Applying Artificial Neural Networks to Promote Behaviour Change for Saving Residential Energy

Yaqub Rafiq[1], Shen Wei[2], Robert Guest[3], Robert Stone[3] and Pieter de Wilde[2]

[1]School of Marine Science and Engineering, Plymouth University, Plymouth, U.K.
[2]Building Performance Analysis Group, Plymouth University, Plymouth, U.K.
[3]School of Electronic, Electrical & Computer Engineering,
University of Birmingham, Birmingham, U.K.

Abstract. In this paper Artificial Neural Networks (ANNs) is used to model effects of various human behaviour on energy consumption of the residential buildings in the UK. A virtual model of a bungalow has been developed in which various aspects of the, physical changes in the building such as wall and floor insulation, single and double glazing combined by the human behaviour aspects such as thermostat setting, various periods of door and/or window opening etc. are modelled using EnergyPlus software for evaluating energy consumption for a combination of scenarios. ANNs were then used to learn the effects of various human behaviours on energy consumption. The results demonstrated that the ANN is capable of learning the effects that changes in the human behaviour have in evaluating energy saving in residential buildings and it generated results very quickly for unseen cases.

1 Introduction

Reducing residential energy consumption is essential for achieving the UK Government's 2050's target of lowering CO_2 emissions. This is due to a high contribution to the CO_2 emissions as the total energy consumption of the residential buildings in the UK is about 30% [1]. Occupant behaviour plays an important role in energy usage in residential buildings [2, 3]. Due to high importance of occupant behaviour on the energy consumption, the UK government has funded several projects in the past 10 years, such as the green deal [4] and the 22 (Build)TEDDI projects [5], exploring how to improve occupant behaviour in residential buildings for energy saving.

Currently, dynamic building performance simulation (DBPS) is being explored to help occupants make informed decisions on adopting ways to save energy in their houses [6-8]. An advantage of using DBPS is its flexibility in conducting parametric studies by changing one aspect with respect to the definition of either the building, building system or occupants' building operation in DBPS, while keep other aspects constant. Therefore, the impact of that particular change on the building energy consumption can be reflected clearly by the simulation results. In this process, the energy saving potential of possible behaviour change options was evaluated as the difference between the predicted energy consumption before changing the behaviour with the

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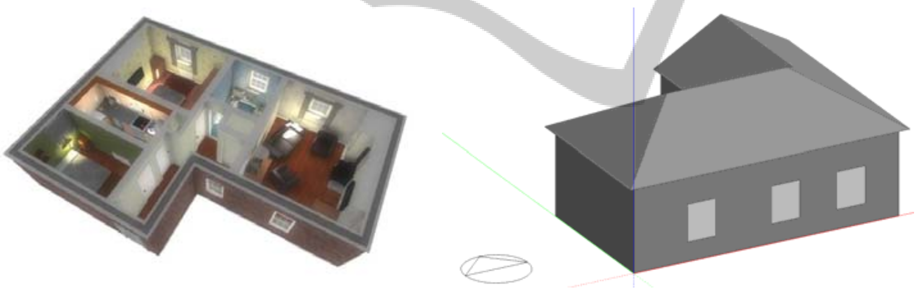
one after the change.

In reality, behaviour change options, especially those relevant with occupants' building operations, are complex [9, 10]. For example, the thermostatic setting in winter can be set at any values within a reasonable range, i.e. between 14°C and 22°C. Therefore, using DBPS to predict the building energy consumption of all possible scenarios defined by these options or adding other options to this can make it a complicated combinatorial problem, which would be unfeasible using DBPS. Therefore, this paper has preliminarily tested the use of ANNs to model the energy consumption with respect to behaviour change in buildings, and the performance of using the ANN model for the prediction of changes in energy consumption has been validated against prediction results from DBPS.

2 Methodology

2.1 Case Study Building

The simulation model was developed based on a virtual UK bungalow building, as shown in Figure 1a, by the teammates at the University of Birmingham. This house has two bedrooms, a living room, a kitchen, a bathroom and a main corridor. The main façade of the house faces the North.



