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Prediction of Indoor Temperature in an Institutional Building

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Abstract

The importance of predicting building indoor temperature is inevitable to execute an effective energy management strategy in an institutional building. An accurate prediction of building indoor temperature not only contributes to improved thermal comfort conditions but also has a role in building heating and cooling energy conservation. To predict the indoor temperature accurately, Artificial Neural Network (ANN) has been used in this study because of its performance superiority to deal with the time-series data as cited in past studies. Network architecture is the most important part of ANN for predicting accurately without overfitting the data. In this study, as a part of determining the optimal network architecture, important input parameters related to the output has been sorted out first. Next, prediction models have been developed for building indoor temperature using real data. Initially, spring season of Australia was selected for data collection. During model development three different training algorithms have been used and the performance of these training algorithms has been evaluated in this study based on prediction accuracy, generalization capability and iteration time to train the algorithm. From results Lovenberg-Marquardt has been found the best-suited training algorithm for short-term prediction of indoor space temperature. Afterwards, residual analysis has been used as a technique to verify the validation result. Finally, the result has been justified by applying a similar approach to another building case and using two different weather data-sets of two different seasons: summer and winter of Australia.

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Keywords: Prediction; Indoor temperature; Artificial Neural Network (ANN); Performance improvement.

1. Introduction

Building energy consumption is regarded as one of the major energy consuming sectors in the world. Improvement of building energy efficiency provides both environmental and economic benefits. To achieve an

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optimum level of energy consumption in buildings, it is importance to implement appropriate operational and management strategies along with installation of efficient energy systems [1]. Appropriate operational and management strategies necessitate continuous monitoring and management of the time series data of the important parameters affecting building energy consumption. As a part of continuous monitoring and management of energy consumption in existing buildings, prediction plays an important role [1]. It is a kind of dynamic filtering, in which past values of one or more time series are used to predict future values. Indoor air temperature is the most important parameter of building indoor thermal comfort and significantly influences building energy consumption [2]. The prediction of the indoor air temperature of a building can contribute to reducing building heating and cooling energy consumption.

To achieve an effective energy management strategy in institutional buildings, an accurate indoor temperature prediction model is essential. It can provide a set of future boundary conditions and targets, which can guide a building facility manager to optimize the indoor temperature set-point so that ultimate improvement in building energy consumption and indoor thermal conditions are achieved. It also provides an initial check for facility managers and building automation systems to identify any inconsistency between the expected and actual indoor space temperature. The prediction algorithm can also be integrated with smart sensors and predictive control system and train them for future scenarios [3]. Moreover, an accurate indoor space temperature prediction model can be combined with other building simulation models e.g. energy models to generate useful operating variables.

Different modelling techniques are available in literature to predict the building indoor temperature. The analytical or physics based models are usually computationally complex [4-6], necessitate specification of many physical parameters [5, 7, 8] and may result in poor prediction accuracy because of the involvement of assumptions that may not exist in real practice [9, 10]. On the contrary, data-driven models completely rely on experimental data [9-12] and provide good prediction accuracy when sufficient training data is available [9, 10, 13]. Since the ultimate aim of this research is to optimize the indoor environmental conditions of an existing institutional building for which sufficient data log is available, therefore, based on the characteristics of existing modelling techniques it is more appropriate to apply data-driven modelling technique to predict indoor space temperature.

From existing literature on prediction model where data-driven modelling techniques have been used, it is evident that nonlinear models such as neural network are more effective than linear models for prediction of indoor temperature [14-16]. Among different data-driven non-linear modelling techniques Artificial Neural Network (ANN) has proved performance superiority in predicting indoor space temperature [17, 18] and therefore, this modelling technique has become more popular in recent years. Numerous studies have been using ANN for predicting building indoor temperature. Mba, *et al*. [19] used ANN to predict the air temperature in a building and showed the best performance of the prediction model in terms of correlation coefficient which is 0.9850 when the network structure was 36-10-2 (i.e., 36 input neurons, 10 neurons in one hidden layer and 2 output neurons in one output layer). Gouda, *et al.* [17] developed indoor air temperature prediction model using ANN and then this predicted value was utilized as input in the Fuzzy Logic to reduce overshoots of air temperature and energy consumption and found better result compared to PI controller. Suitability of ANN for predicting indoor temperature was examined by Lu and Viljanen [18] and found satisfactory results with correlation coefficient 0.998 and mean squared error (MSE) ranging from 0.239-1.9242 in the testing stage. However, this study did not perform residual analysis which is an important part of validation. If that analysis was done, those residuals might have some degree of correlation with past data and inputs as some important information like heating power and ventilation rate were missing in the network. Numerous studies [12, 18, 19] concentrated on increasing the step-ahead in predictions without much compromise with the prediction accuracy. Several studies [12, 19] focused on identifying the exact number of hidden neurons as a way to avoid overfitting caused by the network. During model development using ANN, different studies have used different training algorithms to train the network. Mba, *et al.* [19] and Mustafaraj, *et al.* [12] used Lavenberg-Marquardt training algorithm while Moreno, *et al.* [20] used Bayesian Regularization in their indoor temperature prediction model. Levenberg-Marquardt is regarded as the fastest training algorithm and confirms the best convergence to a minimum of mean square error (MSE) for function approximation problems [21]. On the other hand, Bayesian regularization modifies and minimizes a linear combination of squared errors and weights so that the resultant trained network has good generalization qualities. For large problems, however, Scaled Conjugate Gradient performs better than other two training algorithms. However, no comparative studies have been found in literature where the performance of these training algorithms has been evaluated to determine which training algorithm best suits with building indoor and weather data and how these algorithms perform with the change in the size of datasets.

