Neural network modelling of naturally ventilated spaces

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ABSTRACT. During operation, buildings consume a large amount of energy, in developed countries around 40% of total final energy use. A major challenge is to reduce the amount of energy used while still providing a comfortable environment for building occupants. The use of passive techniques, such as natural ventilation, is promoted in certain climates to provide low energy cooling and ventilation. However, controlling natural ventilation in an effective manner to maintain occupant comfort can be a difficult task, particularly during warm periods. One area which has been identified as having the potential for reducing energy consumption while maintaining occupant comfort is the use of more advanced control techniques and a move towards "intelligent" buildings. A technique which has been much explored in recent years for application in mechanically ventilated buildings is Model Predictive Control (MPC). The essential component of an MPC strategy is the predictive model of the building's thermal dynamics. In this paper a data driven, neural network approach to system modelling is taken to model internal temperatures. Building data from a recently built naturally ventilated school and an office building are used to train multilayer perceptron neural network models and the resulting models performance are examined. The models developed were found to have good prediction capabilities over reasonable prediction horizons; however the effect of the control input was not captured.

KEYWORDS. MPC; Neural Networks; Ventilation.

INTRODUCTION

Energy costs, climate change, mounting political and social pressure are examples of some of the drivers for the increasing attempts to reduce energy consumption. Buildings account for around 40% of total final energy consumption in developed countries [1], and in European countries around 76% of the energy consumed by buildings is used for comfort control, i.e. heating, ventilation and air conditioning (HVAC) [2]. Reducing the amount of energy required by HVAC systems can be approached in a number of ways, for example increasing airtightness, better insulation, increasing appliance efficiency, passive ventilation techniques etc. In addition to energy concerns, there has been a growing awareness of the impact of indoor environmental quality (IEQ) upon occupants' wellbeing [3]. IEQ refers to the quality of a building's environment in relation to the health and wellbeing of those who occupy the space [4]. There is a number of factors which contribute to IEQ including air quality, temperature, lighting, contaminants etc.

Natural ventilation is the process of supplying and removing air to an indoor space without the aid of mechanical systems. Natural Ventilation is driven by pressure differences caused by wind or temperature differences. As natural ventilation is affected by a number of factors such as external temperature, wind speed, wind direction, internal temperatures etc. It can be hard to predict the consequence of opening a window or vent. This makes control of naturally ventilated spaces more challenging than mechanically ventilated or air-conditioned spaces [5]. In this paper we propose a control method which has the potential to reduce energy consumption and optimise occupant comfort in naturally ventilated spaces. Model Predictive Control (MPC) is a control method which originated in process industries [6]. MPC utilises a system model to optimise future outputs based upon possible inputs over a finite receding horizon. At each time step a minimisation of some objective function is carried out in order to determine the optimal control signals over a finite horizon. At each iteration only the first step of the control strategy is then implemented. The control horizon is then shifted one step forward and the process is repeated [6].

PROBLEM DESCRIPTION

Modelling Strategy

In order for MPC to be successful, an accurate model of the system is required. The model should be as simple as possible and have good prediction characteristics over the control horizon [7, 8]. There are two main approaches to system modelling which can be taken when applying MPC to HVAC systems. One approach is the use of first-principles models, typically multizone-network models such as EnergyPlus, TRNSYS etc. These models are based upon our knowledge of the physical processes taking place within the building.

The alternative to the first-principles models is the use of black-box data-driven models. These models are typically less computationally intensive to use and once a suitable workflow has been devised, relatively simple to create. Empirical models have the advantage of modelling the processes which are actually happening within a space without including the assumptions which are necessary with a first-principles model. For example, with a simulation tool, such as EnergyPlus, it is possible to include detailed occupancy and activity schedules but it will be hard to fully capture the stochastic manner in which occupants interact with the building and their effect upon the building's thermal environment. Additionally, as we move towards "smart buildings", there are an increasing amount of data available about how buildings are actually running, which have the potential to drive a data-driven approach.

In this paper, we take a data driven approach using multilayer perceptron (MLP) neural networks to predict zone temperatures in naturally ventilated spaces. Neural Networks have been used in previous studies for control of HVAC systems [9] and automated window blinds [10]. The Neural Network Toolbox within MATLAB was used to train and test the networks using the workflow shown in Fig. 1.

