Potential of deep learning-based models for predicting the supply air temperature from air-handling units

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Abstract

Machine learning-based data-driven models have shown considerable potential for fault detection and diagnosis (FDD) in building energy systems due to their flexibility in model development and the availability of data from the building automation systems (BAS). This paper discusses the potential of deep learning (DL) techniques for the prediction of the supply air temperature of the air-handling unit (AHU) as the first step of FDD. The deep neural networks (DNN) are trained using BAS trend data. The effect of model hyperparameters on the performance of DNN is discussed, and the results are compared with other models. The optimized DNN model provides good predictions with the Mean Absolute Error of 0.17°C compared with the sensor's overall uncertainty of 0.38°C. The DNN model could be employed for the re-calibration of faulty sensors.

Keywords: *Neural networks, deep learning, hyperparameters, air handling unit, supply air temperature*

INTRODUCTION

Modern buildings account for a significant amount of primary energy use over the world; this energy consumption keeps increasing year by year. Heating, ventilation, and air-conditioning (HVAC) systems consume approximately half of the total energy use in buildings (Yang et al., 2014). It has been estimated that the energy-saving potential in an HVAC system could reach 15-35% for commercial buildings (Goetzler et al., 2017; Pérez-Lombard et al., 2008). The total energy use in institutional and commercial buildings is about 30-45% higher compared to residential buildings (Gul & Patidar, 2015).

Air handling units (AHUs) are extensively used in HVAC systems of commercial buildings. Measuring the supply air temperature accurately from the AHU is critical to provide optimal occupant thermal comfort while avoiding energy waste. For this reason, faulty supply temperature sensors can have a significantly detrimental effect. Prediction models based on measurements from other sensors could provide a temporary solution while waiting for the physical correction/replacement of faulty sensors. Such models could be used for virtual measurements or for corrections (e.g., fault detection and virtual calibration) of the supply air temperature.

The improvement of models for the prediction of building energy use and HVAC target variables is a growing field of the application of artificial intelligence (AI) and machine learning (ML). Prediction/forecasting models for building energy systems are mainly grouped into two categories: physical or white-box models and data-driven black-box models. Data-driven black-box models use data from BAS, which represent the real building/system operation and performance. Black-box models generally have higher accuracy than knowledge-based models for fault detection and diagnosis and can work even if some critical variables are missing (Zhao et al., 2019). The performance of black-box models depends on the prediction techniques and the quality of model inputs. Different types of black-box models –such as multilayer regression (MLR), artificial neural networks (ANN), support vector regression (SVR), random forest, and decision trees– have been used to study energy use in buildings. Previous studies (Ahmad et al., 2014; Amasyali & El-Gohary, 2018) indicated that support vector regression (SVR) and artificial neural networks (ANN) worked relatively well for predicting the building energy load and thermal parameters; most of these studies have developed machine learning models using hourly data. Most ANN models were used for the prediction of the whole building demand/load (81%), while only 5% were used for the prediction of target variables at the component level (e.g., chiller, fan) (Runge & Zmeureanu, 2019). Ruano et al. (2006) developed an ANN model to predict the indoor room temperature for the control of an air-conditioning system. Mustafaraj et al. (2011) developed autoregressive linear and nonlinear neural network models to predict the room temperature and relative humidity of an open office; both types of models provided reasonable predictions, but the nonlinear neural network model outperformed the autoregressive linear model. Kusiak & Xu (2012) used an ANN ensemble model to forecast the energy consumption of an HVAC system and the indoor temperature of two thermal zones 30 minutes ahead. The validation showed that the mean absolute error (MAE) and the mean absolute percent error (MAPE) are 0.31°C and 4.0%, respectively. Hong & Kim (2018) used an ANN model to forecast the supply air temperature of an AHU in a hospital building. A forecast of the supply air temperature was made 24 hours ahead by using time lags up to 6 days of some inputs such as the outdoor, return and mixing air temperatures. The RMSE value for the forecasting model was between 0.51 to 0.63°C.

