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A clustering-based approach for "cross-scale" load prediction on building level

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ABSTRACT

A new cross-scale load prediction model on building level based on the k-means clustering method is proposed in this paper. An office building with 26 conditioned thermal zones is the main research object. The data set is composed of 5785h cooling/heating load data by Energyplus simulation and real-world monitoring, besides, a kind of accumulative effect considered data is also included. The proposed model is based on quantifying the intra-cluster relationships. The quantification tool consists of a well-trained LSTM model and a representative load time series input which create by cluster centroid zone in one prediction cell. By combining the prediction cells under different scales, the cross-scale prediction model from the zone to building scale is built. To investigate the association between each explanatory variable and cluster belongings, ANN logistic regression model is applied. Some explanatory physical variables (e.g. the ratio of "non-equilibrium" temperature difference) calculated by "non-equilibrium" thermal insulation method are first proposed and used in logistic regression. Applying the simulation and accumulative effect considered data to the proposed model, the result shows that there is a trade-off between the ratio of the sample size of the cluster and mean cross-scale prediction accuracy, and the optimal prediction period can be obtained. In logistic regression, the result shows the maximum demand, start and end time of HVAC system, the west to the south ratio of temperature difference, and the exterior window area together determine the belonging of the cluster. At last, the proposed model is validated by real-world data and showed it's effectiveness, and the cumulative effect makes the cross-scale prediction accuracy better.

Keywords: Cross-scale load prediction, Building level, Long short-term memory (LSTM), Accumulative effect, "Non-equilibrium" thermal insulation

1. INTRODUCTION

Load clustering is an important means to investigate building energy use patterns, characterize individual household electricity demand [1], and then to suggest pricing strategies of different times of using on various building types, such as households [2] or business district [3]. Fintan McLoughlin et al. [2] studied 345,645 households and found that dwelling type, number of bedrooms et al. were the key factors to influence energy consumption patterns. Omid Motlagh et al. [4] validated the clustering performance on various technologies including (Principal Component Analysis (PCA), unsupervised Hebbian-based clustering, and a semi-supervised SOM clustering) based on a data set of just 300 sample households with rooftop PV panels.

Besides, proper data pre-processing investigation for better clustering results was another research focus of clustering. Omid Motlagh et al. [5] proposed a strategy to convert any types of load time series into map models that could be readily clustered. In Ref. [5] time series data was reshaped into daily curves by stacking. Raw data in Ref. [6] was processed by two steps. However, hourly data could not contain the information about time-delay well, as a result, a special data processing method was used to investigate the effect of the cumulative effect on load clustering by adding the current and the previous hourly load. And a new kind of cumulative load could be generated and used in clustering in this study.

Apart from the two popularly investigated aspects, cluster technology had been applied to solve some "cross-scale" problems. Rui Jing et al. [3] regarded the k-means clustering as a type of hierarchical based approach and divided large-scale problems (district scale) into small-scale problems (neighborhood scale) to solve urban energy system design optimization quickly. Zheng Yang et al. [7] used an agglomerate hierarchical

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clustering-based iterative evaluation algorithm to eliminate occupancy diversity in one university building. In the ordinary clustering process, the intra-cluster relationships between the members in one cluster already existed by maximizing one certain distance such as Euclid distance, and then to determine the optimal cluster number. In this study, the long short-term memory (LSTM) model was used to describe the intra-cluster relationships and make predictions， and the whole building load data could be represented some "LSTM models + loads of some cluster centroid zones".

This study applied support vector machine (SVM) and ANN model to investigate the correlation between input features and cluster belongings or energy consumption patterns.

The contributions of this article include the following: (1) filled the research gap of cross-scale load prediction from thermal zone level to cluster-level than to building level scale. (2) "non-equilibrium" thermal insulation method was introduced to create some easy measurable features to the feature pool which decides the cluster belonging. (3) The cumulative effect caused by the envelope was considered by processing hourly data into an accumulated load data of two hours before and after, and the clustering and cross-scale prediction performance based on accumulative load were investigated.

