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Developing Learning-Based Models for Occupant Centric Control

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ABSTRACT

Use of advanced building control strategies, including model predictive control, is an enabling strategy to achieve Grid-interactive Efficient Buildings (GEB). Many literature-reported control strategies are designed around an ideal building and do not account for the behavior of occupants. Yet research and field studies have shown that occupant behaviors have strong impact on building operation and energy consumption. Occupants who are uncomfortable with the control strategy will often adjust the thermostat, open/close a window, or use a personal fan/heater to better suit their comfort. How to incorporate occupant behaviors into advanced control strategies has been a focus in many of the recent occupant centric control (OCC) studies. Major challenges for OCC development include forecasting occupants' thermal comfort and behaviors and forecasting building energy with the consideration of occupant behavior. This study explores the feasibility of employing machine learning techniques, including active learning, Artificial Neural Network (ANN), and feature selection, to develop energy forecasting models that incorporate the occupant behaviors into the forecasting. To generate training and testing data needed for the control model formation, a co-simulation virtual building testbed, which utilizes a DOE Prototype residential building model developed in the EnergyPlus environment is developed. The virtual testbed also includes an Occupant Behavior Module (OBM) which is based on a previously reported agent-based-model to simulate occupants' thermal behavior in the MATLAB SIMULINK environment. Functional Mockup Units (FMU) is used to interface between the EnergyPlus environment and the MATLAB Simulink environment. The virtual testbed is used to generate both training and testing data for typical summer weather. The accuracy and scalability (under different weather and operation conditions) of the ANN-based control models are reported and compared with conventional control models. How to select and evaluate the architecture of the ANN model that is computationally efficient but also can capture the complexity of the interaction between building systems and occupants, is discussed.

1. INTRODUCTION

Advanced building control strategies have been developed in recent years with promising performance that enables Grid-interactive Efficient Buildings (GEB) to be realized. Thereunto, high-fidelity building energy forecasting modeling is critical for those control strategies and energy abnormality detection. Data-driven energy forecasting modeling approaches, especially those that use artificial intelligence methods, have demonstrated better cost-effectiveness and ease of application in the field, when compared with traditional physics-based methods (Zhang and Wen, 2021). However, these developed strategies are often developed without accounting for the behavior of its occupants. Building control strategy can be disrupted if it does not account for these stochastic occupant behaviors (Wei *et al.*, 2018). Occupant-centric Control (OCC) has therefore been a focus of many recent studies attempting to develop control strategies that incorporate occupants' needs and behaviors.

Recent OCC studies with implementation in real buildings have largely focused on individual zone level controls (e.g. thermostat, light switches) of commercial and academic buildings. These studies focused on sensing and collection of energy usage data with occupant comfort (collected by survey) considered (Park *et al.*, 2019). Other studies have used personal occupant thermal comfort sensors (e.g. wearables, smartphone apps) to collect data from occupants in real commercial buildings for use in training several types of machine learning-based models for forecasting of occupant thermal comfort (Xie *et al.*, 2020). Many studies that include machine learning-based methods, namely artificial neural networks (ANN), and support vector machines (SVM), for OCC focus on developing forecasting models for a group of occupants' thermal comfort. Studies focusing on personal comfort models (PCM) for individual occupant comfort rather than group models were the next largest category, surpassing OCC studies focused on developing models for optimization of the HVAC systems. These machine learning-based studies were found to outperform traditional predictive mean vote (PMV) occupant comfort models by significant margins (Fard *et al.*, 2022).

Based on these review papers, a gap exists in the literature, which is a lack of high fidelity and cost-effective energy forecasting model for MPC purposes in residential buildings when occupant behavior is included. Additionally, the use of machine learning methods, such as active learning, to increase the accuracy of these forecasting models, has been identified as a gap in the literature. The focus of this study has therefore been the development of a high-fidelity energy forecasting model that considers occupant behavior in residential buildings for use in a future occupant centric advanced control strategy. This study focuses heavily on the impact of occupant behavior and active learning on the accuracy of energy forecasting models. Data-driven approaches are the focus of this study based on their cost-effectiveness reported in the literature. In lieu of real building data, a virtual testbed is developed and used to generate data for this study.

