ARTIFICIAL INTELLIGENCE APPLICATIONS IN HOURLY ENERGY USE INTENSITY PREDICTION

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Overview

With the growing population and the economic development, the global energy demand has been continuously increasing. Buildings contribute a substantial share to world energy consumption (32%)[1] and greenhouse gas emissions (17.5%)[2]. To achieve carbon neutrality by 2050, a complete transition of the energy system—especially the building sector—is required. Accurate prediction of building energy use is therefore a crucial need for better energy planning, management, and conservation.

In this paper, the contribution is two-fold. First, we propose a deep transfer learning strategy for cross-building energy use prediction using the indicator—energy use intensity (EUI); this helps identify the general trends of building energy performance on an hourly scale. Second, we employ artificial intelligence techniques in building energy management and demonstrate their potential to help reduce energy consumption and CO_2 emissions.

Methods

Background

Building energy prediction is crucial for enhancing decision-making towards reducing energy consumption and CO_2 emissions; a large number of energy prediction methods have been proposed in the recent years. However, the scale of the building electricity consumption will vary significantly according to the selected building size, so it is difficult to compare the model prediction performances among different literatures. To fill the aforementioned research gap, this study proposes to normalize the building energy performance to energy use intensity (EUI) as model inputs to avoid scaling bias. Then various artificial intelligence techniques are applied and compared for future energy use prediction. The building EUI, defined as electricity consumption per square floor area, is more suitable for evaluating the prediction performance between different buildings.

This study selects the Civil Engineering Research Building of National Taiwan University as a case study. The target building is a ten-stories building (including one underground story and nine overground stories) with a total floor area of 10,084 m^2, located in Da'an Dist., Taipei City in Taiwan. The time range of load data is from January 1, 2014 to December 31, 2020, totaling seven years with a time resolution of one hour; we select the years 2014 to 2019 as training data and the year 2020 as testing data.

Models

High-precise building energy prediction is difficult to achieve due to a variety of factors such as building characteristics (e.g. building type, age, floor area, orientation, and sustainable design), appliance(e.g. sustainable designs), lighting, habitual behavior, and weather conditions. Artificial intelligence (AI) technologies are able to learn with experience and provide a high level of capability in handling a range of complex tasks in many spheres of life. Applying AI methods to time series overcomes various limitations, such as the poor generalization capability, the sensitivity to model parameters, and the unsuitability of large-scale and non-linear predictive analysis for traditional statistical modeling[3]. In this study, data-driven artificial intelligence-based approaches are implemented to project the building energy consumption at one-hour resolution, and the prediction performance of seven predictive methods are compared: machine learning models including eXtreme Gradient Boosting (XGBoost), and Facebook Prophet; deep learning models including simple recurrent neural networks (SimpleRNN), long-short term memory (LSTM), bidirectional long-short term memory (BiLSTM), gated recurrent unit (GRU), and bidirectional gated recurrent unit (BiGRU).

Results

Performance evaluation

The performance of prediction models is evaluated and compared through the following commonly used four metrics: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R-square (R^2) (Table 1).The forecast accuracy is reflected by the four evaluation metrics from different aspects of the prediction. In general, the lower values of RMSE, MAE, and MAPE and the higher values of R^2 indicate a better fit. Among seven selected artificial intelligence-based methods, the BiLSTM model best fits with testing data—with the RMSE, MAE, MAPE, and R^2 values of 0.00097 kWh/m²·hour, 0.00058 kWh/m²·hour, 4.444%, and 0.948, respectively (Figure 1).

