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A transfer learning method for building energy prediction using long short term memory and domain adversarial neural network

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ABSTRACT
To overcome the data shortage problem of model training, this study proposes a novel transfer learning strategy for short term cross-building energy prediction using long short term memory (LSTM) and domain adversarial neural network (DANN). The proposed strategy can utilize transferred knowledge learnt from related domains with sufficient historical data. LSTM based feature extractor is used to extract temporal features across source and target domains. DANN attempts to find domain invariant features between the source and target domains via domain adaptation. Then, the domain adaptation based transfer learning model (i.e. LSTM-DANN) trained with data from different buildings can be directly applied to predict the target building energy without having its prediction performance degradation caused by domain shift. Experiments are conducted to evaluate the performance of the proposed transfer learning strategy in different scenarios. Results demonstrate that domain adaptation can well overcome the domain shift between the source and target domains by learning the domain invariant features. Furthermore, the proposed strategy can significantly enhance the building energy prediction performance compared to models trained on the target only data, the source only data, both the target and source data, but without domain adaptation.

Keywords: transfer learning, long short term memory, domain adversarial neural network, building energy prediction

1. INTRODUCTION

The building sector is responsible for an important proportion of global energy use and greenhouse gas emissions. It is estimated that buildings account for about 40% of the global energy consumption and one third of the greenhouse gas emissions [1-3]. Therefore, it is necessary to develop advanced building energy systems (BES) to improve the efficiency of building energy utilization. With the wide availability of BES, it has become easier to acquire large amounts of building operational data. Therefore, building energy predictions combined with the intelligent technology, such as big data analytics and machine learning have drawn great attentions [4, 5].

The building energy prediction research can be divided into short term, medium term and long term based on the prediction time horizons [6-8]. The short term building energy prediction is closely related to daily operation model of energy systems, which can provide useful guidance to develop cost effective and energy saving measures for the users. Based on the short term prediction results, the short term future operation mode of BES can be adjusted to achieve better energy allocation, which is of great significance to implement the goal of smart grid infrastructure [9, 10]. Thus, researches on short term building energy prediction using machine learning algorithms have attracted great attentions from researchers.

Although advanced machine learning methods can achieve satisfactory performance in short term building energy predictions. However, the superior performance of these methods heavily rely on sufficient historical data from the same building to train the models. The challenge is that, for newly built buildings or those with limited measurements due to time consuming data collection process, they cannot provide sufficient data to train the models [6, 11-13].

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To address this issue, the learning model trained with specific data adapt to input data with different characteristics and distributions from various domains, i.e. domain adaptation. As one of the most commonly used transfer learning methods, domain adaptation breaks the basic assumption of traditional machine learning, that is, the training and testing data should be drawn from the same feature space and satisfy similar data distribution [12, 14, 15].

In this paper, a transfer learning strategy is proposed for cross-building energy prediction based on long short term memory and domain adversarial neural network (LSTM-DANN). LSTM-DANN combines feature extracting and domain adaptation in one model training process. LSTM based feature extractor is used to automatically extract the temporal features across source and target domains. DANN attempts to find domain invariant features between the source and target domains via adversarial domain adaptation of LSTM feature extractor and domain classifier. Experiments are conducted to evaluate the proposed method in different scenarios.

2. PROPOSED LSTM DOMAIN ADVERSARIAL NEURAL NETWORK

The proposed LSTM-DANN structure consist of three main parts, including the feature extractor, regression predictor and domain classifier. The feature extractor is LSTM layer, regression predictor and domain classifier are both fully connected layers.

The feature extracted by LSTM are shared by the regression predictor and domain classifier. The domain adversarial idea is contained in the feature extractor and domain classifier of the proposed LSTM-DANN structure. The domain classifier is trained to correctly identify the domain labels (source:0, target 1) of extracted features, while the feature extractor is trained to deceive the domain classifier so that the domain classifier cannot correctly discriminate the domain labels. The domain classifier finally cannot discriminate whether the extracted feature comes from the source domain or target domain due to the adversarial behavior between the feature extractor and domain classifier. At this time, the feature extracted by LSTM is domain invariant.

The training optimization loss of LSTM-DANN model includes regression loss and domain classification loss. The regression loss of the energy prediction is defined as the mean square error:

$$\phi_y^i(\theta_f,\theta_y)=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \tag{1}$$

Where n is the batch size of the training data. y_i and $\hat{y}_i$ denote the actual and prediction value of building energy, respectively.

The loss of domain label classification is defined as binary cross entropy:

$$\phi_d^i(\theta_f,\theta_d)=\frac{1}{n}\sum_{i=1}^{n}(d_i\log\frac{1}{\hat{d}_i}+(1-d_i)\log\frac{1}{1-\hat{d}_i}) \tag{2}$$

Where d_i and $\hat{d}_i$ respectively denote the actual domain label (source: 0, target: 1) and the predictive domain label.