The rest of this paper is organized as follows: First, the virtual testbed and its virtual measurements are described. Following is background information on the feature selection and active learning processes. Secondly, we discuss machine learning models used throughout this study, followed by an analysis on the test cases designed and the generation of data for these cases. Finally, the results of the model testing are presented.

2. VIRTUAL TESTBED

This study utilized data generated from a DOE Prototype Residential Building (DOE) virtual testbed developed in EnergyPlus. The building is a two-story detached single-family home in Houston, TX, with one conditioned living zone and an unconditioned attic zone. Within the conditioned zone, there are three occupants and typical residential appliances, while the HVAC system components are primarily housed in the attic zone. The HVAC system is a dual-setpoint controlled central air heat pump system, using schedule-based fixed setpoint control. The three occupants, including their thermal comfort and behaviors, were simulated using a literature-reported occupant behavior model (OBM) based on Bayes' theorem and adopted as an agent-based simulation, as reported by Langevin (2015). Based on the simulated indoor environmental conditions, the OBM forecasts occupants' thermal sensation. Occupants' thermal comfort was determined by comparing their thermal sensation with their thermally acceptable range based upon the Predicted Mean Vote curve detailed by De Dear (1998). If an occupants' thermal sensation was outside the acceptable range, the occupant would have a probability of taking actions to bring their sensation back into their acceptable range. Table 1 summarizes each occupant's thermally acceptable range. Figure 1 highlights the OBM occupant thermal behavior process.

Table 1: Occupant thermally acceptable ranges

Occupant	Thermally Acceptable Range	Notes
1	-1 to 1	Prefers neutral temperatures
2	-2 to 0	Prefers cooler temperatures
3	0 to 2	Prefers warmer temperature

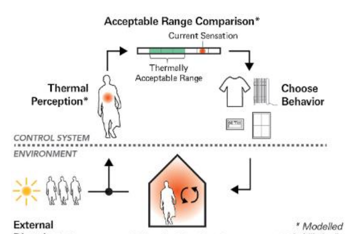

Figure 1: Occupant thermal behavior model using agent-based modeling (Langevin, 2016

The behavioral actions available to occupants' were changing their clothing level, drinking a cold/hot beverage, using a personal fan/heater, opening/closing the windows/doors/blinds, and adjusting the thermostat setpoint. These behavioral actions were assigned to both "action" and "action reversal" hierarchies that determined the order in which available behaviors were taken and/or reversed. Action reversal means adjusting the device back to its original state (e.g. occupant turned on a personal fan but now feels cold and will turn off the fan before other behaviors).

2.1 Co-Simulation Environment

A co-simulation environment was developed to incorporate the two components of the virtual building testbed, i.e., the EnergyPlus model, and the OBM in MATLAB. Moreover, two more components were connected with the virtual building testbed in this study: 1) active learning module coded in MATLAB, used for generating training data as explained later; and 2) developed energy forecasting models coded in both MATLAB and PYTHON. To allow for co-simulation of EnergyPlus and MATLAB/Python, Functional Mockup Units (FMU) were used. Figure 2 illustrates the active learning part (discussed below) of the co-simulation environment, while other parts of the co-simulation environment follow the same structure.

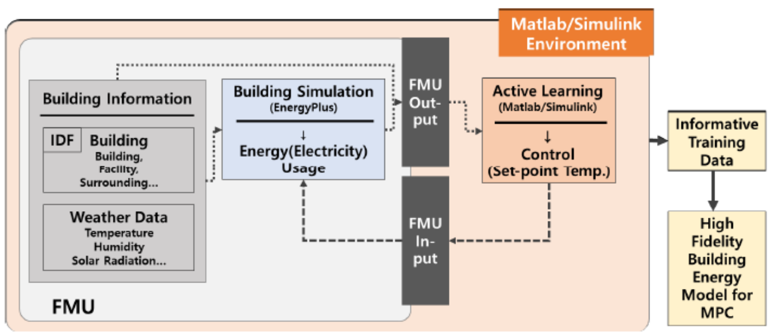

Figure 2: FMU co-simulation environment integrating EnergyPlus and MATLAB for use with active learning (Zhang and Wen, 2019).