Despite the efforts of past studies, there are still issues with modelling such as selection of all important and identical input parameters, performance evaluation of prediction model using three different training algorithms which will be addressed in this paper. Categorization of all relevant and identical input parameters that can completely represent the outputs helps in optimizing the network architecture and this eventually provides an accurate prediction model. The performance of a prediction model using three different training algorithms will be analyzed in this study based on statistical performance matrices e.g. Mean Squared Error (MSE) and Regression (R) for limited size of data sets. MSE indicates the error in prediction while R provides an indication of data fitting with the network. And the best-suited training algorithm in terms of prediction accuracy, generalization capability and iteration time will be identified from this study which will be cross-validated later by performing residual analysis. Finally, to compare the initial findings similar approach will be applied to another building case and two different weather datasets will be used.

2. Methodology

Modelling was carried out in three steps as follows:

2.1 Data collection, processing and sorting of input variables related to output

To identify the input parameters for the indoor space temperature prediction model, a time series 5 minutes interval real-time data of 25 relevant parameters was collected for a period of 13 days starting from 1 October, 2016 representing the spring season of Australia. The selection of 25 relevant input parameters was primarily performed based on domain knowledge. Next Neural Fitting tool was used to sort out the more relevant input parameters among 25 parameters based on the results of network performance where individual input parameter has been used to estimate the output. The network performance has been analysed using the performance metrics MSE and R.

2.2 Selection of problem type and network structure

To predict the building indoor temperature Nonlinear Autoregressive with External (Exogenous) Input (NARX) has been chosen because of the characteristic of this network that aligns with data availability of this study. The characteristics of NARX is to predict future values of a time series $y(t)$ from past values of that time series and past values of a second-time series $x(t)$ and can be written in the form:

$$y(t) = f(y(t-1), \ldots, y(t-d), x(t-1), \ldots, (t-d)) \quad (1)$$

Where,
d=Number of time delays,
x(t) = Input time series,
y(t) = Output time series.

The network used in this study has is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer.

2.3 Training, testing, validation of network and identification of the best-suited training algorithm

The first step in a time-series neural network analysis is training. It involves modification of the synaptic weights until the predicted output is close to the measured actual output. That means in the training step the network is adjusted according to its error. A defined set of relationship between the neurons across various layers is formed after the training step. This relationship can be used to predict new outputs with a new set of input data. Next validation was done to measure network generalization, and to halt training when generalization stopped improving. The last step in the network analysis is testing which has no effect on training and so provided an independent measure of network performance during and after training.

In this study the total 3347 time steps time series data for each input and output parameter have been divided into three portions training (70%), validation (15%) and testing (15%) of total data.

The training step starts with selection of training algorithms. In this study three different training algorithms e.g. Levenberg-Marquardt, Bayesian Regularization, Scaled Conjugate Gradient were used. The performance of each training algorithm was evaluated based on the value of MSE and R. Lastly, residual analysis was conducted to cross-validate the results.

3. Results and Discussion

3.1 Sorting of input variables based on relevance with output parameter

The important and unique input variables were sorted out from 25 primarily selected input variables based on relevance with the output parameter. Based on the results of MSE and R, building indoor temperature set-point and outdoor temperature were found the most important parameters to predict the indoor space temperature followed by wind speed, wind direction, dew point temperature, barometric pressure, relative humidity and solar radiation. However, in the absence of any of these eight input parameters the network did not provide satisfactory prediction accuracy.

