# IoT Augmented Physical Scale Model of a Suburban Home


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## Abstract


Using a scaled model of a suburban home allows the performance of accelerated experiments in hypothetical external circumstances, and in a variety of environments that would be prohibitively expensive to do with real world homes. Data was collected from the model home and machine learning models were trained to predict the temperature and humidity within the home's environment. A predictive AI can be used to automate the operation of doors and windows to best regulate the climate in a more financially and environmentally conscious way.


## Background

- A **Raspberry Pi** is a small single board computer which is extremely energy-efficient, but its processing capabilities are limited
- A **Pi hat** is a module for the Raspberry Pi that allows the control of up to sixteen servo motors through pulse width modulation by adding an additional external power source
- A **Breadboard** is a programmable circuit board module for Raspberry Pi.

**Figure 1.** Plywood used to create house is drying after being painted and stained.

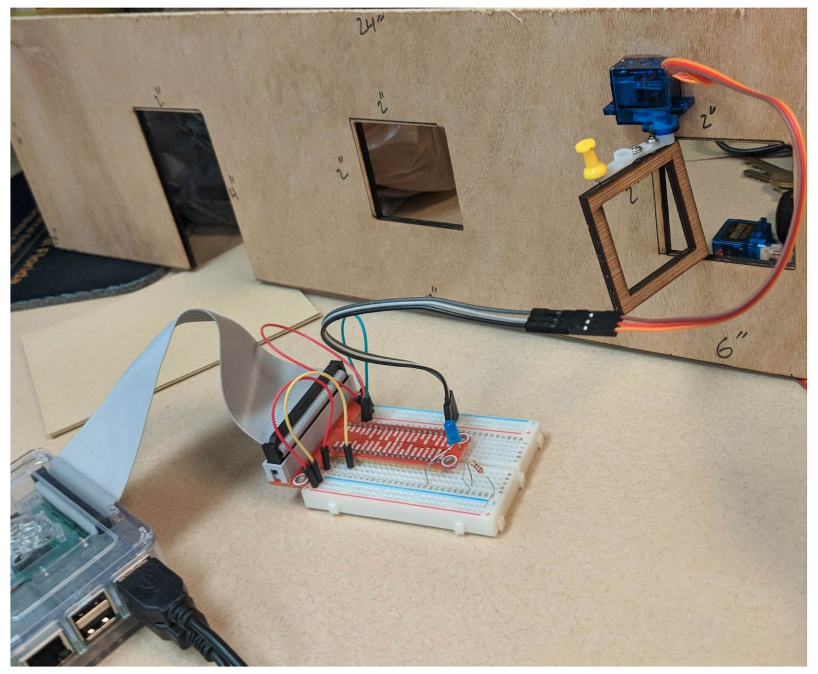

**Figure 2.** Testing configuration of motor and window on extra materials utilizing Raspberry Pi (left) and breadboard (center)