2. DATASET OF BUILDING LEVEL

The physical subject in this paper is an office building in Hengyang City, Hunan Province, China including 26 conditioned thermal zones which coded by D1~D26 ("thermal zone" also be called "zone" in Energyplus simulation document [8]). The building height is 21.6m, the area is 10257.2 m2, and the HVAC system is an air source heat pump system, the monitoring period is 1 hour, and all the thermal zones are determined according to the installed HVAC systems. The building shape is shown in Fig.1.

The expression of the data set in this study is shown in Table 1.

Table 1 Introduction of the data set.

Tool	Types	Frequency	Length	Unit
Energyplus software	surface inside face temperature	hourly	5785h	℃
	surface outside face temperature			℃
	zone ideal loads supply air total heating rate			w
	zone ideal loads supply air total cooling rate			w
sensors	cooling and heating load		5785h	w

3. METHODOLOGY

There were three steps of the proposed system as expressed in Fig. 2. In step one, the dataset as introduced in Section 2 was prepared. And a new "non-equilibrium" thermal insulation method was used to calculate some representative and easily measurable parameters to reflect different load characteristics in this step. The new accumulative effect considering data was created. In step two, 4 most-widely used clustering technique algorithms: *k*-means, minibatch *k*-means, density-based spatial clustering of applications with noise (DBSCAN), and affinity propagation (AP) [9] were applied based on well-processed data to analyze the clustering performance. In step three, the relationships between each centroid zone of the cluster and the cluster member zones were functioned by some LSTM prediction cells, as a result, a cross-scale load prediction model from zone to building scale could be built. Furthermore, logistic regressions were made to show the association between each explanatory variable and clusters, and help users to identify the key parameters which determine the clustering, and data pre-processing of logistic regression and feature selection by PCA also should be made.

3.1 "Non-equilibrium" thermal insulation of the wall

Different from "equilibrium" thermal insulation designing, the "non-equilibrium" thermal insulation design assumed the heat transfer through the unit area of the envelope was the same. The mathematical form of this method of the wall could be given by:

$$q_w^* = q_{w.s}^* = q_{w.n}^* = q_{w.w}^* = q_{w.e}^* \quad (1)$$

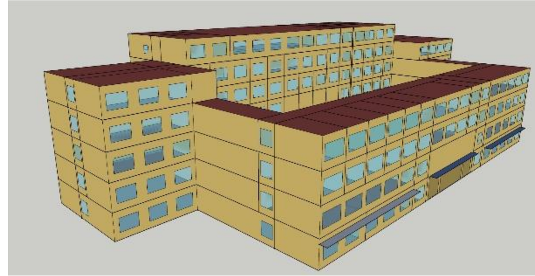

Fig 1 The overall appearance of the physical subject.

$$q^{*}_{w.s(n,w,e)} = K^{*}_{w.s(n,w,e)}(t^{*}_{se.s(n,w,e)} - t_i) = K^{*}_{w.s(n,w,e)}\Delta t^{*}_{w.s(n,w,e)} \quad (2)$$

$$Q_w = q^{*}_{w.s}S_{w.s} + q^{*}_{w.n}S_{w.n} + q^{*}_{w.w}S_{w.w} + q^{*}_{w.e}S_{w.e} \quad (3)$$

Where, $K^{*}_{w.s}$, $K^{*}_{w.n}$, $K^{*}_{w.w}$, $K^{*}_{w.e}$ was the heat transfer coefficient of the wall, $t^{*}_{se.s}$, $t^{*}_{se.n}$, $t^{*}_{se.w}$, $t^{*}_{se.e}$ was the outside surface temperature of the wall in a different orientation and $\Delta t^{*}_{w.n}$, $\Delta t^{*}_{w.s}$, $\Delta t^{*}_{w.w}$, $\Delta t^{*}_{w.e}$ were the temperature difference of the wall in different orientation under "non-equilibrium" thermal insulation condition.

