Minimising Error: Artificial Neural Network Configurations for a User Overridable Dynamic Shading System

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Abstract

This research explores the possibilities of integrating environmental and human inputs to achieve precise architectural goals. Specifically, the aim is to create an adaptive façade, trained on historical data relating to human (an override capability) and environmental inputs to maintain optimal internal lighting conditions for inhabitants. The study was conducted using a physical louvered shading system constructed in the Bartlett School of Architecture, University College London. The historical data collected by the system provided a sample data set to train the Artificial Neural Network (ANN) for which the system would operate. A multi-layer perceptron was the neural network used in the study and a series of experiments allowed for the optimal network architecture to be ascertained. Based on the trained network, further testing was carried out to assess the accuracy of the results with regards to the louver angle suggested during system recall. It was found that the complexity derived from receiving both environmental and human data provided some confusion when recalling, however the system displayed a high level of accuracy, correctly recalling the desired blade angle over 70% of the time. Further testing found that the remaining recall error could be accounted for through environmental input data similarities. By physically building and testing the system this research suggests that a trained physical system based on computational principles can provide an adaptive architectural entity that considers building occupants behaviour and wants as well as the external environments natural imposition.

Keywords: Artificial Neural Network, Multi Layer Perceptron, Adaptive Façade, User Interaction, Envelope Design.

1 Introduction

Dynamic shading is one of many routes currently being explored under the environmental agenda. The building envelope is seen by many to be one of the most important design parameters determining the indoor physical environment related to visual comfort and occupant working efficiency (Oral & Yilmaz, 2003). However, the generic rules with which many autonomous systems operate often require routinely consistant input from the user should they wish to alter its behaviour for their own comfort (and in many cases this option may not be available at all). Artificial intelligence displays the characteristics of being able to integrate such user input with diminishing user involvement over time through the learning of human behavioural desires.

Most non-residential spaces have regular occupancy hours. With regularity – particularly in spaces with fixed open/closed times – conformative behavioural trends result. While the thought of devices learning occupant behaviour is a seemingly attractive prospect, it is peoples' reluctance to adopt such technology which has been deemed to be the reason for its lethargic uptake. Even rudimentary forms of regulation, such as operating a thermostat are inordinately difficult for people (Gregorek, 1991). There has been a plethora of pioneering research surrounding the topic of automation in buildings (Miller & Seem, 1991; Seem & Braun, 1991; Scott, Shavlik & Ray, 1992). Michael Mozer's *Neural Network House* was an important study with regards to systems learning occupant behaviour. Mozers' study highlighted the importance of inhabitants' behaviour on the chances of prediction success, "the question we must answer is whether there are *sufficiently robust regularities* in inhabitants' behaviour to benefit from" (Mozer, 1998). More recently, ANNs in buildings have been used as a means of short term future event prediction such as hourly cooling loads in buildings, with the aim of optimising the heating, ventilation and air conditioning system operation timing (Li, 2009). There is wide support for the use of ANNs' ability to solve such forecasting problems and the non-linear mapping ability of neural networks is widely accepted as a technology offering an alternative way to tackle ill-defined problems in building envelope automation (Kalogirou, 2001). The potential for such technology to comprehend human wants as inputs to its system nominates ANNs as a potential conduit for satisfactorily predicting when those wants are required.

The ability to adopt protocols and procedures enables human beings to operate effectively in spite of contrasting conditions one might experience throughout the day. Conversely, buildings as a means of providing a user-friendly, environmentally regulated environment do not operate with the same elegance because buildings are subjected to a wider range of internal and external conditions, and posses the additional handicap of being unable to relocate themselves to more favourable environments (Lee and Selkowitz, 1997).