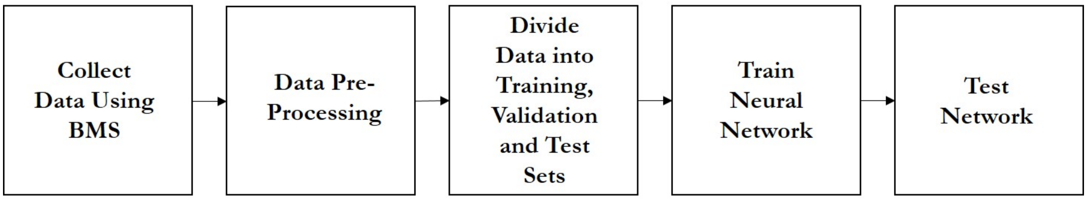

Figure 1: Workflow for Neural Network modelling strategy.

Building Descriptions

The essential component in the empirical approach taken in this paper are the building data with which a model can be trained. Obtaining suitable data was found to be challenging. There were two main problems experienced when attempting to obtain real building data for this project. Firstly, convincing building managers, owners and other stakeholders to give access to data which could highlight poor performance in their buildings. In cases where this initial hurdle was overcome there are practical difficulties related to gathering building data. While most building management systems (BMS) are capable of recording data they are not typically designed to store large amounts of data over prolonged periods. It was additionally quite common that there were gaps in the data and erroneous sensor readings. This had implications for the amount of pre-processing which was required before the models could be trained.

The building data used in this project comes from two sources: a recently-built school, and an office building in the north of England. Both are naturally ventilated and have a range of single-sided, cross and buoyancy ventilated spaces. The windows are a combination of occupant-controlled manual windows, and automated windows and vents. Data are available for the opening position of the automated windows in both buildings, however due to the lack of sensors on the manual occupant-operated windows, there is no information available. For this reason the manual windows can be treated as a disturbance which will affect the models. A total of eight zones within each building were studied. Data was collected for a full year and sampled at 10 minute intervals.

SYSTEM IDENTIFICATION

The first stage in system identification is pre-processing. In this study there were two distinct phases in the pre-processing. First was the processing carried out to extract and clean the data recorded by the BMS. This included linearly interpolating to replace missing data points and removing any obvious outliers. Outlier removal was carried out by calculating the standard score for each variable and then removing all values which fell outside of an expected range. The second phase of pre-processing was carried out to improve network training. This included normalization to prevent saturation of the sigmoid transfer units in the network and to adjust the magnitudes of the various inputs. Typically, it is beneficial for network performance if inputs to have a similar magnitude unless there is intentional weighting being applied.

Following the initial data cleaning and pre-processing, the data were divided into three subsets using three contiguous blocks of the original data set. The first set is used for model training, the second for validation (this set is used to prevent over-fitting) and the final set is withheld from model training and used as an unseen test set.

For the control of natural ventilation we want to model internal zone temperatures based upon the previous zone temperatures and the effect of other inputs shown in Tab. 1. These are all inputs that were collected using the building management system. This is essentially a non-linear autoregressive with exogenous external inputs (NARX) model. The defining equation for a NARX model is given by:

$$y(t) = f\left(y(t-1), y(t-2), ..., y(t-n_y), \mathrm{u}(t-1), \mathrm{u}(t-2), ..., \mathrm{u}(t-n_u)\right) \quad (1)$$

where the target (y) is a function of previous values of itself and of other inputs (u). In a NARX network the target can be considered to be an estimation of the true output of the system being modelled. During training of the network, the true output is available. This allows a series-parallel or "open-loop" architecture to be used (as shown on the left in Fig. 2). There are two key advantages to a series-parallel architecture. Firstly, the input to the network is more accurate and hence the resulting network tends to have a greater performance. Secondly, the network has a purely feedforward architecture allowing static backpropagation to be used in training [11]. This means that training is less computationally intensive.

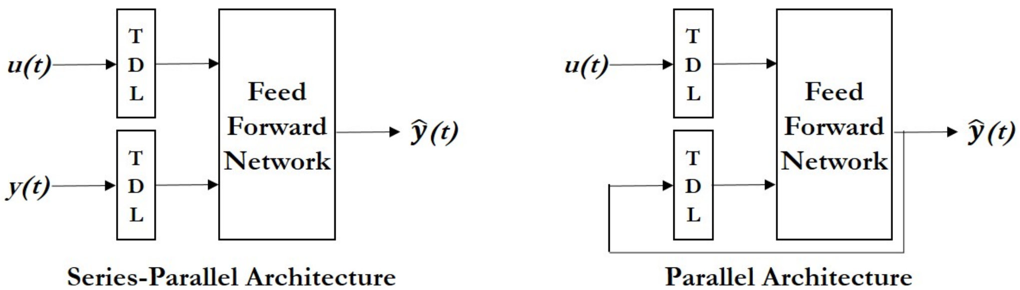

Figure 2: Feed forward network architectures for NARX networks. On the left is the series-parallel or open-loop configuration ideal for one-step-ahead prediction and on the right is the parallel or closed loop configuration. In a parallel architecture model predictions are fed back into the network through a tapped delay line (TDL) allowing for multi-step-ahead predictions. Adapted from Beale et al. [11].

