CALIBRATION AND MODELING FOR A DASHBOARD THAT PROVIDES REAL-TIME FEEDBACK ON ENERGY SAVING STRATEGIES

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ABSTRACT
A new approach toward using building dashboards to educate building users is proposed, and a modeling framework tested for a sample building. The goal was to create a methodology that allows the user to select from a variety of potentially energy saving actions or green building operation strategies and see how the hypothetical change would affect the building’s energy consumption both at the current moment and over the year. Neural networks, trained with extensive stochastic runs of a calibrated Energy Plus model, provide a quick estimate of the instantaneous savings or cost of implementing a given scenario, with a level of calculation intensity that can be completed repeatedly on a tablet or a server serving multiple tablets. The error was tested with a year of simulation data, and each scenario demonstrates less than 6% bias error in the energy savings.

INTRODUCTION
Buildings are responsible for the consumption of 40% of primary energy in the US, 80% of which derives from fossil fuels (Primary, 2010; Energy, 2010). In order to reduce the energy intensity of the building sector, advances can be made not only in system design, but also in efficient operations and occupant behavior and education. Research and development efforts are increasing for stationary and mobile dashboard applications that inform building occupants of the current and historical energy consumption of their building. In order to show occupants how to make the most energy-conscious decisions at a given time, a prediction capability could be added to these applications. Depending on the time of day, state of the building, and weather, the optimal behaviors for occupants or the expected return for a given choice changes. This paper explores a computational method, which is simple enough to be run on a mobile device, for creating real-time predictions for a number of optional occupant behavior, constructions and operational scenarios. To accomplish this, neural networks were trained using data from extensive runs of a calibrated building model.

A number of recent papers have demonstrated the significant effect that occupant behavior has on the energy consumption of a building. One simulation study found that modeling results have particularly high sensitivity to occupant equipment use, lighting use, temperature set points, schedules, and after-hours setbacks (Azar, 2012). In a residential setting, the energy consumption of a building inhabited by occupants with energy intensive behavior patterns can be several times higher than a building with energy conscious occupants (Peng, 2012). Shading is a strategy that has been studied extensively, and is very sensitive to the occupant’s understanding and consistent operation (Hoes, 2009). The uncertainty in a pre-occupancy model has been shown to range from -29% to 79%, resulting from the inability to predict the behavior of the occupants and methods of operations (Wang, 2012). Occupant behavior and interaction with building systems is clearly a source of unpredictability in building performance prediction and an opportunity for improving the energy efficiency of buildings.

There have also been a number of recent applications of neural networks in the building modeling field. They were primarily used for finding energy requirements, predicting air temperatures and thermal comfort, and analyzing or optimizing HVAC systems and controls (Kumar, 2013). Neural networks were used to predict real-time energy consumption and comfort, where those metrics were not directly measureable (Boithias, 2012). Similarly, a research group trained them to compute the thermal comfort metric of predicted mean vote (PMV) for use in predictive modeling and the optimization of controls (Ferriera, 2012). Neural networks were shown to successfully predict the real-time cooling load from a few weather variables and building states (Kwok, 2011). Another approach used them with environmental variables and an electricity meter as a proxy for occupancy to compute the cooling energy consumption (Leung, 2012). One study set up a neural network-based system to analyze the applicability of daylighting to a proposed design, showing them to be more accurate than multi-variable regression (Fonseca, 2013). Neural networks...
provide a low-computation, but often high accuracy, approximation to complex models. This study fits neural networks to model data in order to make real-time predictions of the energy savings of a number of occupant behavior, building construction and building operations scenarios.

The methods presented in this study are intended to be used in the framework of a mobile dashboard to add a module for educating building occupants on the energy savings of alternative behaviors, operational scenarios, and constructions. A building dashboard application is a system that displays real-time building states such as energy consumption and comfort metrics. It often displays historical data, uses a graphical, user-friendly format, and may be internet-based or developed for mobile devices. Some dashboards include energy targets or integrated remote controls.