The literature review showed that ANN and SVM models had been the most widely used machine learning (ML) approaches for predicting/forecasting energy or thermal parameters of building components/systems (Runge et al., 2020). However, only a few studies have used a deep neural network (DNN) model for building energy systems. Amber et al. (2018) studied the prediction accuracy of five different computational intelligent techniques (MLR, genetic programming, ANN, DNN, and SVM) for forecasting the daily electricity consumption of an office building. The multilayer feedforward neural network outperformed DNN and other methods. Fallah et al. (2018) stated that overfitting issues related to DNN could be a concern as compared with "shallow" ANN.

The purpose of this paper is to conduct a preliminary evaluation of the potential of deep learning (DL) algorithms based on artificial neural networks to predict the supply air temperature from AHUs.

CASE STUDY

The AHU of an institutional building located in Montreal, Canada, was considered as a case study. The building has a total conditioned floor space of 5,400 m^2, consisting of five levels, including a basement and a mechanical penthouse. The AHU is composed of two identical units connected in parallel, each one composed of a pre-heating coil, a mixing box, heating and cooling coils, a humidifier, and two variable speed supply fans (Figure 1). Measurements recorded at 15-min time interval, from April 25th to September 25th, 2016, were used in this study. Most of the previous studies (Ahamed et al., 2019; C. Fan et al., 2017; Lee et al., 2019) for data-driven models considered the single split technique (training dataset and testing dataset) as good enough to avoid the risk of over-fitting. Depending on the data type and size, the splitting ratio of data into training and testing set could be 50%–50%, 60%–40% and 75%–25%. However, the splitting ratio of 75%-25% provided a better estimation than other splitting ratios (Kisi & Heddam, 2019). Therefore, the entire dataset was divided into a training dataset and a testing dataset (75% and 25%, respectively) using the split method. Table 1 lists the variables available from the BAS with their corresponding bias and random errors and the overall uncertainty of the measurements.

Data Pre-processing and Feature Selection

Only data recorded during the cooling operation (i.e., heating coil OFF / cooling coil ON) were used for model training and testing.

In any data-driven model, it is important to consider all variables that could significantly affect the model output. However, the historical data from BAS in their original form could result in redundant information. Therefore, the extraction of feature variables is important for the removal of redundant information as inputs for the model.

The process of feature extraction could reduce the possibility of overfitting. The computational load in model development could also be lessened by reducing the dimensionality of model inputs (Fan, Xiao, & Zhao, 2017). The correlation analysis technique was applied to eliminate the redundant input variables related to the supply air temperature from AHU.

The Pearson correlation coefficient quantifies the correlation between two variables (x, y) (Equation 1):

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_i^n(x_i-\bar{x})^2}\ \sqrt{\sum_i^n(y_i-\bar{y})^2}} \quad (1)$$

Previous studies (Guo et al., 2017; Reddy, 2011) reported that a correlation coefficient greater than or equal to 0.7 indicates a moderate to a strong correlation between two feature variables. To avoid excessive elimination of feature variables –and loss of useful information– a threshold value of 0.75 was considered in this study. In other words, one of the two feature variables were removed when the correlation coefficient (r_{xy}) was greater than or equal to 0.75.

Figure 2 shows the results of the correlation analysis of eleven feature variables (T_{chwin}, T_{chwout}, m_{chw}, T_{oa}, RHoa, T_{ra}, RH_{ra}, T_{ma}, FR_{sa}, RH_{sa}, X_{cc}) which could affect the supply air temperature (Tsa) from air handling units. The shape of the ellipses in the upper triangle of the figure represents the size of the correlation coefficient. Ellipses that are "more inclined" and dark ellipses indicate stronger correlations.