In principle, the use of computational algorithms present themselves as a useful tool in aiding the ever progressing transition of building envelopes from static to dynamic entities. But prior to implementation of such an approach, the question arises as to the implications of such potential paradigmatic change in the built environment, and the subsequent upshots of a theoretical uptake in such building envelope technology. While internal occupant comfort underpins the research, a key concern of the authors was that of the environmental performance of the building. Would the side effects of mass façade automation *further increase* the operational energy use of buildings? Or perhaps have effects on the urban landscape aesthetic and become criticised in the same vein as other positive initiatives such as wind turbines?

2 Method

The method is split into two parts. The *Building Envelope Design* explains the physical systems design and presents the data collected that provided the input data to the ANN. The second part discloses the steps taken to *optimise the ANN* and presents its optimal network architecture. The flow of data from part one to part two is shown in Fig. 1.

2.1 Building envelope design

The experiment and collection of input data was set up in a $3m^3$ room oriented towards South-West. The system operates using 4 blades resting on 4 pivot points, constituting a louver system. Using one servo on one of the blades pivot points, rotational movement is translated into linear movement with which all other blades respond and turn from zero to ninety degrees in tandem. Four lux sensors were used when collecting data; two placed in the internal space and two in the external space. The averages of the lux readings allowed for a more accurate estimation of the amount of ambient light both inside and out. The kinetic movement of the system was actuated using Arduino – an open source software/hardware controller platform. The data visualisation and collection was carried out using the Processing platform (version 2.09b). The graphic user interface (Fig. 2.) provides a form of visual feedback for the user, by which he or she can make future decisions to override the system. The functionality of the system is two-fold and consists of *two separate states* with which the system can be running. The system caters for environmental inputs in the form of lighting levels and user preferences by enabling blade override capabilities when desired. Control theory underpins the logic behind the environmental behaviour of the system, which aimed to maintain a steady level of 500 lux internally. The user override – in the form of a potentiometer – allowed the user to adjust the blade angle to fully open/ closed respectively.

The graphic user interface (GUI) gives the user information regarding the state of the shading system as well as both the internal and external environments. The *blade angle monitor* reports the status of the louvres at any given point as well as their current angle. The lighting monitor displays the proportion of light admitted into the space through a gradient RGB visual. The key information (lighting override level, blade override level, external light level, internal light level and average light level) is given to the user in the form of graphs on a thirty-minute time loop. A time loop was used in this instance to help inform the user of the system and the environments most recent activity as a form of feedback with which to make future decisions.

