Data-driven outdoor and indoor temperature prediction for energy-efficient building operation

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DATA-DRIVEN OUTDOOR AND INDOOR TEMPERATURE PREDICTION FOR ENERGY-EFFICIENT BUILDING OPERATION

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ABSTRACT

Outdoor and indoor temperature prediction of local buildings is important for optimal building operation and energy-demand management. This study collects data from a commercial building, covering outdoor and indoor climate, and variables of occupants and building system operation. Based on the selected data, two different data-driven methodologies using machine learning techniques are proposed to predict local outdoor and indoor temperatures at a high resolution. The proposed data-driven models with learning capabilities are based on k-nearest neighbor and artificial neural networks, showing good prediction performance for the case study building.

Keywords: data-driven modeling, temperature prediction, machine learning, energy efficiency, smart buildings

NOMENCLATURE

Abbreviations	
HVAC	Heating, ventilation, and air conditioning
ANN	Artificial neural networks
KNN	k-nearest neighbor
NLARX	Nonlinear autoregressive with exogenous input
Symbols	
T_{oa}	Outdoor air temperature
T_{ia}	Indoor air temperature
$T_{oa,lcMs,m}$	Local measured T_{oa} at 10-minute intervals
$T_{oa,lcMs,h}$	Local measured T_{oa} at hourly intervals
$T_{oa.onPd,h}$	Online weather forecast at hourly intervals
$T_{oa.mg,h}$	Daily merged T_{oa} at hourly intervals
$T_{oa.lcPd,m}$	Local predicted T_{oa} at 10-minute intervals

1. INTRODUCTION

Buildings have a significant impact on worldwide energy use, accounting for around one-third of total final energy usage [1]. Outdoor and indoor temperatures are two of the key factors influencing the energy consumption of building systems and the comfort of the built environment. In pursuit of energy-efficient and comfortable buildings, outdoor and indoor temperature prediction is required by energy- and comfort-optimal operation [2] and demand management [3].

To control building systems of heating, ventilation, air conditioning (HVAC), artificial neural networks (ANN), dealing with non-linear problems, were used to predict the outdoor air temperature (T_{oa}) in [4,5]. The data used by them included horizontal global solar radiation, T_{oa}, and humidity. Standard deviations of prediction errors in [4] ranged from 0.45°C to 1.31°C for 6 time horizons. For a similar purpose, the Hammerstein-Wiener model was employed to predict the hourly local T_{oa} in [6]. Its minimal and maximal prediction errors were 0.2°C and 2.4°C. To model the energy load of buildings in the study of [3], the hourly forecast of T_{oa} was generated by daily probabilistic minimum and maximum temperature.

In a similar manner of predicting T_{oa}, ANN was also used by the studies of [4,5] to predict indoor air temperature (T_{ia}) based on the data of T_{oa}, humidity, global solar radiation, and T_{ia} setpoint. Standard deviations of prediction errors in [4] ranged from 0.10°C to 0.47°C for 6 time horizons. Root mean squared errors in [5] spanned from 0.06°C to 0.65°C within the defined horizon. In another study, Afroz et al. [7] used more variables to model indoor temperature using ANN. The variables were extracted from outdoor and indoor climate, HVAC equipment, air handling and variable air volume control units. The maximal mean squared error is 0.08. Different to the above studies, Cui et al. [8] used hybrid modeling (RC network and supervised learning algorithms) to predict the average T_{ia} and the temperature difference between the downstairs and upstairs for two-story houses. The 14 variables used consisted of weather data, building properties, and measured\estimated data from a building. The achieved root mean squared errors ranged from 0.50°C to 0.77°C for seven models.

For similar research purposes, this paper proposes two different data-driven methodologies to predict both local outdoor and indoor temperatures. Features are extracted from time of day, outdoor and indoor climate, occupant-related variable, and HVAC operation parameters. Both models are evaluated using actual data measured from a commercial building.