(a) Case study house (b) Simulation model

Fig. 1. Case study Building and Simulation model.

2.2 Dynamic Building Performance Simulation

Generally, in residential buildings there are two ways for reducing energy consumption [11]. The first way is by upgrading the insulation of the building façade or the efficiency of the building systems, so that the building itself can be more energy-efficient; the second method is by improving occupants' operation of the building, e.g. opening/closing windows and setting the temperature values for the heating system etc., so that the building can be used more energy-efficiently. Based on this classification, the behaviour change options, investigated in this study, are listed in Table 1 with corresponding simulation scenarios defined for the DBPS.

Table 1. Simulation scenario definitions.

Behaviour change options	Simulation scenario (before)	Simulation scenario (after)
Upgrading external wall insulation	No	50mm insulation
Upgrading ground floor insulation	No	50mm insulation
Upgrading pitched roof insulation	No	50mm insulation
Upgrading ceiling insulation	No	50mm insulation
Upgrading window layers	Single glazing	Double glazing
Upgrading door layers	Single glazing	Double glazing
Lowering thermostatic setpoint	23°C	22°C, 21°C, 20°C, 19°C, 18°C, 17°C, 16°C or 15°C
Reducing window opening time	4 hours	3 hours, 2 hours, 1 hour or 0
Opening curtains during the day	No	Yes

Based on the information presented in the above table, 5760 possible scenarios can be used to assess energy consumption in the building.

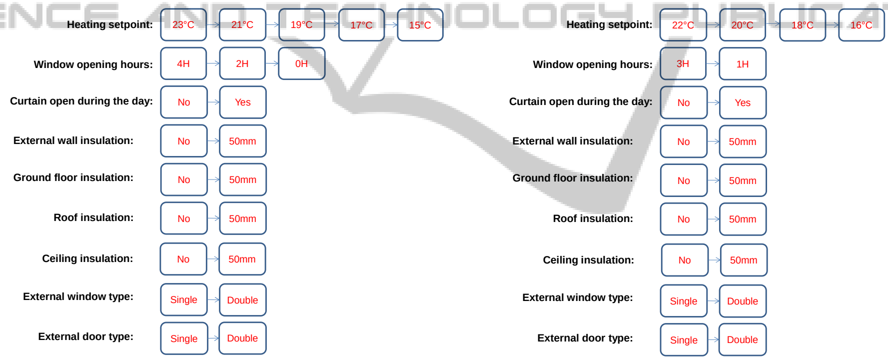
Figure 1b shows the simulation model of the case study building developed using DesignBuilder [12], a commercial graphical user interface of EnergyPlus [13], which is one of the popular DBPS tools in assessing building energy usage. In this paper, EnergyPlus V7.2 was adopted as the simulation engine and the simulation model was exported from the DesignBuilder to EnergyPlus. The weather data used in this simulation was provided by the Climate Design Data 2009 ASHRAE Handbook, for Birmingham UK applications. The simulation period was chosen as from 1st to 31st January, based on an interval of 30 minutes. The inputs of the simulation include definitions of building construction, systems, occupants' building operations and weather conditions, while the output is heating energy demand during the simulation period. In this study, the energy saving potential of each intervention listed in Table 1 was calculated as difference between the predicted heating energy demand before the intervention applied and the one after the intervention applied.

2.3 Artificial Neural Networks

ANNs have been widely used in a number of applications in buildings [14], e.g. predicting building energy consumption [15, 16], predicting thermal comfort in buildings [17], designing [18, 19] and managing buildings [20, 21]. A Neural Network has the ability to learn from experience and examples and then to adapt with changing situations [22], imitating some of the learning activities of the human brain. The ANN model used in this study consists of two hidden layers of 10 and 5 neurones using TANSIG activation function; one output layer of one neurone using LINEAR activation. It is a back propagation Neural Network [23] that was used to model the simulated energy consumption at different behavioural scenarios, presented in Table 1. The data for the Neural Network model was generated using EnergyPlus as discussed in section 2.2. Both Levenberg-Marquardt (trainlm) and Bayesian regulation (trainbr) back-propagation learning algorithms were used. In this study MATLAB R2013b Neural Network Toolbox was used for developing the ANN model [24]. The training and testing data consist of 8 input and one output variables.