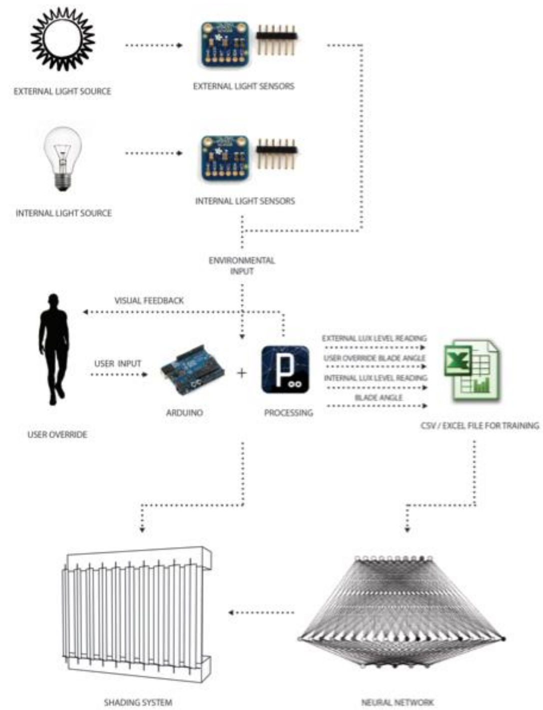


Figure 1: Data flow diagram of the dynamic shading system

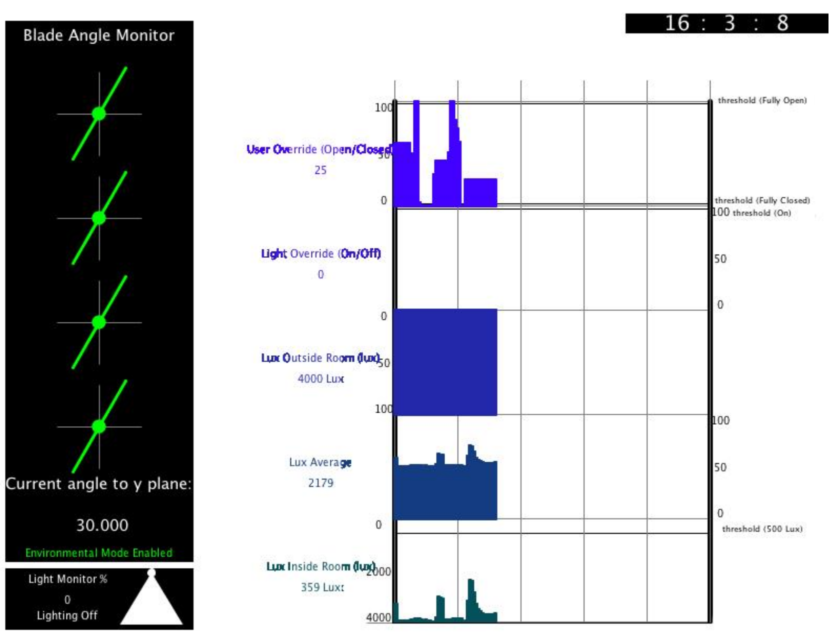


*Figure 2**:** Louvre system scope of movement*

2.1.1 System mode 1: User override

User Override Mode setting refers to any system movement acting on data received from the user. In this instance, the user is able to override the system at any point he or she deems necessary. Once overridden, the system discounts any environmental data and the impact it may have on the blade setting (i.e. control theory function temporary shut down) and acts entirely on the users' desired angle. In this study, the user has the ability to override the system to angles 0^o (closed full) and 90^o (open full).

2.1.2 System mode 2: Environmental

The Environmental Mode setting refers to any system movement acting on data received from the natural environment only. In this instance, the lux readers installed provide quasi-real time data regarding the internal and external lighting conditions. Based on the data read by the sensors (and on the understanding that the user has no desires to override the blade angle), the system evaluates the data chronologically and makes a decision on the blades position angle by *stepping towards* the desired lux level.

2.1.3 Control theory

A stepper control function was introduced to find the optimal blade angle based on constantly fluctuating environmental data. The step towards the desired lux level is a chronological calculation based on preceding information. When data is read in from the lux sensors, its *deviation* is calculated based on a comparison between the *internal lux level* and the *desired lux level*. The step that the angle should take is based on the inverse of the deviation multiplied by a *step proportion*. The current angle in addition to the recommended step gives the new angle. In this instance the step proportion is set to 0.1 (10%) so as not to overshoot the desired blade angle. This loop is running as long as the environmental mode is enabled. This allows the system to adjust the blade angle so as to converge on the desired internal lux level.

2.1.4 Output data

The system collected data over the course of one working week in an architecture studio in the Bartlett School of Architecture, University College London (Sunday 28th July to Friday 2nd August 2013). Resident architects were encouraged to use the system when they felt necessary to aid the provision of real-life output data with which to train the ANN. Readings taken at each minute throughout the course of the day have the corresponding values associated: internal lux reading, external lux reading, lux average, blade override, blade output. The results collected show a fair consistency between the days. The internal lux level in Fig. 3 sits regularly around the 500 lux level irrespective of the more external dynamic fluctuations displayed. Where the internal lux level rises or falls from this benchmark figure generally indicates the use of the override function imposed by the user (although in some instances, the lux level drops or rises due to anomalies such as exceedingly high daylight or extremely overcast skies). With each point during the day there is a blade angle associated. The blade angles recorded from the system give a resultant angle to the nearest degree (Actual – blue line). Each degree has been rounded to the nearest 10 degrees (Rounded – black line). The difference between the actual blade angle and its rounded equivalent was seen to be negligible and in-keeping with the discrepancies seen in the internal lux level variance maintainance. The data recorded between the hours of 9am and 5pm (a typical UK working day) is used for training and subsequent testing. The hours between 5pm and 9am have not been included in network training.