2. METHODOLOGY

In this study, two types of machine learning algorithms (i.e. k-nearest neighbor and artificial neural networks) are selected to predict outdoor and indoor temperatures based on the defined prediction problems and our prior research on the data-driven modeling.

According to the building control purpose, the time horizon of the prediction is defined to 2 hours at a resolution of 10-minute intervals.

2.1 Case study building and data

The case study building located in Singapore is used as an office building. Singapore has a tropical climate with warm outdoor temperature [9]. Room temperature of the case study space is controlled by a water-based chilled ceiling system [10]. Sensor data is transformed at 10-minute intervals, measuring from the case study building and an on-site weather station. All sensors are off-the-shelf products calibrated by the suppliers before the study.

2.2 Outdoor temperature prediction

The online weather forecast provided by weather websites is delivered hourly, a resolution of which is lower than building operation cycles that are in minutes. Additionally, the weather measurement for the online weather forecast is located on a different site, away from local buildings (i.e. target buildings). The distance between them and the surroundings of buildings cause temperature errors. To improve prediction resolution and reduce prediction errors for local buildings, this subsection presents a learning-based method to predict local T_{oa}. As shown in Fig 1, this prediction includes three parts: 1) data of the current day, 2) historical database, and 3) module of the local T_{oa} prediction.

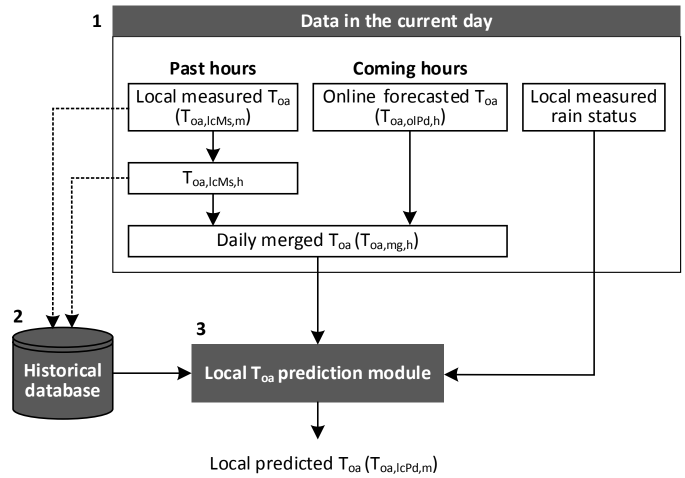

Fig 1. Local T_{oa} prediction

The data in the current day consists of two types of information. Online weather forecast is read from AccuWeather via REST API, updating the hourly forecast for the next 12 hours. The outdoor weather of the local building is monitored from an on-site weather station, including outdoor air temperature and rain status. Local measured T_{oa} of the past minutes of the current day is transformed at a 1-hour resolution ($T_{oa,lcMs,h}$) from 10-minute intervals ($T_{oa,lcMs,m}$), averaging sampled $T_{oa,lcMs,m}$ for each past hour. As online forecasted T_{oa} provided at hourly intervals ($T_{oa,olPd,h}$), a daily merged T_{oa} ($T_{oa,mg,h}$) required by the local T_{oa} prediction module is formatted to a vector with 24 elements to store hourly T_{oa} data: two sectional vectors record $T_{oa,lcMs,h}$ and $T_{oa,olPd,h}$, respectively.

The historical database comprises of historical T_{oa} measured by the on-site weather station. It stores the daily local T_{oa} at two data resolutions: 10-minute and 1-hour intervals. In the last sample cycle of a weekday, the local measured T_{oa} is updated automatically to the historical dataset for the prediction on the next day.

