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Towards Machine Learning-Based Demand Response Forecasting Using Smart Grid Data

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Abstract—Demand response is a valuable tool for improving the reliability, stability, and financial efficiency of smart grids. With the intention of altering customer power consumption patterns, utility companies often implement strategies such as time-of-use (TOU) programs. Although effective in some situations, TOU programs struggle to perform in highly developed countries due to the complexity of human behavior. In this study, we analyze power consumption readings from smart meters from 5567 households in London, UK from November 2011 to February 2014 to measure the success of the TOU program. We additionally consider the variability of weather conditions and customer demographics when determining program outcome. We establish a relationship between time of day and low/high power consumption both in standard (STD) customers and TOU customers. Furthermore, we apply deep learning via a Long short-term memory (LSTM) model and determine predictability based on weather features through drill down operations.

Keywords—ToU, sustainability, time-series, data analysis

MONTCLAIR STATE UNIVERSITY

Towards Machine Learning-Based Demand Response Forecasting Using Smart Grid Data

by

Matthew Johnson

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TOWARDS MACHINE LEARNING-BASED DEMAND RESPONSE

FORECASTING USING SMART GRID DATA

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I. INTRODUCTION

As ToU programs continue to shape the forefront of sustainability efforts led by power companies, more studies concerning their retention and acceptance rates are being conducted [1]. Although, the complexity of human behavior may bound the general efficacy of programs to local changes. For example, in certain models, heating/cooling demands are driven by significant differences between indoor and outdoor temperatures [2]. This metric may be ineffective for areas where frequent weather changes occur. Likewise, household temperatures may also be kept lower/higher depending on sociological factors [1].

Like the above example, we also give an analysis of human factors regarding the relationship between time of day and power consumption. We also consider the climate of London, UK during the analysis [13]. Contrary to popular belief, London is a relatively dry city. According to the UK's Meteorological Office climate data, from 1981 to 2010, London only experienced around 106 rainy days per year on average [3]. So, any bias towards humidity/precipitation was discarded. Although local perception of climate may be a determining factor in power consumption in general.

Through drill down operations, frequent sequence mining, and association mining, we discover that ToU customers accounted for lower total average power use, more low consumption hours, relatively more above-average and high consumption hours, and longer periods of low power consumption than STD customers. We also find correlations between the hour of day, month and power consumption. Day of the week is discarded due to lack of any significant correlation with power consumption. We also find a correlation between acorn group/socioeconomic class and power consumption. Furthermore, we use a long short-term memory model to predict power consumption based on the same weather feature time-series data for 1, 2, 3, 4, 5, 10, and 20 hourly windows. We use a stacked LSTM approach with a mean squared logarithmic error loss function and adaptive optimizer. We chose to use a stacked LSTM to allow for greater model complexity and achieve better results than single layer hierarchies [7]. The primary purpose of these predictions is to compare the trainability/predictability of each customer group based on the drill down operations from customer type, acorn, and individual customer.

II. Prior Work

Measuring demand side energy flexibility is critical to implementing demand response. Due to recent advances in smart meter technology, it is extremely convenient to monitor customer power consumption and analyze their individual consumption behaviors down the specific appliance [7]. By using smart meters, customer data can be collected, and subsequently Deep learning (DL) and Reinforcement learning (RL) algorithms can be applied to effectively inform customer on making the right decisions when implementing demand response [7]. Demand response at the individual household level is of particular importance to researchers due to the ability to predict at the local level. Previously researchers have suggested layering LSTM neural network hierarchies to predict one-hour and one-minute time step loads [9]. Standard LSTM architecture was found to be insufficient at prediction when compared to two layered implementations. Prior research indicates the importance of integrating weather data into learning algorithms due to weather having such a large impact on power consumption. In short, it remains largely an open question as to what DL methods are best, how to choose the number of layers and parameters, and which are applicable to a given situation/ dataset.

This, coupled with the random aspects of human behavior opens a challenge in the predictability of power consumption of demand response customers. Furthermore, it creates issues pertaining to the overall effectiveness of the program implemented [7]. For example, customers may be more apt stay on a standard plan if offered a demand response plan because they prefer are predisposed to the default option [1]. Opt-out programs generally fared better in customer acceptance and retention than Opt-in programs for this reason. Factors such as information technology integration into the smart grid is integral to higher demand peak reductions. Technologies such as in-home display (IHDs) and programmable communicating thermostats (PCTs) have the potential to lead to greater peak demand reductions. According to the US department of energy's interim report on Customer Acceptance, Retention, and Response to Time-Based Rates from the Consumer Behavior Studies "Peak demand reductions are generally higher for CPP and CPR customers with PCTs (22% to 45%) than they were for customers without PCTs (-1% to 40%)." [1]. PCTs can provide a window into customer power consumption patterns. Also, some demand response applications such as heat-pump thermostat, are influenced by meteorological factors so including meteorological data is essential to our approach [7].

While these advances in thermostats are promising towards using machine learning as a tool in power consumption prediction, some customers tend to have negative experiences with them. For example, paper [8] has found that customers tend to shut down the automation due to things as simple as smart thermostats learning the wrong behaviors. Thus, concern arises over what input, output, and level of intelligence to incorporate to such sensors. Integrating PCT's with known patterns in weather may be a possible solution. Yet, the same issues may develop where a customer feels dissatisfied with the level of complexity of an interface or sensor automation [8]. The primary question that emerges is “Accounting for meteorological data, what level of machine-learning is necessary for the ideal level of user satisfaction with PCTs while maintaining optimal peak demand reduction?”.

III. Data Sets

Data was collected from by using the “SmartMeter Power Consumption Data in London Households” dataset aggregated by UK Power Networks and published by London Datastore News [4]. We additionally used the refactorized version of the dataset available on Kaggle which includes data taken from the Darksky api and acorn data from Consolidated Analysis Center, Incorporated (CACI) [5]. SmartMeter power consumption data and Darksky api data were then consolidated and joined on an hourly basis. All customer data was then separated by customer identification number and saved to independent CSV files in **Acorn>Std or Tou> Cust ID** hierarchies. Entire acorns were also concatenated to CSV files for analysis of socioeconomic status. Categorical data was then dropped from original Darksky api resulting in the dataset displayed in figure 1.

```
time,visibility,windBearing,temperature,dewPoint,pressure,apparentTemperature,windSpeed,humidity,KWH/h
2011-12-11 00:00:00,12.5,210,2.83,1.17,1015.67,1.11,1.78,0.89,101.01700030000003
2011-12-11 01:00:00,12.65,204,2.48,0.81,1014.96,0.31,2.11,0.89,89.84999999999995
2011-12-11 02:00:00,13.02,214,2.7,1.29,1014.42,0.11,2.57,0.9,70.017
2011-12-11 03:00:00,13.05,211,3.47,1.41,1013.78,0.66,3.0,0.86,63.48800010000002
2011-12-11 04:00:00,12.97,204,3.74,1.53,1012.94,1.29,2.64,0.85,56.196
2011-12-11 05:00:00,12.68,201,4.23,2.48,1012.42,1.82,2.7,0.88,59.9299999
2011-12-11 06:00:00,12.54,199,5.16,3.01,1011.74,3.03,2.57,0.86,67.3560001
2011-12-11 07:00:00,12.5,198,4.98,3.13,1011.26,2.39,3.12,0.88,67.66100019999999
2011-12-11 08:00:00,12.01,190,5.79,3.73,1010.85,3.13,3.48,0.87,84.3929999
2011-12-11 09:00:00,12.57,194,6.43,4.85,1010.44,3.72,3.79,0.9,111.02000010000005
2011-12-11 10:00:00,12.54,195,7.05,5.44,1009.82,4.1,4.55,0.9,116.5149998
2011-12-11 11:00:00,12.73,197,7.97,6.02,1009.13,4.95,5.23,0.88,120.6340003
2011-12-11 12:00:00,11.7,197,8.06,6.04,1007.99,4.78,6.02,0.87,148.44800000000004
2011-12-11 13:00:00,13.16,194,8.56,5.92,1006.74,5.44,5.9,0.83,148.6960006000001
```

Figure 1. View of merged CSV file containing weather/power consumption data

Data including weather summary, precipType, and icon because were dropped they were found to have no significant correlation with spikes in power consumption through descriptive analytics. New parameters for descriptive analytics were established by binning existing features into categories such as datetime based features (month, day etc.), apparent temperature, Beaufort wind force scale (km/h), wind direction, and humidity. This categorical data was not used for predictive mining but rather gaining preemptive descriptive insight into the data used in the LSTM.

