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Real-time prediction model for indoor temperature in a commercial building

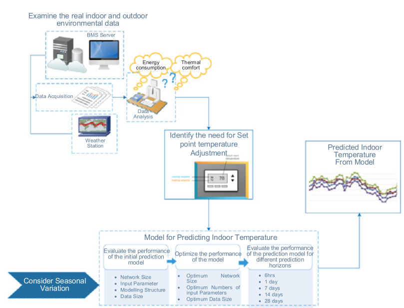
Zakia Afroz[a,*], Tania Urmee[a], G.M. Shafiullah[a], Gary Higgins[b]

[a] School of Engineering and Information Technology, Murdoch University, 90 South Street, WA 6150, Australia
[b] Energy Management Facility, Murdoch University, 90 South Street, WA 6150, Australia

HIGHLIGHTS

- The proposed input selection method can efficiently determine the input parameters.
- The model performance improves by considering all relevant key aspects.
- Prediction performance deteriorates quite drastically after a certain time span.
- The proposed model provides good prediction performance till 28 days ahead.

GRAPHICAL ABSTRACT



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ABSTRACT

Indoor environmental parameters have significant influence on commercial building energy consumption and indoor thermal comfort. Prediction of these parameters, especially that of indoor air temperature, along with continuous monitoring and control of real world parameters can aid in the management of energy consumption and thermal comfort levels in existing buildings. An accurate indoor temperature prediction model assists in achieving an effective energy management strategy such as resetting air temperature set-points in commercial buildings. This study examines the real indoor environmental data for multiple adjacent zones in a commercial building in the context of thermal comfort and identifies the possibility of resetting air temperature set-point without compromising the occupant comfort level. Also, the value of predicting the indoor temperature accurately in such a building is established through this case study. This study presents a nonlinear autoregressive network with exogenous inputs-based system identification method to predict indoor temperature. During model development efforts have been paid to optimize the performance of the model in terms of complexity, prediction results and ease of application to a real system. The performance of single-zone and multi-zone prediction models is evaluated using different combinations and sizes of training data-sets. This study confirms that evaluating the performance of the model in the context of major contributing aspects such as optimal input parameters and network size, optimum size of training data, etc. offers optimized model performance. Thus, when the developed model is used for long-term prediction, it provides better prediction performance for an extended time span compared to existing studies. Therefore, it is anticipated that implementation of this long-term prediction model will offer greater energy savings and improved indoor environmental conditions through optimizing the set-point temperatures.

* Corresponding author.
E-mail address: Z.Afroz@murdoch.edu.au (Z. Afroz).

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1. Introduction

Building sectors are responsible for consuming around one-third of the total primary energy resources around the world [1,2] and releasing 30% of global CO_2 [2]. Energy used by the building sector is increasing over the years due to the broader application of HVAC systems in response to the growing demand for better thermal comfort within the built environment. Therefore, improvement in building energy efficiency is essential considering the environmental and economic benefits the resultant action can offer. However, improving the building energy efficiency may create a multi-faceted problem if the resulting outcome cannot maintain the quality and comfort of the indoor environment to a satisfactory level [1]. To overcome this problem, it is essential to maintain an optimum level of energy consumption in buildings that does not detrimentally affect thermal comfort levels or indoor air quality. This can be achieved by implementing an effective management system [3]. This system performs the task of energy optimization through applying suitable operational strategies, controlling and monitoring the energy usage and the indoor environmental conditions, and maintaining the building indoor environment to a satisfactory level [4].

Research shows that implementing efficient energy management strategies can lead to 5–15% energy savings in existing buildings [5]. As a part of continuous monitoring and management of energy consumption in existing buildings, prediction of indoor environmental parameters plays an important role [3]. Of the various indoor environmental parameters such as air temperature, air humidity, CO_2 concentrations, etc. air temperature is the most significant parameter relating to indoor thermal comfort and influences building energy consumption significantly [6]. A real-time accurate predictive model for indoor temperature assists in efficiently controlling the indoor temperature set-point. This eventually optimizes the building energy consumption and improves the indoor thermal conditions [7].

To accomplish effective energy management strategies in commercial buildings, such as buildings located in University campus, an accurate indoor temperature prediction model is necessary. It provides a set of forthcoming boundary conditions and targets, manages initial checking and identifies any inconsistency between expected and actual situations [8]. An accurate indoor temperature predictive model also improves and deepens understanding of such systems. The prediction algorithm can be integrated with smart sensors and predictive control systems and train them for future scenarios [8].

