A Data-Driven Approach for Providing Frequency Regulation with Aggregated Residential HVAC Units

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***Abstract*— The growing level of integration of renewable energy sources into power grids around the world has increased the need for cheap, reliable and effective fast frequency regulation resources. On that note, most grid operators are already considering the usage of demand-side resources for frequency regulation purposes. A major candidate for such initiatives is the heating, ventilation and air conditioning (HVAC) unit in both residential and commercial buildings. In this paper, we present a simplified data-driven approach for providing frequency regulation using aggregated residential HVAC units. The approach involves the use of a residential load model to generate data for frequency regulation model identification. Afterward, a relationship between instantaneous aggregated HVAC power consumption, HVAC power changes and thermostat setpoint offsets is established using a simple multiple linear regression model. Actual regulation qualification signals from the PJM market and the regression model are then used to evaluate the ability of the units to satisfactorily respond to frequency regulation signals. The obtained results show that while the results are satisfactory using PJM's performance metrics, improvements can still be made by accounting for model errors.**

***Index Terms*-- Demand side management, residential HVAC units, frequency regulation.**

I. Introduction

Over the last several years, bulk electric power systems around the world have experienced enormous growth in the integration of renewable energy resources, especially solar and wind. In 2018, renewable generation provided about 742 million MWh of the United States' electricity – about twice the quantity produced in 2008 - as shown in Fig. 1 [1]. The same goes for Europe, where the average renewable electricity per capita more than doubled in 2016 when compared with 2005 [2]. This trend is expected to continue as sustainability, and low emissions have become significant constructs of the modern-day energy industry parlance. However, the mass adoption of renewables does come with challenges which are embedded in the intermittent nature of these resources. A significant problem arises from the need to instantaneously balance electricity supply and demand at the grid level in the face of these intermittent sources. While energy storage technologies, especially batteries, are expected to play a critical role in mitigating many of these problems, there is still the need to explore other options to cheaply maintain the much-needed balance between electricity demand and supply. This need has motivated several research efforts to explore the usage of demand-side resources for frequency regulation.

Previous research works on the usage of demand-side resources for frequency regulation have generally focused on customer-side batteries, electric vehicles and thermostatically controlled loads (TCLs) including water heaters, heating, ventilation, and air-conditioning (HVAC) units and refrigerators. However, this work focuses on HVAC applications, which can be sub-divided into residential and commercial HVAC types. This sub-division is motivated by the inherent differences in residential and commercial HVAC units. While the former is typically an on/off type unit, the latter often has more involved control loops with complexities proportional to the size of the buildings.

In [3], an evaluation of the potential of aggregated residential HVAC loads for providing fast intra-hourly load balancing is presented. The author introduces a temperature-priority-list based algorithm with a simplified forecast model to estimate the temperature in each house at 1-minute resolution. Actual temperature measurements at 15-minute intervals are then taken to correct deviations in the model. Also, [4] presents a similar temperature priority list approach for using residential HVAC units for frequency regulation in addition to a model predictive control (MPC) based algorithm for controlling continuous-state HVAC units typically found in large commercial buildings. Ref. [5] presents a statistically developed open-loop model of the response of an actual commercial HVAC unit to global thermostat reset (GTR) signals. The model developed in [5] is used in [6] to measure the response of the same commercial HVAC unit to actual frequency regulation signals obtained from the PJM market's data repository.

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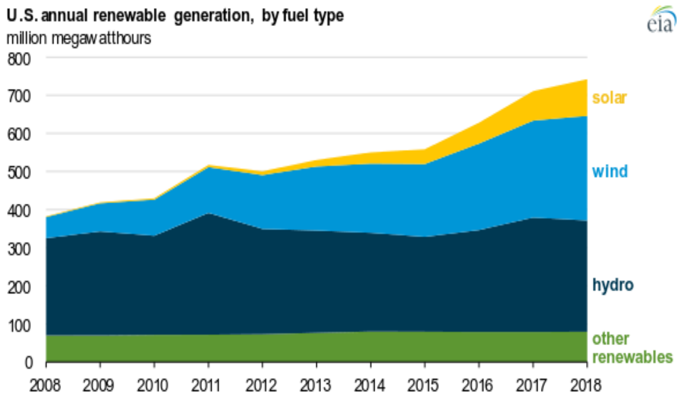