IV. Descriptive Mining

A. *overview*

Figures 2 and 3 provide histograms of energy usage in Kilowatt hours (KWH) per hour where x is the power consumption in KWH and y is the number of hours at that given power consumption level. Figure 2 is a comprehensive unscaled side by side view of the power consumption data while figures 3 utilizes min-max normalization to better visualize data when placed into 20 and 5 bins, respectively. The quantity of 5 bins was chosen to visualize data later placed into equal bins for association mining.

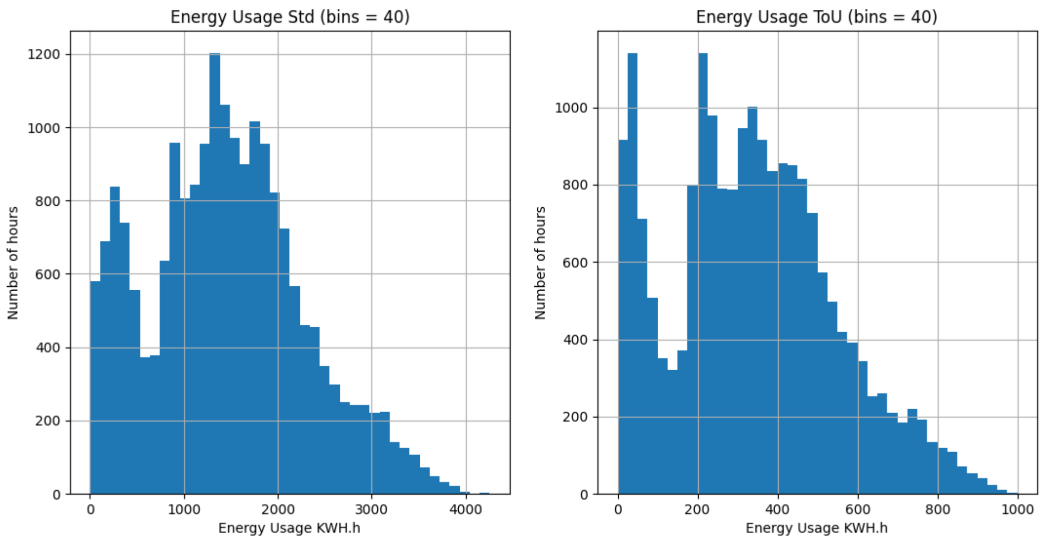

Figure 2. Unscaled side by side view of power consumption vs number of hours for Std and ToU customers in 40 bins

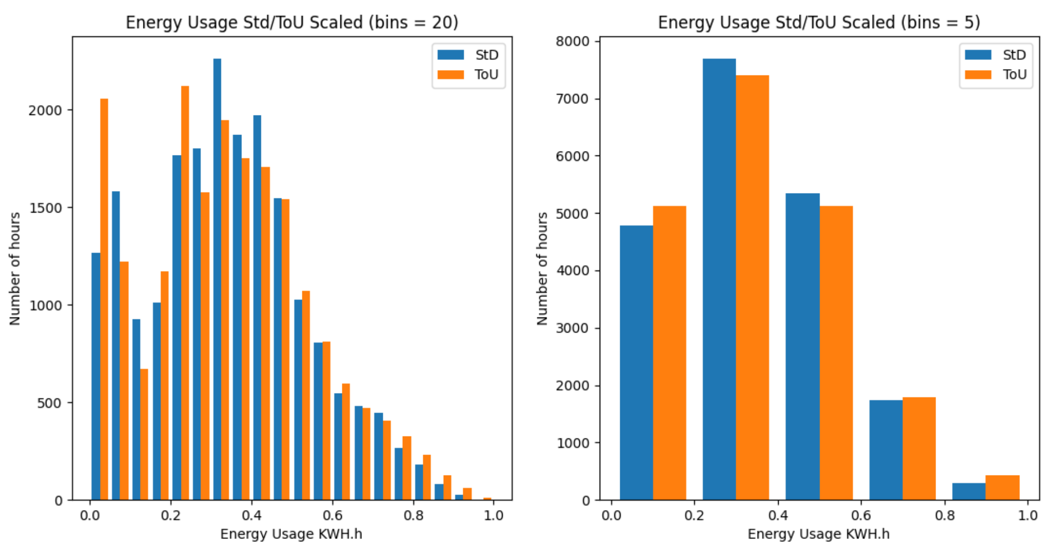

Figure 3. Min-max scaled data comparing ToU and Std customer power consumption in 20 and 5 bins respectively

Figure 2 reveals that ToU customers generally had lower power consumption hours. However, when min-max normalization was applied, figure 3 shows that ToU customers tended to have relatively more high use hours. Parameters for association mining were established by binning meteorological and power consumption data into categories. Power consumption was first binned by equal width relative to each drill down operation on general population data. That is, Std and ToU customers followed by acorns. For example, figure 4 demonstrates binning for power consumption for ToU customers in lines 46 through 50 by applying a mask to the Dataframe.

```
46  tou_df.loc[(0 <= tou_df["KWH.h"]) & (tou_df["KWH.h"] < 200), 'energy_usage'] = "low"
47  tou_df.loc[(200 <= tou_df["KWH.h"]) & (tou_df["KWH.h"] < 400), 'energy_usage'] = "bel_avg"
48  tou_df.loc[(400 <= tou_df["KWH.h"]) & (tou_df["KWH.h"] < 600), 'energy_usage'] = "avg"
49  tou_df.loc[(600 <= tou_df["KWH.h"]) & (tou_df["KWH.h"] < 800), 'energy_usage'] = "abv_avg"
50  tou_df.loc[(800 <= tou_df["KWH.h"]) & (tou_df["KWH.h"] < 1000), 'energy_usage'] = "high"
```

Figure 4. Example code snippet of equal width binning method applied to ToU power consumption data

Like figure 4, all power consumption data was binned into 5 buckets, but this time being labeled "low", "bel_avg" (below average), "avg" (average), "abv_avg" (above average), or "high". Like all min-max normalized data, equal width binned ToU customers had relatively more high hours of power consumption. Although on average each customer had a lower lifetime power consumption.

Equal width bins were also created according to "low", "ideal", and "high" humidity as in figure 4. Furthermore, equal width bins were applied to apparent temperature as "very cold", "cold", "cool", "warm", "hot", and "very hot". Wind direction was binned upon the degree according to direction. Finally, wind force was then binned according to the Beaufort scale. The Beaufort scale is an empirical measure of wind force as it relates to the conditions at sea or on land [6]. Binning was applied similarly through all drill down operations of customer and weather data.

Affluent, comfortable, and adversity acorns were compared generally at first without scaling. As seen in figure 6, comfortable and adversity corn groups were found to have more low power consumption hours than affluent acorn groups when the bin numbers were set to 40. However, when min-max scaling was applied to all 3 graphs, adversity and comfortable acorns comprised most of the high and low consumption hours as seen in figure 6.