As the LSTM based feature extractor and domain classifier act adversarial roles in the LSTM-DANN structure, their effect on the domain classification loss is opposite. The feature extractor tries to maximize the domain classification loss, while the domain classifier aims to minimize the loss. This min-max operation cannot be directly implemented by the gradient update in the backpropagation process of neural network at the same time. The gradient reversal layer (GRL) is inserted between the feature extractor and the domain classifier to achieve this desired target. The GRL acts as an identity transformation in the forward propagation process, while obtains the gradient from the subsequent level and changes its sign in the backpropagation process. In particular, the GRL can be treated as a "pseudo-function" R_λ defined by the following Eqs. (3) and (4) for its forward and backward propagation process:

$$R_\lambda(x)=x \tag{3}$$

$$\frac{dR_\lambda}{dx}=-\alpha I \tag{4}$$

$$\alpha=\frac{2}{1+\exp(-\gamma\cdot p)}-1 \tag{5}$$

$$p=\frac{j+k\cdot L}{m\cdot L}(1\le j\le L/n, 0\le k\le m) \tag{6}$$

Where I is an identity matrix. α is a positive hyper-parameter which implements the trade-off between regression loss and domain classification loss, γ is set to 10. j is current number of batches, k is the current number of iterations, m is the total number of iterations, L is the length of the minimum total batches of the source and target training data.

Then the final objective "pseudo-function" can be optimized by the gradient descent using our method, which can be expressed as:

$$\begin{aligned}\phi(\theta_f,\theta_y,\theta_d) &= \frac{1}{N_S}\sum_{i=1}^{N_S}\phi_y(G_y(G_f(x_i;\theta_f);\theta_y),y_i) \\ &+\frac{1}{N_T}\sum_{i=1}^{N_T}\phi_y(G_y(G_f(x_i;\theta_f);\theta_y),y_i) \\ &+(\frac{1}{N_S}\sum_{i=1}^{N_S}\phi_d((G_d(R(G_f(x_i;\theta_f);\theta_d),d_i) \\ &+\frac{1}{N_T}\sum_{i=1}^{N_T}\phi_d((G_d(R(G_f(x_i;\theta_f);\theta_d),d_i))\end{aligned} \tag{7}$$

Where N_S and N_T respectively represent the number of source and target domain data, $\theta_f,\theta_y,\theta_d$ denote the network connection weights of feature extractor, regression predictor and domain classifier, respectively.

The loss function ϕ is optimized by searching the minimize point $\theta_f,\theta_y,\theta_d$ such that:

$$(\hat{\theta}_f,\hat{\theta}_y) = \arg\min \phi(\theta_f,\theta_y,\hat{\theta}_d) \tag{8}$$

$$\hat{\theta}_d = \arg\min \phi(\hat{\theta}_f,\hat{\theta}_y,\theta_d) \tag{9}$$

And the learning weights in the LSTM-DANN model are updated by gradient descent expressed as:

$$\theta_f \leftarrow \theta_f - \lambda(\frac{\partial \phi_y^i}{\partial \theta_f} - \alpha\frac{\partial \phi_d^i}{\partial \theta_f}) \tag{10}$$

$$\theta_y \leftarrow \theta_y - \lambda\frac{\partial \phi_y^i}{\partial \theta_y} \tag{11}$$

$$\theta_d \leftarrow \theta_d - \lambda\frac{\partial \phi_d^i}{\partial \theta_d} \tag{12}$$

Where λ represents the learning rate. Running Eqs. (10)-(12) can be implemented by doing gradient descent algorithm to find the optimization weight parameters. After the learning, the regression predictor G_y can be used to predict labels for both target and source samples.

3. RESULTS AND DISCUSSIONS

To validate the proposed method, the building dataset from the Building Data Genome Project are used for the model performance evaluation in this study. The dataset mainly contains five types of buildings, including office, primary classroom, college classroom, college dormitory and college laboratory. Three office buildings located in America are selected for analysis. Table 1 shows the detailed information of the source and target buildings. The source building (Building A) is an office located in Phoenix. One target building (Building B) is another office with different energy profile located in the same city, while the other target building (Building C) is an office located in New York with different weather condition.

Table 1. Building information of the source and target building.