Fig. 1. U.S. renewable energy growth (Source: EIA)

From the works mentioned above, it can be deduced that most residential HVAC focused applications use the temperature-priority list algorithm, which relies on frequent temperature measurements from the individual buildings in the aggregate. While this approach is expected to provide more accurate results, it requires considerable investments in communication infrastructure and poses serious privacy concerns to residential customers who could be wary of the utility company (or demand response aggregator) directly measuring the temperature in their homes at such high time resolutions. Furthermore, the approach could result in more frequent cycling of the units when high regulation demands are placed on the resources leading to increased wear and tear of the HVAC units.

To address some of the concerns highlighted in the preceding paragraph, this paper proposes a simple data-driven approach for providing frequency regulation with residential HVAC units. The proposed approach utilizes an aggregated residential load model, which is based on low-resolution load data. The sequential energy disaggregation (SED) algorithm presented in [7] and [8] is used to estimate the aggregated HVAC load for a given number of residential buildings. This estimate and prior knowledge of the typical characteristics of the residential buildings in the aggregate are then used as inputs into a residential load model developed using GridLAB-D software, thereby providing an approximate representation of the residential buildings. Using the residential load model, different simulations are then run to obtain data used to establish the relationship between the instantaneous total power consumption of the HVAC units, thermostat setpoint offsets and the resultant change in HVAC power consumption representing the response of the units to frequency regulation signals.

II. Residential Load Model

As highlighted in the introduction, the proposed approach involves a residential load model, which is based on low-resolution load data. The ERCOT South Central (including the Austin area) hourly load data for 2017, which is available on the Pecan Street data port [9], was scaled down to four hundred hypothetical single-family residential buildings in Austin, Texas using customer population data available on Austin Energy's website [10]. The residential load model and the frequency regulation approach proposed in this paper are part of a broader effort aimed at developing approaches for the coordination of different customer-side resources for participation in electricity markets, hence the usage of a model consisting of 400 houses. To obtain more realistic results, load consumption data recorded at the distribution transformer level can be used based on the assumption that houses connected to a particular transformer have similar characteristics.

A. *Sequential Energy Disaggregation (SED) Algorithm*

The SED algorithm and a closely related variant proposed in [7] and [8] respectively provide a way of estimating HVAC load consumption from low-resolution load data. This reduces measurement costs as low-resolution measurements imply lesser communication requirements. While [7] focuses on load data for single residential buildings, the SED algorithm is applied to aggregated load data in this paper. For a detailed description of the algorithm, the interested reader can refer to [7].

The SED algorithm consists of two sub-algorithms, the day type classification (DTC) and the average value subtraction (AVS) algorithms. The DTC algorithm divides the total number of days within a year into three categories – mild, hot, and cold. The energy consumption and load profiles of the mild days are then averaged, and the resulting average energy consumption values and load profile are taken as the base energy consumption and aggregated baseload profile, respectively. Subtracting the total energy consumption for each day from the base energy consumption value gives an estimate of the aggregated HVAC load for each day in the hot and cold day type categories.

Applying the SED algorithm to the scaled load data, the resulting Energy vs. Temperature (EvT) curve and the day-type categories are shown in Fig. 2 and Table I respectively. Also, the average baseload profile for a single house, obtained by dividing the aggregated baseload profile by 400, is shown in Fig. 3. The U-shape of the curve implies that most of the houses use electricity for both heating and cooling, which is corroborated in [11]. Also, the number of hot days and the average energy consumption on hot days are both significantly higher than corresponding values for cold days, which is typical of the southern part of the United States.