3.2 Selection of best-suited algorithm

The straight regression lines between the predicted and observed data are presented in Fig. 1. The value of R shows the correlation between the observed and predicted values for building indoor temperature and provides an indication of data fitting with the network. Since one of the main problems of ANN is that it can over-fit the data therefore, regression analysis is very important to validate the network. From Fig. 1 it is seen that Lovenberg-Marquardt and Bayesian Regularization training algorithms give slightly better fit compared with Scaled Conjugate Gradient.

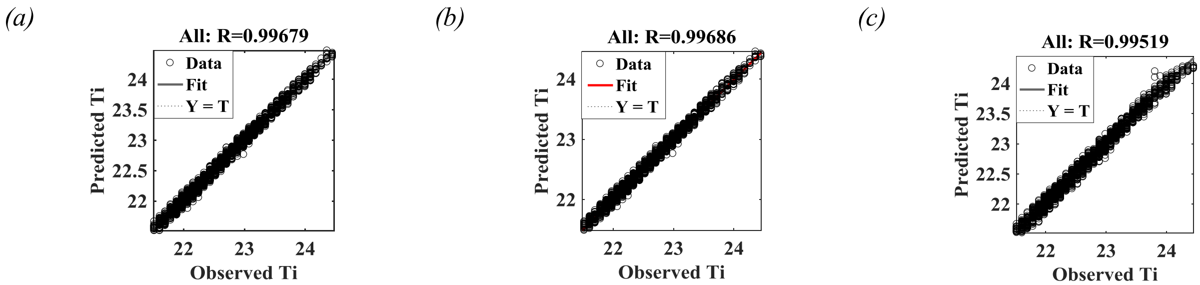

Fig 1. Regression lines between observed and predicted values for building indoor temperaturs (T_i) (a) Lovenberg-Marquardt, (b) Bayesian Regularization, (c) Scaled Conjugate Gradient

The comparison of NARX networks' results for three different training algorithms are presented in Table 1.

Table 1. Comparison of results using three different training algorithms for ANN architecture 8-10-1 (for October)

Step	MSE			R			Iteration time (sec)		
	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient
Training	2.61706e-3	2.52072e-3	3.94224e-3	9.96839e-1	9.96930e-1	9.95306e-1			
Validation	2.52233e-3	0.00000e-0	4.09500e-3	9.96686e-1	0.00000e-1	9.94560e-1	2	39	2

Testing	2.83084e-3	2.86616e-3	3.79943e-3	9.96632e-1	9.96453e-1	9.95231e-1
All	$2.63e^{-3}$	$2.62e^{-3}$	$3.94e^{-3}$	9.9679e-1	9.9645e-1	9.9519e-1

The developed predicted model has good generalization capability since the performance of the model is consistent in all stages: training, validation and testing using different training algorithms (Table 1). Good generalization capability indicates that the model is not too complex to cause overfitting and that the network architecture used in this study is optimal in terms of the number of input signals, output parameters and number of neurons in the hidden layer. Besides, the mean squared error which indicates the accuracy of a prediction model is calculated for three different training algorithms and illustrated in Table 1. From Table 1 it is found that both Lovenberg-Marquardt and Bayesian Regularization can provide high prediction accuracy while the prediction accuracy of the indoor temperature model using Scaled Conjugate Gradient is slightly low.

In case of using large datasets to train the network, iteration time is an important factor in selecting the training algorithm. As shown in Table 1 Scaled Conjugate Gradient algorithm and Lovenberg-Marquardt algorithm can train the network much faster than the Bayesian Regularization.

Therefore, according to the analysis done in this study, Lovenberg-Marquardt is the best-suited training algorithm based on prediction accuracy, generalization capability, data fitting with the network and iteration time for short-term prediction of indoor space temperature.

3.3 Cross-validation through residual Analysis

Residual analysis is used to cross-validate the result and this is done by plotting error autocorrelation function. Figure 2 shows the error autocorrelation function of the prediction model for the studied training algorithms. It describes how the prediction errors are related with time. For a perfect prediction model, there should only be one nonzero value of the autocorrelation function which indicates the MSE, and it should occur at zero lag. For Figure 2a and 2b the correlations, except for the one at zero lag, fall approximately within the 95% confidence limits around zero, and therefore, these two models can be said to be acceptable. However, in Figure 2c there is a significant correlation in the prediction errors. So, the performance of this model is not satisfactory. Hence, the result of residual analysis aligns with the result found in previous section of this study.