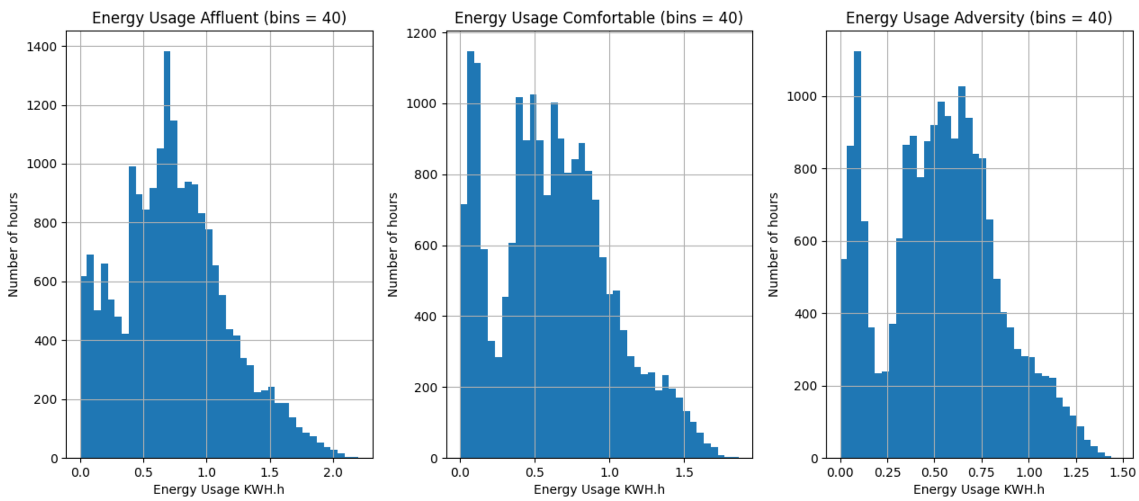

Figure 5. Unscaled side by side view of power consumption vs number of hours for affluent, comfortable and adversity customers in 40 bins

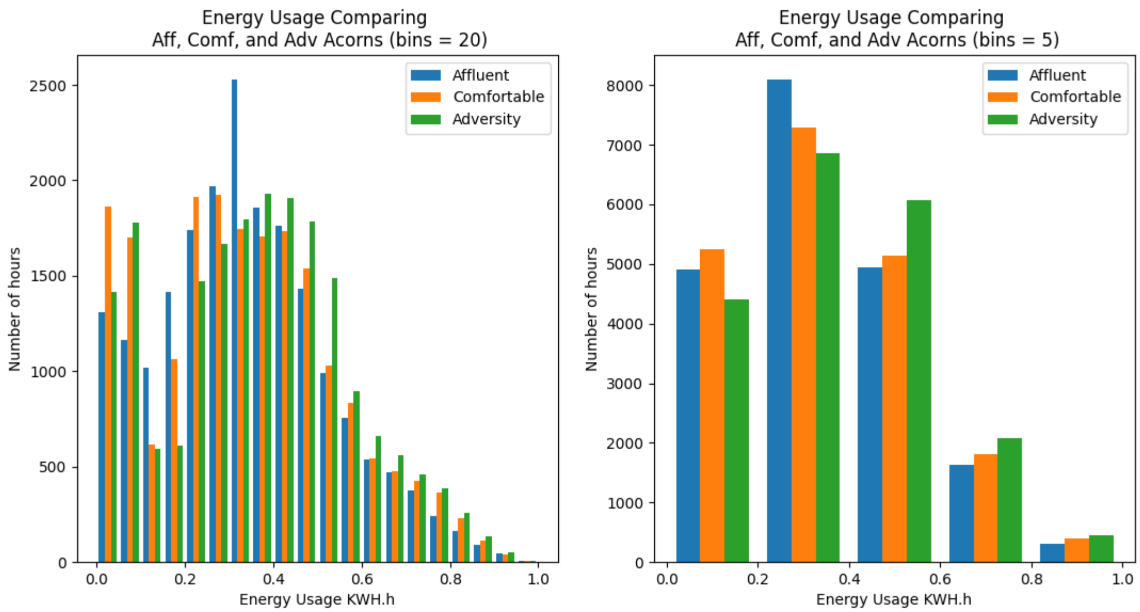

Figure 6. Min-max scaled view of power consumption vs number of hours for affluent, comfort, and adversity of 20 and 5 bins respectively

B. *Association Mining*

Association mining was performed using the pymining module which implements the relim algorithm [12]. Significant associations were found between the hour of the day and power consumption for both Std and ToU customers. 1:00 am, 5:00 am, and 6:00 am were associated with below average power consumption using a minimum support of 500 hours and .60 confidence. Above average consumption hours were centered around hours 5:00 pm, 6:00 pm, and 7:00 pm but did not meet the minimum support and confidence threshold. If only above average/high usage hours are sampled, then a correlation can be established between evening hours and above average power consumption. This may be useful when trying to specifically train models based on high power consumption. Months associated with below average power consumption were June, July, August, and September with a minimum support of 800 and .60 confidence. This can be accounted for by the mild summer months of London [3].

Beaufort scale and wind direction were not directly associated with power consumption in any way. This could be due to the complexity of the data not being captured by simple binning techniques. However, warm apparent temperatures for both Std and Tou customers was significantly associated with below average power consumption with a minimum support of 700 and minimum confidence of .70. This is not unusual given that customers tend to use less electricity as the outdoor temperatures approach indoor temperatures. [2]. Humidity had no association with power consumption when equally binned.

Affluent, comfortable, and adversity acorn customers had no considerable differences when association mining was applied to each customer grouping despite differences in low power consumption hours. Significant associations with below average power consumption were still found for the summer months of June, July, August, and September. Moreover, warm apparent temperatures were also associated with below average power consumption. Hence, leading to the belief that summer months will be more predictable across all groups.

C. *Frequent Sequence Mining*

Frequent sequence mining was also completed using the pymining module by implementing the relim algorithm [12]. Both Std and ToU customers were most likely to have a below average hour followed by at most 4 below average consumption hours. Which could be interpreted that most of the average, above average, and high power consumption can be relegated to spikes rather than periods of excess consumption.

Moreover, it was found that ToU customers had a higher number of consecutive below average consumption hours than Std customers. All acorn groups were most likely to have a below average hour followed by at most 4 below average consumption hours as well. Although comfortable acorn customers were found to have the highest number of consecutive below average consumption hours.

V. PREDICTIVE MINING

Long short-term memory models are recurrent neural networks (RNNs) designed to model long range dependencies of temporal sequences more accurately than conventional RNNs [10]. In the figure below is the basic structure of an LSTM cell. LSTMs work similarly to other RNNs except they do not suffer from the vanishing gradient problem. Even memories from early cells can be carried all the way through to later time steps without loss of memory. As shown in figure 7 and equations 1 through 6, x_t, f_t, i_t, o_t, c_t, $\overline{c}_t$ represent the input vector, forget gates activation vector, inputs activation vector, outputs activation vector, hidden state vector, cell input activation vector, cell state vector, and W and b are weight and biases learned during training, respectively [10]. The sigmoid and tanh activation functions are denoted by σ and $tanh$ and $\circ$ is the element-wise operator.

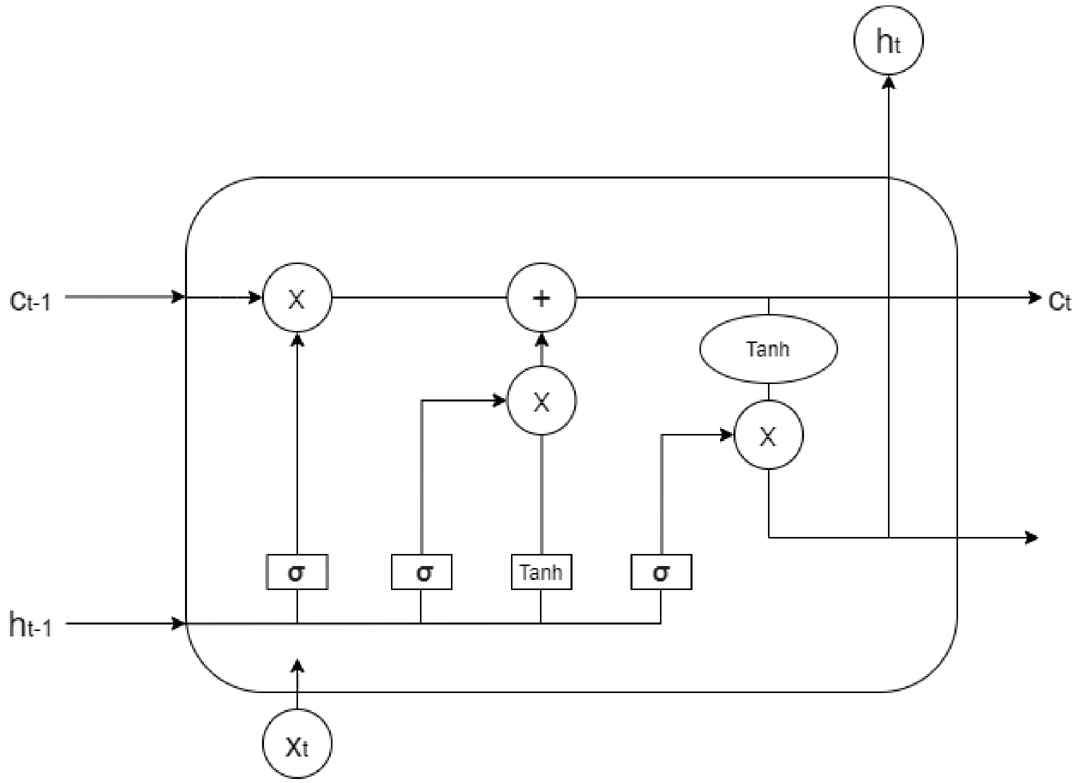

Figure 7. Internal view of an LSTM unit 1 [10]