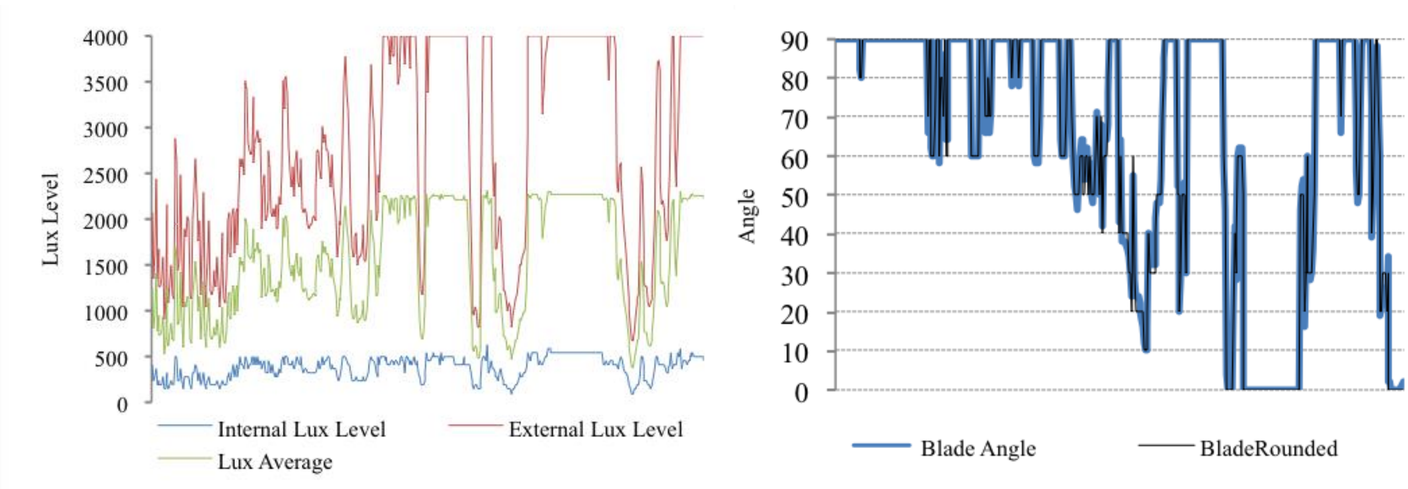


Figure 3 and 4: Lux level data and User override data recorded using the dynamic system

2.2 Façade back propagation optimisation

The artificial neural network (ANN) approach is a generic technique - developed from the areas of artificial intelligence and cognitive science - for mapping non-linear relationships between inputs and outputs *without knowing* the *details* of these relationships (Yang et al, 2003). ANNs, and in this case feed-forward neural networks with back propagation (also known as multi layer perceptrons - MLP), are parallel distributed processing models used to model the brain's learning process. The likeness is drawn because the brain receives inputs from the outside world via neurons, processes the inputs via further neurons and produces a response.