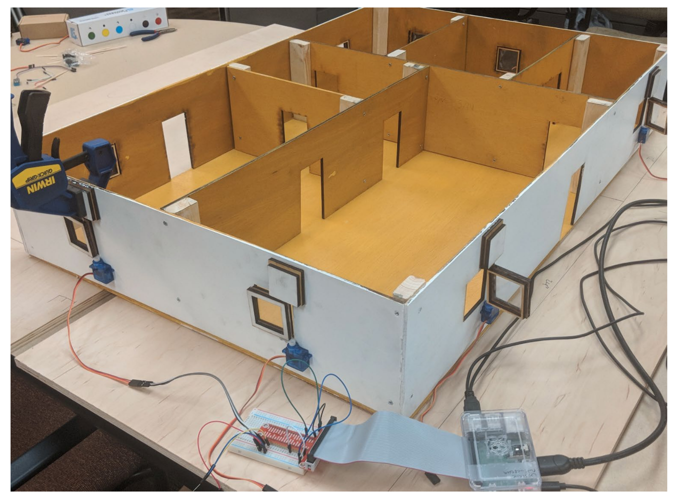

**Figure 3.** Two outside motors attached to windows and wired to breadboard. Other windows attached but not wired.

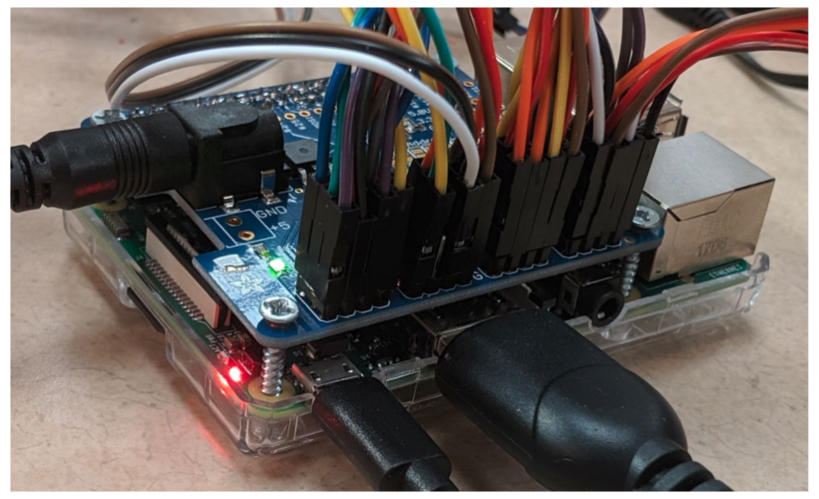

**Figure 4.** Pi hat attached to all fifteen motors, and is running separately from Raspberry Pi used for data collection.

## References


[1]. J. Ling, S. Zehtabian, S. S. Bacanli, L. Bölöni, and D. Turgut, "Predicting the temperature dynamics of scaled model and real-world IoT-enabled smart homes," Submitted to *IEEE Globecom* 2019.


## Experimental Set-up / Methods

- Using a random lottery based system to determine which motors will change state
- Up to six motors activate per lottery drawing
- Sensors report data on temperature and humidity once per minute
- Lottery drawing happens once every five minutes
- Fan changes state every thirty minutes
- Heat lamp changes state every sixty minutes