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

$$\bar{c}_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \bar{c}_t \quad (5)$$

$$h_t = o_t \circ \tanh\,(c_t) \quad (6)$$

The variability and unpredictive nature of sensor data make a long short-term memory model the ideal candidate to carry out predictive analytics on the merged weather-power consumption data. The importance of predicting consumer power behavior relative to meteorological data over hourly, or even minute-long time steps is crucial to the future of PCTs. Therefore, we chose to implement a stacked LSTM to predict energy usage based on meteorological feature data.

A. *Preprocessing*

Data preprocessing is essential before any data is entered into the model for prediction. All NaN values were removed, data was aggregated, and converted to a supervised learning problem. Features were then normalized from 0 to 1 and subsequently reframed and split into 70% training hours and 30% test hours as seen in figure 8. Features considered were time (hourly), visibility (meters), wind bearing (degrees), temperature (Celsius), dewpoint (Celsius), pressure (Pa), apparent temperature (Celsius), wind speed (Km/h), humidity (%), and power consumption in KWH/h.

```
# split into train and test sets
values = reframed.values
n_train_hours = math.floor(0.70 * len(values))
train = values[:n_train_hours, :]
test = values[n_train_hours:, :]
# split into input and outputs
train_X, train_y = train[:, :-1], train[:, -1]
test_X, test_y = test[:, :-1], test[:, -1]
```

Figure 8. Code snippet of splitting train and test data

B. *LSTM application*

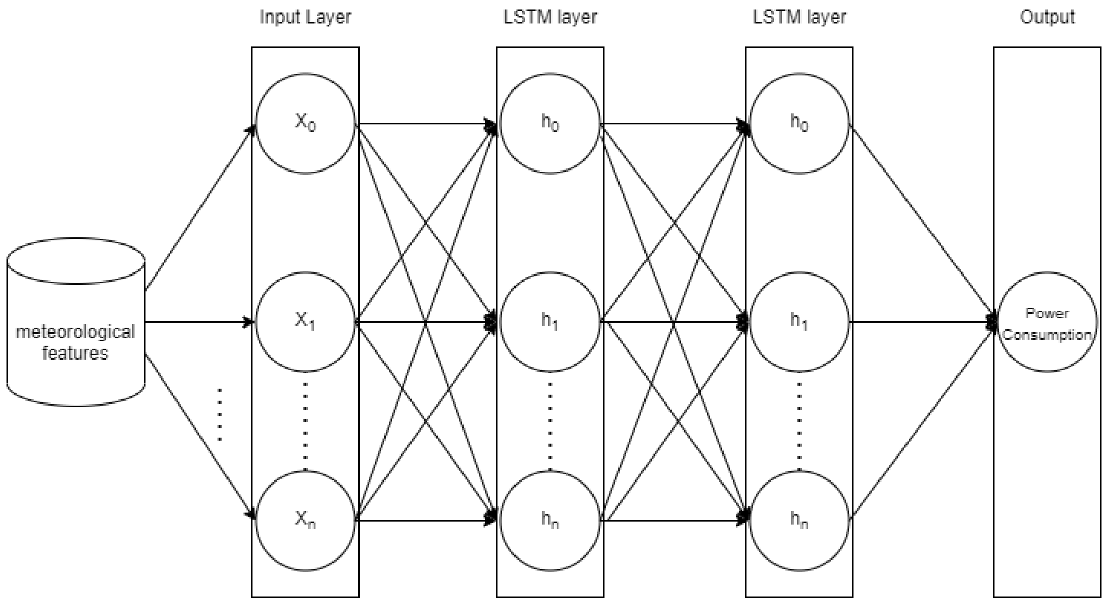

Figure 9. Meteorological features based on the time, visibility, wind bearing, temperature, dewpoint, pressure, apparent temperature, wind speed, humidity being passed to two LSTM layers to predict power consumption

As shown in figure 9, based on varying window size, the number of features being passed to the LSTM will vary. We chose to use at least *n* LSTM hidden units for each stacked layer to match the number of *n* meteorological features being passed to the LSTM model. For example, if we wanted to include the previous 2 time steps, we would have 18 meteorological features based on the time, visibility, wind bearing, temperature, dewpoint, pressure, apparent temperature, wind speed, humidity. In addition, the training set has been divided into batches of 50 and the number of epochs was set to 20 to optimize the learning rate. This was determined by adjusting for overfitting based on the root mean squared error, mean absolute error, and mean log squared error values for several batch and epoch sizes.

Optimizers are algorithms used to change optimize attributes of neural network such as weights and learning rate to reduce loss. Adam is currently one of the best known adaptive optimizers for sparse gradients on noisy problems [11]. Adam is based on adaptive estimates of lower-order moments. Adam is also well suited for problems that are large in terms of data and contain many parameters. Our data contained many parameters, and the volume of data was large thus, we chose the Adam optimizer.

The loss function chosen for our proposed model was the root mean squared logarithmic error function as shown in equation 7 where N is the number of data points. It was chosen because the outliers contained in the data have far less effect on the loss.

$$RMSLE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|log(y_i + 1) - \log(y_i' + 1)\right|^2}$$

(7)

The potential drawback to this function is that when points of data are underestimated there is a greater penalty than the root mean squared error function. Yet, if points are over estimated penalties are much less severe than the RMSE function. The RMSE loss function was also chosen because the target data conditioned on input was assumed to be mostly normally distributed.

C. *Analysis of Results*

To justify the correctness and feasibility of the stacked LSTM approach, meteorological times series data is used to calculate power consumption for each category of data. Testing is done by comparing the accuracy of predicted and actual data. The different group accuracy metrics are presented in Table 1, and loss/model prediction curves shown in figures 10 through 24. Experiments were run for Std, ToU, affluent, comfortable, and adversity groups as well as a randomly sampled customer. Although power consumption behavior was different throughout each group of customers, all customer groupings were similarly predictable. Which shows that hourly demand response can be effectively carried out at the building level using LSTM models. Application of the random customer model to summer data yielded similar results to all season data. Which also shows that although power consumption is lower in the summer, it is not any more predictable when creating a model based exclusively on summer data.

D. *All Customers*

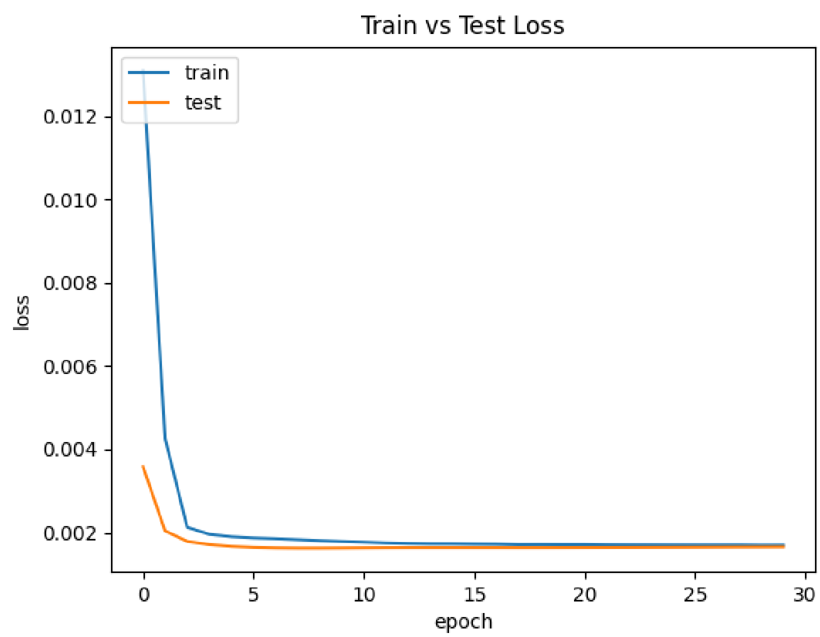

Figure 10. Graph of train vs test loss for all customers.