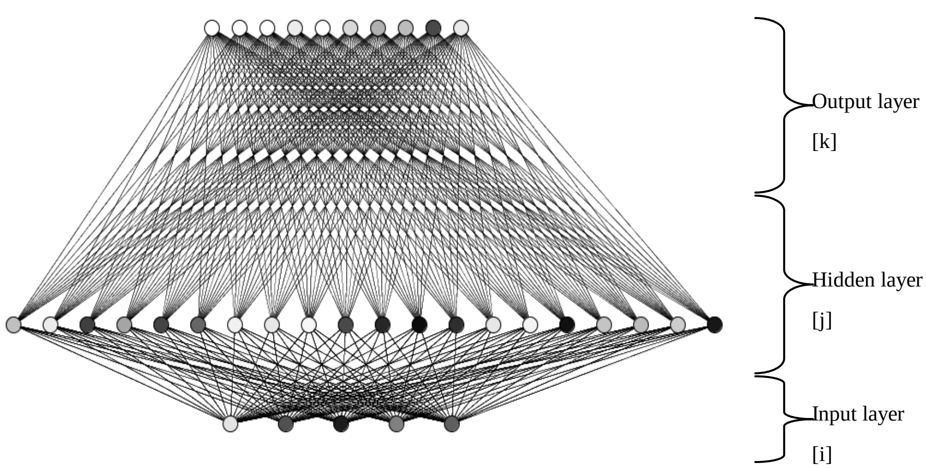


Figure 5: ANN architecture visualisation using Processing 2.09b

The network in this instance is a set of interconnected 'neurons' and consists of three (or more as demonstrated in this study) layers: an input layer, a hidden layer and an output layer. Information is fed into the input layer and through a series of weighted synapses; the information is passed forward through the hidden layer of the network through further connections, to the output layer. Sigmoidal function thresholds on the differing layers neurons determine whether the neuron 'fires' (feeds forward further information) or not. The theory behind the method of back propagation is that once the signals have been sent from input layer to output layer, the resulting answer is compared to the known actual answer and the weights between neurons in preceding layers are adjusted to step towards and accommodate the error. Each iteration involving the successful feeding forward of data (from input to output neurons) is known as a 'training cycle', with each complete set of training cycles constituting a 'training epoch'.

The concept of learning via back propagation consists of input patterns of each input node (i) being fed-forward to the hidden layer (j) and output generated in the output layer (k – Fig. 5). Whilst training, the output values are compared to the target values for each epoch and if a difference between the two is apparent, the weighted connections adjusted and step towards the desired value, thus progressively decreasing the error rate. The resulting adjustment is propagated backwards from the upper layers to the lower layers, subsequently altering the weights across the entire network. As the weights are the obvious respondents across any length of training, they are a useful indicator as to how well the system is performing. The training data used across all of the experiments is the same five days data collected. The data is collected every half second, however in this study minute-by-minute data has been used, constituting 4218 lines of sample data. The data used has been taken from between the times of 9am – 5pm. In this instance, the aim of the experiments is to establish a credible network formation based on the training data, which will enable efficient learning to be able to cope with *unique* data. The data is split in two parts - training set and testing set - the first uses 90% of the data set and the latter utilises the remaining 10%. The network is run for 3000 epochs in every training case and 300 while conducting final testing based on the optimised network configuration.

2.2.1 ANN architecture optimisation

The model learning is initiated with the setting of affecting factors in the form of input variables. The influencing factors are internal light level, external light level, the variance rate between internal and external light level and user blade override. The minimum and maximum values for the inputs (as seen in Table. 1) are normalised between 0 and 1.

Table 1: Maximum and minimum values for input neurons

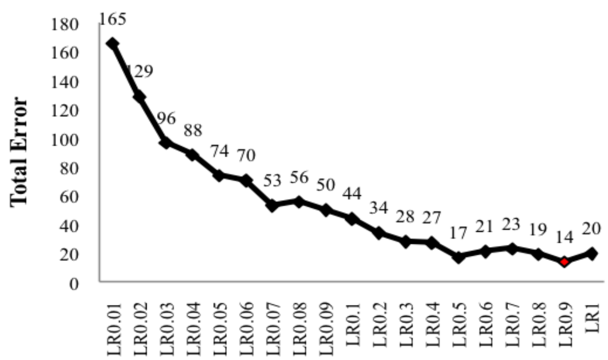
Input (X_i)	X_{min}	X_{max}
$Lux_{internal}$	*44*	*1842*
$Lux_{external}$	*246*	*2921*
$Lux_{mediated}$	*449*	*4000*
User Override	*0*	*90*