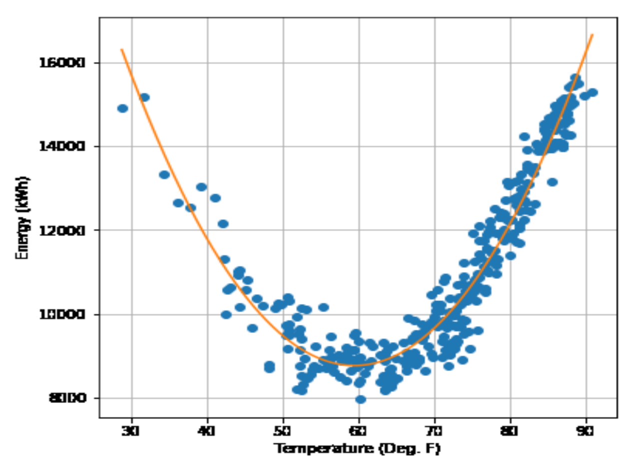

Fig. 2. Energy vs. Temperature (EvT) curve

TABLE I. DAY TYPE CLASSIFICATION RESULTS

Day Type	No. of Days	Average Energy (kWh)
Mild	82	8790.03
Cold	42	10686.91
Hot	241	11869.58

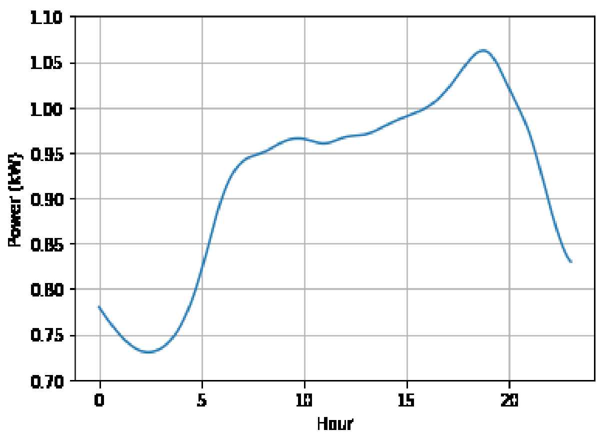

Fig. 3. Average mild day profile (taken as baseload profile) for a single house

B. GridLAB-D Model

A GridLAB-D based residential load model was developed to represent the time evolution of the total energy consumed by the aggregated residential buildings. The residential load model in GridLAB-D uses the equivalent thermal parameters (ETP) model, which is suitable for modeling and simulating the energy consumption of residential and small commercial buildings [3]. Although the HVAC load is the only load whose output is varied for frequency regulation purposes, it is vital to capture the other loads for the calculation of the HVAC to total energy consumption ratio for the aggregated buildings. In addition to comparing the energy consumption obtained from the model with the actual load data, this ratio can be compared with the same ratio calculated from the SED algorithm results to confirm that the HVAC loads are not grossly oversized or undersized.

The typical loads in each building, except for the HVAC load, were modeled as ZIP loads with schedules based on the average baseload profile obtained from the SED algorithm. The average base profile values for a single house, shown in Fig. 4, were randomized with a normal distribution, and the resulting random values were applied to each building to achieve load diversity. Furthermore, weather data for Austin obtained from the National Oceanic and Atmospheric Administration (NOAA) database [12] were used as weather inputs to the model. For the HVAC load, the critical parameters influencing the thermal mass and heat flow path are the floor area, thermal integrity level (TIL) and coefficient of performance (COP) of the HVAC units [13]. The floor area parameter was randomized and assumed to be between 1500 and 1800 square feet based on data obtained from [14]. The TIL and COP values were tuned using the same procedure presented in [13]. For each building, typical heating and cooling setpoints were assumed to be known. Table II gives a summary of some of the parameter values used in the model.

From Austin Energy's website, the peak load day in 2017 was June 23. Hence, the house model was tuned under the weather conditions for this day. Total energy consumption of the aggregated buildings was then simulated using the tuned model. Fig. 4 shows the results obtained. Furthermore, the HVAC to total energy consumption ratios obtained from the simulation results and actual load data for June 23 and the simulation period are shown in Table III.

TABLE II. HVAC SYSTEM PARAMETERS

Parameter	**Range (or Value)**
Floor area	1500 to 1800 ft^2
Heating setpoint	70 to 75ºF
Cooling setpoint	65 to 70ºF
Thermal integrity level	6 (on a scale of 0 to 7)
COP	5