Simultaneous Eqs. (1)-(3), the differences in heat

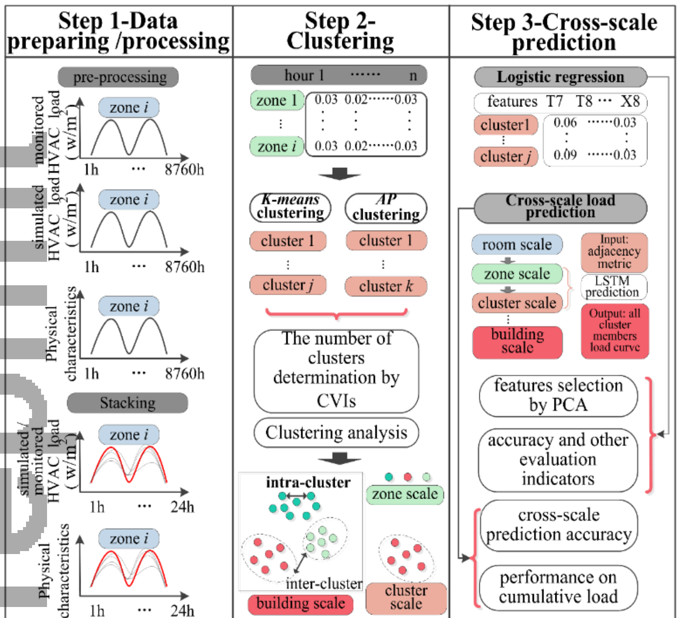

Fig 2 The framework of the proposed cross-scale load prediction model.

transfer between the walls in different directions could be reflected by the ratio of temperature difference in a different orientation.

$$\begin{cases} \Delta t^{*}_{w.n} / \Delta t^{*}_{w.s} = x_{R1} \\ \Delta t^{*}_{w.w} / \Delta t^{*}_{w.s} = x_{R2} \\ \Delta t^{*}_{w.e} / \Delta t^{*}_{w.e} = x_{R3} \end{cases} \quad (4)$$

$$K^{*}_{w.s} = x_{R1}K^{*}_{w.n} = x_{R2}K^{*}_{w.w} = x_{R3}K^{*}_{w.e} \quad (5)$$

$$x_{1(2,3)} = \frac{1}{n}\sum_{1}^{n} x_{R1(2,3)} \quad (6)$$

Where x_1, x_2, and x_3 was the "non-equilibrium" factor of the zone; x_{R1}, x_{R2}, and x_{R3} was the "non-equilibrium" factor of the room. A thermal zone consisted of n roo ms.

3.2 Clustering analysis

Centroids of the cluster were determined by cluster members through a special minimization algorithm (e.g. Eq. (10) of *k*-means clustering), the purpose of clustering in this section was to separate the thermal zones into correct clusters, then to find the typical rooms or centroids of the cluster.

The first step of clustering (except AP clustering) was determining the optimal number of clusters after data pre-processing. As a result, the CVIs (CH score, DB score [10], and silhouette coefficient) were introduced in this study. After the optimal number of clusters was determined, the clustering could be made by different clustering methods. Then the centroids of the clusters could be obtained for cross-scale prediction readily. Last, the data with the accumulative effects would be tested.

3.3 Cross-scale prediction

3.3.1 Cross-scale prediction

It was not appropriate to use the linear techniques to express the relationships between the centroids of the cluster and the members of one certain cluster, as a result, the only non-linear data-driven model could be applied here. Hence, the LSTM, a data-driven model has been proved effective in HVAC load prediction [11], was adopted to model the relationship between the centroids of the cluster and the cluster members. and the cross-scale load prediction cell was expressed in Fig. 3.