3 Training scenarios

The training scenarios are a series of experiments based on altering the ANN configuration to assess the differences in error rate, with the aim of improving prediction accuracy and performance when tested. All experiments have been conducted five times, with the averages taken for each. Learning the data collected from the shading system optimises the network architecture. Each variable factor has been progressively varied in turn until the best value with the smallest total error over the training series is discovered. Once discovered, this variable will become fixed and the following experiment will commence, adopting this fixed value. This process will continue until all floating variables have been fixed; constituting the optimal network configuration.

3.1 Learning rate variation results

In determining the optimal learning rate, other aspects of the network needed to be fixed to allow for consistency when comparing results. The fixed factors are as follows: input layer neurons - 4 (internal lux level, average lux level, external lux level, user override), hidden layers – 1, hidden layer neurons – 6, output layer neurons – 10. The testing period was halted at a learning rate of 1 because it is near asymptotic. Learning rate 0.9 exhibited a maximum error figure of 0.078 and a minimum error figure of 0.0033 (at random training iteration 2213 – Fig. 6.).



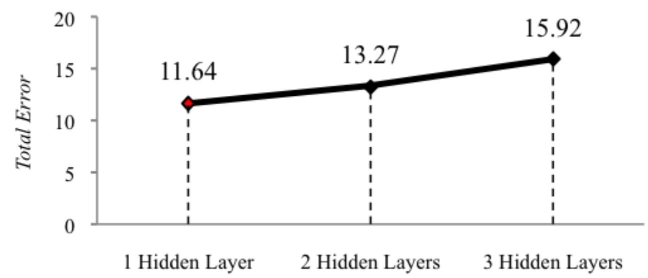


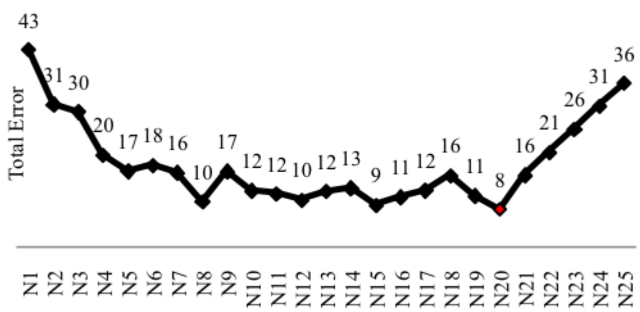
Figure 6 and 7: Patterns of error according to varying learning rate and Patterns of error according to varying hidden layer (3000 epochs)

3.2 Hidden layer variation results

In order to determine the optimum number of hidden layers, other factors were fixed as follows: 0.9 learning rate 4 input layer neurons, 6 hidden layer neurons per layer and 10 output neurons. The number of hidden layers was altered in three phases from 1 to 2 to 3. The total error according to the differing number of hidden layers is linear in fashion and the results can be seen in Fig. 7. The total error value between hidden layers 1 and 2 is relatively small, with 1 hidden layer boasting the optimal efficiency. The difference between the minimum and maximum value (1 hidden layer being the minimum and 3 hidden layers being the maximum respectively) is approximately 13%.

3.3 Hidden neuron variation results

The difference between the maximum and minimum total error rates is vast. Between 1 and 12 neurons a steady decline in the total error rate is apparent, save for neuron 8. Within the single hidden layer configuration, 20 hidden neurons proved to yield the lowest overall error rate with a total of 8.25 over 3000 training epochs. Beyond 20 neurons the error rate rises steeply, offering no improvement on the 20-hidden layer neuron formation. Probing into the two highest performing hidden neuron results graphs, clear distinctions can be seen that are not initially directly visible based on figure 15. The comparison shows that over the course of the 3000 training data sets, sample 20 converges to a far more stable error rate than sample 15 (Fig. 9.).