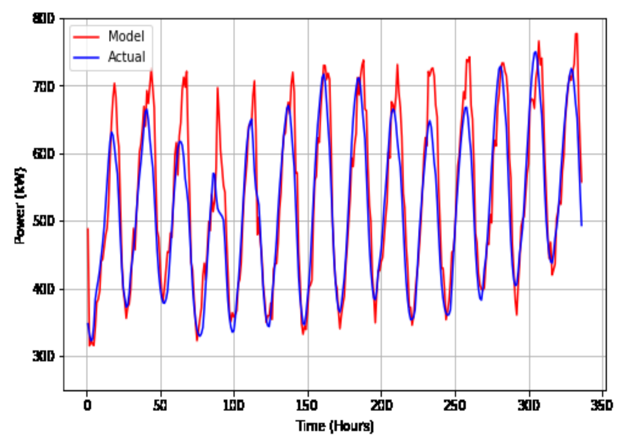

Fig. 4. Actual vs. Model power consumption values

For the model and actual power consumption values shown in Fig. 4, the mean absolute percentage error (MAPE) is 6.8%, which shows that the model is considerably accurate for the simulation interval. Also, similar actual (i.e. from SED algorithm results) and model HVAC to total energy consumption ratios (i.e. SED algorithm results) as shown in table III confirms that the HVAC units are not grossly oversized or undersized. However, the frequency regulation model identification simulations, which will be discussed in the next section, were restricted to the summer period since the accuracy of the model for this period has been established. For the frequency regulation simulations, the power consumption results from the model are taken as base power consumption values for calculating changes in power consumption.

TABLE III. HVAC TO TOTAL ENERGY RATIO

Day	HVAC to Total Power Consumption Ratio (Actual)	HVAC to Total Power Consumption Ratio (Model)
June 23	0.43	0.44
June 1	0.23	0.26
June 2	0.29	0.35
June 3	0.25	0.33
June 4	0.17	0.26
June 5	0.25	0.28
June 6	0.28	0.32
June 7	0.31	0.32
June 8	0.32	0.34
June 9	0.30	0.34
June 10	0.26	0.33
June 11	0.28	0.35
June 12	0.34	0.36

III. FREQUENCY REGULATION MODEL IDENTIFICATION

Unlike commercial HVAC units, residential HVAC units are typically on/off units. This implies that a residential HVAC unit is less flexible for frequency regulation purposes when compared with a commercial unit, which can be controlled in several ways, as shown in [15] - [17]. However, when several residential units are aggregated, the inherent load diversity helps with improving responses to regulation signals. Each unit in the aggregate can be turned on or off directly (i.e., direct load control or DLC) or uniform setpoint offsets can be applied to all of the units (i.e. global thermostat reset or GTR). Both approaches require some form of information about the present state of the HVAC units to achieve desired responses from the units. For DLC based methods, the temperature in each of the buildings provides this information while GTR methods often use the instantaneous power consumption of the aggregated units. In this paper, the latter approach is used.

It is worth mentioning that since the energy consumption of an HVAC unit is dependent on the prevailing weather conditions (most importantly temperature and relative humidity), the instantaneous power consumption of an aggregate of HVAC units at specified intervals over a long period can be said to reflect the response of the units under varying weather conditions.

A. *Model Identification*

Using the residential load model developed, setpoint offsets of ±2°F, ±1.5°F, ±1°F, ±0.5°F and ±0.1°F were applied to a cluster of 25 houses representing houses connected to a single transformer. The setpoints of the remaining 375 houses in the model were not adjusted. A maximum offset of ±2°F was applied to ensure compliance with the ASHRAE 55-2010 standards which specifies a maximum indoor temperature change of 2°F within a 15-minute time window for residential buildings [18]. For each setpoint offset signal pair (i.e. ±x), the positive offset was applied to the units within the cluster for 30 minutes followed by the negative offset value for another 30 minutes. The 30-minute duration was selected to ensure that the states of all the units change in response to the setpoint-offset signals. The simulations for each setpoint offset signal pair were run for a 2-week period from June 1 to June 14. Also, the total power consumption of the HVAC units in the cluster, just prior to each offset signal being applied, was measured.

Due to the different thermal properties of the houses and the on/off nature of the HVAC units, the expected response of individual units to the setpoint offset signals occurred at different times within the 30-minute window. Hence, the average change in total power consumption of the aggregated units was recorded instead of steady state values. The recorded values were then binned and averaged to reduce the considerable scatter in the measurements. The results obtained are shown in Fig. 5.