Much of the literature on these systems focuses on the study of the disaggregation of energy consumption to end use or specific appliances, for display to the occupant. The ergonomics and layout of the systems are important in order for them to be adopted by and understandable to occupants, and this is also the subject of study. One research group developed an ‘ecofeedback’ dashboard for dormitory residents, and tested multiple variations of the application indicating a possible preference for consumption data that is disaggregated and an easy view of historical consumption data (Jain, 2012). Another study of a residential dashboard showed that a simpler form with dollar-feedback and appliance specific data was preferred (Krishnamurti, 2013). One dashboard used a virtual environment combined with physical sensors to display energy consumption (Alahmad, 2011). The display of real time energy data alone can result in a 2% to 11% reduction in consumption (Martinez, 2010). While these results are promising, this study explores the concept and possible outcomes of going beyond disaggregation and display of real-time consumption data to the display of real time hypothetical savings data. As an example, this is the difference between seeing on the display the consumption of an unused office printer, and seeing the quantitative impact on the energy consumption of all building systems of turning the printer off.

One way to accomplish the calculations for this purpose would be simultaneous co-simulation of each parametric model using the weather and other building states as boundary conditions. This is not possible, due to computational limitations. The 20-node neural networks used in this study are comparatively simple functions that can be implemented in most programming languages and are computationally inexpensive enough to be calculated on a mobile device.

The first step in model development was the calibration of an Energy Plus model for the case study building, the (Removed for double blind). Then, parametric models were created to represent each scenario. The simulation results were used to train neural networks using each time step’s energy use and weather states as inputs, and the energy savings as the target. The resulting networks were validated using a different set of simulation outputs, and the resulting error margins are presented here.

**BUILDING ENERGY MODELING**

A building energy model was created and calibrated for the (Removed for double blind), shown in Figure 1. This is a multi-purpose building with office, open office, dry lab, wet lab, and atrium spaces. The building is rated LEED Gold, with a sealed envelope and variable air volume (VAV) heating, ventilation and air conditioning (HVAC) system supplied by campus district heating and cooling. It spans three floors and approximately 3,400 m2 of occupied space. A building dashboard wirelessly displays data from the building automation system (BAS) such as space temperatures and energy consumption, in addition to dynamic life cycle assessment metrics on the life-cycle environmental impacts of the building (Collinge, 2012).

The building model included the annex shown in Figure 1 and the second floor of the adjacent tower. The center and south-east portions of the tower are large wet-lab spaces with four fume hoods. The opposite two sides are lined by offices, with student work spaces in the corridor. The annex has offices, a reception area, and a conference room on the first floor. The second floor is mainly open office and dry lab spaces, with a conference room. The third floor is open office and a conference room. The right side of Figure 1 shows the atrium space, which has a stairway spanning the three floors and is open to the tower.

A base geometry model was created, and edited using EnergyPlus IDF Editor. Three air loops were modeled to represent the three air systems in the building. An outside air system with heat recovery serves the wet labs and fume hoods. An economizing system provides air for the other spaces. Both of these systems had variable frequency drives on the pumps and fans and supply reheat boxes with hot water reheat. A third loop recirculates air to supply
cooling to the server rooms. A district plant provided the heating and cooling to the air handling units and reheat boxes. To model the district plant, a constant EER and boiler efficiency were applied to the total heating and cooling loads because no data were available for the campus plant performance.

The building automation system (BAS) and an air quality monitoring system provided extensive high resolution data for calibration and schedule creation. This system includes hot and cold water meters, plug load and lighting consumption meters, fan meters, CO₂ sensors, and air flow, temperature and humidity meters for each air handling unit and reheat branch. To create schedules, the occupancy levels were found by using a mass balance of CO₂ exhausted from, ventilated to, and generated in each space. The electric, lighting, and occupancy data were resolved enough to create four plug load, two lighting, and six occupancy schedules.

The building structures were modeled based on construction documents, and each component of the HVAC system was calibrated to the data available from the BAS system. Fan performance and pressure drop, economizer controls, temperature set points and other controls parameters were confirmed or adjusted to match the data. As the calibration proceeded, the model results for 2012, run with the hourly occupancy and gains schedules and a weather file for Pittsburgh International Airport, converged to the energy consumption as calculated from the BAS data for that year. The model is considered calibrated for both the hourly and monthly methods.

The Energy Plus model of the building was calibrated using the evidence-based methodology described by Raftery et al. (Raftery, 2011). The resulting calibration error for monthly validation was 1.3% normalized mean bias error (NMBE) and 7.1% coefficient of variation of the root mean square error (CVRMSE), and hourly error was 1.2% bias error and 15.2% CVRMSE. Both are well within the guidelines set forth by ASHRAE for a calibrated model, where the CVRMSE is the normalized root mean square error of the hourly predictions and the NMBE is the average error as a portion of the total energy consumption.