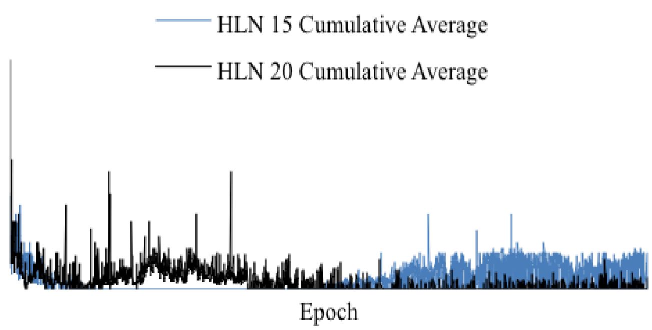


Figure 8 and 9: Patterns of error according to varying hidden neuron number and A comparison of the lowest scoring error rates (3000 epochs)

3.4 Optimal values for ANN architecture

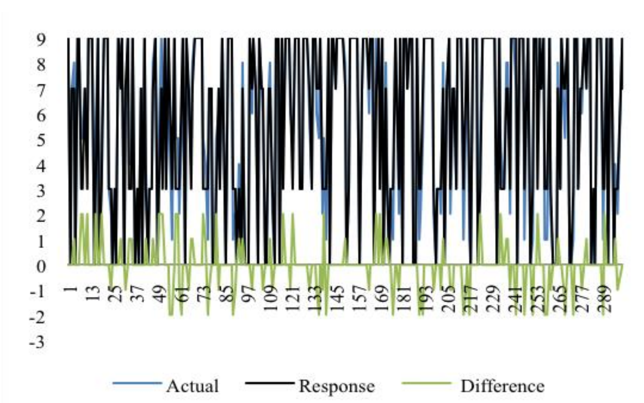
The optimal values of the floating variable learning factors have been fixed through variation and response analysis. The optimised values for to determine the correct louver angle upon recall is summarised in Table 2.

Table 2: Optimised values to be used in louver ANN architecture

Variable	*Optimum Value*
Learning Rate	*0.9*
Number of Hidden Layers	*1*
Number of Hidden Neurons	*20*

4 Evaluating the optimised model

The values of each learning factor have been determined with the intention of reducing the overall errors in the network to the minimum value possible. Theoretically, a lower value ascertained while learning should minimise the errors in louvre angle prediction when tested. The neural networks demonstrated ability to learn must be assessed to determine whether it can regulate the correct blade angle with precision. The performance of the network has been assessed through the comparison of the result given through network recollection (*response*) to the output learning data gathered from the physical shading system (*actual*). Testing the system has been done using the following deduced ANN configuration: 4 input neurons, 1 hidden layer, 20 hidden neurons, 10 output neurons and 0.9 learning rate. Overall, the network averaged a blade error of 4.3^o per epoch suggesting modest prediction accuracy. Over 70% of the tested sample was correctly recalled by the newly trained neural network (71.3% - 214/300- Fig. 10). Such a large percentage further illustrates the success of the delineation of the variables' in previous experiments. Approximately one fifth (15.6%) resulted in a ten-degree error swing, 8.6% of this was undershooting by ten degrees with the remainder overshooting by ten degrees. The remaining 13% resulted in a twenty-degree error swing, 6.25% of this subtotal was undershooting by twenty degrees with the remaining 6.75% overshooting. The small errors displayed are a direct result of the readings taken while stepping towards the desired lux level at the time of data collection. It also explains the reason why the error in network recall never exceeded 20 degrees. This data overlapping can be deemed as the cause for any difference in blade angle. The reason the amount of incorrect recall rates seem lower at the extremities (i.e. 0 degrees and 90 degrees) is due to the difference in user override function (i.e. 100/0 = -1/+1) tipping any seemingly similar results in terms of lux level into distinction from one another.