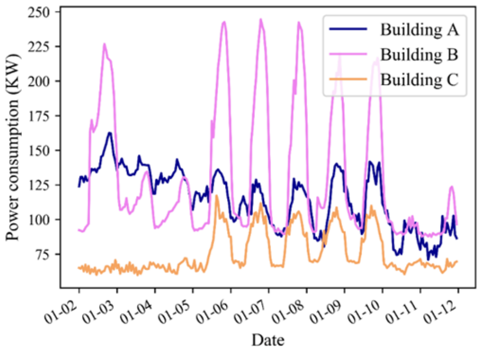
Items	Source building (Building A)	Target building (Building B)
Collecting period	01.02-04.30	01.02-01.11
Sample number	2856	240
Location	Phoenix	Phoenix
Usage types	Office	Office
Area (m2)	11282	13759

The sliding window is employed to process the original input time series to input-output pairs. Each input dataset contains 9 variables with a length of 24. Table 2 shows the dataset variables of model inputs. Among them, the 3 temporal variables include month type (i.e. January to December), day type (i.e. Monday to Sunday), and hour type (i.e. 0:00 to 23:00). These three variables are regarded as categorical variables with 12, 7 and 24 levels by the one-hot encoding, which are used as indicators of seasonality and indoor occupancy. The remaining six variables including building power consumption, outdoor temperature, dew point temperature, relative humidity, wind speed and atmospheric pressure are all numeric.

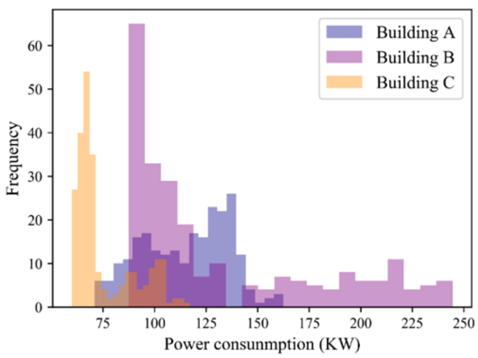
Table 2. The dataset variables of model inputs.

Variable	Type	Units/Range
Outdoor temperature	Numeric	℃
Dew point temperature	Numeric	℃
Relative humidity	Numeric	%
Wind speed	Numeric	Km/h
Atmospheric pressure	Numeric	hPa
Power consumption	Numeric	KW
Month type	Categorical	Jan-Dec
Day type	Categorical	Monday-Sunday
Hour type	Categorical	0:00-23:00

Figure 1 shows the measurement and frequency histogram of power consumption during January 2-11 for the selected three buildings. Each building has an hourly power consumption measurement. It can be seen that the power consumption profile for each building shows a similar trend in a certain period of time. However, due to the obvious differences of building scales and personal activities, there exist large variations in the power consumption of three buildings. The power consumption of Building B has a wide fluctuation range. The power consumption of Building C has obvious weekend and weekday effect. The power consumption of Building A varies irregularly. Therefore, the building energy prediction models should be modeled separately to acquire desirable performance.



(a) Measured power consumption

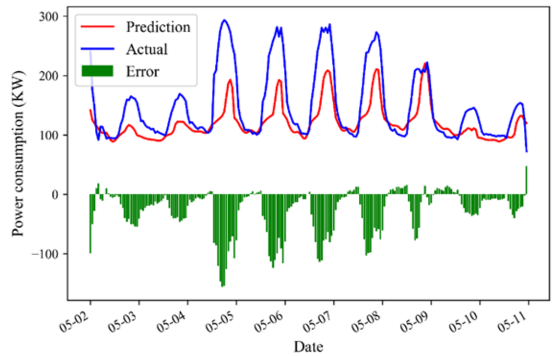


(b) Frequency histogram

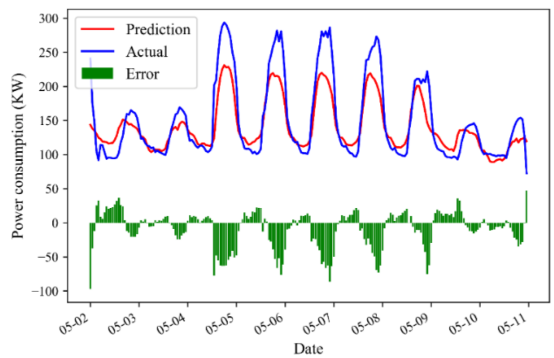
Figure 1. Statistics of power consumption for the three buildings. (During January 2-11)

The source and target building data are utilized to train the deep-DANN model, our task is to predict the target building energy during May 1-10 using the trained model. We assess the proposed approach on one transfer learning energy prediction tasks: Building A → Building B. The source domain related dataset are from Building A and the target domain related dataset are from Building B. And then, four different prediction models are implemented for prediction performance evaluation and analysis as follows:

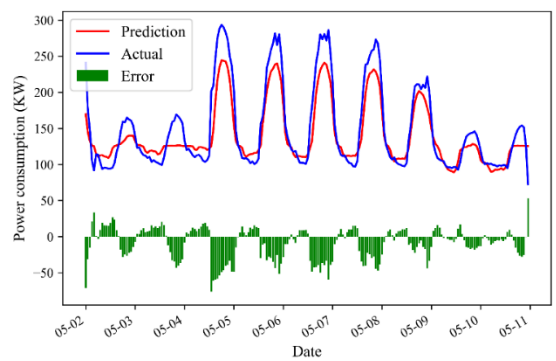
(1) Model A: LSTM trained on data only from the target building for prediction.
(2) Model B: LSTM trained on data only from the source building for prediction.
(3) Model C: LSTM trained on data from the source and target buildings for prediction without domain adaptation.
(4) Model D: LSTM trained on data from the source and target buildings for prediction with domain adaptation (i.e. LSTM-DANN).



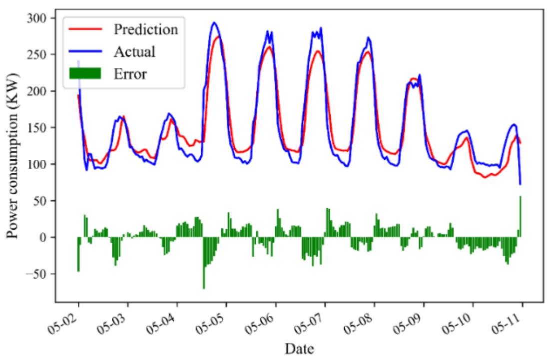
(a) Model A



(b) Model B



(c) Model C



(d) Model D

Figure 2. The actual values and the prediction values of four different models

Figure 2 respectively show the building power consumption prediction results using the four different models. It can be seen that the prediction values of the four different models show similar trends with the actual values. It is mainly because both source building and the target buildings belong to the office building type with similar power consumption period. We note that the prediction values of model trained on data only from the target building (Model A) are significant lower than the actual values. The prediction values of model trained on data only from the source building (Model B) show similar results. This is expected because the training data distribution is different from the testing data, the prediction values depend on the relationship of training data. The model cannot well learn the temporal characteristics inherently involved in the time series data and finally make poor predictions. The model trained on data from the source and target buildings (Model C) shows some improvements while the prediction values still deviate from the actual values in most points. We note that the proposed domain adaptation model (Model D, i.e. LSTM-DANN) fits best with the actual building power consumption compared with the other three models trained on target only data, source only data, and all the data but without domain adaptation.

The mean squared error (MSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the coefficient of variation of the root mean squared error (CV-RMSE) are used to evaluate the model performance. These four performance evaluation metrics are calculated as Eqs. (13)-(16) respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (13)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (14)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \quad (15)$$

$$CV - RMSE = \sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 / n} / (\sum_{i=1}^{n} y_i / n) \quad (16)$$

Table 3. Prediction performance metrics of four models

Model	MAE	MSE	MAPE	CV-RMSE
Model A	32.6346	2284.8462	0.1788	0.3196
Model B	20.7474	827.6728	0.1265	0.1924
Model C	18.4808	580.8107	0.1149	0.1612
Model D	15.5032	352.5078	0.1128	0.1256

Performance evaluation metrics of four different models are respectively shown in Table 3. It can be seen that performance metrics of the proposed model are the best among the four different models. The model trained on data from the target building (Model A) shows the worst predictive performance as the training and testing data are from different seasons. The MAE is 32.6346 KW and MAPE is 17.88%. The model trained on data from the source building (Model B) also performs not so well. The model trained on data from the source and target buildings (Model C) but without domain adaptation shows some improvements compared to the Model A and Model B, while the MAPE and CV-RMSE are still in a high level. The proposed domain adaptation model (Model D) has the smallest values of these four evaluation metrics, which is far smaller than that of the other three models. The MAE is 15.5032 KW and MAPE is 11.28%.

4. CONCLUSIONS

In this paper, a domain adaptation based transfer learning strategy is proposed for cross-building energy prediction using LSTM-DANN. LSTM based feature extractor is used to extract the temporal features across source and target domains. DANN attempts to find the domain invariant features between the source and target domains via adversarial domain adaptation of LSTM feature extractor and domain classifier. Experiments are conducted to evaluate the performance of the proposed method in different models. Main conclusions are obtained as follows:

(1) The novel transfer learning method can significantly enhance the building energy prediction performance compared to models trained on the source-only data, the target-only data, and both the target and source data, but without transfer learning.

(2) Domain adaptation can well overcome domain shift between the source and target domains by learning the domain invariant features.

(3) LSTM can extract temporal features better than convolutional and fully connected layer in DANN based network.

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