Using the calibrated model as a baseline, eleven alternative models were created to represent the scenarios described in Table 1. These include six occupant behaviors or choices such as changing the shading or temperature set point. The other five scenarios are operational characteristics of the HVAC system or changes to the physical building, including night setback, demand control ventilation, and insulation levels. The scenarios were chosen to provide a range of understandable options to the dashboard user for exploration. They include hands-on measures that a building occupant can control independently, and aspects of the green building and its systems of which the user may be less aware.

Each model was simulated for three sample years. These are the weather years from 2010 to 2012. Weather data for the nearby Pittsburgh International Airport was obtained in the Energy Plus weather file format (.epw) from a commercial provider. Different hourly electric, lighting and occupancy schedules were developed for each year, based on the gains data recorded by the BAS. The days of recorded schedule data were divided into day types. Then, each new stochastic annual schedule was created by randomly assigning data days to each day of the simulation year, according to day type. This method preserved the statistical properties of the gains data while also representing random variations present in occupancy and building use and creating three unique schedules.

Table 1. Behavior, Constructions and Operations Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shading</td>
<td>Behavior</td>
<td>Interior roll blinds, 20% transparent, rolled down over sun-facing windows</td>
</tr>
<tr>
<td>Shading 50%</td>
<td>Behavior</td>
<td>Interior roll blinds, 40% transparent, rolled down over sun-facing windows</td>
</tr>
<tr>
<td>Temperature Decrease</td>
<td>Behavior</td>
<td>Interior space temperature set-points decreased by 1°C</td>
</tr>
<tr>
<td>Temperature Increase</td>
<td>Behavior</td>
<td>Interior space temperature set-points increased by 1°C</td>
</tr>
<tr>
<td>Widen Temperature Band</td>
<td>Operational</td>
<td>Upper set-point increased and lower decreased by 1°C</td>
</tr>
<tr>
<td>Decrease Plug Load</td>
<td>Behavior</td>
<td>10% reduction in space electrical loads, not including server room equipment</td>
</tr>
<tr>
<td>Night Temp Setback</td>
<td>Operational</td>
<td>2°C setback from 9 PM to 7 AM</td>
</tr>
<tr>
<td>Less Reflective Roof</td>
<td>Construction</td>
<td>Roof material with 50% increased absorptance</td>
</tr>
<tr>
<td>Increase Insulation</td>
<td>Construction</td>
<td>Insulation with 50% increase in thickness</td>
</tr>
<tr>
<td>Daylight Dimming</td>
<td>Operational</td>
<td>Continuous dimming in office, open office and dry lab spaces</td>
</tr>
<tr>
<td>Demand Control Ventilation</td>
<td>Operational</td>
<td>Demand controlled ventilation in office, open office, dry lab, and wet lab spaces.</td>
</tr>
</tbody>
</table>

ARTIFICIAL NEURAL NETWORK MODELING

A number of assumptions were made in the real-time modeling of the scenarios. The model is intended to provide a real time prediction of the instantaneous hypothetical energy savings for each measure for the current one-hour timestep, not a prediction into future timesteps. It neglects the dynamic effects of the measures and the building operation due to the thermal mass of the components and delays in
Air conditioning and heating HVAC controls, and the effect of this assumption is further discussed in the Results section. The model is tested for the baseline operation of the building, using building energy model results. It does not have the capability to determine the interactions between measures, and has not been tested for robustness to noise or changes in the building operation away from the baseline. The model is developed for use as an educational tool to demonstrate the effects, compared to the baseline, of hypothetical behavioural, operational and construction changes in real time, depending on the states of the weather and building operation.

