MAINTAINING THERMAL COMFORT OF A NATURALLY VENTILATED RESIDENTIAL HOUSE BY INTELLIGENTLY ACTUATING WINDOWS

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Abstract. In New Zealand's (NZ) mild climatic conditions, most residential houses are ventilated naturally, mainly by opening windows. However, maintaining the indoor thermal comfort characteristics of a house by modulating natural ventilation is particularly challenging, as the solution is not explicit. Determining a solution requires a technique that adjusts openable window area while encapsulating the complexity, dynamics, and nonlinearity associated with the natural ventilation driving forces and building thermal behavior. By verifying that there exists a significant potential of regulating indoor thermal comfort of a relatively airtight and insulated house by adjusting window openable area; this work additionally confirmed an excellent capability of Artificial Neural Network (ANN) technique in predicting air temperature time-series of the naturally ventilated house. On the basis of these examinations, this work particularly developed a co-simulation strategy between building thermal-airflow model and the ANN model and demonstrated that windows could be regulated intelligently to modulate the natural ventilation and maintain indoor thermal comfort level during the summer period by applying Artificial Neural Network (ANN) based predictive controller technique.

Keywords. Natural Ventilation; Thermal Comfort; Artificial Neural Network (ANN); Residential House; Intelligent Windows.

1. Introduction

In mild climatic conditions, most residential houses are ventilated naturally, mainly by opening windows (Buckett and Burgess, 2009). However, maintaining the indoor thermal comfort characteristics of a house by modulating natural ventilation is challenging, as the solution is not explicit. In this respect, by examining the thermal behaviour of single-sided natural ventilated house located in a mild climatic region of Auckland, Pokhrel et al. (2016, 2018) verified that there is a significant potential of regulating thermal behavior of a relatively airtight and insulated naturally ventilated house by considering different operating conditions and values of Window Opening Factor (WOF).

However, determining a solution requires a technique that adjusts openable window area while encapsulating the complexity, dynamics, and nonlinearity

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associated with the natural ventilation driving forces and building thermal behavior. In this respect, the problem appears to be well suited to the application of an Artificial Neural Network (ANN). ANNs are widely accepted as a tool offering an alternative way to tackle complex and ill-defined problems and are able to deal with nonlinear problems. Once trained, ANNs can perform predictions and generalizations at high speed making them well suited to dealing with these situations (Kalogirou, 1999). Previous studies (Krauss et al. 1998 and Salque et al., 2014) have successfully demonstrated the use of ANNs for predicting and controlling the building indoor environment, typically the air temperature in a closed occupied space. In achieving this, the researchers used an ANN technique to predict solar radiation and the outdoor air temperature. Similarly, a recent study for forecasting time series global solar irradiance in NZ locations verified the applicability of the neural network technique with specific reference to Nonlinear Autoregressive with Exogenous Input (NARX) ANNs (Ahmad et al, 2015). Building up on this knowledge base, Pokhrel et al. (2017) demonstrated that the ANN technique can solve the associated intricacy; and was able to predict a time series of the occupied space air-temperature of a naturally ventilated house.

Capturing all this initial work, this paper particularly aims to demonstrate that the windows could be actuated intelligently to modulate the natural ventilation and maintain indoor thermal comfort level by applying ANN-based predictive controller technique.

2. Methodology

2.1. CREATING A COUPLED THERMAL-AIRFLOW MODEL

To determine the performance of the coupled thermal and airflow environment in a typical NZ house, the TRNSYS Type 56 model was used in conjunction with a COMIS (COMIS, 2005) airflow analysis based on a network model of the house. For this study, a single room of 3 m length, 3 m width and 3.6 m reference height, as shown in Figure 1, was modeled.

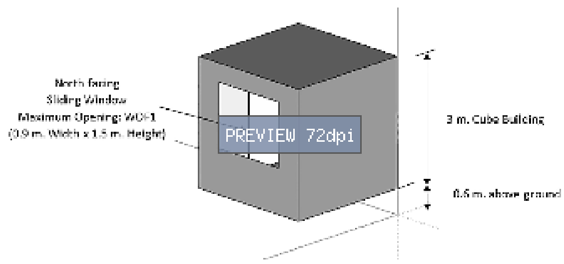

Figure 1. Building 3D Model.

