Intelligent Control Strategy of Air Handling Unit Based on Digital Twins

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Abstract

In this paper, a digital twin air handling unit system was proposed by building a real-time monitoring system for the air handling unit, using TRNSYS to build a digital model of the air handling unit, to achieve the goal of the lowest energy consumption of the system through the intelligent control strategy with the linkage control algorithm between air handling unit’s fan-pump and room cooling load. The performance of this digital twin system was evaluated through practical cases to show that compared with the traditional fixed air volume and fixed water volume, the energy consumption using the variable air volume air conditioning system by the optimal control strategy saves 56% of the energy in summer under high cooling load conditions (100% of the peak load) and 69% under medium cooling load conditions (75% of the peak load).

Highlights

• A digital twin system architecture is built for air handling units to optimize the operation of building energy saving
• Collection of site data for input into TRNSYS software for linkage control
• Different algorithms (MLP, DNN) for room cooling load prediction are compared, and it turns out that DNN is more suitable for small batch data learning
• Optimal control strategy can save 56% energy at high cooling load conditions (100% of the peak load) and 69% under medium cooling load conditions (75% of the peak load)

Introduction

Buildings account for 28% of China’s total energy consumption, and the ability to reduce energy consumption in the building sector is decisive in achieving the goal of energy saving and emission reduction. As air conditioning accounts for the largest share of energy consumption in buildings, reducing the energy consumption of building air conditioning systems is one of the most important tasks in the design and operation and maintenance of energy-efficient buildings.

The operation of central air-conditioning systems in today’s buildings suffers from the serious problem of wasting a large power source on a small energy system. How to optimise the control of air-conditioning systems according to demand has attracted the attention of scholars. M. Al-Rousan et al. (2004) established a mathematical model of each component of the air conditioning control system, such as the controlled room, coils, ductwork, fans and mixing devices, and analysed the air conditioning control system based on the physical meaning of the objects. Wang Bin et al. (2019) have simulated the HVAC system of the Sino-French Energy Centre by building the corresponding HVAC module in Matlab/Simulink using mathematical models of the components, working under different load rate operating conditions and changing the control strategy. It can be seen that this field of research mainly focus on mathematical models.

Digital twin technology is a new technology that digitally creates physical objects in the physical world, mapping them to virtual spaces, thus enabling real-time monitoring, simulation and predictive control of the physical world. Optimization of the physical world will be made by deep analysis and data mining. Digital twin technology is currently being used in engineering and construction, and with advances in artificial intelligence and sensor technology, data from the entire lifecycle of construction equipment can be collected, making it possible to combine digital twins with building operations and maintenance. Several scholars have reviewed the current applications of digital twins in engineering and introduced the framework that digital twins should have if applied to the construction sector. Pieter de Wilde (2023) presents a variety of emerging technologies in the digital field, with a focus on the use of digital twins in building simulation processes. In the case of real-life projects, the headquarters building of Bee’ah in the UAE (2022) was built to maximise the efficiency of resource use. It reduces energy consumption by 5% and achieves net zero carbon emissions during operation by building a digital twin system for the building’s equipment and automating its control. The success of this building demonstrates that the integration of digital twin technology and architecture is possible.

However, there is currently little integration of digital twins at the equipment level in buildings, and the potential for energy savings in this field is yet to be explored. Haidar Hosamo Hosamo et al. (2022) propose a digital twin prediction model for air conditioning units that克服s the limitations of the current common Facility Maintenance Management (FMM) approach, and by comparing the three prediction methods it finds that operational fault diagnosis of air conditioning boxes can...
be better accomplished by combining air conditioning box performance monitoring systems and machine learning. Vering et al. (2019) developed a digital twin model of a energy recovery ventilation using Modelica, and the final model can effectively predict the energy consumption under different scenarios.

Based on a comparison of domestic and international research results, it can be seen that research in the industry on the application of digital twins in building equipment is in its infancy, with research on air conditioning energy efficiency mainly focusing on a single air or water system, and less on a comprehensive analysis of the two systems. There is also a lack of research on the use of real-life data for air conditioning models.