Artificial neural networks (ANNs) consist of multiple layers of nodes, connected with weighting factors and biases. In a feed-forward, back-propagation ANN, there is an input layer, one or more hidden layers, and an output layer. For a three layer, single output network the output of each hidden layer node is given by (Eq. 1):

\[
y_1, i = \frac{2}{1 - e^{-2(a_1, ij + b_1, i)}} - 1
\]  

Here, \(y_1, i\) is the output of hidden layer node \(i\), \(a_{1, ij}\) is the first weighting factor for node \(i\), input \(j\), \(x_j\) is the input \(j\), and \(b_{1, i}\) is the second weighting factor for hidden node \(i\). The output layer, which in this case consists of a single node, is represented by (Eq. 2):

\[
y_2 = \frac{2}{1 - e^{-2(a_2, i + b_2)}} - 1
\]  

\(y_2\) is the output, \(a_{2, i}\) is the first weighting factor for the input from hidden node \(i\), and \(b_2\) is the second weighting factor for the output layer.

The artificial neural network is characterized by the architecture, the number of nodes and layers, and the weighting factors. The weighting factors can be chosen by one of a number of training algorithms using sample data. The Levenberg-Marquardt algorithm was used in this study. This algorithm minimizes the root mean square error in the outputs of the ANN for the training data set, compared to the actual training outputs. It interpolates between the Gauss-Newton algorithm and the method of gradient descent (Levenberg, 1944).

The first two simulation years were used for training neural networks, and the third for validation. Each time step formed an input-target pair, with the inputs being: outside air dry bulb temperature, outside air relative humidity, wind speed, wind direction, diffuse radiation, direct radiation, occupancy, day of the year, hour of the day, plug load, lighting load, fans consumption rate, heating load, cooling load, and total energy consumption. Each of these is monitored by a weather station and the BAS. The targets for training the networks were the total and individual end use energy consumption savings ratios. This ratio is the difference between the baseline and scenario energy consumption for the given hour divided by the baseline consumption.

The training module randomly divided the two years of training inputs into 80% training entries, 10% validation entries, and 10% test entries. It stopped training when a mean square error of the test data started to record an increasing level of error, thereby preventing overtraining. To find the optimal number of nodes, parametric runs for two to forty nodes were completed, as shown in Figure 2. For each model, twenty was found to be an adequate hidden layer size. A higher number may increase accuracy for the end use calculations, but twenty was chosen for consistency and computational simplicity. Adding multiple hidden layers did not increase the accuracy of the fit to the data.

![Figure 2: Error as a function of the number of hidden nodes for a) each scenario, and b) each end use in the daylight dimming sample scenario](image)

Finally, the neural networks were run for the entire third year of input data and the resulting outputs were compared to the simulated savings for each hour. This comparison of an entire year of simulation data was used to estimate the CVRMSE and bias error, normalized to the average savings ratio.

**RESULTS**

The neural network fits to the model outputs of total energy consumption were tested for an entire simulation year not used in training, and the results are shown in Figure 3 and 4. Figure 3 shows the error normalized by consumption. The mean bias error is very small for all scenarios, with the largest error of 0.15% for night temperature setback. The CVRMSE is also relatively small for most scenarios at around 2%, although it reaches 6% for the night setback scenario.

Figure 4 shows the error normalized by energy savings. The mean bias error for the neural network approach was less than 6% for all of the scenarios tested, with the smaller normalizing factor of energy savings. This indicates that on average, the functions estimate the savings for each scenario well. The CVRMSE is calculated by normalizing the root mean square error with the average energy savings, which is relatively small in some cases, and indicates a higher degree of uncertainty for some of the scenarios. Demand controlled ventilation and the temperature set point changes have a low CVRMSE, indicating a close fit over most of the time steps. Increasing insulation, daylight dimming, and decreasing the plug load have slightly higher CVRMSE of approximately 20% when normalized.
by savings. The networks don’t fit to the night temperature setback as well as the other temperature scenarios because the neural networks have trouble discriminating between night and day time steps with high precision. The effects of insulation and wall thickness are highly dynamic because of the effects of the thermal mass of the wall and other building components, and therefore may not be approximated by the static fit as easily. Shading has a higher CVRMSE because of the complicated solar angle and dynamic building interactions, as well as a relatively low normalizing factor. The scenario with a normal roof rather than the high albedo green roof also has a very low normalizing energy savings ratio.

Figure 5 shows the breakdown of error for networks trained to each energy end use for the daylight dimming scenario, which had a medium overall error. The error in this figure is normalized by energy consumption. With this method of normalization, the magnitude of the bias error reaches 2% for pumps and the CVRMSE reaches 2.5% for lighting.