3. VIRTUAL MEASUREMENTS AND CANDIDATE FEATURES

To develop a machine learning based model, inputs, i.e., features, are needed, which are typically selected from building measurements. The virtual testbed produces many outputs, namely virtual measurements. The candidate features used for this study were limited to features that could be measured in a real residential building. Some of the features, such as those related solar radiation, may not be easily measured for a residential building, but could be potentially obtained from a local weather station. The occupants' thermal comfort values were assumed to be obtained from market-available mobile tools, such as a smartphone app. These candidate features are summarized in Table 2. A feature selection process was used to identify the most relevant features for the energy forecasting model.

The features provided in Table 2 are shown with units in both the I-P and SI systems, denoted by [I-P, SI]. Features provided with empty [] are unitless. All features in the candidate feature set were provided at times t (current time), t-1 (previous time step), t-2 (two time steps earlier), and time t-3 (three time steps earlier). Time lag features were included because they can provide a richer dataset to capture any delayed effects on the target feature. The measurement sampling time used in this study was 1-hour for the development of an hour-ahead energy forecasting model. However, the virtual building, including its systems and occupants, were simulated with a one-minute time interval. The developed framework can be easily adapted for other energy forecasting horizons, such as 15-min ahead or 3-hour ahead. The candidate features also include control variables that are determined based on the need of the model predictive control strategy. The first three features in Table 2 represent the three setpoint control features used in this study while the fourth feature in Table 2, Whole Building Electric Energy Usage, is the target feature that the energy forecasting models predict, at time t+1 (one time step ahead).

Table 2: Candidate Feature Set

Feature Acronyms	Feature Name	Feature Acronym	Feature Name
ZTCSP	Zone Thermostat Cooling Setpoint Temperature [ºF, ºC]	SRDIR	Site Direct Solar Radiation Rate per Area [hp/ft^2, W/m^2]
LIGHT	Interior Lighting Level Fraction []		
DISH	Dishwasher Operational Fraction []	VMFR	Zone Ventilation Mass Flow Rate [slug/s, kg/s]
BLDGEE	Whole Building Electric Energy Usage [kWh, J]	ZAT	Zone Air Temperature [ºF, ºC]
OADB	Outdoor Air Drybulb Temperature [ºF, ºC]	ZARH	Zone Air Relative Humidity [%]
OAWB	Outdoor Air Wetbulb Temperature [ºF, ºC]	HPSS	Central Air Heat Pump Staged Signal []
OABP	Outdoor Air Barometric Pressure [psi, Pa]	SFMFR	Supply Fan Mass Flow Rate [slug/s, kg/s]
OAWS	Site Wind Speed [ft/s, m/s]	OCC1	Occupant 1 Thermal Comfort Value []
OAWD	Site Wind Direction [deg]	OCC2	Occupant 2 Thermal Comfort Value []
SRDIF	Site Diffuse Solar Radiation Rate per Area [hp/ft^2, W/m^2]	OCC3	Occupant 3 Thermal Comfort Value []

4. FEATURE SELECTION PROCESS

A systematic multi-step feature selection process, using historic building data (generated from the virtual testbed in this study), was performed firstly to identify the best set of features used to forecast the building energy. Figure 3 shows the steps of the process. Step 1 of this process was performed offline and results in the candidate feature set shown in Table 2. Step 2 utilized Pearson's Correlation Coefficients to remove irrelevant and redundant features while Step 3 used a machine learning based model structure, which is MARS/ANN for this study, to determine the final feature set with the best goodness of fit. The features selected from this process are specific to each test case described below.