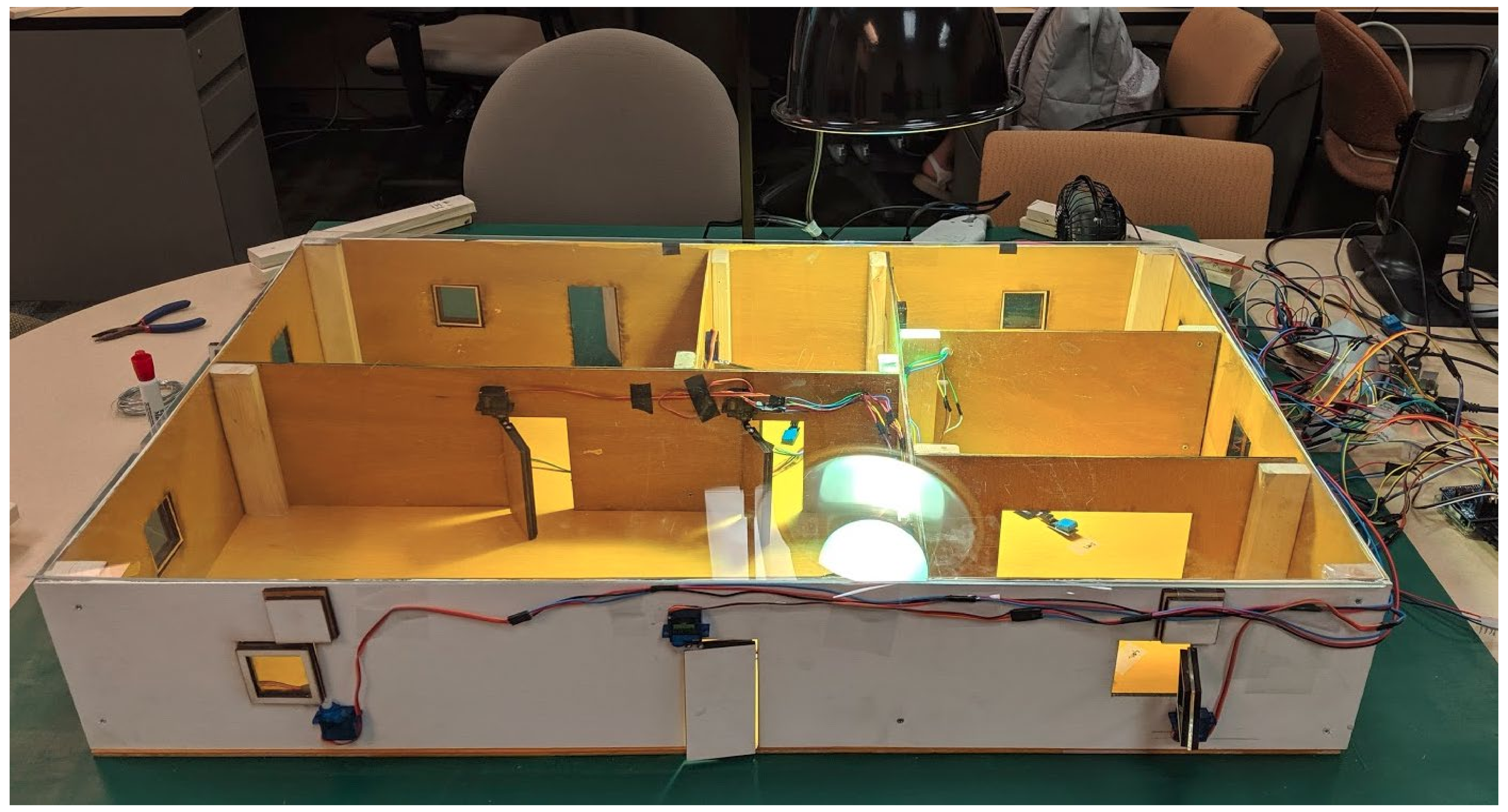

**Figure 5.** Gathering data of our 'random' scenario to train/test machine learning model. Heat lamp is turned on to simulate solar energy from the sun. Fan is turned on to simulate wind.

- Gathered data is used to train and test our machine learning model to predict expected temperature and humidity for the rooms of the house throughout a set of pre-prepared scenarios.
- We focused on a Long Short Term Memory (LSTM) model since the previous year's research [1] concluded that LSTM was more accurate than a Fully Connected Neural Network (FCNN).
- The LSTM was first modeled using 90% of the data as training (Fig 8, 9), followed by models using 70% for training (Fig 10, 11).

## Conclusion

The training/testing dataset consisted of around three hundred sixty data points collected over the course of about seven hours. The accuracy of the models would improve with more data points.

- The accuracy of our LSTM models varied with size of the training data, batch size, number of features, and number of epochs.
- The training set accuracy reached acceptable levels for the data.
- The testing set accuracy was not as accurate as we had originally hoped. As more data is gathered for the training set, we would expect dramatic improvements in model accuracy.

For the future work on this project, we envision:

- increasing the amount data being gathered
- implementing additional machine learning algorithms
- having a temperature controlled environment
- extensively testing in a variety of scenarios

## Results

- Figures 6 & 7 show temperature and humidity recordings from seven sensors inside the house.
- Asymptotes every sixty minutes represent the heat lamp changing state (starting with 'on' then 'off', respectively)
- Every other hour, the lamp changes position to mimic time of day (above bedroom 1, bathroom, then bedroom 2)