After eliminating redundant variables by using the correlation analysis, the supply air temperature from AHU is written as a function of seven variables (regressors) (Equation 2 and Table 1):

$$T_{sa} = f(T_{ma}, X_{cc}, T_{chwin}, T_{chwout}, m_{chw}, FR_{sa}, RH_{sa}) \quad (2)$$

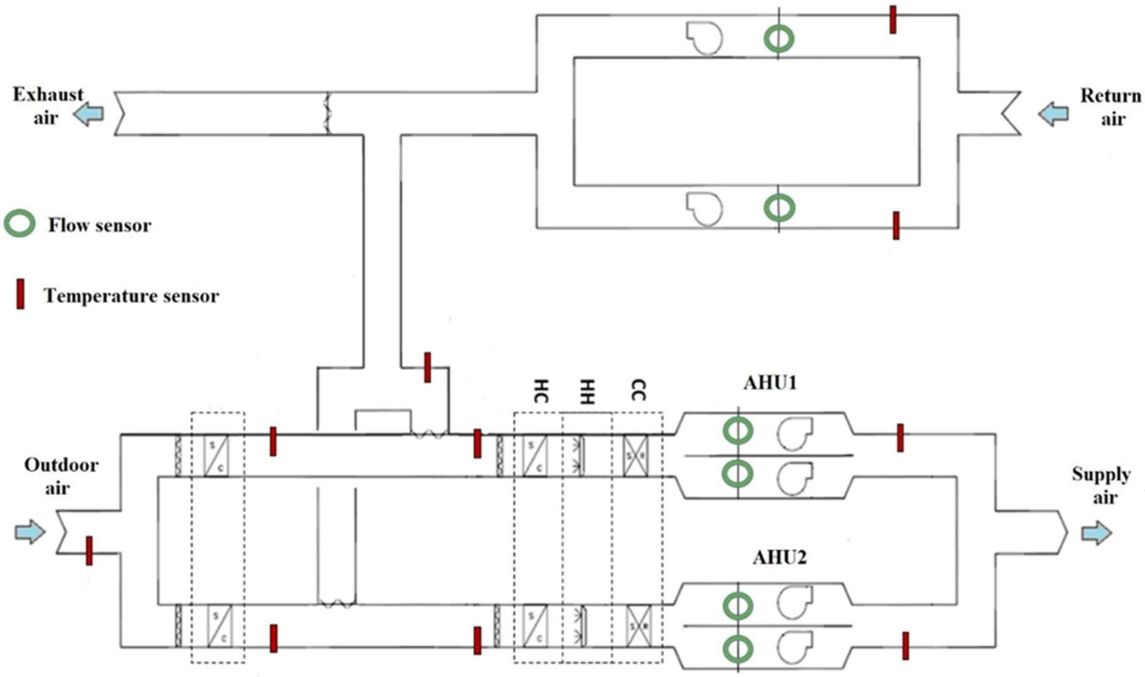

Figure 1: Schematic diagram of the case study building's air handling units (Cotrufo & Zmeureanu, 2018).

Table 1: Variables available from BAS and their measurement uncertainty.

Measured parameters	Mean	Standard deviation	Bias error (B_x)	Random error (R_x)	Overall uncertainty (U_x)
Outside air temperature, T_{oa}, °C	20.58	5.47	0.43	0.09	0.44
Outdoor air relative humidity, RH_{oa}, %	33.71	12.66	5.00	0.21	5.00
Return air temperature, T_{ra}, °C	21.73	0.34	0.43	0.01	0.43
Return air relative humidity, RH_{ra}, %	42.13	8.42	5.00	0.14	5.00
Mixed air temperature, T_{ma}, °C	22.83	3.04	0.6	0.13	0.61
Supply air temperature, T_{sa}, °C	15.83	0.98	0.38	0.04	0.38
Supply air relative humidity,RH_{sa}, %	66.08	17.23	5.00	0.28	5.01
Supply air flow rate, FR_{sa}, L/s	9924	1898	222.0	32	224
Chilled water inlet temperature, T_{chwin}, °C	7.60	0.85	0.18	0.01	0.18
Chilled water outlet temperature, T_{chwou}t, °C	11.14	1.76	0.21	0.03	0.21
Chilled water flow rate, m_{chw}, kg/s	282.94	167.35	-	-	-
Cooling coil valve opening, X_{cc}, %	42.68	30.68	-	-	-