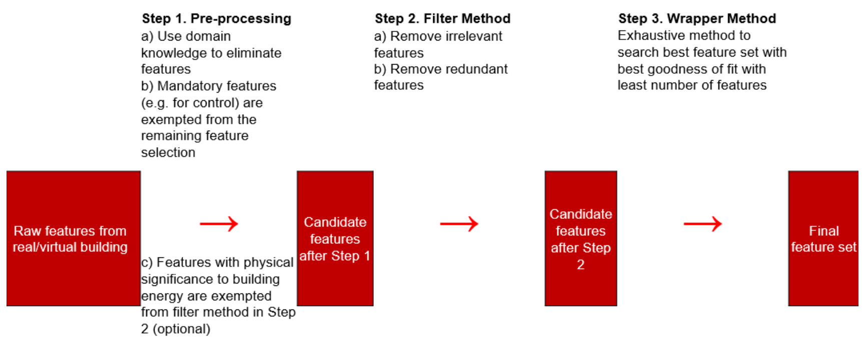

Figure 3: Systematic Multi-Step Feature Selection Process (Recreated from Zhang and Wen, 2019)

5. ACTIVE LEARNING PROCESS

A commonly reported issue with data-driven model development using historical building data is data bias. Buildings often are operated under very limited operation range. For example, zone temperature setpoint typically is not varied during normal operation. Models trained with such biased data do not have good generalization when used for MPC. To reduce data bias and increase training data quality, active learning, a machine learning technique was used to generate information-rich data for some of the forecasting models described below. A detailed description of active learning can be found from Zhang and Wen (2021). In brief, the active learning algorithm perturbs building operation in a cost-effective manner, to produce information-rich building operation data that are outside of normal operation conditions. Active learning can be used for both real buildings and virtual buildings (in this study). These conditions generated through the active learning algorithm would be similar to how the building would perform under demand response conditions. This process requires a baseline model (Model 0 below) to be used as a starting point for the forecasting model. The process is shown through pseudo-code in Figure 4 below. In a real building, active learning could be applied during the unoccupied time.

Algorithm: Expected Error Reduction in the Context of Building Energy Forecasting Model

1: Input: Normal operation data L (labeled), all possible setpoint combinations to be selected from U (unlabeled)
2: Repeat:
3: Train the building energy forecasting model $P_L(y_i|(x_i, w))$ on L. For each $x_i \in C$; x_i is controllable inputs (setpoints), w is disturbances, y_i is predicted building energy consumption.
4: for each $x_i \in U$, and its corresponding $y_i \in C$:
5: Re-train the energy forecasting model on $L' = L \cup k^*(x_i, w, y_i)$, k is the weight of added training data. The new model is marked as $P_{L'}(y_i|(x_i, w))$.
6: Calculate $V(x_i, w, y_i)$, which is the cross-validation error of $P_{L'}(y_i|(x_i, w))$.
7: end for
8: The selected (x_i, w, y_i) with the lowest $V(x_i, w, y_k)$ is marked as (x_k, w, y_k)
9: Query (or get energy consumption when applying the selected setpoint into the building) the instance (x_k, w, y_k), its energy consumption is labeled as y_k^*. The new training data is $L_i = (x_k, w, y_k^*)$. Update $L = L \cup k^*L_i$. Remove the selected combination of setpoints from the remaining setpoint combinations in the pool: $U = U \setminus x_k$.
10: Until running out of budget

Figure 4: Pseudocode of expected error reduction in the context of active learning for building energy forecasting models (from Zhang and Wen, 2019).

6. MACHINE LEARNING MODELS

Many regression or machine learning models have been reported in the literature for energy forecasting modeling (Zhang et al. 2020). For this study, two types of models are selected: Multivariate Adaptive Regression Spline (MARS) models, and Artificial Neural Network (ANN) models. MARS models had shown good performance for energy forecasting models without occupant behavior in previous studies (Cheng and Cao, 2014). ANN, however, have been reported in the literature to be able to capture stochastic occupant behavior better than other ML models (Fard *et al.*, 2022).

6.1 MARS

MARS models are non-parametric regression models that create a series of non-linear basis functions to predict target values. These basis functions are hinge functions that allow non-linearity. A final MARS model is created in two stages, a forward phase which creates a host of candidate basis functions, and a backward phase which deletes basis functions until the final selection of functions is made. They were developed by Friedman (1991). MARS does not require too much training data but can be sensitive to input data behavior.