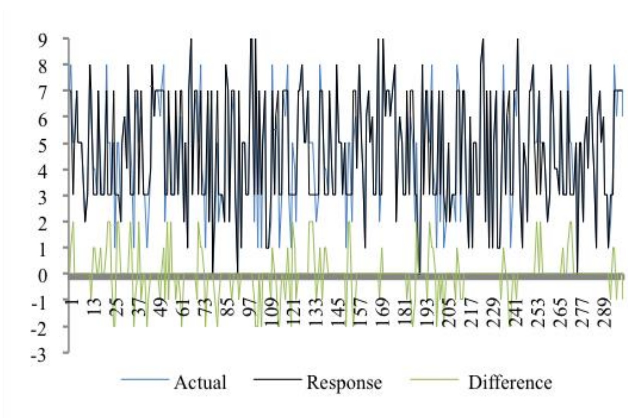


*Figure 10 and 11**:** Trained accuracy and Tested accuracy based on user override function (300 epochs)*

5 Testing the model seperately

To confirm the suspected theory arising as a result from the previous test, a final experiment was conducted. The previously mixed environmental and user override data has now been split into two separate training categories respectively. The first test was concerned primarily with the user override recall prediction accuracy. The second looked at the environmental input recall prediction accuracy. By isolating the two modes it allows for a deeper understanding of which part of the physical system was contributing to the eventual errors in recall. There were zero testing inaccuracies when recalling user-overridden preferences to set the blade angle fully open or fully closed. The optimised network produced a 0% error rate when tested randomly over 300 overridden epochs. Fig. 11 highlights the recall accuracy of the network based on the blade angle when in environmental mode. In this instance the recall prediction accuracy was at 70.5% (constituting an error rate of 29.5% -212/300 correctly recalled). In a similar vein to the previously amalgamated experiment, the recall inaccuracy never falls below 20^0, corroborating the theory discussed previously relating to the physical systems stepper function and subsequent data recording while the stepper function was engaged.

6 Conclusions

In this paper, a method consisting of a series of experiments has been presented in an attempt to compile a supervised artificial neural network configuration to enable the successful recall of the shading systems blade angles based on environmental and user inputs.

The research involved the creation of dynamic, adaptive façade and to understand how such a system, once trained, would perform autonomously. The experiments conducted allowed for the convergence of differing variables within the ANN to be ascertained in a bid to minimise the error in the weightings between adjoining layers in the network. The minimisation of error translated into what would be the optimal system based on the fixed inputs and outputs. What has successfully been achieved is the proof of concept that underpinned the subsequent aim of the research. This study was related to whether an adaptive façade could be trained to handle multiple inputs from environmental and human origin and translate such inputs simultaneously to achieve an adaptive architectural entity. In the pursuit of global stability within the system, the series of learning experiments informed the network architecture configuration prior to the assessment of its recall ability when tested. The training results appeared amicable and showed a clear demonstration of the benefits of the optimised neural network configuration.

One underlying drawback was the appearance of duplicate or overlapping data within the training set (as a result of the stepper function while in environmental mode), which subsequently led to adverse effects on the networks recall capacity. While an average recall error of less than 5^o over the 300 testing sets could be considered a successful demonstration of a systems ability to learn based on multiple inputs, there is room to improve these results in future.

Specific questions arising from the research are as follows:

1) To what degree can time improve the recall rate of the neural network?
2) To what degree does sufficiently robust user regularity improve the recall rate of the neural network?
3) To what degree would the user override function be a feasible input beyond the fully open/ fully closed configuration and what impact would an expansion of user override ability affect future recall success?

Such questions have emerged from the results of the work to date because they still remain almost wholly unanswered. The scientific contribution of the work was focussed on network performance and the questions listed above have arisen as a consequence of the results of the analysis. The questions outlined seem the next feasible step in building upon the current knowledge achieved within the scope of this research.

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