However by training the network using a series-parallel form, training has been optimized for one-step-ahead prediction. While this is a good starting point, multi-step-ahead prediction is required for MPC. One possible approach is to train the network using a series-parallel architecture and then close the loop to create a parallel architecture. However as the training has been carried-out using actual values of the network output and then tested with predicted values, performance is not optimal. However, it is undesirable to train the network in a closed-loop form from the outset due to the time and computational effort required. In order to achieve an accurate final model without a large computation requirement, the workflow shown in Fig. 3 was utilised. By carrying-out the training initially using a series-parallel architecture and then using the resulting weights and biases as the starting point for the closed loop network, a 46% reduction in training time was observed (based upon a study using data from 5 zones and repeating training 10 times per zone).

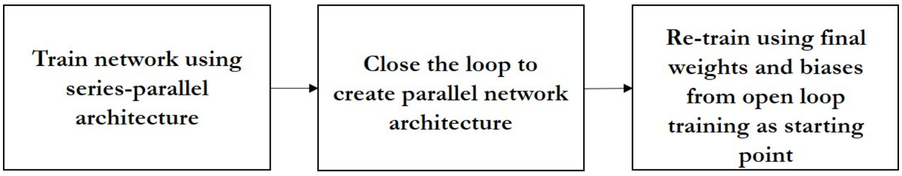

Figure 3: Optimal workflow for training neural network models.

The structure of neural network models is in some respects determined by the system being modelled (number of input and output nodes), however it is up to the user to determine the optimum number of hidden layers and hidden nodes contained within them. Although there is some guidance in the literature, this can often be contradictory [12, 13, 14]. Therefore, determining the optimum structure for a particular problem and set of data is largely a process of trial and error. In addition to training networks with a range of architectures a number of combinations of inputs and input delays were also tested.

Variable	Type	Notes
Zone Temperature	Output	
Outdoor Temperature	Input	
Wind Speed	Input	
Wind Direction	Input	
Window Opening Percentage	Input	Only available for automatic windows
Heating Status	Input	Boolean value showing heating on/off state

Table 1: Variables used for system identification.

RESULTS

The models developed in this paper were found to perform well upon the unseen test data. The first models generated were for one-step-ahead prediction. As can be seen in Fig. 4 the one-step-ahead models almost perfectly track the target temperatures, typical mean squared errors (MSE) were in the range of 0.1-0.2. This performance is good, however the prediction horizon of 10mins is very short. When the models were trained in a parallel architecture the multi-step-ahead prediction capabilities were also found to be good; as can be seen in Fig. 4. When predicting the zone temperature at twenty-steps-ahead (n=20, i.e. 200mins in the future) the typical MSE was approximately 0.5. MSE was used as an initial metric by which to judge model performance as it was the performance function minimised during network training [11]. Other measures of model performance such as the standard deviation and mean absolute percentage error were also calculated and used for model selection [15]. However, for analyzing results a visual comparison of model outputs and targets was found to give the best insight into how the model performed. It can be seen in Fig. 4 that the model outputs closely track the target temperatures for the unseen test data. Upon closer inspection it was observed that model performance was poorer during unoccupied periods. Fig. 4 shows test data for a week in one of the zones within the school. It can be seen that at the end of the week and during the nights the predictions stray further from the target temperatures. This seems to indicate that occupancy can have a high impact upon the models. Potentially this could be overcome by creating two models for each zone; one for occupied periods and one for unoccupied. This is likely to improve accuracy, however the degree to which this would impact upon the control performance may not justify the extra complexity.

While the initial results appeared very promising, upon closer inspection there were clear inadequacies with the models developed. During training of the models a number of different combinations of the inputs shown in Tab. 1 were used. The addition of further information to the model did not improve performance over a purely autoregressive model based upon previous values of zone temperature. This suggests that previous values for zone temperature are a good enough predictor without additional weather data. While being able to discard weather inputs could have potential benefits in reducing model complexity, it is essential that the influence of control inputs (window opening positions) are captured by the model. It was confirmed by carrying out a sensitivity analysis that the window position had no impact upon the output temperature. This would prevent the models from being suitable for an MPC application.