Based on the prepared data, the module of local T_{oa} prediction deduces local T_{oa} for the next 2 hours in three steps. First, k-nearest neighbor is used to find k days on which T_{oa} are most similar to $T_{oa,mg,1h}$ from the historical data at 1-hour intervals, computing Euclidean distances between them. Second, according to the identified dates, corresponding daily T_{oa} are extracted from the historical dataset at 10-minute intervals. The segments of their next 2-hour T_{oa} are computed into 3 vectors at the same resolution, representing the minimum, average, and maximum values, respectively. Lastly, the final local predicted T_{oa} ($T_{oa,lcPd,m}$) for the next 2 hours is selected from the above vectors based on the current rain status and outdoor temperature of the local building.

2.3 Indoor temperature prediction

To model indoor temperature, this study considers the impacts from five categories of features: time of day, outdoor climate, indoor climate, occupant-related factor, and HVAC operation parameters. The features, collected from the sensor network of the case study building, are listed in Table 1.

Table 1. Description of features

Category	Features
Time	Hour of day
Outdoor climate	Outdoor air temperature (°C)
Indoor climate	Indoor air temperature (°C)
Occupant-related variable	Room carbon dioxide concentration (ppm)
HVAC operation parameters	Room temperature setpoint (°C) Water supply temperature of chilled beams (°C)

Nonlinear Autoregressive with Exogenous input (NLARX) aims to predict time series values from past data streams. For this reason, this study employs NLARX to predict T_{ia} using the features listed in Table 1. Predicted value at time t is regressed from delayed input (u(t)) and output (y(t)) variables, as shown in Eq. 1. And, a two-layer feedforward network is used as a nonlinearity estimator for NLARX, which is trained by Bayesian regularization backprogation.

$$y(t) = F(y(t-1), \dots, y(t-d), \dots, u(t-1), \dots, u(t-d)) \quad (1)$$

3. RESULTS AND DISCUSSION

3.1 Prediction results of outdoor temperature

The historical dataset included around 1-year $T_{oa,lcMs,m}$ and $T_{oa,lcMs,h}$ data measured by the on-site weather station. And, the proposed methodology was conducted to predict local T_{oa} of the case study building from mid-April to August 2018.

For the T_{oa} prediction, Fig. 2 summarizes $T_{oa,lcMs,m}$, $T_{oa,olPd,h}$, and $T_{oa,lcPd,m}$ during the 4-month experiment. The period of the daily prediction follows the HVAC operation schedule of the building, displayed by two dotted lines as shown in Fig 2 a). This subfigure also presents the range of $T_{oa,lcMs,m}$ during the experiment (the grey area) and indicates that the means of $T_{oa,lcPd,m}$ (blue line) predicted by the proposed model is closer to the means of actual T_{oa} (black line) than $T_{oa,olPd,h}$ (red line). Different from $T_{oa,olPd,h}$ drifting up to 2°C compared to $T_{oa,lcMs,m}$, Fig 2 b) presents that the local predicted T_{oa} is kept in the range of the actual T_{oa}. As shown in Fig 2 c), the majority of errors between $T_{oa,lcPd,m}$ and observed $T_{oa,lcMs,m}$ are reduced to a small band (less than 0.6°C) as compared to around 2°C generated by the online weather forecast. Furthermore, the mean squared error of $T_{oa,lcMs,m}$ is reduced to 1 °C as compared to 2.9°C when predicted by the online weather forecast.

For the T_{oa} measurement, positions of the weather station for a building might cause different values. To reduce such difference, the local weather station in this study was installed based on the standard requirement.