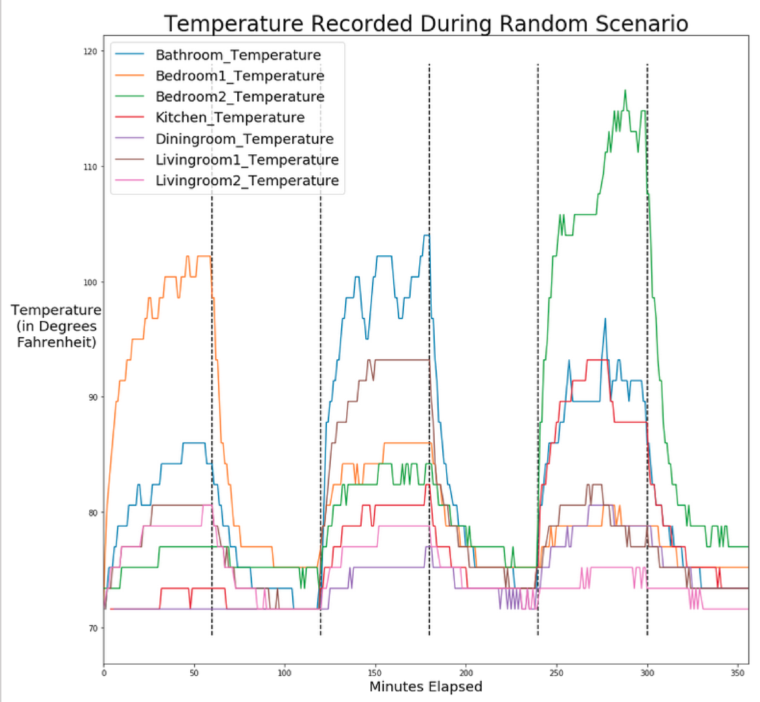


**Figure 6.** Temperature recordings from each of the sensors. (Smoothed)

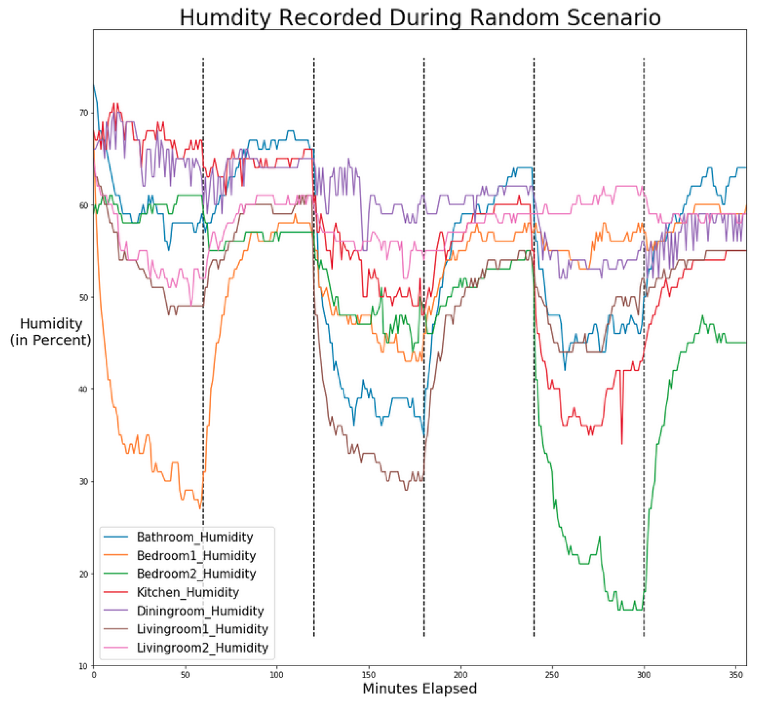


**Figure 7.** Humidity recordings from each of the sensors. (Smoothed)

- The data from Figures 6 & 7 is also used to train/test the machine learning algorithm.
- Figures 8, 9, 10, & 11 show LSTM models predicting temperature in 'living room sensor 1'