2.4 Training and Validation of the ANN

In this study, two sets of data were prepared using EnergyPlus, one for training the ANN and another for validating the trained ANN model. Figure 2a presents the combination of the simulation scenarios used in training the ANN and Figure 2b shows those used in validating the trained ANN model. The input data of the ANN are various parameter definitions with respect to occupant behaviour in buildings and the output of the ANN is the energy consumption for that simulation scenario. In Figure 2, the most left hand side parameters define the base case scenario of the case study building against which the energy saving potential could be calculated for comparison purposes. The remaining parameters on the right hand side columns define the possible interventions. Changes in the energy consumption is evaluated by replacing the house original conditions from those of base case scenario to the one or a combination of scenarios presented on the right hand side column in Figure 2.



(a) ANN training dataset definition (b) ANN validation dataset definition

Fig. 2. Dataset definition.

After considering the possible combination of all simulation scenarios defined in Figures 2a and 2b, finally, 2941 possible scenarios were generated for the ANN training and testing processes (1917 for training the ANN and 1024 for validating the ANN).

3 Results

As mentioned before the MATLAB Neural Network toolbox was used for both training and testing the Neural Network. Both 'trainlm' and 'trainbr' back-propagation algorithms were used. At first, due to the speed of learning, 'trainlm' was used in the learning process. A back-propagation network architecture having 2 hidden layers and one output layer, was adopted for both learning algorithms.

Initially the data was divided into two sets for training and testing/validating purposes. The training data included all data for 23°C, 21°C, 19°C, 17°C and 15°C covering upper, lower and intermediate temperature sets of data. This constituted a total of 1917 set of data. The testing date included the rest data (1017 sets of data in total).

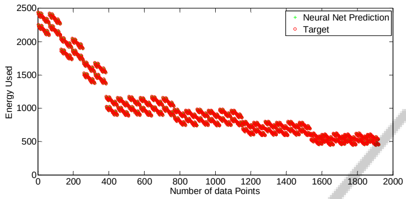


Fig. 3. Neural Network training results for selected data.

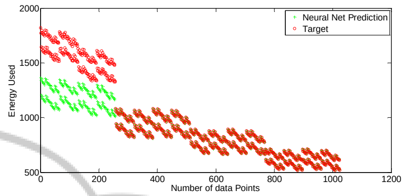


Fig. 4. Neural Network testing/validating results for selected data.

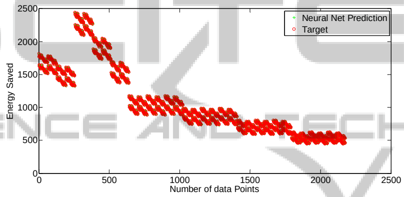


Fig. 5. Neural Network training results for extended data.

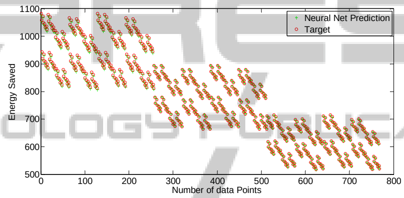


Fig. 6. Neural Network testing/validating results for reduced data.

Figure 3 shows the results of the ANN learning 1917 sets of data. The network successfully learned the presented data in a few minutes. Figure 4 shows results of the validation/testing to see if the Neural Network has satisfactorily learnt and generalised necessary information presented to it. In all Figures the horizontal axis shows the number of data points used in training and testing the ANN model and the vertical axis shows energy usage. From Figure 4 it becomes clear that the Neural Network has learned the data within the range 15°C to 19°C perfectly but failed to learn the rest of the data outside this range. A quick fix would be to add the upper range (all data higher than 19°C) to the training set. Figures 5 and 6 show that by doing this both training and testing of the Neural Network processes are successful.