To deal with the above deficiencies, an air handling unit in a commercial building in Shanghai is now selected as an object, and different algorithms are used to predict the room loads and compare the effects. A digital twin model is established in TRNSYS software to build a digital twin system for the air handling unit, and its energy saving effect is verified in conjunction with the case to provide new ideas for intelligent control of the air handling units.

**Methods**

**Digital twin system architecture for air handling unit**

A complete digital twin system is consisted of a physical system and a digital system. The digital twin system in this study is based on a realistic air handling unit, and the architecture of the digital twin system established is as shown in Figure 1.

**Physical system monitoring and load forecasting**

The air conditioning system includes two parts: the air side and the water side. The parameters to be monitored are, on the one hand, parameters related to the air side, such as air supply volume, fresh air volume, return air volume, air supply humidity, air supply temperature, fresh air humidity, fresh air temperature, return air humidity, return air temperature, etc., and, on the other hand, parameters related to the water side, including chilled water flow, water supply temperature, return water temperature and pressure difference.

The collection of monitoring parameters in the project requires the establishment of a complete detection system. The monitoring system is generally made up of four components, namely the on-site sensors, communication equipment, the lower computer and the upper computer. The field sensors connect the collected data to the end LoRa communication module via the RS485 bus. The end communication module will communicate with the upper computer communication module to complete the data transfer. The host computer is connected to the 4G module via a switch and external users can access and obtain data from the host computer via the network. The specific framework is shown in Figure 2.

As the focus of the modification of the fixed air volume fan is to enable the fan to adjust the size of the air supply according to the dynamic changes in load, it is crucial to accurately predict the cooling loads. At this stage, the commonly used building load prediction methods can be
divided into white box and black box in terms of principle. White box methods are based on physical models and is mainly applied in the system design stage with a large modelling workload. Black box methods include parametric regression method, support vector machine (SVM), artificial neural network (ANN) and so on. Among them, the parametric regression method has a simple structure and fast prediction speed, but is less robust, SVM is applied later and has a high learning ability but is more sensitive to missing data.

The mainstream prediction method at this stage is prediction by ANN, which have its origin in the classical perceptron algorithm. Perceptron algorithm is the simplest form of ANN and contains a single neuron where the input data is superimposed by multiplying it with a weight w, introducing a bias and finally obtaining the output value by means of an activation function. However, the perceptron is only applicable to the case where the pattern to be classified is itself linearly separable, so the multilayer perceptron (MLP) model was subsequently proposed. MLP is a superposition of single layer perceptrons and replaces the non-linear step excitation function in the perceptron with a continuous excitation function to facilitate the learning of the network parameters. One popular learning method is the back-propagation (BP) algorithm, where the output layer error signal is obtained by comparing the actual output of the network with the desired corresponding, and the signal is back-propagated to the layers for weight updating.

With the maturity of deep learning theory, deep neural networks (DNNs) have now emerged, whose parameters are learnt in two steps: firstly, using unlabelled data, the network parameters are learnt layer by layer incrementally through unsupervised learning to discover deep abstract features in the input data, i.e. pre-training; furthermore, using the labelled data, the model parameters are tuned using traditional algorithms for neural network learning (e.g. BP algorithm) supervised tuning, i.e. model fine-tuning.

The exact algorithm used in the case for prediction needs to be compared with the error to obtain the results. In building load prediction the parameters that correlate well with the load should be identified as inputs from the large number of parameters collected through data correlation processing. After inputting the parameters the number of layers of the neural network needs to be determined. Too few layers may lead to underfitting, while too many may lead to overfitting, so a suitable number of layers needs to be found by constant adjustment. Finally, the optimiser learning rate should be set, which determines how much the current weights are changed at each step of the weight update and is an important super-reference in the neural network, which also needs to be adjusted in practice to allow the neural network to find the optimal solution relatively quickly.