The model was used to simulate values of the airflow through the opening, occupied temperature based on heat and mass conservation laws with its well-mixed assumption (Hiller et al., 2002). While doing this, the temperature was calculated in the thermal model at each time-step and passed to the airflow model, so that updated information was used to estimate node pressure and mass flow. While doing this, it was assumed that 0 to 5 occupants, producing heating of 100 Watts per person (sensible-60 and latent-40), occupied the room randomly. Further, it was assumed that the building was located in Auckland NZ at 36.85˚ S, 174.76˚ E with each wall aligned to the cardinal directions and a single window on the north face. In addition to this, Table 1 presents the building facade details for a baseline envelope thermal Resistance (R-value) (Case 1) just meeting the current standard schedule method for non-solid construction (NZS 4218, 2009), resulting in a weighted average envelope thermal Resistance (Ravg) value of the house equivalent to 2.01. Further, intermediate insulation layer R-values of 2.6 (case 2), 3.2 (case 3) and 3.6 (case-4) were considered on the envelope components (wall, roof, and floor) to explore the overall improved average envelope Ravg of 2.6, 3.22 and 3.44 respectively.

To achieve the ventilation a Large Vertical Opening (LVO type 1) (COMIS, 2005) with a maximum opening size of 0.9 m (width) by 1.5 m (height) as shown in Figure 1 was used to model a sliding window. In doing this, a WOF defined as 1 for fully open and 0 for fully shut was applied. In addition, intermediate discrete WOF values of 0.1, 0.25, 0.5, and 0.75 were also considered to explore the effect of the various window openable area on the thermal conditions.

Table 1. Building facade description.

Building Facade	Description	R-Values			
		Case 1 R-NZBC	Case 2 R 2.6	Case 3 R 3.2	Case 4 R 3.6
External Wall	Timber frame direct fixed cladding	1.9	2.4	3.1	3.2
Floor	Suspended floor with lining under the joists [illegible] insulation and lining	[illegible]	3.1	3.5	3.8
Roof	Timber frame skillion roof	2.9	3	3.4	3.8
Window	Vertical double glazed sliding window (1.8 m. width x 1.5 m. height) Northern wall	0.34	0.34	0.34	0.34
Area weighted average envelope resistance (R_{avg})		2.01	2.6	3.22	3.44

In addition to this, the housing stock was also discretized by its airtightness level from a least-airtight Draughty (DTY) house with 0.9 ACH to the most-airtight Ultra Airtight (UAT) house with 0.03 ACH. While doing this, the un-controlled infiltration equivalent to intermediate airtightness levels defined as Airtight (AT) (0.3 ACH), Average (AVG) (0.5 ACH) and Leaky (LKY) (0.7 ACH) houses were also considered. Finally, the thermal behavior of the zone was assessed by computing the indoor room temperature and a thermal comfort Index for the free running condition, with no additional heating, cooling or plug loads. Now, concerning the thermal comfort, index-Predicted Mean Vote (PMV) is categorized into three comfort categories as shown in Table 2 (EN ISO 7730 2005). Values of PMV ranging between ± 0.5 are broadly considered as a comfortable environment (ASHRAE-55 2010). The “C” category, having a higher PMV comfort scale range (± 0.7), was considered acceptable to people accustomed to naturally ventilated environments in this study.

Table 2. Thermal comfort categories (EN ISO 7730 2005).

Categories	Predicted Mean Vote (PMV) range	Percentage of People Dissatisfied (PPD)
A	± 0[illegible]	< 6
B	± 0.5	< 10
C	± 0.7	< 15

2.2. CREATING THE ANN MODEL FOR PREDICTING THE INDOOR ROOM TEMPERATURE

While creating the ANN model, the NARX-ANN technique was used to predict the occupied space air-temperature time-series. In doing so, the work predicted future values of a time series y(t) from d past values of that time series and d past values of another time series x(t) as shown in Equation 1 (MATLAB, 2017).

$$y(t) = f(y(t-1), \dots, y(t-d), x(t-1), \dots, (t-d)) \qquad (1)$$

In the development of the ANN, input quantities with low correlation with the indoor air temperature were eliminated so that the final ANN model could be as simple as possible without compromising the accuracy. The final NARX model comprises a set of time series database of hourly values of different input quantities as mentioned in Table 3. Similarly, the hourly values of the indoor room air temperature predicted by the TRNSYS simulations formed the database for target time series.

Table 3. Input quantities for ANN model.