3.3.2 Accumulative effect considering

As a result, the total load of two hours before and after should be concerned to characterize load characteristics. At the same time, another similarity or adjacency metric was defined as Eq. (18), the superscript t represented for hour t. Similarly, this adjacency metric concerned the load in two hours. In addition, the user could define other kinds of similarity by their requirements of precision.

$$C^{t}_{pi-c} = \left(1+\frac{(q^{(t)}_{pi}+q^{(t+1)}_{pi}).(q^{(t)}_{pci}+q^{(t+1)}_{pci})}{\left|q^{(t)}_{pi}+q^{(t+1)}_{pi}\right|.\left|q^{(t)}_{pci}+q^{(t+1)}_{pci}\right|}\right)e^{-\left|(q^{(t)}_{pi}+q^{(t+1)}_{pi})-(q^{(t)}_{pci}+q^{(t+1)}_{pci})\right|} \quad (7)$$

3.4 Logistic regression analysis of the clustering results

3.4.1 Logistic regression input

SVM and ANN were applied in this study. The inputs were expressed in Table 2.

Table 2 Inputs and output in logistic regression.

inputs	code	unit
mean accumulative load at 7:00~19:00	T7~T19	w/m^2

the maximum mean accumulative load between 7:00~19:00	Tmax	w/m^2
the north to the south ratio of temperature difference	x_1	/
the west to the south ratio of temperature difference	x_2	/
the east to the south ratio of temperature difference	x_3	/
window-wall ratio	x_4	/
exterior window area	x_5	m^2
indoor lighting power	x_6	w
heat dissipation of the human body	x_7	w
interior thermal zone or not	x_8	0 or 1

3.4.2 Logistic regression algorithms

There were many classic references introducing SVM, as a result, the ANN model was introduced in detail in this section, and was built in a Python environment using the TensorFlow library. The training and testing data accounted for 80% and 20% of the total data respectively. The parameter settings of the ANN were expressed in Table 3.

Table 3 Settings of the ANN model in this study.

variables	settings
number of hidden layers	2
number of hidden neurons	8
hidden layer activation function	"Relu"
output layer activation function	"Softmax"
loss function	"categorical cross-entropy",
optimizer	stochastic gradient descent (SGD)

4. RESULTS AND DISCUSSION

4.1 Clustering results

4.1.1 CVIs and optimal cluster number

Fig. 3 showed the CIVs score of *k*-means, agglomerative, and minibatch *k*-means method on the simulation data set, three methods showed almost the same trend of the CIVs. The results showed the silhouette coefficient with 4, 5, and 6 clusters in AP clustering was 0.529, 0.568, 0.590 separately. Considering the AP clustering results, the optimal cluster number was determined to be 5.

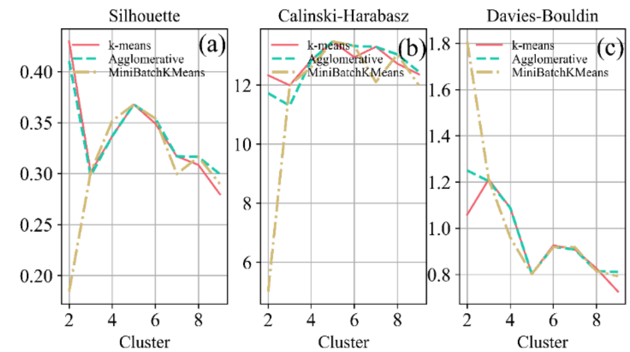

Fig. 3. The CIVs score of k-means, agglomerative and minibatch k-means method on the data set; (a) silhouette; (b) calinski-harabasz; (c) davies-bouldin;

4.1.2 Clustering

Fig. 4 showed the classification of all the 26 individual thermal zones processed by three cluster models, three clustering methods presented almost the same trend.