1.1. Related work

1.1.1. Modelling techniques used to predict indoor temperature and associated parameters

Modelling techniques used in the literature have gradually become more sophisticated with the objective of improving the performance of prediction models. Numerous studies e.g. Mba et al. [9], Li et al. [10], Lu and Viljanen [11], Ashtiani et al. [12] etc. have concentrated on improving the performance of indoor temperature predictive models combined with application in the real world. Prior to data-driven modelling techniques physics-based modelling techniques were used vastly to control the building indoor environment. However, these types of models do not accurately reflect existing building systems due to the following reasons: complex characteristic of the model [13–15], the need for detailed information about the physical parameters [14,16,17] and purely theoretical assumptions leading to poor prediction accuracy [18,19]. Modern Building Management Systems (BMS) have the ability to simultaneously capture and store large quantities of sensor data and use them as a real-time reference for controlling system operation. The availability of large amounts of time-series data from real systems has enabled data-driven modelling to flourish in recent years. Data-driven models possess certain characteristics such as simplicity, capacity to deal with large data-sets, high accuracy in prediction although this is not strictly true for all types of data-driven model [20]. Numerous studies, e.g. [9,10,21–27] etc. used data-driven techniques such as data mining algorithms, statistical approaches to predict indoor temperatures, building thermal load or HVAC energy consumption. Mba et al. [9] presented an ANN-based approach for predictions between one day and one month in advance of the hourly indoor air temperature of a modern building in a hot-humid climatic region. They found good prediction results for one day ahead prediction with the correlation co-efficient 0.985. An Elman neural network multi-step prediction model for building indoor temperature was presented by Li et al. [10]. The study proposed a control method for indoor temperature based on that model. Also, Özbalta et al. [22] and Fan et al. [21] developed models for predictions of daily mean indoor temperature and building energy consumption respectively. Lü et al. [24] demonstrated a methodology for energy demand forecasting that addresses the heterogeneity challenges in energy modelling of buildings. Different methods were used to predict building cooling load e.g. hourly building cooling load prediction model based on support vector machine with root mean square error ranging from 0.006 to 1.182 [25], a dynamic forecasting model for building cooling loads that combines an artificial neural network with an ensemble approach [23], deep learning-based methods to predict 24 hr ahead building cooling load profiles [26]. von Grabe [27] used neural networks (NN) to predict thermal sensation votes on the ASHRAE scale and identified that it outperforms the classical PMV index in terms of prediction quality and the range of information contained in the prediction.

Several past studies e.g. [11,12] made comparisons between different data-driven modelling techniques in predicting indoor space temperature or other relevant parameters and found better prediction result for Artificial Neural Network (ANN). Lu and Viljanen [11] examined the suitability of ANN for predicting indoor temperature and found satisfactory results with correlation coefficient 0.998 and mean squared error (MSE) ranging from 0.239 to 1.9242 in the testing stage. Ashtiani et al. [12] conducted a cross-comparison study to evaluate the performance of two indoor dry-bulb temperature predictive models based on regression technique and ANN. Their results showed a better prediction accuracy for the ANN model. However, prediction of indoor temperature involves dealing with time series data which adds the complexity of a sequence dependence among the input variables. An influential type of neural network designed to handle sequence dependence is called recurrent neural networks (RNN). Nonlinear autoregressive network with exogenous inputs (NARX) is a special case of RNN. This network is also called the further extension of the Time-Delay Neural Network (TDNN) since this network considers not only its own previous outputs but also incorporates the exogenous inputs, and this is equivalent to a neural network version of the generalized time series model [28]. NARX network already proved to be a very effective modelling tool for nonlinear systems especially dealing with time series data-sets as cited in previous studies e.g. [29–32] and possesses certain superior characteristics such as faster convergence and better generalization capabilities than other networks. To predict indoor temperature, a NARX model outperforms the linear auto-regressive model with external inputs (ARX) since temperature is governed by nonlinear diffusion equations [33].

1.1.2. Selection of input parameters

The selection of input variables is an important part of model development. It helps to minimize the risk of over-fitting, reduce the computation costs, retain or moderately improve the model performance, and identify the inherent dimensionality of a given problem [34].

Despite large number of studies used neural network to predict or forecast indoor environmental parameters limitations to those models' applicability persist because of the involvement of large numbers of input parameters. Using excess or redundant input parameters creates unnecessary complexity, increases the probability of overfitting the network and decreases the computation speed during the execution of