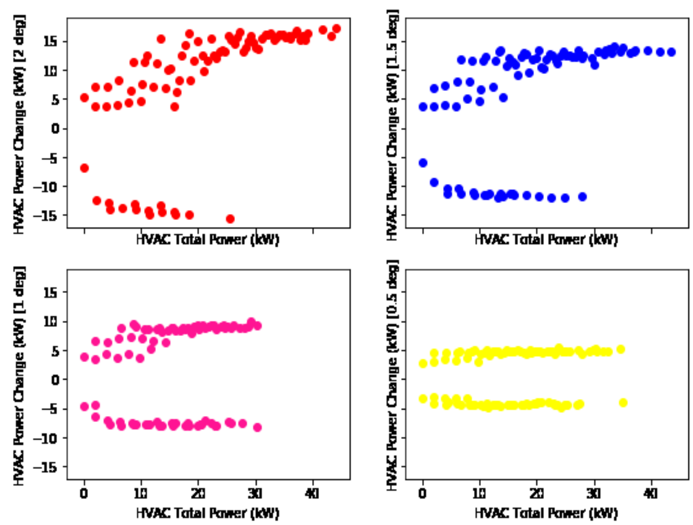

Fig. 5. Frequency regulation model identification data

In Fig. 5, each subplot corresponds to the results obtained for a certain setpoint offset signal pair (i.e. ±2°F, ±1.5°F, ±1°F, and ±0.5°F). The positive y-axis represents the response of the HVAC units to positive setpoint offsets while the negative axis corresponds to negative offsets. The positive y-values represent reduction in power consumed by the HVAC units due to increased thermostat setpoints while the negative values reflect increase in power consumption due to reduced thermostat setpoints. As expected, the x-axis, which represents the instantaneous total power consumption of the HVAC units, spanned 0 to about 50 kW. A minimum value of 0 kW confirms the typical on/off nature of the units. For commercial HVAC units, the minimum value will be non-zero [5]. Furthermore, although the average rating of the HVAC units is 2 kW (i.e. a total of 50 kW for 25 units), the maximum HVAC power change recorded was around 20 kW. This can be attributed to the limitations imposed on the setpoint offset values to satisfy the ASHRAE 55-2010 standards.

Furthermore, Fig. 5 shows that the changes in total power consumption of the HVAC units reduced as the setpoint offset signals reduced, which is also as expected. In fact, the relationship between the setpoint offset and the change in total power consumption of the units is approximately linear as shown in Fig. 6. Also, for each setpoint offset signal pair, the response of the units can be approximated by an ellipsoidal shape as corroborated in [5]. This implies that after several units have been turned on in response to a setpoint offset signal, the changes in power consumption of the units will start to decrease if the same offset is applied.

B. *Multiple Linear Regression Model Fitting*

The data obtained from the regulation simulations described above encapsulate the relationship between the three variables (i.e. instantaneous total HVAC power, HVAC power change, and setpoint offset). A simple multiple linear regression model fitted to the data can then provide a simplified mathematical relationship between the three variables. In the regression model, the setpoint offset and total HVAC power consumption are taken as the independent variables while the HVAC power change is the dependent variable.

Fig. 7 shows the actual HVAC power change values and the values predicted by the multiple linear regression model. The regression coefficients and the y-intercept are combined to form (1) where ΔP is the HVAC power change, ΔT is the setpoint offset signal and P is the instantaneous total HVAC power consumption. The R-squared and root mean square error (RMSE) of the regression model are 0.935 and 4.2 kW respectively.