6.2 ANN

ANN models are designed to mimic the neural networks found in the human brain and are comprised of layers of neurons that use weights and biases to learn representations of data. Each neuron in a network contains an activation function that processes the inputs and results in new outputs. A common activation function is a Sigmoid function (Seo *et al*., 2019). ANN models can solve incredibly complex problems by creating a network with varying layers of connected neurons to map the data. The structure of an ANN is split into three categories, the input layer, the hidden layers, and the output layer. The computation is performed within the hidden layers and includes the activation functions. These ANNs require significant amounts of training data to accurately learn the problem without overfitting. ANN models are widespread in forecasting problems and have shown excellent performance (Afram *et al.*, 2017). For this study, a simple feed forward MLP ANN was used for most of the study, and a deep ANN – in the form of a recurrent neural network (RNN) - was introduced late into the study for comparison’s sake.

7. TEST CASES FOR MODEL COMPARISON

In order to compare model performance under different scenarios, two test cases were designed for this study to understand how occupant behavior and active learning would affect energy forecasting accuracy. The two cases are summarized below in Table 3.

Table 3: Test Cases and Model Information for Energy Forecasting Model Comparison

	Model 0			Model 1		
Test Case	**Name**	**Model Type**	**Training Data**	**Name**	**Model Type**	**Dataset**
Case 1 (Ideal)	C1M0	MARS	Normal operation	C1M1	MARS	Normal operation + active learning operation
Case 2 (Real)	C2M0	MARS	Normal operation with occupant behavior	~~C2M1~~	~~MARS~~	~~Normal operation + active learning operation, with occupant behavior~~
	C2A0	ANN	Normal operation with occupant behavior	~~C2A1~~	~~ANN~~	~~Normal operation + active learning operation, with occupant behavior~~

Each of the two test cases were designed to provide a different combination of datasets with regard to occupant behavior. Test case 1 was the ideal building test case in which the occupants could not disrupt the building control system at any time, neither during the normal operation period nor the active learning operation period (both described below). As a result, the features related to occupant comfort are not included in Test case 1. Test case 2 represents a real building scenario where the occupants could disturb the building control system (e.g., changing their clothing level, drinking a cold beverage, operating a small personal fan, adjusting the thermostat) at any time. Both test cases are proposed to include a Model 0 and a Model 1. Model 0 is trained only on normal operation data while Model 1 is trained on an enriched dataset that includes normal operation data as well as active learning operation data.

During the study, it was found that the MARS model structure can be sensitive to input data. If the input data for a specific feature does not have enough variability, the MARS model building forward phase will fail to create any basis functions in that feature dimension and thus will not consider that feature in its forecast. While there is merit to the model not selecting a feature that is not informative to the forecast, the model failing to select a control feature (defined above) disrupts the ability for the OBM to interface with the building control scheme. To combat this sensitivity of MARS to input data, the MARS model is trained both with and without active learning data to provide a richer, more informative dataset that is less sensitive. Results are reported below for Case 1 Model 0 (C1M0) and Case 1 Model 1 (C1M1) on the performance of forecasting Whole Building Electric Energy Usage at time t+1. The ANN models trained do not have as great sensitivity to input data, rather are influenced more by the amount of training data and thus for this study, the training of Case 2 ANN Model 1 (C2A1) was not deemed necessary (given the performance of C2A0 below) and is not included but will be the topic of future studies.

8. DATA GENERATION

The generation of the data sets discussed in Table 3 is detailed in this section. All data for this study was generated using the above co-simulation environment of EnergyPlus and MATLAB/SIMULINK, designed around the summer season in Houston, TX. For Case 1 which utilizes the MARS models and does not include occupant disruption, the normal operation dataset was generated by co-simulating the virtual testbed during the first week of July (7/01 – 7/08) for summer conditions and was used to train C1M0. The active learning operation was generated during the following weekend in July (7/09 – 7/10) and utilizing C1M0 as a baseline, is used to trained C1M1. For Case 2 which utilizes an ANN model and does include occupant disruption, more historic building data was required for training due to the nature of ANN model development. Thus, the normal operation dataset was generated by co-simulating the virtual testbed for the month of June (6/01 – 6/30) to represent these conditions.