**Digital system modelling and optimisation methods**

Modelling methods can be divided into two types according to their modelling principles: physics-based methods and data-driven methods. Most of the models established by energy consumption simulation software at this stage are models based on physical methods. This modelling method requires the user to have a full understanding of the system and requires more parameters in the early stage, so it is more difficult to construct the model, but after the model is established, the relationship between variables can be well described and can be used to determine the equipment control strategy in practical engineering projects.

In this study, TRNSYS is used to establish a digital system for the air handling unit, which mainly includes models of components such as cooling coil, frequency conversion fans, air mixing devices, frequency conversion pumps and PID controllers, and the system formed by these components is shown in Figure 3.
The input parameters of the model include the water supply temperature, pump flow rate and air supply volume. The independent variables include the load forecast for the next moment, the return air temperature, the fresh air temperature and the fresh air volume, and the return water temperature for the next moment is obtained through the metered cooler to calculate the total energy consumption of the fans and pumps.

The objective function of this system is to minimize the total energy consumption of fans and pumps. The optimization variables include water supply temperature, pump flow rate and air supply volume, and the independent variables include load forecast value at the next moment, return air temperature, fresh air temperature and fresh air volume, and the return water temperature at the next moment is obtained through the table cooler, etc. The total energy consumption of fans and pumps is obtained through calculation, and the combination of wind-side and water-side parameters that minimizes the total energy consumption is obtained by comparing different parameter combinations. The specific process is shown in Figure 4.

**Real case introduction**

This study selected a platform located a large integrated commercial building in Shanghai, whose air conditioning terminal units mainly include single-cooled air handling units and fresh air units, and the control principle of the units is shown in Figure 5. The site data were collected from July 2021 to October 2021 for the subsequent construction of the digital twin.

![Figure 4: Flowchart of optimization process in this study](image)

**Figure 4:** Flowchart of optimization process in this study

![Figure 5: Electrical mech. plan of AHU.](image)

**Figure 5:** Electrical mech. plan of AHU.
Results and discussion

Digital twin model verification

The purpose of using a digital twin is to simulate the real world, so the accuracy of the digital twin model to reflect the real world is an important evaluation metric. The accuracy of the digital twin model can be evaluated by comparing the simulated results with the measured data on 19th October 2021. Figure 6 shows a comparison between the simulated turbine energy consumption and the actual corrected turbine energy consumption. The trend of the two lines in the figure shows that the simulated and actual turbine energy consumption trends are basically the same, and the correlation coefficient reaches 0.8, which indicates that the digital twin model can simulate the real world well.

Comparison of building load forecast results

This paper focuses on load prediction by applying the two neural networks described above: MLP and DNN. In practice, we have used Python 3.9 in the Pycharm compiled environment to build a deep learning neural network prediction model based on the keras class and a linear regression prediction model based on the sk-learn class respectively. The training data was collected in October 2021 and after pre-processing there were 560 valid samples. After data correlation processing, the parameters with strong correlation with the load are summarised: supply air temperature, supply air volume, fresh air volume, fresh air temperature, supply air humidity and active power of the fan to predict the room cooling load.

In the MLP network, three layers were set up, the number of neurons was 128-256-512, the optimiser learning rate was 0.001, the number of iterations was 1000, and the mean absolute percentage error (MAPE) fluctuated above and below 3% after a five-fold cross-validation.

For the DNN neural network, two-, three- and four-layer networks were built for prediction, with the number of neurons being 6-6, 12-24 and 12-24-96, respectively, with an optimiser learning rate of 0.001 and a number of iterations of 1000. The final MAPEs were 0.818%, 0.512% and 0.160% respectively. Figure 8 illustrates the MAPE of the DNN neural network for the four-layer network.

Comparing the above MAPE values, it is easy to see that although MLP can also reach 3%, the error is still larger compared to DNN. Using a multi-layer DNN neural network can make a more accurate prediction of the load, and because DNN neural network has better performance in learning small batches of data, it is recommended to use this algorithm when the amount of data is not large.