$$\Delta P = -1.80 + 6.58\Delta T + 0.11P \tag{1}$$

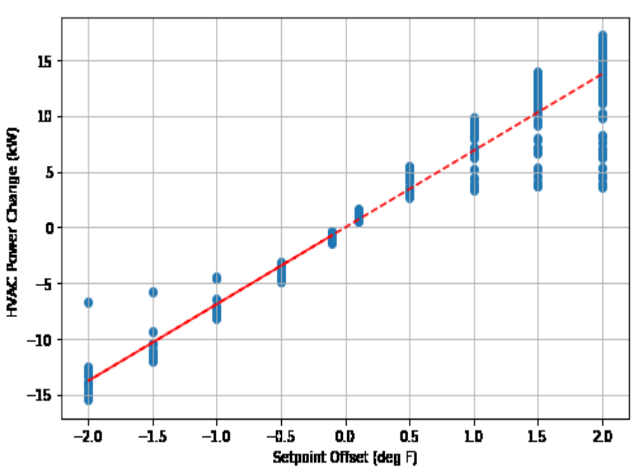

Fig. 6. Relationship between HVAC power change and setpoint offset

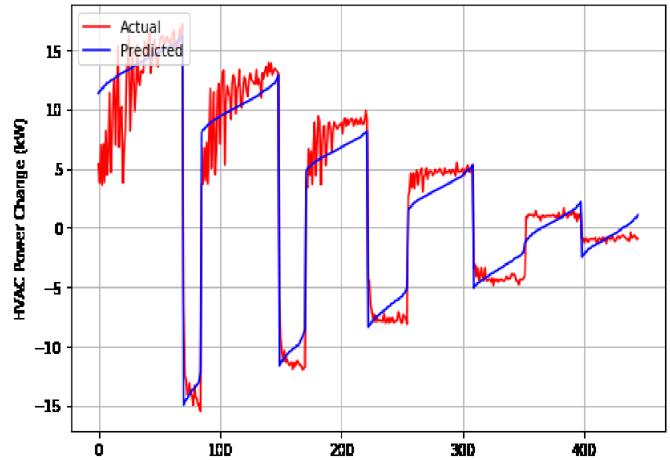

Fig. 7. Multiple linear regression model predictions

IV. Frequency Regulation Results and Discussions

In the previous section, a simple mathematical relationship between setpoint offset, total HVAC power consumption and HVAC power change for units within this specific cluster was established and stated in (1). Using this relationship and fast RegD qualification test signals from the PJM market, the response of the aggregate to fast regulation signals was then simulated. At every 15-minute interval, the total power consumption of the HVAC units was measured. This value is taken as the total HVAC power consumption for the next 15 minutes and used in conjunction with corresponding regulation signals to obtain the equivalent thermostat setpoint offset.

The response of the units to the RegD signals is shown in Fig. 8. Also, the performance score of the aggregate using scoring metrics defined by PJM [19] is summarized in Table IV. Fig. 4 shows that although the aggregated units tracked the regulation signal qualitatively, the precision of the response is low. This observation is corroborated by the scores shown in

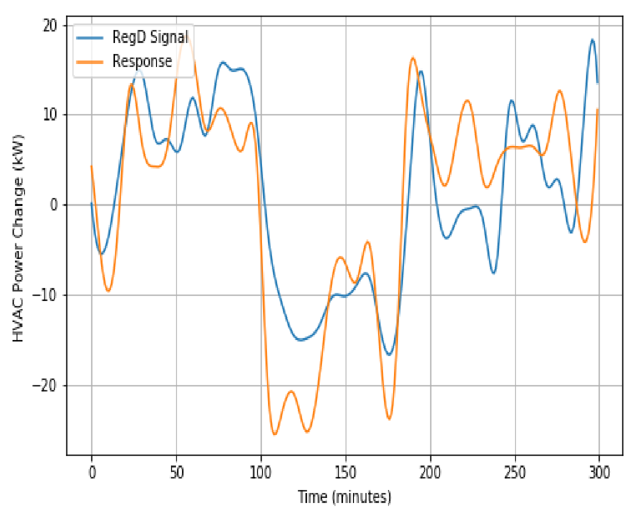

Fig. 8. Response of aggregated HVAC units to RegD signals

TABLE IV. REGULATION PERFORMANCE SCORES

Metric	Value
Precision	0.30
Accuracy	0.57
Delay	0.80
Composite	0.57

Table IV, where the precision score had the least value. This can be attributed to the gross dimensionality reduction used to estimate the value of the variables and the effect of the RMSE from the multiple linear regression model. However, although the composite score of 0.57 is less than PJM's qualification score of 0.75, it is still higher than the required score for continued participation in regulation markets, which is 0.40.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a data-driven approach for providing frequency regulation from residential HVAC units has been discussed. While this simplified approach showed some satisfactory results given the high dimensionality reduction, the errors associated with the frequency regulation model identification highly affected the precision of the regulation response. This can be reduced by accounting for these errors in the final relationship between HVAC power change, setpoint offset and instantaneous total HVAC power consumption. Also, more frequent measurements of the total HVAC power consumption could reduce the precision errors. However, such frequent measurements in real-world implementations could incur significant costs.