Table 1. Comparison of model performances based on the RMSE, MAE, MAPE, and R^2 metrics

	XGBoost	Prophet	SimpleRNN	LSTM	BiLSTM	GRU	BiGRU
RMSE	0.00189	0.00202	0.00107	0.00103	0.00097	0.00102	0.00100
MAE	0.00132	0.00158	0.00069	0.00062	0.00058	0.00063	0.00058
MAPE	10.677%	13.513%	5.495%	4.798%	4.444%	4.857%	4.527%
R^2	0.806	0.779	0.934	0.943	0.948	0.943	0.946

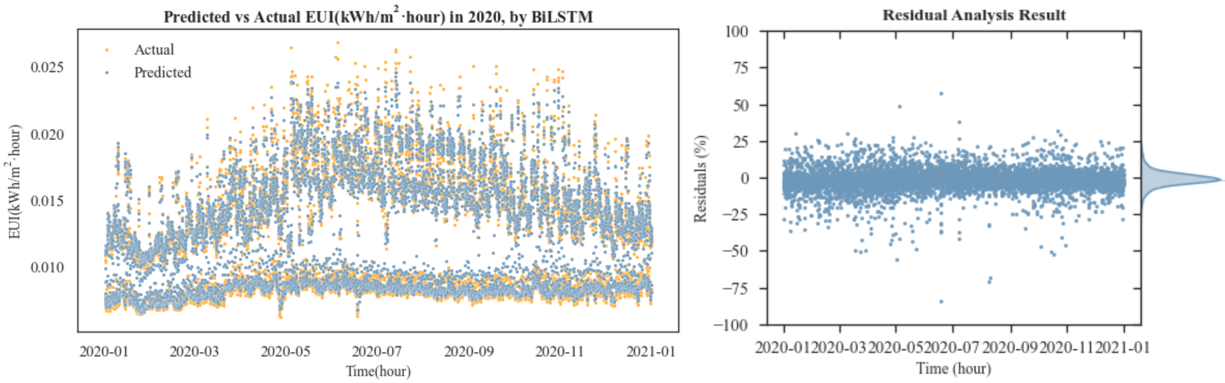

Figure 1. (a) Predicted and actual EUI of the selected building in 2020; (b) Residual analysis result.

Applications

Precise forecasting of building energy demand can enhance the performance of building energy management systems (BEMS) and facilitate the decision-making process in Internet of Energy (IoE). IoE is the integration of Internet of Things (IoT) and smart grid. By connecting the grid to the internet, IoE is able to customize intelligent energy management solutions according to the real-time energy load through bi-directional data exchange. With the developed AI-based models for building energy consumption, we are able to perform the following tasks: (1) utilize real-time hourly energy demand forecasts to optimize energy use and minimize the impact on the environment simultaneously; (2) further form a local energy community or urban energy internet to facilitate urban energy infrastructure planning and promote the circular economy transition in cities; (3) realize systematic real-time energy management among different building clusters.

Moreover, AI-based building energy consumption prediction models can also be leveraged to reduce peak power demand in buildings through vehicle to building (V2B) strategy. Vehicles are parked most of the time; as vehicles are electrified, they can serve as flexible energy storage batteries to moderate the variability of renewable generation and building energy use (i.e., being charged when excess solar power is produced and discharged to the building when the building's demand peaks). Having a reliable building energy use prediction would increase the effectiveness of V2B strategy, and thus reducing power surges and power outages without additional investment.

Conclusions

Towards smart and sustainable cities, applying AI techniques to realize energy and emissions saving potential in buildings is needed. In this study, we first normalize the data to EUI and then adopt seven AI-based methods to simulate the building energy consumption patterns. The evaluation results show that the BiLSTM model achieve better prediction performace for the selected research building than the others, with RMSE, MAE, MAPE, and R^2 values of 0.00097 kWh/m²·hour, 0.00058 kWh/m²·hour, 4.444%, and 0.948, respectively. Using the normalized indicator EUI as model inputs allows us to compare energy performance across different buildings. Accurate forecasting of building energy demand plays a crucial role in building energy management and conservation, as it facilitates energy efficiency evaluation, building operation and maintenance, fault detection and diagnosis (FDD), demand-side management (DSM), supply-side management (SSM), and decision support for building retrofitting. This study explores the capability of AI-based models to predict the constantly changing demand of building energy management. With such models, further study about real-time charging management of V2B strategy is being conducted; the research findings can be used as the guideline and criteria of building energy management process to facilitate transitions towards nearly zero-energy building (NZEB).

References

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