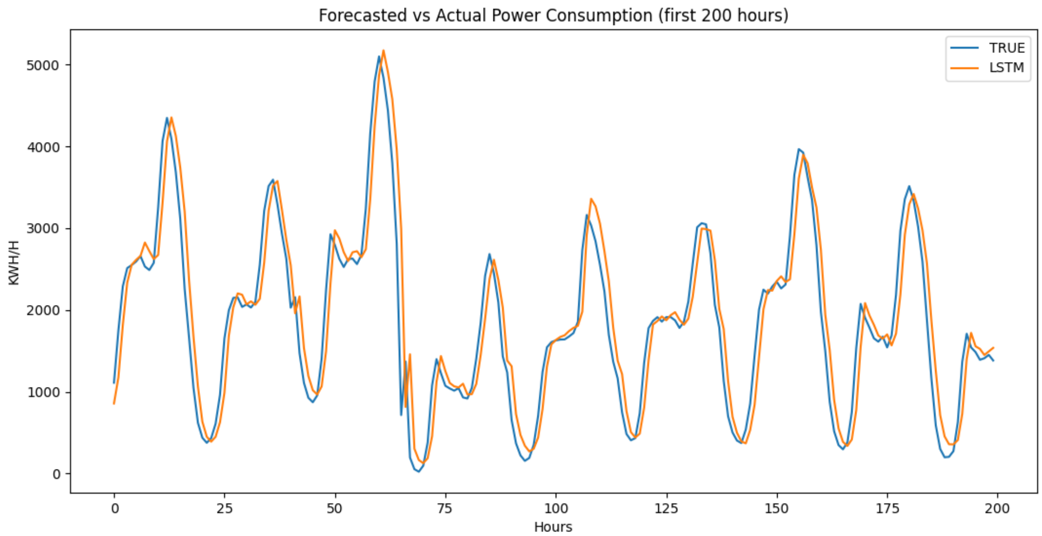

Figure 11. Graph of actual vs predicted power consumption for all customers.

E. Std Customers

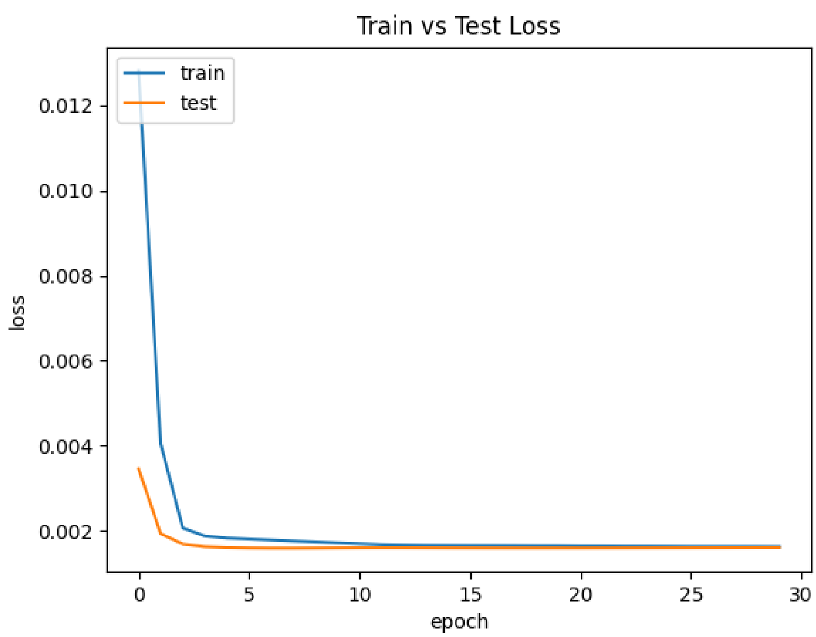

Figure 12. Graph of train vs test loss for std. customers.

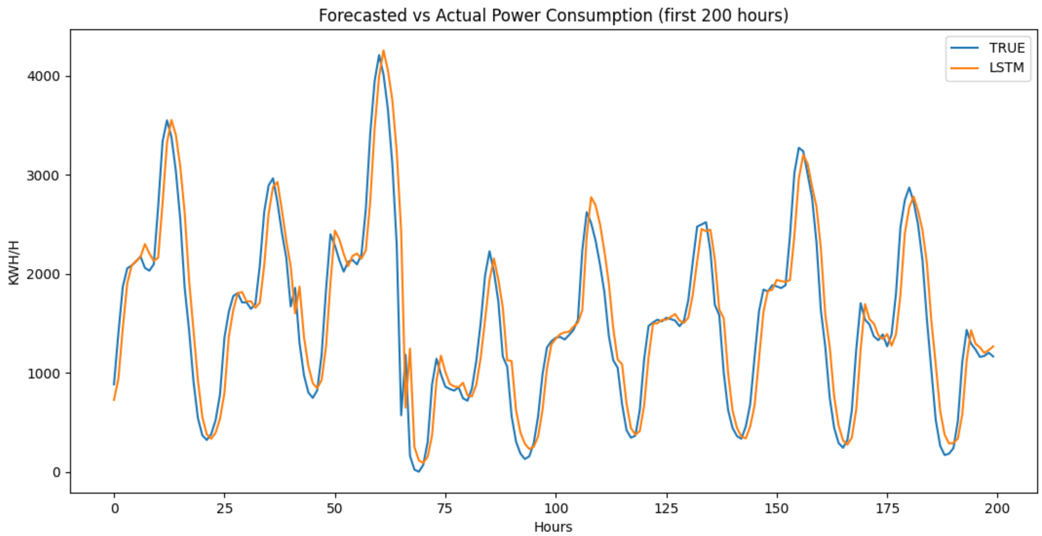

Figure 13. Graph of actual vs predicted power consumption for std. customers.

F. ToU Customers

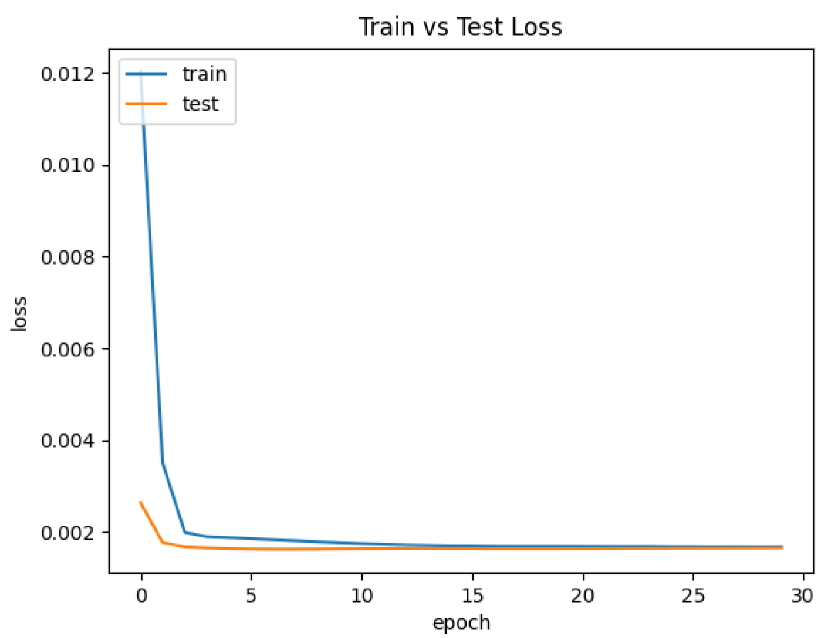

Figure 14. Graph of train vs test loss for ToU customers.