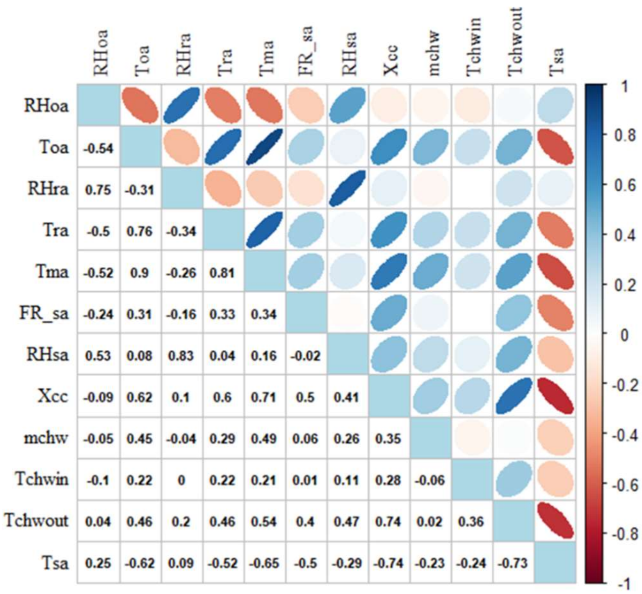

Figure 2: Results of the correlation analysis for selected feature variables.

The wide range in the numerical values of the variables in the dataset could be problematic. Consequently, data normalization is a technique often applied as part of data processing for ML algorithms. Therefore, the ANN models were trained and tested using the normalized data to avoid possible errors and poor performance in prediction. The Z-score normalization method is one possible way to rescale features so that all values are centered around the mean value of zero with a standard deviation of 1. In this study, the Z-score method was used for data normalization and can be expressed as follows (Equation 3):

$$z = \frac{x-\mu}{\sigma} \tag{3}$$

where μ is the mean, and σ is the standard deviation from the mean.

DEVELOPMENT OF MODELS

Artificial neural network (ANN) is one of the most popular and powerful machine learning-based methods for fault detection and diagnosis and operational management of building energy systems. The neural network is suitable for solving complicated non-linear problems through a series of nonlinear transformations. A typical neural network consists of three different types of layers: input, hidden, and output layers. The input layer receives the numerical value of possible input variables, and the output layer supplies the predicted results assessed by the network. The hidden layers combine the input information and generate new features to generate the expected output. In this study, a feedforward neural network (Figure 3) based on the Levenberg-Marquardt (LM) optimal algorithm using MATLAB was used due to the advantage of quick convergence as well as calculation precision (Fan, Du, Jin, Yang, & Guo, 2010). The selection of suitable architecture (input neurons, hidden layers, transfer functions, hidden layer neurons, output layers neurons) of the neural network is vital for its successful implementation. In general, four main approaches (heuristics, cascade-correlation, evolutionary algorithm, and automated architectural search) can be used for the selection of appropriate ANN architecture (Runge & Zmeureanu, 2019). However, there are no standard methods for the selection of a near-optimal architecture for ANN models. In this study, the input neurons were selected based on the correlation analysis method described in the previous section. The hyperbolic tangent activation function with a range between -1 and +1 was used by the neurons of the hidden layer, and the simple linear activation function was used for the output layer. In general, the number of neurons in the hidden layer is equal to or higher than the number of inputs. In this study, the optimum number of neurons of the hidden layers was selected based on the automated grid search approach to find the best possible structure for the trained model. Common statistical indices (MAE, MBE, and RMSE) were used to evaluate the prediction accuracy of the trained model.

