information

In the above case, the heat demand of the target buildings can be predicted by ANN that is trained by the historical data of the same buildings. However, one purpose of this paper aims to verify the method of training ANN with data from a few buildings to estimate the heat demand of all types of buildings. In addition, the ANN results are compared with the IES models of all buildings but not the measured data. If comparing between ANN trained result and the actual data, their difference contains both the ANN training error and the IES model error. It will be difficult to separate the different error and the result will not validate the method of ANN. Thus, the next case study is to train the ANN using both the environmental parameters and building information from several sample buildings in IES model, and then use the trained network to estimate the heat demand of all the buildings in the university campus and compare the result with the IES modelled results of all buildings.

On the other hand, the training of ANN using both environmental parameters and different building information will take very high computational cost. That

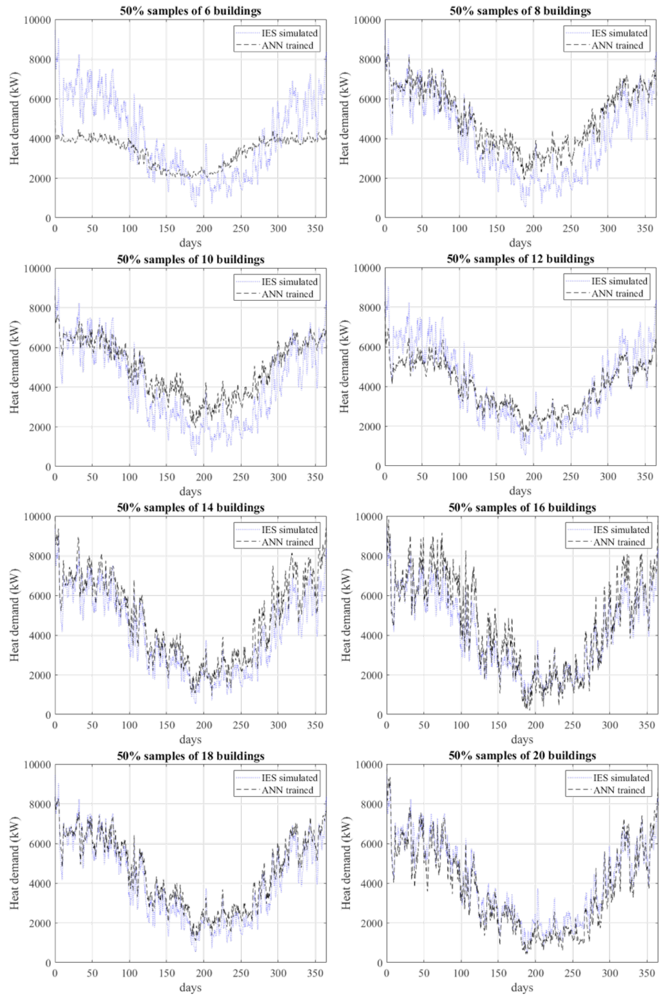

Fig 6 The heat demand prediction results of ANN using different number of sampling data from sample buildings.

is because the historical heat demand data of each building is a big database and the different types of buildings will make the database extreme large. Due to this, the training data are chosen with part of historical data from randomly sampled buildings. For example, the ANN will be trained by 50% of total heat demand and environmental data from the random sampled ten buildings with their building information, and after training, it will be used to predict the heat demand of the total 33 buildings.