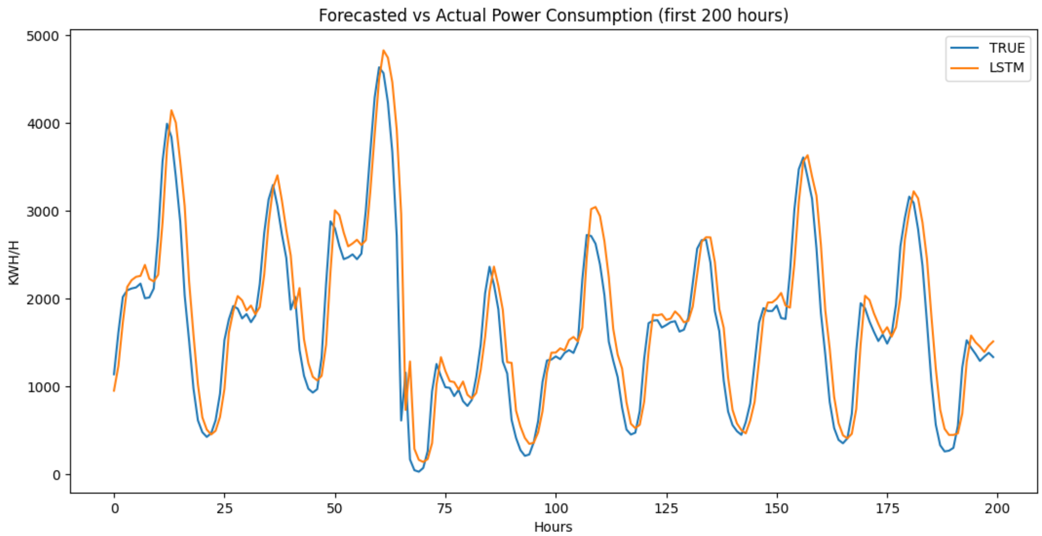

Figure 15. Graph of actual vs predicted power consumption for ToU customers.

G. *Affluent Customers*

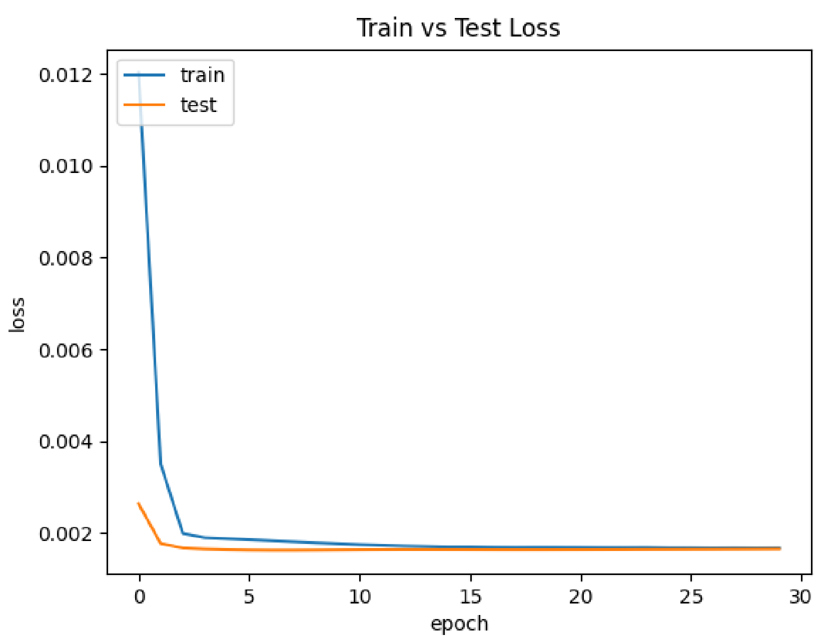

Figure 16. Graph of train vs test loss for affluent customers.

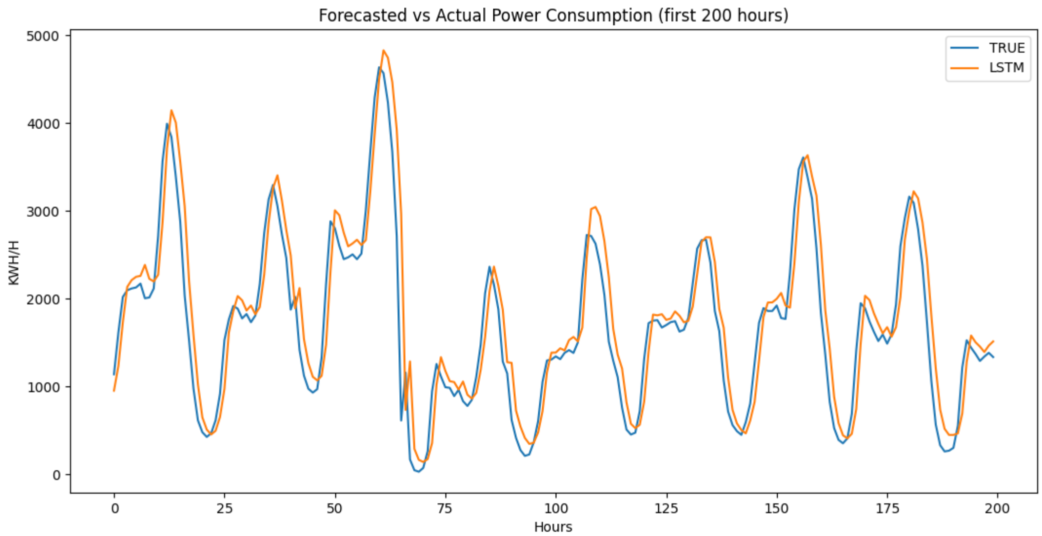

Figure 17. Graph of actual vs predicted power consumption for affluent customers.

H. Comfortable Customers

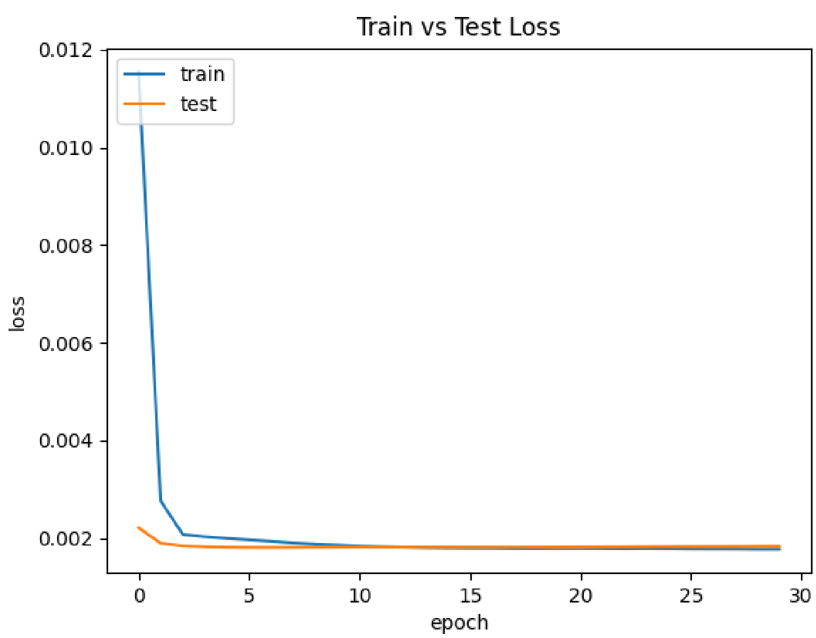

Figure 18. Graph of train vs test loss for comfortable customers.

