Machine Learning Approach to Predict Cooling Load for Existing Buildings

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Abstract

The objective of this study is to predict air conditioning loads for existing buildings using operational data, weather forecasts and visitor forecasts. The proposed prediction method is based on a neural network approach. However, it is important to note that the proposed method does not learn the entire loads. Loads are divided into factors which can be predicted by traditional thermodynamics and factors which are subject to machine learning. The proposed method has been applied to an example instance using operational data from an underground mall in Kobe, and its validity has been confirmed.

Keywords: Cooling Load Prediction, Air Conditioning System, Existing Building Data, Machine Learning

1. Introduction

If air-conditioning load are accurately predicted, it is expected which the system is optimally operated, e.g. setting of changes in chilled water supply temperature, selection of heat source models, setting of operation times, for saving energy [1].

The purpose of this study is to predict future load of an air conditioning systems on the next day for which exists, using operational data of existing buildings, weather forecasts and visitor volume forecasts. The prediction algorithm is combining mathematical calculation and neural network (hereafter NN) methods. The proposed method has applied to an example based on operational data of an underground shopping mall in Kobe and compared with the actual measured cooling load.

Air conditioning load prediction for existing buildings differ from load calculations for new buildings in the followings.

1. Therefore historical operating data and corresponding load data exist, they can be used for forecasting by machine learning. The large amount of training data can be used for the load prediction without having to establish physical causal relationships between load calculation conditions and load values.
2. The actual situation regarding how the building is used is known, not the assumptions made at the time of design.
3. The process of changing the parameters and improving the accuracy of the predictions is expected, as results are immediately available on the correctness of the predictions.

The scope of this study is as follows.

1. The proposed approach predicts the hourly heat source load for the next day in the existing building.

2. The target of forecasting is limited to cooling loads, where more energy savings are expected, and does not deal with heating loads.
3. If the predicted cooling load is spatially subdivided, the approach is more valuable for air-conditioning operations, although, load performance monitoring points must also be taken at the same granularity. The detailed measurement has become realistic in recent years due to advances in IT technology, however, this research aims the cooling load forecast for the existing building, considering the suppression of renovation work costs.

2. Air-Conditioning Load

With reference to the dynamic load calculation method based on the response factor method [2], [3], the air-conditioning loads were classified into two categories: those estimated by mathematical calculations and those estimated by machine learning, assuming that each element has its own explanatory variables. The explanatory variables for each load element were selected on the basis of whether they could be measured in a typical building.
In this section, the term "current" indicates the point in time at which the forecast is made.

2.1. *Load Factors Subject to Machine Learning*

1. Load of exterior wall through-flow heat due to temperature difference between interior and exterior including through-flow load from glass. The explanatory variables for this load are: current outdoor air temperature, past outdoor air temperature (going back about 50 hours), past daily average outdoor air temperature (going back about 3 months), current horizontal solar radiation, and past horizontal solar radiation (going back about 50 hours).
2. Load of interior wall penetration heat from adjacent room. The explanatory variables for this load are the current outdoor air temperature and the past outdoor air temperature (going back about 50 hours).
3. Load due to solar radiation transmitted through glass. The explanatory variables for this load are current daylight hours, horizontal solar radiation, and historical horizontal solar radiation (going back about 10 hours).
4. Load due to drafts. The explanatory variables for this load are current outdoor air temperature, current outdoor air humidity, current external wind direction and speed, and building opening condition.
5. Load due to heat storage of intermittent air conditioning operation. The explanatory variable for this load is the past room temperature of the room concerned (going back about 20 hours).
6. System losses, .e.g. fan reheat, duct losses and mixing losses.

2.2. *Load Factors Subject to Actuarial Calculations*

7. Load due to human metabolism. The explanatory variables for this load are current manpower, past manpower (going back about 10 hours), and average work intensity.
8. Load due to heat dissipation of lighting fixtures. The explanatory variables for this load are current power consumption and past power consumption (going back about 10 hours).
9. Load due to heat dissipation from other indoor equipment. The explanatory variables for this load are current heat generation, and past heat generation (going back about 10 hours).
10. Outdoor air load. The explanatory variables for this load are outdoor air intake, outdoor air temperature, and outdoor air enthalpy.

3. Prediction Method for Cooling Load

A prediction method which combines mathematical computation and machine learning approach is build.

3.1. *Learning Phase*

When training with measurement data, the data set is composed for NN [3] as follows.

- Teaching data are the differences between the overall loads and the loads of Section 2.2.
- Input data are the explanatory variables for loads of Section 2.1.