Input quantities	Unit	Abbreviation	Range
Outdoor temperature	°C	T_o	-
Wind speed	m/s	WS	-
Outdoor relative humidity	%	RH_o	0-100
Window opening factor		WOF	0, 0.25, 0.5,1
Envelope airtightness		[illegible]T, LKY	0.03, 0.3, 0.7
Hour of the day		HRS	0-23
Global horizontal radiation		GHR	-
Random number of occupants		OCC	0-5
Weighted average envelope thermal resistance		R_{avg}	2.01, 2.6, 3.44

Subsequently, the input and target vectors were randomly divided into three sets such that 70% of the data was presented to the network for training, 15% for validation and 15% for generalization. In performing the training, the Levenberg-Marquardt algorithm was implemented in a bid to fit the input and target. Despite the good performance demonstrated by the default values, a sensitivity study was carried out with various combinations of their values to identify the most appropriate values of hidden layers and delays for the proposed NARX network. While doing this, the average values of the Regression (R) and corresponding Mean Squared Error (MSE) for each combination of hidden layers and delay was assessed for at least three training runs. As seen in Figure 2, increasing both resulted in better performance (R-value close to 1), however, this is offset by the expense of an increased time required for the training and also the increased likelihood of overfitting the network.

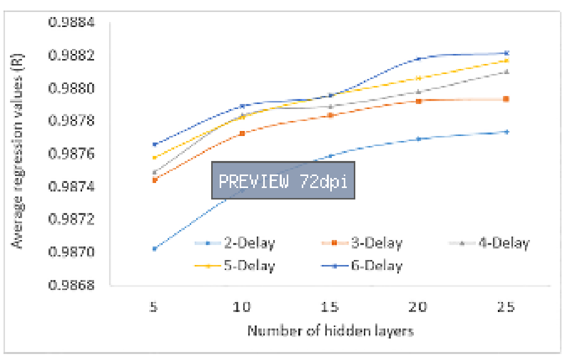

Figure 2. Sensitivity of average regression values with respect to hidden layers and delays.

Therefore, considering a balance between the times required for the training and achievable performance, an ANN-NARX open loop (series-parallel) architecture, as shown in Figure 3, with 15 number of hidden layers and 5 number of delays were considered for further assessment. The weights-W and biases-b as illustrated in Figure 3 were optimized while doing the network training to minimize the MSE.

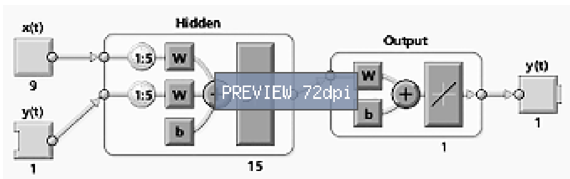

Figure 3. The optimum neural network architecture.

2.3. APPLYING PREDICTIVE CONTROL CONCEPT WITH CO-SIMULATION TECHNIQUE

The coupled thermal-airflow model of a house was simulated for various operating conditions creating big data. The big-data was translated in the form of an ANN function that can be used to predict indoor room temperature of the house. Finally, as shown in Figure 4 schematic, a controller was conceptualized in TRNSYS-MATLAB co-simulation platform based on the simple model predictive control concept such that the operation of the ANN function was reversed to achieve a desired indoor temperature with given ambient conditions.

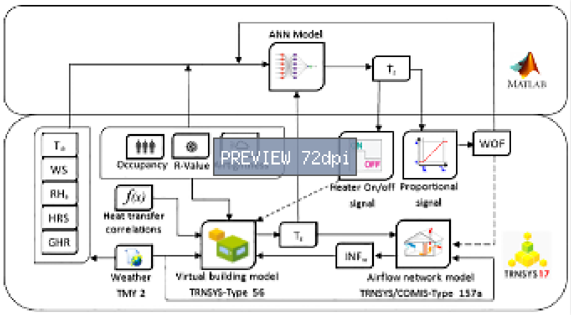

Figure 4. A schematic demonstrating co-simulation strategy of ANN and thermal model.

3. Result and Discussion

Complementing to the preliminary outcomes (Pokhrel et al. 2016, 2018), a further assessment of 120 simulations (each for 8760 Hrs with a time step of 1 hour) was carried out to examine the level of thermal comfort regulation potential of the model house. While doing this, 6 discrete values of different WOF (0 to 1), 5 discrete values of airtightness level (0.03 to 0.9) and 4 different envelope thermal resistance cases (Ravg 2.01 to Ravg 3.44) were considered. These simulations' generated hourly time-series of occupied zone air temperature and the PMV profile for each individual set of operating conditions as defined. Demonstrating the assessment in terms of percentage of thermally comfortable hours, Figure 5 as an example indicates that there is a significant potential of thermal comfort regulation by the opening in a relatively better-insulated (Ravg 3.4) and airtight house.