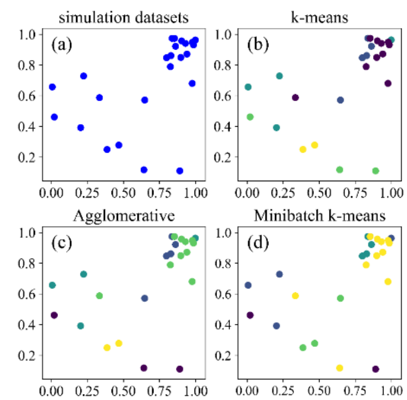

Fig. 4. The simulation data set and clustering performances ; (a) simulation data set; (b) k-means; (c) agglomerative; (d) minibatch k-means method

The details of the statistical characteristics of the clustering results were presented in Table 4.

Table 4 Statistical characteristics of the clustering results.

cluster	sample size		the ratio of sample size		mean-variance	
	k-means	AP	k-means	AP	*k*-means	AP
1	6	6	3/13	3/13	0.138	0.138
2	2	3	1/13	3/26	0.105	0.105
3	6	11	3/13	11/26	0.095	0.095
4	11	4	11/26	2/13	0.081	0.081
5	1	2	1/26	1/13	0.097	0.097

4.2 Cross-scale prediction results

(1) without accumulative effect

The relationships between the centroids of the cluster and memberships in the cluster were expressed by an LSTM model. At the same time, the mean accuracy (given by Eq.(8)) of using the centroids of the cluster to predict the cluster members were shown in Table 5. When comparing the whole building prediction accuracy, the AP clustering results performed better than the *k*-means method.

$$\overline{NRMSE}_p = \frac{1}{n}\sum_{1}^{n} NRMSE_{p-i} \qquad (8)$$

Where, $\overline{NRMSE}_p$ was the mean normalized root mean square error (NRMSE) value of the cross-scale prediction of the cluster *p*, *n* was the sample size of the cluster *p*, and the $NRMSE_{p-i}$ was the NRMSE [11] of using centroids of the cluster *p* to predict the membership *i*.

Table 5 The cross-scale prediction accuracy without considering the accumulative effect.

cluster	1	2	3	4	5	the whole building
mean NRMSE value by *k*-means	0.314	0.143	0.270	0.213	0.250	0.238
mean NRMSE value by AP	0.200	0.295	0.152	0.133	0.270	0.210

To investigate the connections between mean cross-scale prediction accuracy and the ratio of the sample size of each cluster, the exponential, linear, logarithmic, power, and polynomial functions were applied for curve fitting. The results showed the relationship was fitted by a quadratic polynomial was appropriate and as shown in Figs. 5-6. The *k*-means clustering results achieved good fitting performance, and, when a good prediction accuracy want to be got, the ratio of sample size in one cluster would not too low or too high. Fig. 6 showed the opposite trend compared with *k*-means results, and the optimal region was on the right of the apex point.

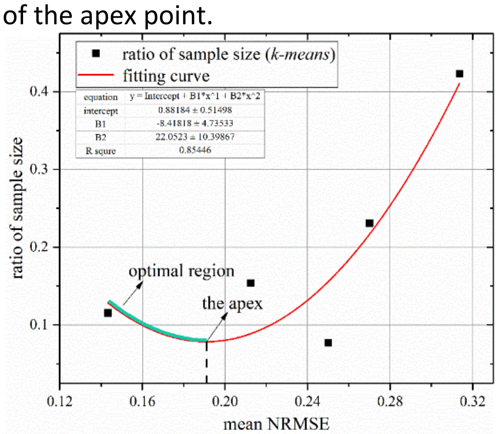

Fig. 5. The fitting details between mean cross-scale prediction accuracy and the ratio of the sample size based on *k*-means clustering results without accumulative