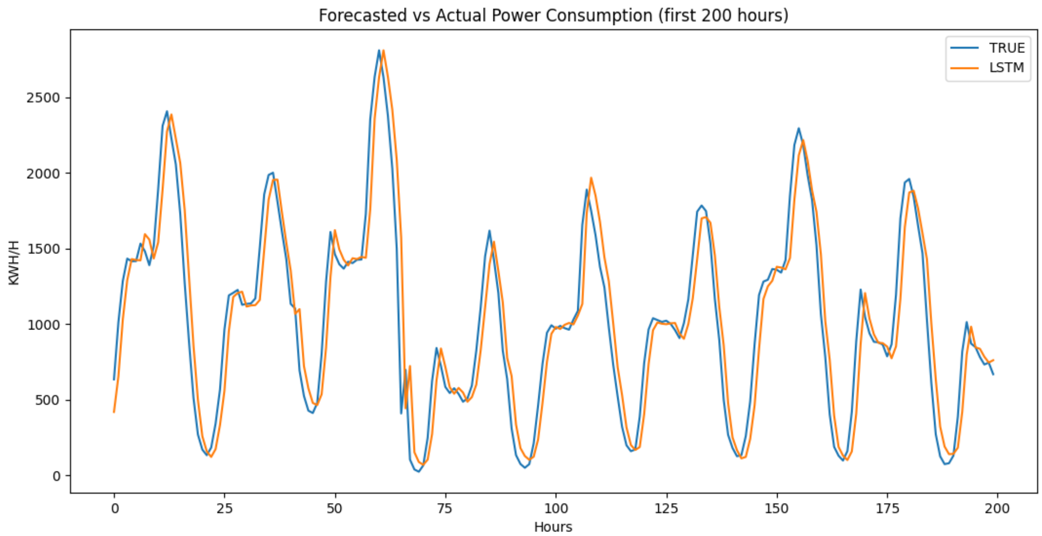

Figure 19. Graph of actual vs predicted power consumption for comfortable customers.

I. *Adversity*

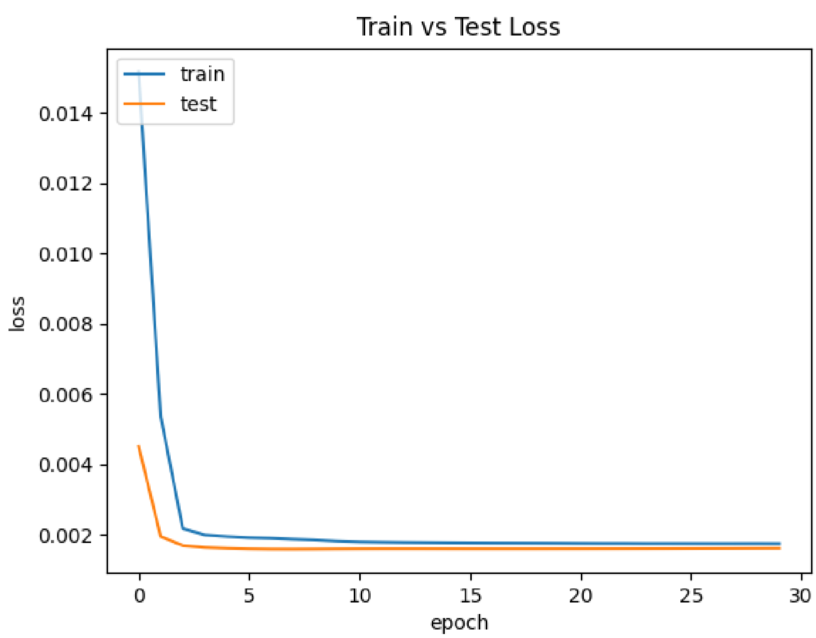

Figure 20. Graph of train vs test loss for adversity customers.

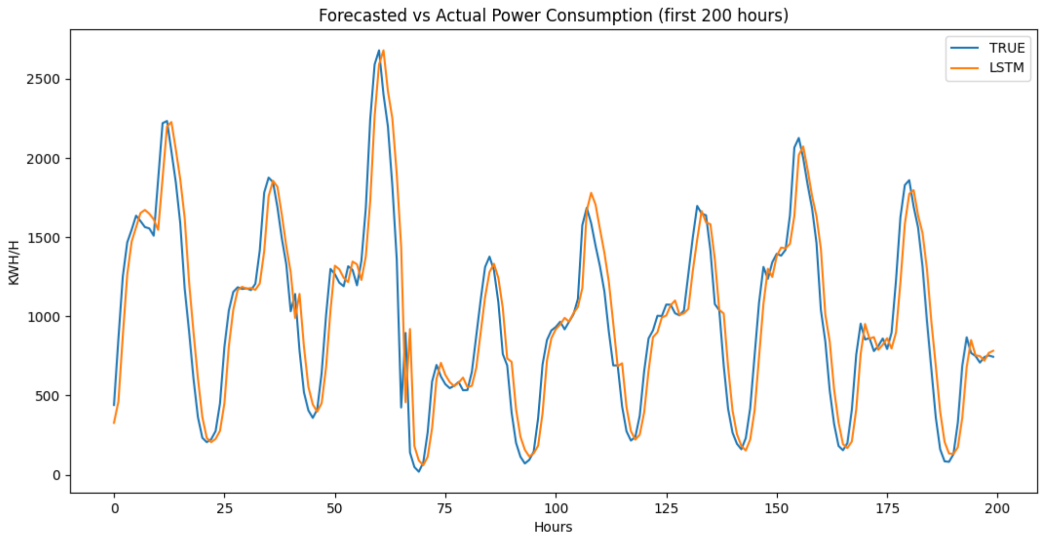

Figure 21. Graph of actual vs predicted power consumption for adversity customers.

J. Randomly Sampled Customer

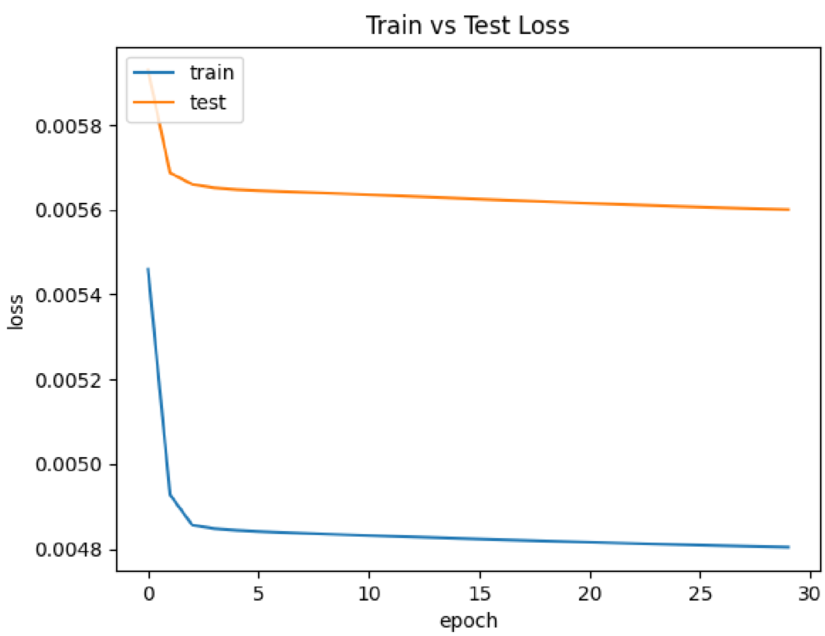

Figure 22. Graph of train vs test loss for randomly the sampled customer.

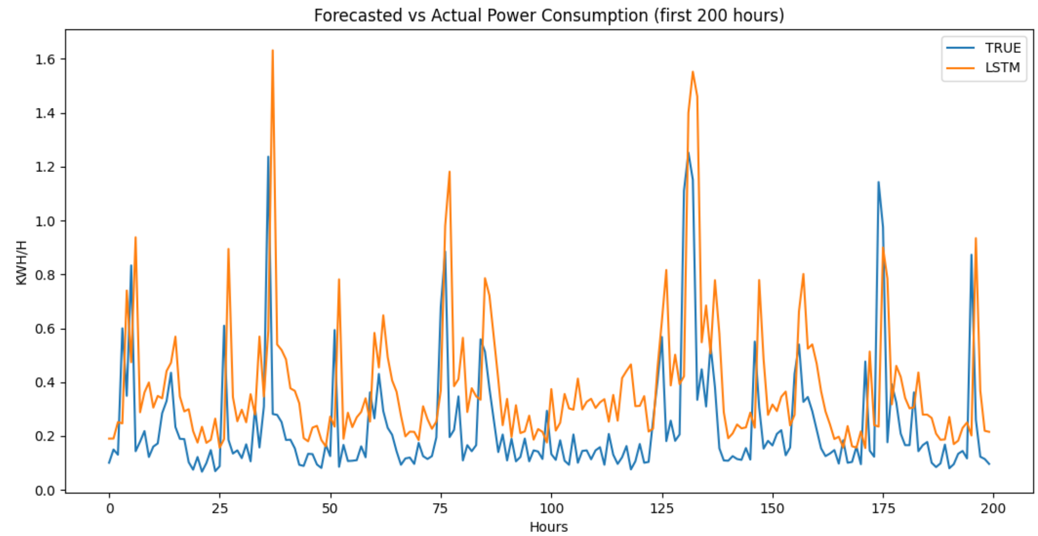

Figure 23. Graph of actual vs predicted power consumption for the randomly sampled customer.