Optimised control strategy development

The main energy-consuming equipments in the air handling units include fans and pumps, both of which can achieve the minimum energy consumption under the condition of large temperature difference and small flow rate, it is necessary to change the temperature difference between the supply and return air and the temperature difference between the supply and return water when looking for the optimal control strategy, while the water supply temperature will also have a greater impact on the energy consumption of the pumps, so its impact on energy consumption will also be taken into account.

According to the current working conditions of the air handling unit system, the supply and return air temperature difference is chosen to vary between 8°C and 12°C, the water supply temperature between 6°C and 9°C and the supply and return water temperature difference between 4°C and 6°C.

The specific different combinations are entered into the software by means of an exhaustive list of parameters to be arranged and combined.

The final results of the optimised combination of air and water side parameters are listed as follows: when under high cooling loads, the return air temperature is 26°C, the optimal control strategy is a supply and return air temperature difference of 12°C, a water supply temperature of 6°C and a water supply and return temperature difference of 5°C; when the return air temperature is 28°C, the minimum total energy consumption is a supply and return air temperature
difference of 12°C, a water supply temperature of 6°C and a water supply and return temperature difference of 7°C; when the return air temperature is 27°C, the minimum total energy consumption is a supply and return air temperature difference of 12°C, a water supply temperature of 6°C and a water supply and return temperature difference of 7°C.

**Optimal energy efficiency assessment**

As air conditioning operates mainly at high and medium loads in summer, energy consumption is compared between the two operating conditions.

Condition 1 is an air conditioning system operating at a constant air volume and constant water volume, condition 2 is an air conditioning system operating at a variable air volume and constant water volume, and condition 3 is an air conditioning system operating at a variable air volume and variable water volume through a control strategy determined by digital twin.

Tables 1 and 2 show the total energy consumption and energy saving rate. Figures 9 show a comparison of the total energy consumption of the fan and pump in one day in which the cooling load is high (100% of the peak load). Figure 10 show a comparison of the total energy consumption of the fan and pump in one day in which the cooling load is medium cooling load conditions (75% of the peak load).

**Table 1: Comparison of different control strategy under high cooling load (100% of the peak load).**

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<thead>
<tr>
<th></th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Energy Consumption (kWh)</td>
<td>87.142</td>
<td>54.170</td>
<td>37.987</td>
</tr>
<tr>
<td>Energy Saving Rate (%)</td>
<td>—</td>
<td>37.837</td>
<td>56.407</td>
</tr>
</tbody>
</table>

**Table 2: Comparison of different control strategy under medium cooling load (75% of the peak load).**

<table>
<thead>
<tr>
<th></th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Energy Consumption (kWh)</td>
<td>79.999</td>
<td>42.173</td>
<td>37.987</td>
</tr>
<tr>
<td>Energy Saving Rate (%)</td>
<td>—</td>
<td>47.283</td>
<td>68.794</td>
</tr>
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</table>

From the above data it is easy to see that by optimising the air and water side of the system a large amount of energy can be saved, contributing to the energy efficiency of the building.

**Conclusion**

Based on the characteristics of the current stage of the air conditioning system in a crude manner, this paper constructs a digital twin system for the air handling unit, and obtains the parameter basis for the subsequent construction of the digital system by conducting on-site data monitoring.

For room load prediction, the MLP and DNN algorithms were used, and it was found that the DNN was better for load prediction by comparing the MAPE values.

A digital twin model of the air handling unit system was constructed in the TRNSYS platform by inputting the monitoring parameters, which correlated with the historical monitoring data to 0.8 with high accuracy.

Finally, this digital twin air handling unit system is conducted in a real commercial building case by varying the supply and return air temperature difference, the water supply temperature and the supply and return water temperature difference, and by exhausting different control strategies under different load conditions and different return air temperatures, and it is found that the optimal control strategy saves over 50% of energy consumption in summer compared to the traditional fixed air volume system.

However, the digital twin model established in this paper is for a single air handling unit, i.e. there is only one fan, one pump and supporting facilities in the model, while in actual engineering projects, one pump is often responsible for the chilled water supply of multiple air conditioning units, so the scale of the system platform can be further increased to establish a system model of building air conditioning chilled water.

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**References**