Furthermore, the usage of load data from actual aggregated residential buildings whose typical characteristics are known, in lieu of scaled load data used in this paper, will provide more insights into the effectiveness of the approach. Possibly, the results from the model simulations could also be compared with the actual response from the aggregated buildings.

REFERENCES

[1] Energy Information Administration, "Electric Power Monthly," March 2019, EIA. [Online]. Available: https://www.eia.gov/electricity/monthly/current_month/epm.pdf

[2] European Environment Agency, "Renewable Energy in Europe - 2018," December 2018, EEA. [Online]. Available: https://www.eea.europa.eu/publications/renewable-energy-in-europe-2018

[3] N. Lu, "An Evaluation of the HVAC Load Potential for Providing Load Balancing Service," in IEEE Transactions on Smart Grid, vol. 3, no. 3, pp. 1263-1270, Sept. 2012

[4] M. Olama, T. Kuruganti, J. Nutaro, and J. Dong, "Coordination and Control of Building HVAC Systems to Provide Frequency Regulation to the Electric Grid," Energies, vol. 11, no. 7, p. 1852, Jul. 2018

[5] G. Goddard, J. Klose and S. Backhaus, "Model Development and Identification for Fast Demand Response in Commercial HVAC Systems," in IEEE Transactions on Smart Grid, vol. 5, no. 4, pp. 2084-2092, July 2014.

[6] I. Beil, I. Hiskens and S. Backhaus, "Frequency Regulation From Commercial Building HVAC Demand Response," in Proceedings of the IEEE, vol. 104, no. 4, pp. 745-757, April 2016.

[7] M. Liang, Y. Meng, N. Lu, D. Lubkeman and A. Kling, "HVAC Load Disaggregation using Low-resolution Smart Meter Data," 2019 IEEE PES Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, 2019

[8] P. Denholm, S. Ong and Chuck Booten, "Using Utility Load Data to estimate Demand for Space Cooling and Potential for Shiftable Loads," NREL Technical Report.

[9] Pecan Street dataset. (March 2019) [online]: http://www.pecanstreet.org/

[10] Austin Energy, "Energy Use and Sales" [Online]. Available: https://data.austintexas.gov/Utilities-and-City-Services/Austin-Energy-Customer-Data-by-Customer-Class/9xdm-yhmb [Accessed: June. 12, 2019].

[11] Energy Information Administration, "Household Energy Use in Texas," 2009. EIA. [Online]. Available: https://www.eia.gov/consumption/residential/reports/2009/state_briefs/pdf/TX.pdf

[12] NOAA Climate Data Online Tools. (March 2019) [online]: https://www.ncdc.noaa.gov/cdo-web/datatools

[13] P. Gotseff and B. Lundstrom, "Data-Driven Residential Load Modeling and Validation in GridLAB-D," 2017 Ninth Annual IEEE Green Technologies Conference (GreenTech), Denver, CO, 2017, pp. 20-25

[14] Rent Café, "Austin, TX rental market trends." [Online]. Available: https://www.rentcafe.com/average-rent-market-trends/us/tx/austin/ [Accessed: June 12, 2019].

[15] Y. Lin, P. Barooah, S. Meyn and T. Middelkoop, "Experimental Evaluation of Frequency Regulation From Commercial Building HVAC Systems," in IEEE Transactions on Smart Grid, vol. 6, no. 2, pp. 776-783, March 2015.

[16] J. MacDonald, S. Kiliccote, "Commercial building loads providing ancillary services in PJM", ACEEE Summer Study Energy Efficiency Buildings, Aug. 2014.

[17] P. Zhao, G. P. Henze, S. Plamp, V. J. Cushing, "Evaluation of commercial building HVAC systems as frequency regulation providers", Energy Buildings, vol. 67, pp. 225-235, 2013.

[18] Thermal Environmental Conditions for Human Occupancy. ASHRAE, pp. 55-2010, 2010

[19] PJM, "PJM Manual 12: Balancing Operations," 2019. PJM. [Online]. Available: https://www.pjm.com/~/media/documents/manuals/m12.ashx