One problem with this quick fix is that the generalisation aspect of the ANN has not been verified. This model can be used within the range of 15°C to 23°C but results from any other data would be doubtful. Another issue with this process is that the data sets used in the learning process is more than that of the testing process. In order to find an acceptable solution to this problem, the following steps have been taken:

1. The data (combined training and testing data) for each temperature degree was plotted using different colours in a single graph. This information is presented in Figure 7. Form Figure 7 it becomes clear that the data is divided into distinct clusters for each °C. The more clear division is observed in the range between 15°C to 21°C with the rest of the data between 22°C and 23°C.

2. Based on the findings from (a), to improve the quality of training and testing data, the training data was sampled from within each cluster and the remaining of the data from each cluster was used for testing purposes.

Figure 8 shows results of the training process using only the training data from each cluster. Similarly Figure 9 presents results from the testing/validating of the trained Neural Network with the rest of the unseen data. The overall result of the combined training and testing data is shown in Figure 10.

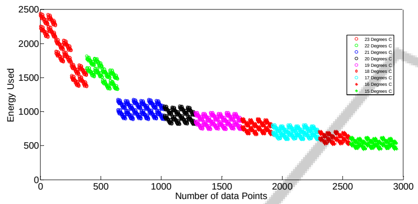


Fig. 7. Combined training and testing data clusters.

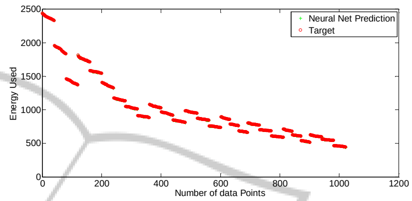


Fig. 8. Training for selected data from each cluster.

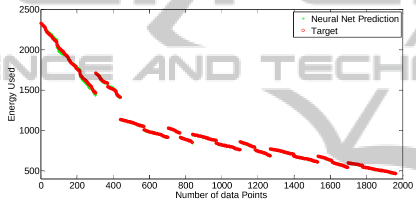


Fig. 9. Combined testing extended data clusters.

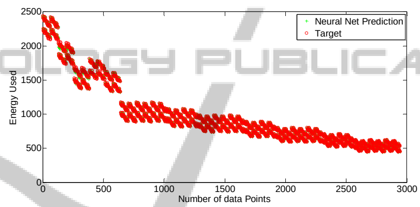


Fig. 10. Combined testing all data clusters.

From both Figures 9 and 10 it is clear that by selecting data within each cluster, the Neural Network was able to learn and generalise the information presented to it. Hence this trained network can be used confidently to predict the energy usage and energy saving using particular scenarios for the case study building.

4 General Applications to Real Structure and Future Research

This paper has demonstrated that the trained Neural Networks can successfully predict the simulated building energy consumption when general behaviour change options are applied to a virtual case study building. For applications to real buildings, there are still some important issues that need to be handled:

1. developing a representative simulation model for the real building and using it for the preparation of data to train the Neural Networks;
2. realistically capturing occupants' real behaviours in operating the building, so that the base case simulation model can be developed as close as possible to real situations;
3. realistically quantifying the behaviour change options in accordance with the

real applications; and,

4. implementing other factors that may influence occupants' choice of applying behaviour change options in the ANN, such as indoor thermal comfort and investment payback period, rather than using energy consumption only.

An initial exploration on solving the above challenges is currently on-going by the authors of this paper, and an Energy Efficient Education tool(s) is being developed to help building occupants make informed decisions on changing behaviour for saving residential energy demand.

5 Conclusions

Reducing energy consumption in residential building is a major problem universally. Occupant behaviour has shown to have an important role in reducing energy consumption. Evaluation of energy consumption, using traditional analytical method using DBPS tools is computationally expensive and very time consuming. In this paper ANNs have been used to instantaneously evaluate the effects of various combination of human behaviour on the residential buildings in the UK. The results demonstrated that the ANN techniques can be used to predict the simulated energy saving potentials of various human behavioural changes which eliminates expensive and time consuming DBPS operations.

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