Figure 6 shows the same error normalized by energy savings. The largest level of energy savings is in the lighting category, and the smallest normalized errors are in this category. This indicates that the network predicts the resulting lighting energy savings due to daylighting with good accuracy. The higher normalized errors are in the secondary energy categories. There is a higher level of interactions in these categories, in addition to lower normalizing savings ratios. The highest NMSE and CVRMSE are for pumps, which are a small proportion of the energy savings. The fans and cooling also have high levels of error, and are secondary energy impacts of the measure. The heating level is more predictable, probably because the reheat, which constitutes the majority of heating consumption, is more directly related to the level of energy spent on lighting in the spaces. The total errors are calculated separately, and are relatively small because the largest component is the more predictable lighting system.

The R-squared values were calculated for each input to explore the impact of each on the prediction capability of the neural networks. A single input neural network was trained for each input, and the R-squared value for each and for the combination of all inputs is shown in Table 2. A high R-squared value indicates that there is a high correlation between the variable and the model output, and the variable is therefore useful in estimating the model output. Dry bulb temperature, solar radiation, hour of the day, and heating and cooling loads have high R-squared values.

Figure 3: Error for an annual test of the neural networks for each scenario normalized by energy consumption, calculated as a) bias error and b) coefficient of variation of the root mean square error

Figure 4: Error for an annual test of the neural networks for each scenario normalized by scenario energy savings, calculated as a) bias error and b) coefficient of variation of the root mean square error
The wind speed and direction, relative humidity, and plug and lighting consumption have lower R-squared and may be unnecessary as inputs. Some inputs are only useful in predicting savings for certain scenarios, such as day of the year for predicting the effect of increasing insulation.

Sample time steps were chosen for winter and summer afternoons to explore the impact of error on the results. Figure 7 is a bar graph comparing the total energy consumption for each scenario for the two time steps. The error bars indicate the 75% confidence intervals. The uncertainty range is very large for the night temperature setback scenario, but for most of the models, uncertainty is small compared to the energy savings. Implementing demand controlled ventilation is by far the most energy-saving measure for both winter and summer time steps and its confidence interval is large in magnitude.
Figure 8 and 9 show a more in depth look at the two time steps for the daylight dimming scenario. Figure 8 shows the end use energy consumption and Figure 9 shows the change in consumption, for the winter and summer timesteps. Again, error bars represent the confidence intervals. There is no change or error in the plug load, which is unaffected by lighting. There are significant lighting savings in both winter and summer. In summer, the reduction in internal loads results in lower cooling load and a lower ventilation rate, reducing the consumption for fans and pumps. The reheat is higher, because of the fixed supply air temperature, minimum ventilation rate, and significant reduction in internal gains. For the winter, there is a similar reduction in lighting consumption, a small relative increase in heating consumption and a large relative increase in cooling consumption. To meet the increased heating load, a higher ventilation rate is required. The cooling is negligible in the winter and appears to have a small increase because of the uncertainty in the output. The small relative increase in heating load negates most of the energy savings from lighting for this time step.

CONCLUSION

To create a method for estimating real-time energy savings for building scenarios for an educational dashboard application, neural networks were used to fit model data and predict the energy savings for a set of building operations and user behavior scenarios based on the states of weather conditions and building automation system variables which are available in real-time. The twenty-node triple layer feedforward backpropagation neural network was shown to have less than 6% bias error for all scenarios and end uses when normalized by energy savings. The CVRMSE ranged from 5% to 40%, depending on the scenario. Total R-squared values measuring the fit of the neural network to the input states were above 0.87 for all scenarios. The uncertainty intervals were demonstrated to be tight enough to allow the use of the data for demonstrative and educational purposes.

NOMENCLATURE

\[ y_{1,i} = \text{output of hidden layer node } i \]
\[ a_{1,j} = \text{first weighting factor for node } i, \text{ input } j \]
\[ b_{1,i} = \text{second weighting factor for hidden node } i \]
\[ x_j = \text{network input } j \]
\[ y_2 = \text{network output} \]
$a_{ji} = \text{first weighting factor for hidden node } i$

$b_j = \text{second weighting factor for the output layer}$

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation under EFRI-SEED Grant No. (Removed for double-blind), an ASHRAE Graduate Grant-In-Aid, and (Removed for double blind).

REFERENCES