The simulation is to test the training performance with data from different sample buildings. Fig 6 shows the hourly heat demand estimated by ANN after been trained with the randomly sampled data from 6 to 20 sample buildings. The first diagram shows the estimation result of ANN trained with 50% total data from 6 sample buildings. Its prediction performance is not good enough due to the small number of sample buildings. In comparison, the last diagram in Fig 6 performs the prediction result of ANN trained with 53% total data from

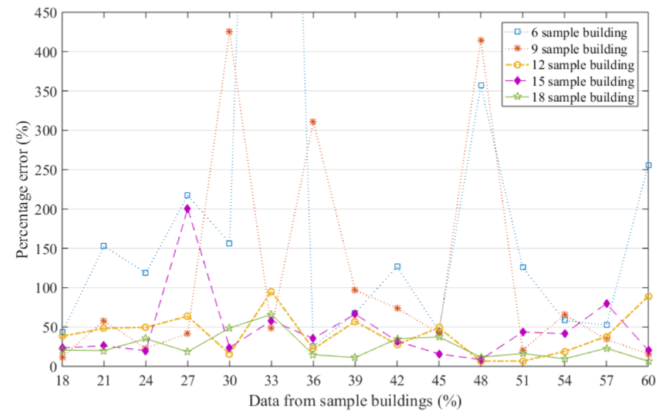

Fig 7 The ANN results of using different number of sampling data

20 sample buildings. From the result, it fits well with the simulated result from the IES building energy simulator.

From the hourly heat demand, it is difficult to analyse the result and improvement of the training performance with different sampling data. Fig 7 shows the estimation error of the ANN predicted result under different number of sample buildings and sampling data. In the figure, the x-axis is the percentage of the sampling data from its entire database while the y-axis is the percentage error of the predicted heat demand. Different lines indicate the result of ANN trained by different percentage of sampling data from 6, 9, 12, 15 and 18 sample buildings, respectively. The training data is hourly heat demand in a year so it contains lots of overlapped data that will cause overfitting problem. The different sampling data within the range of 18% to 60% did not have a significant effect on the ANN training result. However, a greater number of sample buildings will reduce the average estimation error whatever the percentage of sampling data.

To have a clearer view of the effect of different sample buildings to heat demand prediction result, the test in each number of sample buildings has been repeated using 18% to 60% sampling points. Fig 8 shows the statistic results of ANN heat demand prediction trained by data from the different number of sample buildings in a boxplot. In each box, the red central segment indicates the median, the top and bottom edges of the box indicate the ¼ and ¾ percentiles, and the '+' symbol indicates the outliers. Thus, from the boxplot, both the median and range of box show the tendency that the percentage error reduced with the increasing of the number of sample buildings. So, in summary, to achieve a reliable training performance, the data of 16 or more sample building should be used in training the ANN to predict the heat demand of the total 33 buildings.

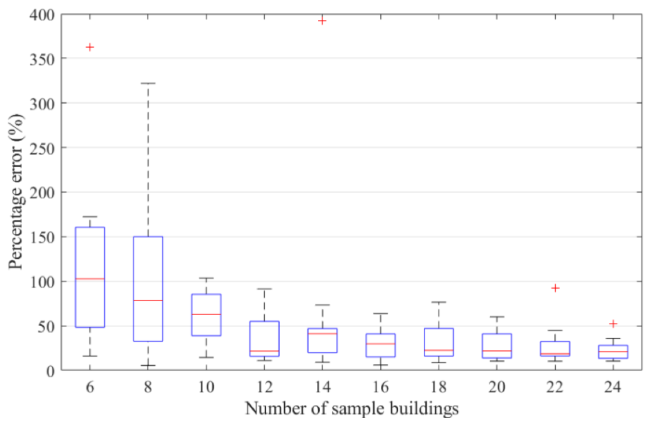

Fig 8 The statistic results of ANN heat demand prediction trained by data from different number of sample buildings training inputs

4. CONCLUSION

This paper used ANN to map a group of factors to heat demand including the environmental parameters and artificial designing building features. In order to predict the heat demand of different buildings, some sample buildings with different fabrics and types of operational functions are chosen to collect data for ANN training. Moreover, to balance the training performance and computational speed, the data collected from the different number of sample buildings is simulated using different sampling data to train the ANN. With this approach, the prediction of heat demand in a district can be achieved by ANN which is efficiently trained using data collected from sample buildings.

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