For both cases, two testing periods were used to assess the performance of the models. Each testing period lasted one week and represented different building operation conditions. The first testing period was generated during the week immediately after the active learning weekend (7/11 – 7/18) and represented normal operation conditions. The second testing period was generated during the following week (7/19 – 7/26) and represented demand response conditions. A dataset was generated for each test case for each testing period. For both cases, the three occupants are always present within the house. The occupants are sleeping between 10 PM and 6 AM. During normal operation, the thermostat controls the indoor temperature to be 72 [ºF] (22.22 [ºC]) when occupants are awake and 75 [ºF] (23.88 [ºC]) when occupants are asleep, for the summer season. The dishwasher appliance and the interior lighting system are both operated following a pre-defined schedule within EnergyPlus that represent a fraction (0 to 1) of their peak energy usage.

During the active learning operation, the algorithm perturbs the setpoints to be at varying levels between 59 [ºF] (15 [ºC]) and 84 [ºF] (28[ºC]). Given that under normal operation conditions, the dishwasher and lighting setpoints vary through most of the available range, the active learning algorithm perturbs these setpoints to simulate on/off control (e.g., 0.1 or 0.9). This perturbation occurs every 2-hours to allow the building and system to stabilize between perturbations. During the testing period that attempts to simulate a demand response operation, the three control setpoints are perturbed randomly. This random perturbation has the same perturbation frequency and setpoint range as those used in the active learning algorithm.

All other conditions are the same between test case 1 and 2, except that in test case 2, occupants can disrupt the system according to their thermal comfort. As discussed earlier, occupants are modeled using an agent-based occupant behavior module. A hierarchy exists in term of the thermal behavior that occupants can adopt. For this study, the rules ranked occupant disruption of the zone thermostat cooling setpoint as the last measure taken to address thermal discomfort. Occupants would try other behaviors such as changing their clothing level, drinking a cold beverage, and operating a small personal fan (low electricity consumption with negligible impact on whole building values) before adjusting the thermostat setpoint. Figure 5 below shows the effect of occupant disruption on the normal operation conditions for zone thermostat cooling setpoint temperature between Case 1 and Case 2. Figure 6 shows the corresponding whole building energy values for the same time period.

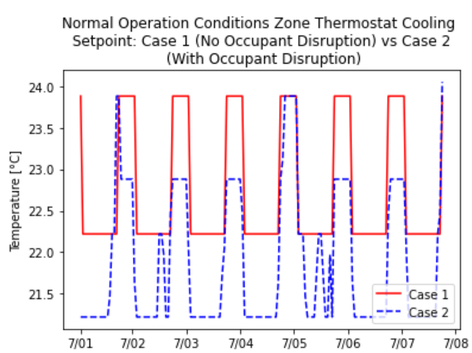

Figure 5: Normal Operation Conditions Zone Thermostat Cooling Setpoint: Case 1 (No Occupant Disruption) vs Case 2 (With Occupant Disruption)

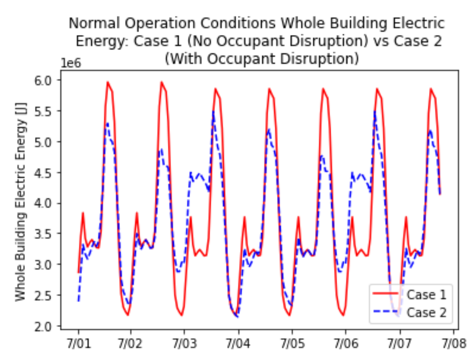

Figure 6: Normal Operation Conditions Whole Building Electric Energy: Case 1 (No Occupant Disruption) vs Case 2 (With Occupant Disruption)

Normalized Root Mean Square Error (NRMSE) of the predicted Whole Building Electric Energy at time t+1 (predicted using the models training data) vs the actual values, is used to evaluate model accuracy. Equation (1) is provided below: where $\hat{y}_i$ is the predicted value, and y_i is the actual value.

$$NRMSE = \frac{\sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}}{max_i y_i - min_i y_i} \qquad (1)$$

9. RESULTS

9.1 MARS Model Results

For Case 1 (Ideal building), two MARS models were created, C1M0, trained on the normal operation data set, and C1M1, trained on the enriched data set, which is obtained from an AL process. Both models were tested on the Case 1 with normal operation dataset as well as enriched dataset. Their performance is summarized in Table 4.