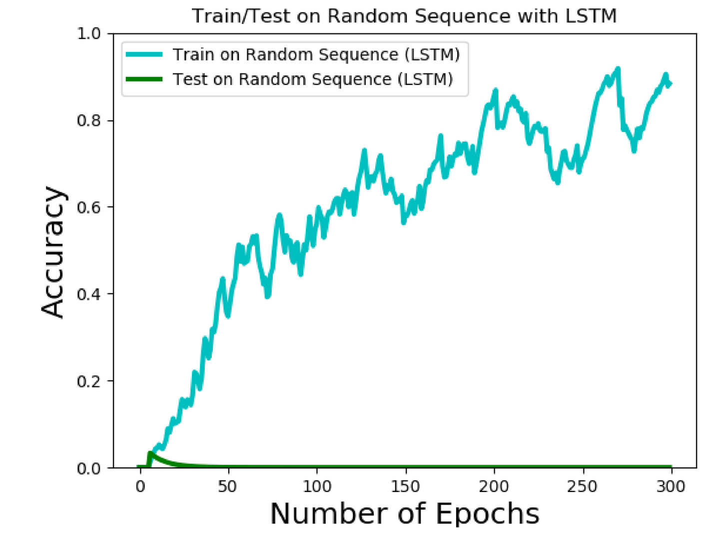


**Figure 8.** Accuracy for training set size: 90%

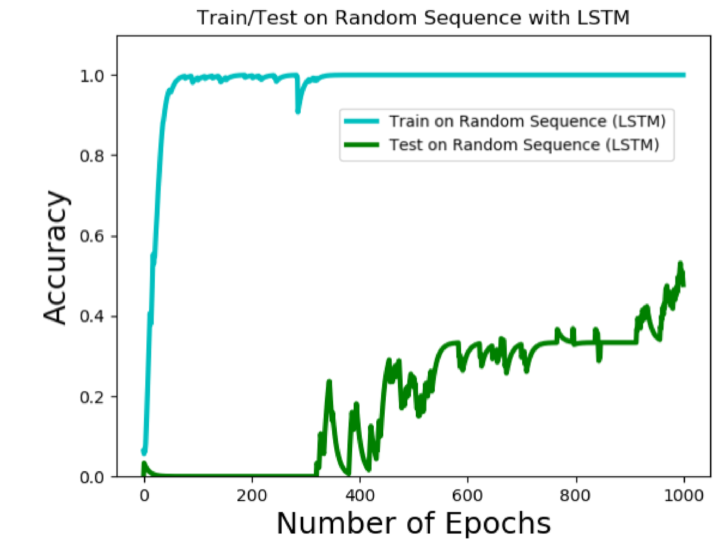


**Figure 9.** Accuracy for training set size: 90%

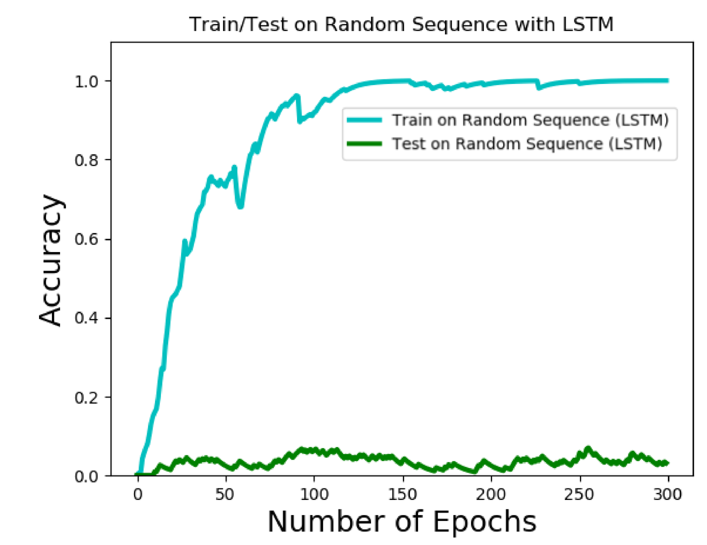


**Figure 10.** Accuracy for training set size: 70%

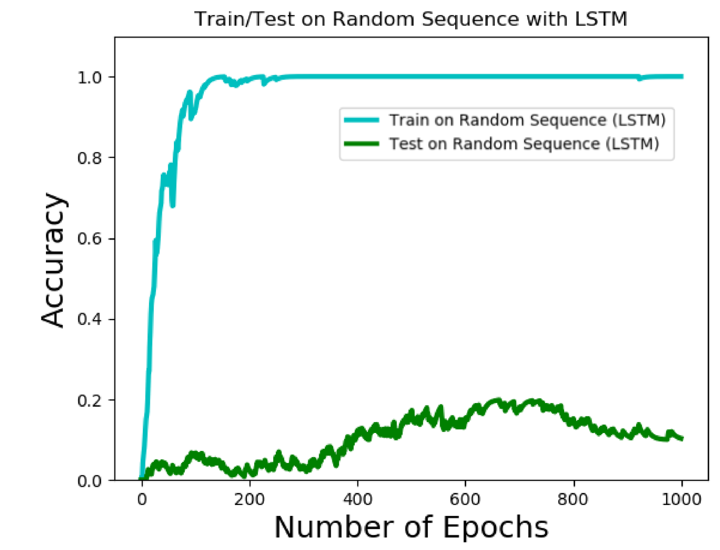


**Figure 11.** Accuracy for training set size: 70%

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