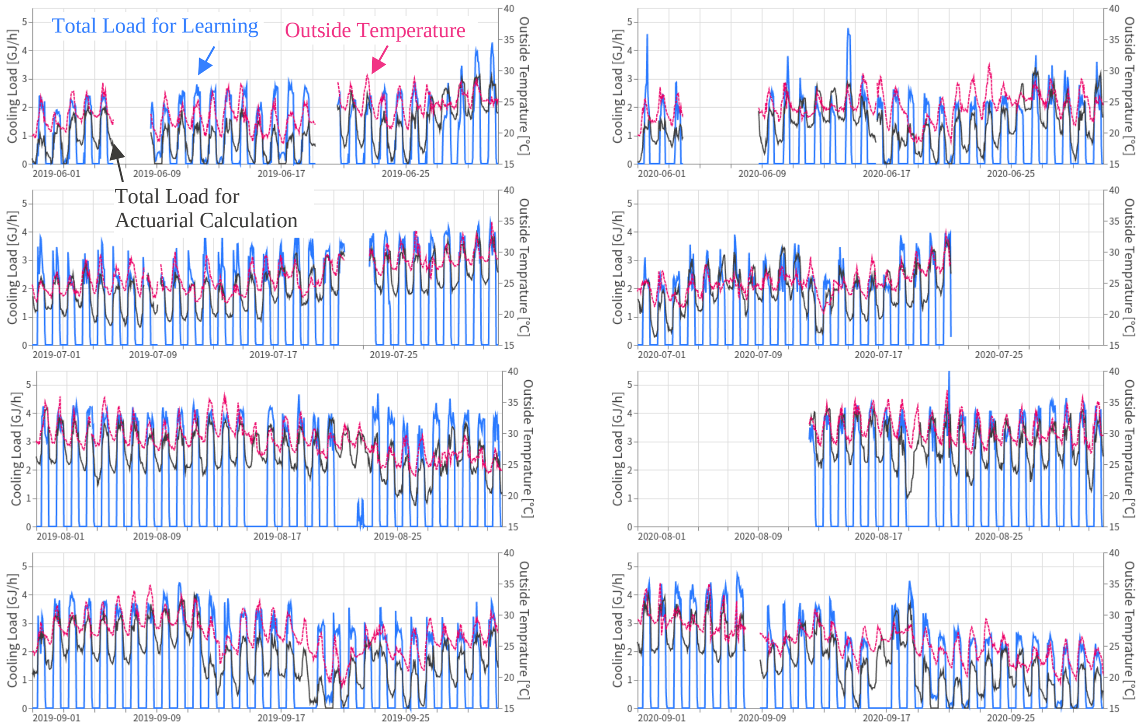

Fig. 1 Monthly Cooling Load of the Example Instance in 2018 and 2019.

4. Computational Experiment

4.1. *Example*

An example of air conditioning load forecasting is consists of two years of measured data for the overall air conditioning load and the explanatory variables for each air conditioning load for the underground shopping mall in Kobe, see Table 1. Fig. 1 shows the cooling loads of 2 years.

Table 1. Outline of Underground Mall

Name	Santica
Year of construction	1963 (1st phase) 1966 (2nd phase)
Management Entity	Kobe Chikagai Co., Lt
Total floor area	19,109m2
Retail area	10,145m2
Business Hours	10:00-20:00 (merchandising) 11:00-21:00 (food and beverage) 6:00 - 24:00 (passageway)

4.2. *Learning setting*

Since the subject is an underground mall, the effect of solar radiation was ignored among the air conditioning load elements. See [4] for the measurement method of the current people flow. The settings of the NN method are shown in Table 2.

Table 2. Setting of NN method.

Input Layer	Input Size	28
Intermediate Layer	Number of Layers	2
	Type	Fully-Connected Layer
	Activation Function	ReLU
	Number of Units	20 (first layer) 10 (second layer)
Output Layer	Type	Fully-Connected Layer
	Output Size	1
Others	Batch Size	10
	Epoch Size	30
	Trial	10

4.3. *Prediction setting*

In this manuscript, calculations are performed on historical data sets to verify the performance of the NN method. Where weather forecasts or other forecasting data should be used in actual use, measurement values are used. The people-flow prediction method is described in [5].

4.4. *Result*

Fig. 2 shows the difference between normalized predicted and actual measurements by time period. The errors are particularly large between 8:00 and 10:00 and at 20:00. The prediction accuracy is expected to improve when the conditions at the start and end of cooling are considered.

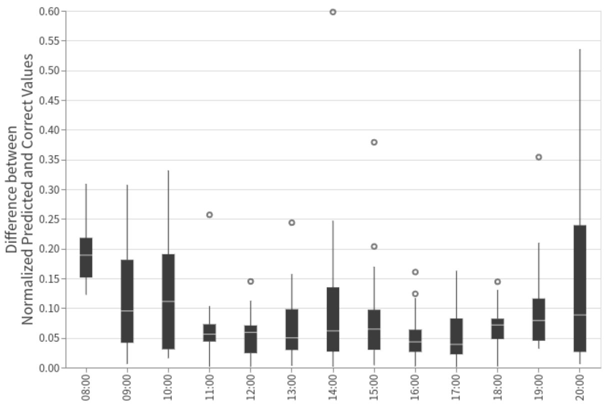

Fig. 2 Result of Prediction.

5. Conclusion

In this study, a method for predicting air-conditioning loads is investigated with the goal of efficient air-conditioning operation in underground malls with open areas. The proposed method has been applied the example based on actual data from the underground mall in Kobe. Future issues include evaluation of predictions based on actual use and examination of accuracy in comparison with existing studies.

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Authors Introduction

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