Table 4: Case 1 (Ideal) MARS Prediction NRMSE

Dataset	C1M0	C1M1	C2M0
Normal Operation Training	2%	5%	32%
Enriched Training	20%	6%	-
Normal Operation Testing	4%	6%	-
Demand Response Testing	81%	19%	-

The C1M0 model, trained on the normal operation dataset performs very well when tested on the normal operation dataset but does not reach the desired performance when tested on the demand response data set. The C1M1 model performs well on both datasets. The C2M0 model was not able to meet desired performance when occupant behavior was included. Figure 7 below shows the C2M0 model predicted Whole Building Electric Energy at Time t+1 vs. the actual values. While use of active learning to generate a more informative dataset showed good results for the C1M0 and C1M1 models, based on the magnitude of the C2M0 inaccuracy when evaluated using its own training data, it was determined that for this study, rather than study the impact of active learning for generation of a C2M1 model, the study would instead shift to focus on ANNs for Case 2. It was concluded that MARS was not comprehensive enough to capture the impact of occupant behavior on building energy consumption and thus ANNs were further studied.

9.2 ANN Model Results

For ANN models, the structure and hyperparameters of the model have a significant impact on the performance of the model, whereas for MARS models, the structure isn't as impactful as the input data is. For this study, significant testing (132 structures tested) for the best ANN structure and hyperparameters for this forecasting problem was performed based on Zhang et al., 1998) as shown in the following order: (1) testing to determine the best macro structure of the number of hidden layers (1, 2, or 3 layers) and the number of hidden neurons in each hidden layer; (2) testing to determine the most efficient optimizer for the ANN (Adam, SGD, etc.); (3) testing to determine the best activation function for the given structure and optimizer (Sigmoid, ReLU, SeLU, etc.); (4) testing to determine best learning rate; (5) retesting of the above for different training epochs if lack of convergence or model overfitting were found. The results this showed that the best structure for C2A0 was three hidden layers with 32, 4, and 1 neurons respectively. Each neuron utilized the Sigmoid activation function. The model was trained for 500 epochs with a learning rate of 0.01, used the ADAM optimizer and contained a 20% cross-validation data split. The model achieved a 3% NRMSE when evaluated on the Case 2 normal operation testing data set. Figure 8 shows the selected structure that predicted Whole Building Electric Energy at Time t+1 vs. the actual values.

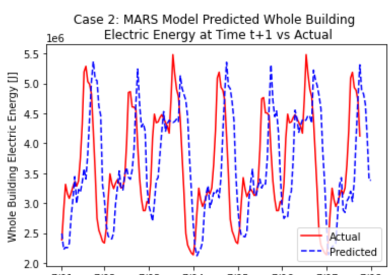

Figure 7: Case 2: MARS Model Predicted Whole Building Electric Energy at Time t+1 vs Actual

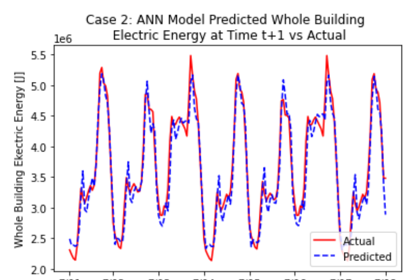

Figure 8: Case 2: ANN Model Predicted Whole Building Electric Energy at Time t+1 vs Actual

At this point it was obvious that a well-tuned simple ANN would have sufficient complexity to accurately forecast building energy when occupants' thermal behavior is included. However, for this study, it was of interest to investigate if a deep ANN would perform better and therefore literature was reviewed and a Recurrent Neural Network (RNN) was found as a suitable candidate for testing (Fan *et al.*, 2019). A model, C2R0 was trained and tested to compare. While extensive testing was required to find the best structure for a simple ANN to forecast building energy with occupant behavior, using an RNN with default parameters (per the Tensorflow Keras package in Python) achieved near equivalent performance (2.91% on Case 2 normal operation testing dataset). Only one RNN test was performed as the initial structure was sufficient.