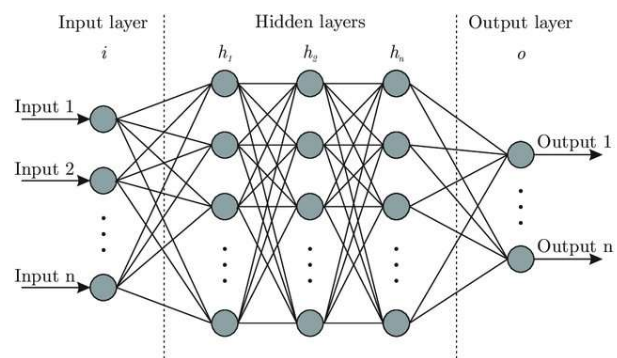

Figure 3: A typical architecture of the feedforward neural network model (Bre et al., 2018).

Performance Evaluation

The predictions of the supply air temperature T_{sa} were evaluated using various statistical indices, including mean absolute error (MAE), mean bias error (MBE), and the root means square error (RMSE) (Equations 4-6) (Fumo & Rafe Biswas, 2015):

$$\text{MAE} = \frac{\sum_i^n |M_i - P_i|}{n} \tag{4}$$

$$\text{MBE}\ (\%) = \frac{\sum_{i=1}^n (M_i - P_i)}{\sum_i^n M_i} \times 100 \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{M_i} - \mathrm{P_i})^2} \qquad (6)$$

where M_i are the measured values of supply air temperature T_{sa}, P_i are the predicted values of T_{sa} at each model instance 'i', and n is the number of data points.

RESULTS AND DISCUSSION

Comparison of Different Data-driven Models

In this study, the predictions of supply air temperature given by different data-driven models, including artificial neural network (ANN), deep neural network (DNN), multi-linear regression model (MLR), and a grey-box model, are compared. The number of hidden layer neurons N was determined according to one rule of thumb: $N = 2\times$Number of inputs+1 (Dong et al., 2017; Yang et al., 2005). A detailed description of the selected grey-box model is presented in Ahamed et al. (2020). The grey-box models (Ahamed et al., 2020; Padilla et al., 2015) predicts the supply air temperature based on three inputs (T_{ma}, Xcc, T_{chwin}). In this paper, we applied the same set of three inputs (T_{ma}, X_{cc}, T_{chwin}) to all selected models for comparison purposes. The unknown parameters of the MLR model and the grey-box model were estimated using the least square method (LSM). The ANN model is composed of three inputs, seven hidden layer neurons, and one output. The DNN model is composed of three inputs, three hidden layers, composed of 27, 17 and 7 neurons, and one output. Based on statistical indices including MAE, MBE, and RMSE, the results indicate that the predictions of DNN model are better than those from other models (Table 2). The statistical indices presented in the table for performance evaluation were estimated using the testing dataset (25%). The prediction accuracy of the MLR model is relatively close to the ANN model. However, the MLR model may result in higher prediction errors for different HVAC systems, which are usually complex and non-linear (Yao, Y., & Yu, 2017). The grey-box model showed a relatively low prediction accuracy against the dataset; however, grey-box models usually require fewer data to obtain an acceptable fit and can be extrapolated outside the range of the dataset. Each model has advantages and disadvantages in different contexts. The ANN models are becoming popular for their relatively higher prediction accuracy for complex non-linear systems, as well as the availability of high-speed computers. However, the computation time in neural network models gradually increased with increasing of the number of neurons and hidden layers.

Table 2: Prediction of supply air temperature: comparative results from different models.