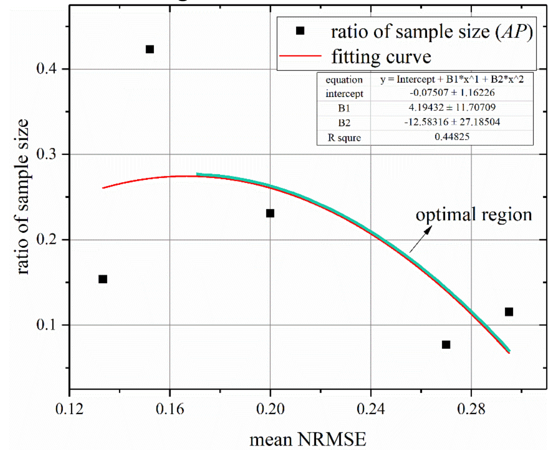

Fig. 6. The fitting details between mean cross-scale prediction accuracy and the ratio of the sample size based on AP clustering results without accumulative effect

(2) with accumulative effect

As shown in Table 6, the mean NRMSE of each cluster and the whole building prediction accuracy when considering the accumulative effect was higher than those not considering the accumulative effect.

Table 6 The cross-scale prediction accuracy when considering the accumulative effect.

Cluster	1	2	3	4	5	the whole building
mean NRMSE by k-means	0.278	0.139	0.216	0.135	0.170	0.187
mean NRMSE by AP	0.148	0.230	0.123	0.140	0.110	0.150

4.3 Logistic regression results

The features “T8”, “T17”, “T19”, “Tmax”, “x2” and “x5” were main factors which impact the cluster belonging. The regression results were shown in Table 7.

Table 7 The results of logistic regression by ANN

evaluating indicator	precision	recall	F1-score
score	0.94	0.82	0.82

4.4 Discussions

Not like the big cluster number (10 or 12) on district-level [3] clustering, the optimal number of clusters on the building level in this study is 5.

In the cross-scale prediction process, as presented in Section 4.3 and Figs. 5-6, there is a trade-off relationship between the ratio of the sample size of the cluster and mean cross-scale prediction accuracy. This finding provides an important guideline for users in cross-scale prediction applying. The apexes (as expressed in Figs. XX) are disadvantageous points which users should be avoided, and the optimal region could be obtained by apexes. What's more, those disadvantageous points could be regarded as the threshold of the ratio of sample size that users can accept.

When considering the accumulative effect. The accumulative effect reduces the distance between load data but improves the cross-scale prediction accuracy (comparing Table 5 and Table 6). The finding can increase the sampling interval from 1 hour to 2 hours without affecting the prediction accuracy, and greatly reduces the investment of sensor equipment.

In the logistic regression process, the ANN model performed well and the SMOTE method was necessary for solving the imbalanced data, this could be proved by the low regression results of the SVM model. This finds is very important to confirm the inevitability of imbalanced data, because the data similarity of building scale is high, so imbalanced data is popular at the building level. By PCA-based feature selection, “T8”, “T17”, “T19”, “Tmax”, “x2” and “x5” are the main components which can explain the logistic regression relationship well. These features, which are determined by logistic regression in this paper, provide direct guidance for users when they need to decide the belonging of the zone in advance.

5. CONCLUSION

The main conclusions are as follows:

(a) The proposed cross-scale load prediction model which based on investigating intra-cluster relationships is effective in real load prediction cases, and the accumulative effect makes the prediction results better.

(b) There is a trade-off between the ratio of the sample size of the cluster and mean cross-scale prediction accuracy, and the optimal prediction period can be obtained.

(c) The maximum demand time, start time, end time of the HVAC system, the west to the south ratio of temperature difference, and the exterior window area together determine the belonging of the cluster.

(d) Building level cross-scale load prediction has fewer clusters but needs a more detailed investigation to determine the optimal number of clusters. At the same time, this study has the limitation of investigating energy savings or profit for cross-scale load prediction. However, the energy savings can be obtained by field experiments. This limitation will be improved in future work, and a more flexible cross-scale load prediction strategy will be provided which considers the user profit.

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