9.3 Summary of Results

Table 5 below shows a summary of the results of the different test cases and model structures. The Case 2 models do not include enriched data sets and are not tested under demand response conditions but will be the topics of future studies.

Table 5: Summary of Model Results

	Model Type	Occupant Behavior	Data Type	Selected Features	Model NRMSE on Normal Operation Testing Data	Model NRMSE on Demand Response Testing Data
C1M0	MARS	No	Normal Operation	ZTCSP @t, LIGHT @t, DISH @t, BLDGEE @t, BLDGEE @t-1, SFMFR @t-2, SRDIF @t-4, SFMFR @t-4, ZAT @t, SFMFR @t-3, SFMFR @t-1, OADB @t-4, VMFR @t-4	4%	81%
C1M1	MARS	No	Normal Operation + Active Learning	ZTCSP @t, BLDGEE @t, BLDGEE @t-1, SFMFR @t-2. SFMFR @t-4, SFMFR @t-3, SRDIR @t-4, SRDIF @t-4, OADB @t-4	6%	19%
C2M0	MARS	Yes	Normal Operation	ZTCSP @t, BLDGEE @t, BLDGEE @t-1, SFMFR @t-1, OARH @t-4, SFMFR@t-3, ZARH@t, ZARH@t-1	38%	-
C2A0	ANN	Yes	Normal Operation	ZTCSP @t, BLDGEE @t, BLDGEE @t-1, SFMFR @t-2, OADB @t-3, SFMFR @t-1, SFMFR @t-3, OARH @t-3	3%	-

The models tested under Case 1 conditions required a significant number of features selected to achieve good performance. The enriched Case 1 model, C1M1, selected fewer features than C1M0, as that dataset was more informative resulting in less features selected to achieve good performance. Similarly, the models tested under Case 2 conditions (C2M0, C2A0, C2R0) required fewer features. The inclusion of occupant behavior in Case 2 resulted in more informative data but at the cost of increased complexity in model training requirements. When stochastic occupant behavior has a significant impact on building energy, MARS models are no longer sufficient and a more complex model, such as an ANN is required. However, ANNs require more training data and simple ANNs require significant testing to find the best tuned structure. Comparatively, a deep ANN (an RNN in this study) can achieve equivalent performance using default settings and little to no tuning. The use of these models can allow for high fidelity building energy forecasting models that can handle the inclusion of stochastic behavior and allow for advanced occupant centric building control systems.

10. CONCLUSION

This study explores the potential of using ML-based models to develop high-fidelity building energy forecasting models for a residential building, when occupant behavior is considered. The study explores several ML model structures, i.e. MARS and ANN (simple and RNN) for use in forecasting Whole Building Electric Energy at 1-hour ahead. A virtual building testbed that includes a detailed agent-based occupant behavior simulation model is used to generate both training and testing data. The impact of training data, i.e., those obtained from normal operation and from an active learning process, on model performance and model generalization is evaluated. Two testing scenarios are adopted using the developed models to forecast energy under normal operation conditions and demand response operation conditions both when occupants can and cannot impact the building control (i.e. adjust the thermostat). Comparisons are made between the different model structures and their ability to accurately forecast energy under the different testing scenarios.

The conclusions of this study are as follows. Using MARS models for energy forecasting is sufficient for forecasting building energy usage provided there is no significant stochastic occupant behavior that impacts building energy strongly. MARS model can achieve sufficient performance for demand response conditions and be able to forecast a robust dataset when active learning is used. MARS models can do so with significantly less data than required for proper training of an ANN model. However, MARS models have high sensitivity to training data and some method, such as active learning, needs to be performed to enrich the training dataset.

Use of simple ANN models will result in good performance for forecasting of building energy with or without the impact of significant stochastic occupant behavior. There is a need for significant amounts of training data as well as comprehensive tuning of model parameters to ensure that a simple ANN model is properly trained. In lieu of a simple ANN model, a deep ANN, such as an RNN, can be used with little to no parameter tuning for comparable model performance. More efforts are needed to understand why for this study, ANN models with Sigmoid activation functions perform better than those with ReLu activation functions, although literature has suggested that ReLu activation functions often perform better for nonlinear systems.

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