Model	MAE (°C)	MBE (%)	RMSE (°C)
ANN (3-7-1)	0.34	0.01	0.49
DNN (3-27-17-7-1)	0.30	0.02	0.43
Grey-box	1.07	-1.29	1.35
MLR	0.48	-0.33	0.67

Optimization of Neural Network Structure

The performance of the data-driven model could be influenced by the number of input variables. Table 3 shows that the developed ANN and DNN model's prediction improved with the increase of the number of inputs. The best performance was obtained using all seven inputs selected from the correlation analysis (Equation 2). The relative improvement of the prediction accuracy of DNN (i.e., MAE=0.22°C) is slightly higher than that of the ANN model (i.e., MAE=0.27 °C). Therefore, the seven feature variables were considered for further analysis targeting the optimization of neural network architecture.

Table 3: Comparative performance for using the different number of input variables in prediction using ANN/DNN models.

Input	MAE (°C)	MBE (%)	RMSE (°C)
T_{ma}, X_{cc}, T_{chwin}	0.34/0.3	0.01/0.02	0.49/0.43
T_{ma}, X_{cc}, FRsa, T_{chwin}	0.31/0.27	0.01/0.008	0.47/0.39
T_{ma}, X_{cc}, FR_{sa}, RHsa, T_{chwin}	0.30/0.25	-0.04/0.07	0.45/0.35
T_{ma}, X_{cc}, FR_{sa}, RH_{sa}, m_{chw}, T_{chwin}	0.28/0.22	-0.01/0.03	0.41/0.31
T_{ma}, X_{cc}, FR_{sa}, RH_{sa}, m_{chw}, T_{chwin}, T_{chwout}	0.27/0.22	0.01/0.06	0.40/0.30

The number of hidden layer neurons plays an important role in predictions. Like other parameters for the optimization of the neural network model, there are no standard rules for the optimization of neuron numbers for the deep learning model.

In this study, a heuristic approach was applied. In the case of DNN with three hidden layers, the number of neurons was first optimized for the last hidden layer of DNN; the neuron numbers of the first and second hidden layers were increased by 10, starting from the neuron number of the last hidden layer. Table 4 and Table 5 show the optimization results of ANN and DNN models. The performance of ANN and DNN models increases with the number of neurons in the hidden layers. The best results were obtained with the ANN model of 47 hidden layer neurons and with the DNN model of three hidden layers composed of 63, 53, and 43 neurons. Increasing the number of hidden neurons after reaching the optimum configuration slightly increases the model's performance but significantly increases the computational cost. Statistical indices (Tables 4 and 5) indicate that the DNN model performs slightly better than the ANN model.

Table 4: Prediction of supply air temperature: Results from the optimization of the shallow artificial neural network (ANN) model.

ANN Structure	MAE (°C)	MBE (%)	RMSE (°C)
7-1-1	0.35	-0.06	0.53
7-2-1	0.33	0.01	0.49
7-3-1	0.31	0.01	0.46
7-4-1	0.31	0.02	0.46
7-5-1	0.30	-0.08	0.45
7-45-1	0.23	-0.02	0.33
7-46-1	0.25	-0.21	0.35
7-47-1	0.23	-0.02	0.32
7-48-1	0.23	0.03	0.33
7-49-1	0.23	-0.02	0.33
7-50-1	0.23	0.002	0.32

Table 5: Prediction of supply air temperature: Results from the optimization of deep neural network (DNN) model.

ANN Structure	MAE (°C)	MBE (%)	RMSE (°C)
7-21-11-1-1	0.23	0.00	0.33
7-22-12-2-1	0.22	0.01	0.32
7-23-13-3-1	0.22	-0.01	0.31
7-24-14-4-1	0.22	0.06	0.32
7-25-15-5-1	0.22	0.07	0.31
7-62-52-42-1	0.19	-0.06	0.27
7-63-53-43-1	0.17	0.09	0.23
7-65-55-45-1	0.19	-0.07	0.27
7-67-57-47-1	0.16	0.12	0.24
7-68-58-48-1	0.19	-0.03	0.27
7-70-60-50-1	0.18	0.00	0.25

The comparison of predictions using the DNN model and the measured supply air temperature of the testing dataset shows a good agreement (Figure 4). The supply air temperature from the air handling units was predicted by using the optimized configuration (7-63-53-43-1).