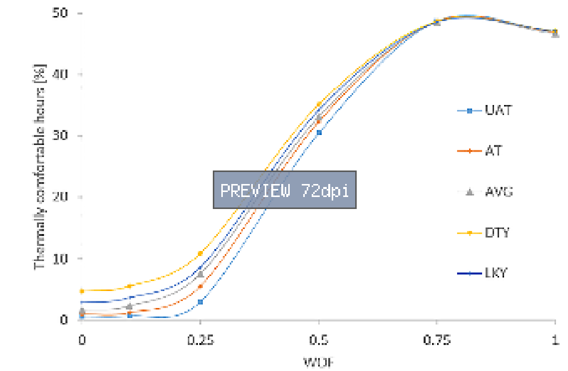

Figure 5. Percentage of thermal comfort duration ($-0.7<PMV<0.7$) relating to discrete values of WOF (Ravg 3.4, January).

As obvious, these preliminary assessments demonstrated that the improved thermal resistance and air-tightness of the envelope helps to store thermal energy generated internally by occupants, solar load and thermal load due to air temperature. Furthermore, the stored thermal energy can either reduce uncomfortably cool periods or result in an increase in uncomfortably warm periods. However, as the fixed window opening increases, it essentially increases the leakiness of the building by allowing higher air exchanges rates to occur. Ultimately, opening the window can help reduce uncomfortable warm period.

Now, the next step was to verify that how robust the ANN technique in predicting the indoor thermal behavior regarding indoor air temperature. While doing this, the optimized ANN model was trained with the hourly input and target values corresponding to the WOF (0, 0.25, 0.5 and 1), average envelope thermal insulation (Ravg 2.01, Ravg 2.6 and Ravg 3.44) and envelope airtightness level (LKY - 0.7, AT - 0.3 and UAT - 0.03) ACH for a year. As the generated function is the core for the deployment of the control concept, the robustness of the function needs to be verified so that it can be used globally for any value of WOF, airtightness, and Ravg within a threshold of the respective variables defined in the model. Illustrating in Figure 6, a comparison was made between time series of the indoor air temperature generated by both models with WOF values of 0.75. The demonstration was tested for Ravg 3.2 and AVG house for the first week of January and July as representative months at the peak summer and winter respectively.

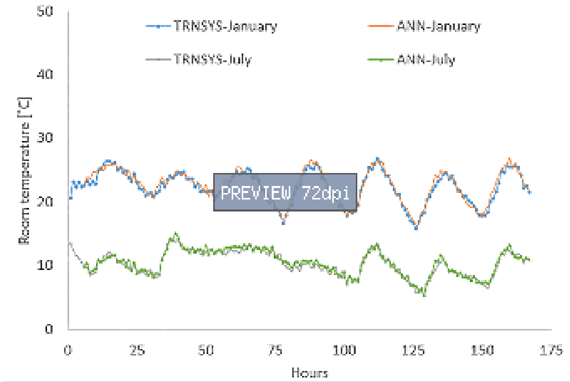

Figure 6. Indoor air temperature from the ANN and TRNSYS model (WOF 0.75, AVG house with Ravg 3.2, 1st week of January and July).

The Figure 6 demonstrates that the predicted time series from the ANN model agrees quite well with the time series generated by the TRNSYS thermal model of the house. This confirms that the prediction capability of the ANN model for the indoor room air temperature is quite reliable at the relatively higher value of WOF 0.75. By exploring this further, additional tests were also carried out for relatively smaller values of WOF (0.4 and 0.1) and for an extended period throughout a year. As expected, the prediction also holds extremely well throughout the year even for the lower opening area, where the balance of the in and out flow from the space is restricted in nature and thus increases the nonlinearity.

As the reliability of the ANN model for predicting the indoor air temperature of the naturally ventilated house model was satisfactory, the potential of it to be used as a basis for actuating windows intelligently for a naturally ventilated house was further investigated by applying the co-simulation strategy as demonstrated earlier in Figure 4. The co-simulation was performed for houses with different combinations of airtightness level and Ravg values. Demonstrating the window actuator performance for a typical day in January for an AVG house with Ravg 3.2, the Figure 7 shows that how the regulation of the values of the WOF between 0 and 1 modulates the natural ventilation (Inf) to help sustain the indoor room temperature (Ta) around the desired indoor set point of 24˚C. By keeping the settings of envelope thermal resistance and airtightness intact, the co-simulation of the thermal and the ANN model was extended for the 1st week of January, to observe the actuator performance for an extended period. The resulting frequency distribution (Figure 8) illustrates that the implementation of this intelligent window actuating system can alone achieve maintaining the thermal comfort level (-0.7<PMV<0.7) of the model house for 92.63% of the instances.