K. Randomly Sampled Customer Summer

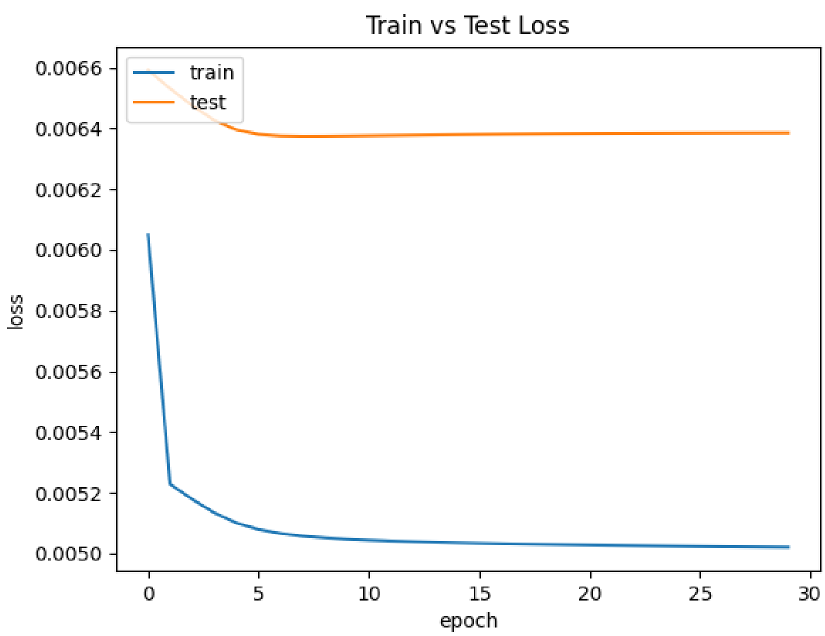

Figure 24. Graph of train vs test loss for the randomly sampled customer.

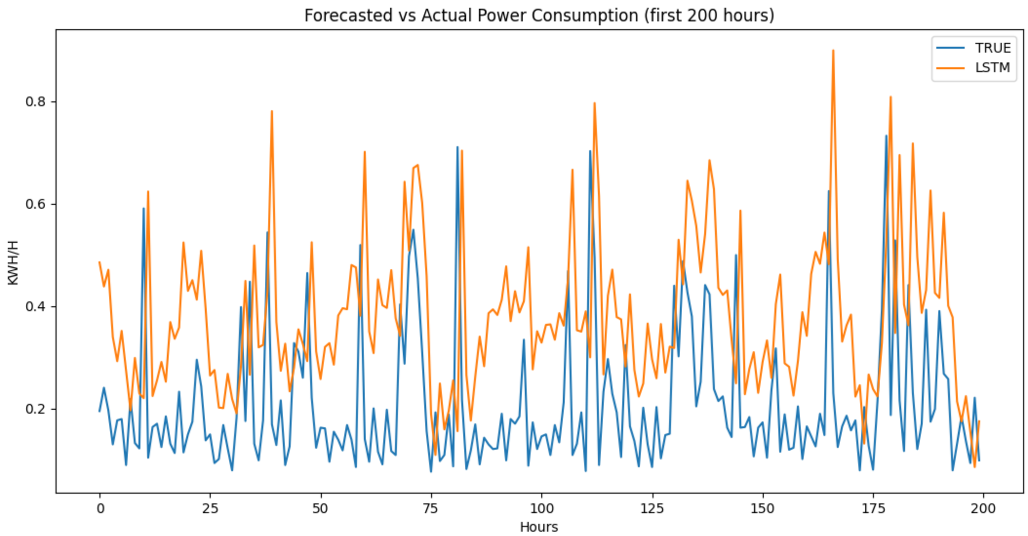

Figure 25. Graph of actual vs predicted power consumption for the randomly sampled customer (summer months only).

	ALL	STD	TOU	AFF	COMF	ADV	R.CUST	R.CUST SUMMER
RMSE	402.450	330.229	79.050	382.196	231.621	209.787	0.275	0.294
MAE	298.407	244.027	58.201	286.384	170.948	157.290	0.207	0.220
MSLE	0.123	0.133	0.126	0.119	0.147	0.133	0.036	0.041

Table 1. Table of Root mean squared error, mean absolute error, and mean squared log error values for each model run.

While all experiments saw similar results, the difference in behavior is apparent when viewing the predicted versus actual for the randomly sampled customer. The behavior of the Std, ToU, and acorn groups do little to model individual customer power consumption at an adequate level. The randomly sampled customer was using a standard plan and from a comfortable socioeconomic acorn. Machine learning customer behavior must be done on an individual basis and scaled to build a system of separate models that consider meteorological data. If no previous data is available, then models may be generalized based on similar household profiles and further adjusted.

Next, we analyze the results from applying varying size windows to the random customer data to test if any correlation between window size and predictability on an individual household basis in table 2.

	2 HOUR	**3 HOUR**	**4 HOUR**	**5 HOUR**	**10 HOUR**	**20 HOUR**
RMSE	0.269	0.237	0.284	0.319	0.335	0.263
MAE	0.204	0.169	0.237	0.279	0.295	0.208
MSLE	0.035	0.027	0.041	0.052	0.057	0.034

Table 2. Table of Root mean squared error, mean absolute error, and mean squared log error values for random customer for each size time window.

Table 2 shows that for the randomly sampled household adjusting window size did not make a substantial difference except for the 3-hour window. Yet, when different window sizes were applied to ToU customers, RMSE and MAE improved for all expect the 20-hour window. The most improvement was shown for ToU customers using a 10-hour window. A larger window size may be used to monitor groups of customers on ToU plans with individual household monitoring in combination to prevent ToU customers from creating spikes in power consumption amongst themselves. PCTs could then provide customers with suggestions based around a reasonable timescale without intrusive load monitoring.

	2 HOUR	**3 HOUR**	**4 HOUR**	**5 HOUR**	**10 HOUR**	**20 HOUR**
RMSE	62.648	66.821	58.521	59.688	46.196	228.139
MAE	48.412	50.615	46.312	48.077	35.773	180.879
MSLE	0.166	0.148	0.199	0.215	0.107	0.861

Table 3. Table of Root mean squared error, mean absolute error, and mean squared log error values for ToU customers for each size time window.

VI. Future Work

Demand response programs and PCTs are a dependable solution with room for future development. Allowing customers to make informed decisions while maintaining an optimal level of control over decisions regarding peak energy usage is the primary purpose of introducing automation. Finding the appropriate level of artificial intelligence while considering external variables such as weather has long been a goal of researchers [8]. Not only is it imperative for researchers to find the proper level of AI, but it is also necessary to find the appropriate parameters, windows of prediction, and provide an accessible and mobile application for consumers to access.

We provided a foundation for the predictability for each hierarchy of consumers drilled down to the household level. The next logical steps forward are further applying LSTMs towards live data to facilitate real time predictions to the smallest possible window. After which, applications could be developed for scalable real-time systems where LSTMs are continuously trained based on household, acorn, and customer type given some external parameters such as meteorological data. From there, UX/UI researchers could develop such applications to fit customer needs such as the appropriate level of input, output, and control [8]. The future of home energy management includes building a simple and intuitive PCT control that integrates home appliances with devices such as cell phones.

VII. CONCLUSION

We have shown that although consumer behavior patterns may differ through descriptive mining, both ToU and Std groups are equally as trainable down to the household level when LSTM models are applied to power consumption/ meteorological data. We also show that ToU customers are more prone to lower power consumption in general. We find that socioeconomic status affects power consumption but, is not a contributing factor to the predictability of customer groupings. In conclusion, customer groupings are not a determining factor in the predictability of power consumption. To continue the success of demand response programs and PCTs, machine learning must be integrated with weather data so that customers are able to make informed decisions about their power consumption. In total, demand response can greatly benefit from the implementation of scalable machine learning platforms.

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