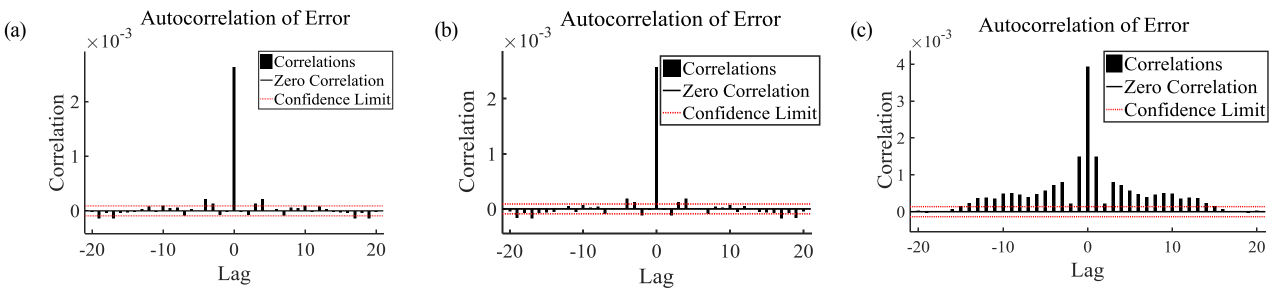

Figure 2. Plot autocorrelation of errors across varying lags using different training algorithms (a) Lovenberg-marquardt, (b) Bayesian regularization, (c) Scaled conjugate gradient.

3.4 Justification of result

From the results found in previous sub-section it can be said that Lovenberg-Marquardt is the best-suited training algorithm in terms of prediction accuracy, generalization capability and iteration time to train the algorithm. To justify this result, a similar approach has been applied to another building case and different weather datasets of two different months: January and July representing two different seasons: summer and winter of Australia have been collected for the selected parameters and used in the model. For both months 5 minutes interval 5473 timesteps of 8 input elements and one output element have been randomly divided into three portions: 70% training, 15% validation and rest of the 15% testing. Table 2 gives a comparison of NARX networks' results for three training algorithms where different building indoor and weather datasets have been used.

Table 2a. Comparison of results using three different training algorithms for ANN architecture 8-10-1 (for January)

Step	MSE			R			Iteration time (sec)		
	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient
Training	3.28566e-3	3.0756e-3	3.76e-3	9.969e-1	9.972e-1	9.966e-1	53	515	423
Validation	3.19e-3	0.00000e-0	3.96e-3	9.973e-1	0.00000e-1	9.9645e-1			
Testing	3.59675e^{-3}	4.12965e-3	3.75e^{-3}	9.969e-1	9.963e-1	9.9647e-1			
All	3.32e^{-3}	2.62e^{-3}	3.7885e^{-3}	9.97e-1	9.97e-1	9.9654e-1			

Table 2b. Comparison of results using three different training algorithms for ANN architecture 8-10-1 (for July)

Step	MSE			R			Iteration time (sec)		
	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient	Lovenberg-Marquardt	Bayesian Regularization	Scaled Conjugate Gradient
Training	4.4921e-3	4.363e-3	6.923e-3	9.9801e-1	9.9807e-1	9.97e-1	72	1498	517
Validation	5.5107e-3	0.00000e-0	8.67e-3	9.9774e-1	0.00000e-1	9.96e-1			
Testing	5.8565e-3	4.88193e-3	6.56e-3	9.973e-1	9.97873e-1	9.97e-1			
All	5.09e^{-3}	4.52e^{-3}	7.15e-3	9.9786e-1	9.9786e-1	9.97e-1			

From Table 2a and 2b it can be said that the results found using different datasets aligns with the results as shown in Table 1. As shown in Table 2a and 2b, Scaled Conjugate Gradient training algorithm gives comparatively lower prediction accuracy and lower value of R for indoor space temperature model than Lovenberg-Marquardt and Bayesian Regularization algorithms. Besides, Lovenberg-marquardt algorithm can train the network much faster than Bayesian Regularization.

4. Conclusions and future work

From this study, it is established that sorting of the relevant input parameters and using the best suited training algorithm provides improvement in a building indoor temperature prediction model. This study confirms that identifying the relevant input variables and sorting them based on the relevance to represent the building indoor space temperature are the key steps to determine the optimal network architecture which in turn gives good prediction accuracy. For both building cases and for all different data-sets used in this study Lovenberg-Marquardt has been found the best-suited training algorithm to predict the indoor space temperature in terms of prediction accuracy, generalization capability and iteration time to train the algorithm.

This study is still in preliminary stage, and further investigation is needed in the following areas:

- Evaluating the performance of the training algorithms by varying the size of datasets and network architecture and comparing with existing similar research studies.

- Developing a long term building indoor temperature prediction model for three different seasons: winter, summer and spring.

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