3.2 Prediction results of indoor temperature

In this study, the time-series data for input features and outputs consisted of over 1-year high-quality sensor values collected from the case study building. Such data was divided into two portions: training dataset (75%) and

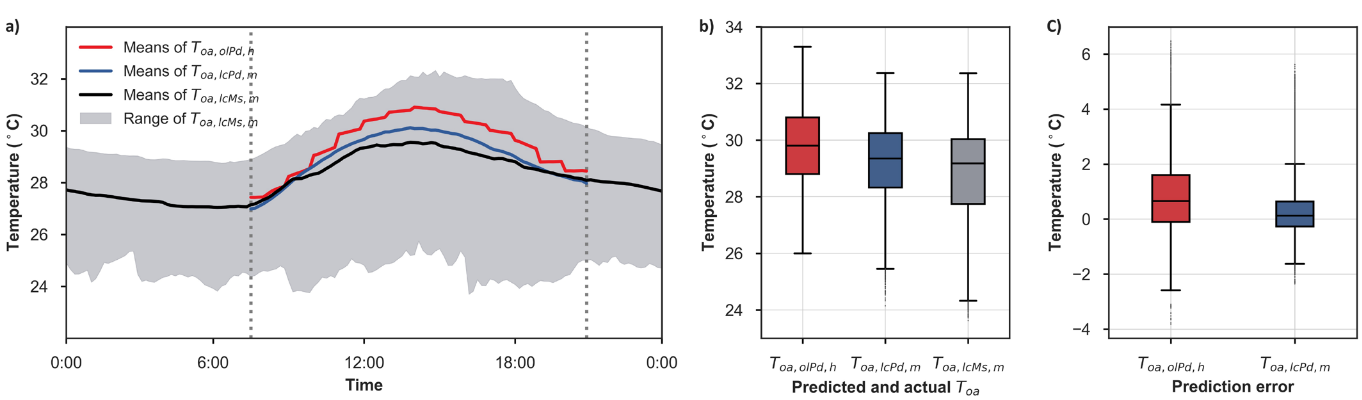

Fig 2.Outdoor temperature prediction. a) Means, b) distributions of T_{oa}, c) distributions of prediction errors.

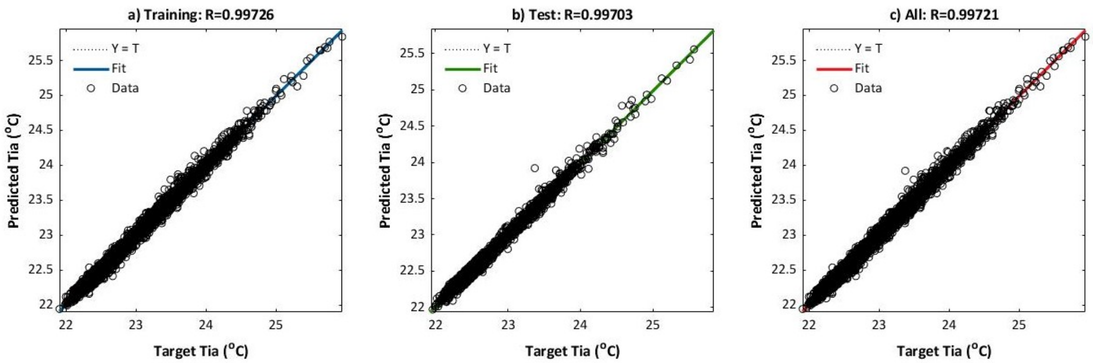

Fig 3. Indoor temperature prediction. a) Training data, b) test data, c) the combined data.

test dataset (25%). Fig. 3 presents the regression results of training, test, and the combined datasets for a thermal zone. R values indicate correlations between predicted and observed T_{ia}, which show good performance of regression for the 3 datasets. The mean squared errors are around 0.002.

4. CONCLUSIONS

In this paper, we presented two data-driven models with learning capabilities to predict outdoor and indoor temperatures. The studies in the literature review showed different prediction performance due to various methodologies, datasets, resolution of the prediction, and assessment methods. Overall, the performance evaluated in this study tracks the actual data well.

The proposed models can not only be used to optimize building operation, but also for load management. To improve the energy-efficient building operation, the proposed prediction models have been integrated into a predictive HVAC control system to optimize indoor temperature based on outdoor and indoor climate, and human behavior. The related evaluation will be presented in our future study.

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