The impact of the number of hidden layers (1, 2, 3, and 4) on the predictions of supply air temperature by using the DNN model was also evaluated (Table 6). There is no significant difference between the results obtained for this case study with DNN models of 2, 3, and 4 three hidden layers. Two statistical indices of performance are almost equal: MAE = 0.17-0.18°C, and RMSE = 0.25-0.26°C. Therefore, the DNN model with two hidden layers can be applied in this case study. The use of more than two hidden layers has no significant impact on the prediction accuracy, but computational cost increases significantly. Therefore, computation costs should be considered for developing the DNN models when the prediction accuracy is not improving significantly with the increase of model architecture.

Table 6: Prediction of supply air temperature: Results from optimizing the number of hidden layers.

Hidden layers	Model architecture	MAE (°C)	MBE (°C)	RMSE (°C)
1	7-43-1	0.22	-0.03	0.32
2	7-53-43-1	0.18	0.07	0.26
3	7-63-53-43-1	0.18	-0.17	0.25
4	7-73-63-53-43-1	0.17	-0.06	0.25

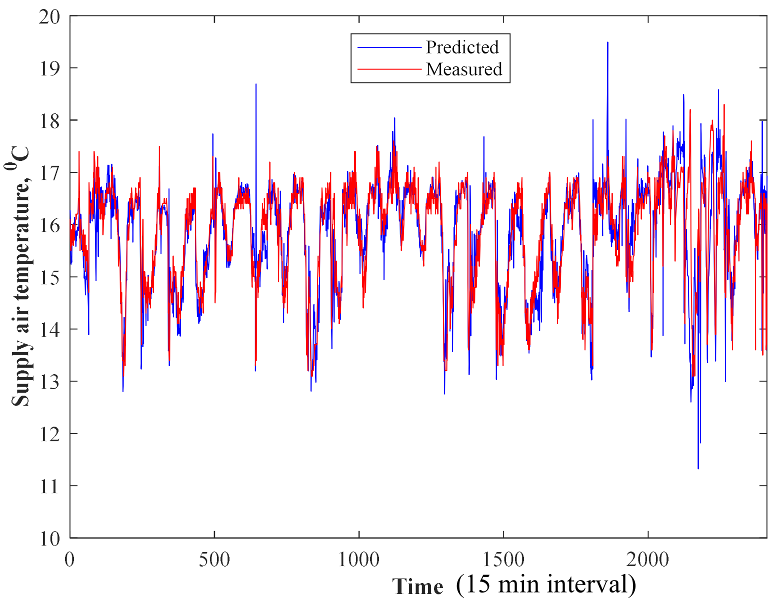

Figure 4: Comparison of the predictions of the DNN model and measured supply air temperature using the testing dataset (August 19th to September 25th).

CONCLUSION AND RECOMMENDATIONS

This article presented the development of ANN and DNN models of supply air temperature from the AHU of an institutional building and the comparison of predictions. The neural network models were also compared with other data-driven models. The architecture of ANN and DNN models was optimized.

The DNN models could be integrated with BAS for the prediction of supply air temperature with good accuracy, MAE= 0.17°C and RMSE = 0.23°C, compared with the sensor's overall uncertainty of 0.38°C.

The DNN model could be employed for the re-calibration of faulty sensors or as a temporary solution while waiting for the physical replacement or calibration of a faulty sensor. Like other machine learning methods, the suitable techniques for model hyperparameter optimization of the DNN models are still challenging. Only a limited number of studies have provided the guidelines for selecting the best architecture for neural network models. The optimal architecture for neural network models (hidden layers and neurons) should be determined based on the characteristics of the application and available data.

In the future, the study should focus on integrating the DNN models for fault detection and diagnosis of air handling units.

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