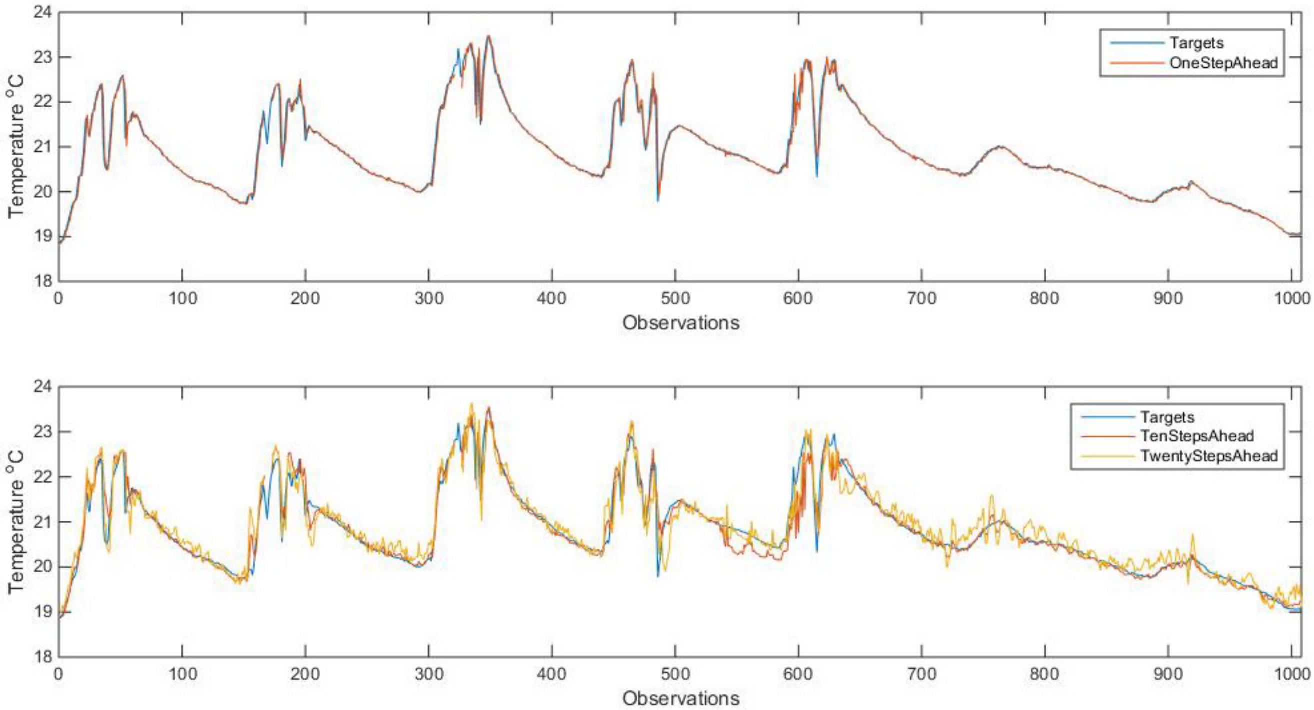

Figure 4: Comparison of model output temperatures and observed temperature for unseen test data. The top graph shows the one-step-ahead performance and the bottom shows n=10 and n=20 (10 minute time step).

DISCUSSION

The models developed were able to predict internal temperature over a reasonable prediction horizon. However the effect of the window opening percentage was not captured by the models. This would make them unsuitable for the MPC approach to ventilation control proposed in this paper. The inability of the models to capture the effect of the control input is most likely due to lack of sufficient input excitation and is one of the common drawbacks when using data driven models [7, 8]. Buildings are typically operated within a tight range and the input is not persistently excited [16, 17]. This can lead to models which while providing reasonable prediction capability, are lacking in essential physical relationships. The inability of the models generated to capture the effect of the control input is most likely due to this issue. This could potentially be overcome by carrying out an identification experiment where more complex signals are used to excite the system over a greater range.

Carrying out-an identification experiment on a real building during occupation has the potential to cause disruption. In some cases it would be possible to carry out identification experiments during periods of low occupancy such as those experienced in schools and other academic institutions [17] or in the case of new buildings it could take place during commissioning.

CONCLUSIONS

Although the models developed are unsuitable for the purpose of MPC, there are other potential uses for accurate data driven models such as those developed in this project. Previous studies have used empirical models for fault diagnosis [18, 19] and to investigate potential overheating [20]. There could also be potential to incorporate a future temperature prediction within a traditional rule based control strategy.

Further Work

In order to determine if the inability of the developed models to capture the effect of window opening is caused by lack of input excitation, an identification experiment is proposed. Due to the high costs involved this will not be performed in a real building or experimental mock up but through the use of computer generated data using a multizone building simulation tool such as EnergyPlus. This experiment is not proposed to increase the accuracy of the model predictions but to generate a model which better represents the physical processes occurring and is suitable for the MPC application.

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