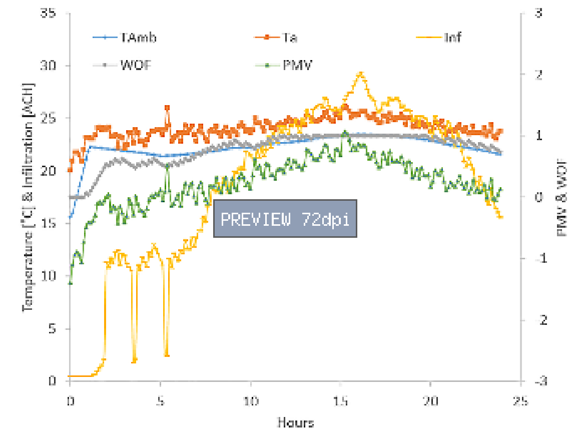

Figure 7. Actuator performance for the model (AVG house with Ravg 3.2) for a typical day in January in Auckland.

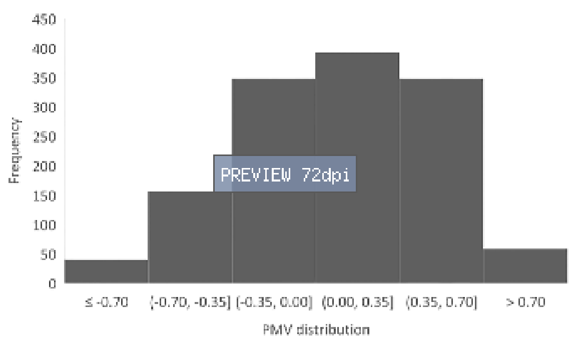

Figure 8. Frequency distribution of PMV after using window actuator (AVG house with Ravg 3.2 for 1st week of January).

Comparing this result with different cases of fixed openings (discrete values of WOF) resulted in achieving a relatively lower proportion of the indoor thermal comfort period as demonstrated in Table 4. This indicates that a significant improvement on maintaining indoor thermal comfort period can be achieved by employing the ANN model predictive control window actuation technique with respect to any fixed opening positions of the window. While doing this, an AVG airtight house with thermal resistance of Ravg 3.2 was considered ensuring that all the settings (including time step size of 7.5 minutes) and input values remain exactly the similar.

Table 4. Comfort period proportion with respect to different values of WOF and window actuation (AVG house with Ravg 3.2 for 1st week of January).

WOF	Window Actuation	Comfort period Proportion ($-0.7 < PMV < 0.7$) [%]
1	OFF	64.16
0.75	OFF	61.85
0.5	OFF	29.36
0.25	OFF	5.79
0.1	OFF	2.15
0	OFF	2
Varies between 0 and 1	ANN model predictive control actuation	92.63

These results illustrate that a relatively higher value of WOF would give better exposure to natural ventilation in the summer period resulting in better achievement of a thermally comfortable period by extending its free cooling potential. However, there are many instances throughout a year, when the indoor air temperature is colder than the desired comfort temperature. Those instances depend on many factors like relatively colder weather condition, lower level of building envelope resistance, weak envelope airtightness, less internal loads, etc. In those situations, any opening of the window resulting natural airflow would obviously worsen the indoor thermal comfort level making it more uncomfortable cold. For those instances, the actuator not only needed to completely shut the window or open it to a minimum threshold to let only a minimum airflow to ensure fresh air ventilation but also needed to trigger any other available auxiliary heating sources (electric heater or heat pump, etc.).

4. Conclusion

The ANN technique could be used to predict the occupied space indoor air temperature time-series of the naturally ventilated house; and that this can be used as part of an intelligent window control strategy for maintaining thermal comfort of the next generation of sustainable naturally ventilated residential houses.

As a future work, a more advanced controller can be conceptualized such that it access the thermal comfort of the residential house in terms PMV or adaptive thermal comfort index criteria rather than only indoor air temperature. As such, the resulting time series function/algorithm of the thermal comfort index might be used as a basis to devise an intelligent model predictive control strategy with the window actuation optimization strategy having objective function to directly maximize the indoor thermal comfort level of a naturally ventilated residential house and minimize the heating or cooling energy consumption.

In a summary, the use of ANN appears to offer a positive outlook in the development of intelligent control of actuated windows for the next generation naturally ventilated sustainable buildings.

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