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Machine Learning Models Application in Daily Forecasting of Hourly Electricity Usage

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***Abstract*—Traditional time-series techniques produce forecasts on future values based on the trend or seasonality of past values. It is not easy for these techniques to consider the impact of other exogenous and calendar-related variables. This paper uses the electricity usage data from Harris SmartWorks to demonstrate an approach to building and training machine learning models to overcome this problem. It is shown that Machine learning models produce accurate daily forecasts for hourly usage. The performance of these models could be evaluated by one conventional metric, and one explicitly built for articulating the model's forecasting accuracy for peak periods.**

***Index Terms*—Electricity usage, Time series, Machine learning, Deep learning applications, Big data.**

I. Introduction

Harris SmartWorks develops and provides utility management software and related information system services to various utility companies in North America and worldwide. The software can record, store, and analyze data of regular utility usage for each virtual and smart meter it manages. Accurate short-term usage forecasts could be produced, allowing the utility companies to manage load and plan for purchase from the open market.

As the first phase in our research program with Harris, we demonstrated how a machine learning model could be developed to assess the impact of the pandemic on utility usage by estimating the "baseline" usage from March 2020 onward if COVID-19 did not happen [1]. In this second phase of the research program, we hope to use machine learning algorithms to produce short-term, daily forecasts of hourly usage using data available up to the day of the forecast.

More specifically, to produce hourly forecasts for the next day, a forecast model should use historical data up until those from the day before. The performance of the model developed would then be evaluated daily over the testing period. For example, suppose a forecasting model is created using data over two years and assessed using a testing data set of one year. In that case, the model will be trained and re-trained using the "rolling" data set (dropping one day's data at the "oldest" period of the time series and adding one day's data to the most recent period.) Daily forecasts from the model would then be generated and compared to the actuals three hundred and sixty-five times.

From a computational standpoint, this is much more complicated and demanding than the model evaluation process than that for estimating baseline usage where the estimates are compared to the actuals once over the entire testing period. To alleviate this computational burden, we opted to perform a model evaluation weekly, producing daily forecasts one week at a time and evaluating their accuracy accordingly. We will discuss Further the training and evaluation process in detail in Section V below.

It is worth pointing out that the accuracy of forecasts for "peak" periods is much more critical than other periods from a planning perspective. The metrics used in the evaluation of the models must take this into account. For this purpose, we will introduce below a set of novel performance metrics for assessing the models.

Therefore this research aimed to create accurate forecasting models of hourly utility usage using machine learning algorithms. Lessons learned in the first phase of the research in data pre-processing, data transformation, feature engineering, and performance evaluation were used and extended. The report here shows that this was achieved to a considerable extent.

Note that the work presented here was conducted as part of the applied research and capstone projects undertaken at Okanagan and Langara Colleges by faculty and students with support from industry [2]–[4], [4]–[7], [7]–[19], [19]–[22].

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II. Related Works

Using traditional statistical techniques, such as Autoregressive Integrated Moving Average (ARIMA) models, is a popular option for generating a short-term, daily forecast for a time series [23]–[26]. A linear regression model is another option [27], [28]. In this context, in addition to "lagged" variables, other exogenous variables that could be linearly related to the variable of interest could be incorporated into the model.

Machine learning algorithms have also been used in time series analysis. The Support Vector Regression (SVR) algorithm, for example, has been used to forecast individual electricity consumption [29]. In addition, some ensemble methods are also used to generate accurate time-series forecasts [30], [31].

Multiple Layer Perceptron (MLP) is another algorithm that has been used in time series forecasting [30]–[33]. This algorithm allows for discovering non-linear relationships between the variable of interest and various numerical or categorical features. On the other hand, any "autocorrelation" or calendar effects in the variable of interest must be explicitly expressed as additional input features or through a transformation technique [33].

Long Short-Term Memory (LSTM) algorithm is also helpful in time series forecasting [25], [31], [34]. This algorithm has a characteristic of feedback connection and is therefore favourable for processing a sequence of data. Since time series data is a type of data sequence, the LSTM algorithm is a good candidate for time series modelling.

III. Feature Set and Data Pre-Processing

A. Feature Engineering

For this research, we used the records from June 16th, 2018, to February 10th, 2021, of a utility company in the United States. This electricity usage data set had an hourly time stamp and was for a particular geographic area. The data set was augmented by the corresponding hourly data on temperature, wind speed, and relative humidity from the exact location for forecasting purposes. The objective was to produce hourly forecasts of usage daily using this time series data set.

To capture the seasonal pattern and other calendar effects, for example, whether certain months or days of the week would have higher or lower usage, we created several indicator variables for each hourly period:

- months of the year (12 one-up variables)
- days of the week (7 one-up variables)
- hours of the day (24 one-up variables)
- whether the day is a weekend (Saturday or Sunday; 1 one-up variable)

Moreover, some holidays on the calendar may also have an impact on usage. As such, we also created an additional one-up variable to indicate whether the forecast day is a holiday.

The autocorrelation effect is another concern in time series forecasting. The temperature, wind speed, relative humidity, and usage in each specific hour of the last seven days before the forecast day were considered to capture this autocorrelation effect. To moderate the impact of the autocorrelation effect, we used the trimmed mean (Equation 1) of the last seven day's temperature, wind speed, relative humidity and usage as additional independent variables (features) for the models.

$$\bar{X} = \frac{\sum_{i=p+1}^{n-p} X_i}{n-2p} \tag{1}$$

Referring to Equation 1 above, X_i stands for a descending or ascending sorted series of values (i.e. temperature, wind speed, relative humidity or usage) in the previous seven days. The lowest and the highest value in the series are removed from the calculation. Therefore, p = 1 and n = 7 in Equation 1.

B. Scaling

To ensure that features are on the same scale, either the standardization process (refer to Equation 2) or the Min-Max normalization process (refer to Equation 3) was applied to all numerical features included in the model.

$$X_{standardized} = \frac{X - E(X)}{SD(X)} \tag{2}$$

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

C. Training and Testing Data Sets

The original data set contained the electricity usage records from June 16th, 2018, to February 10th, 2021. The most recent one-year records were used as the testing data set (from February 09th, 2020, to February 10th, 2021). The remaining data set (from June 16th, 2018, to February 08th, 2020) was used as the initial training data set for model building. As discussed in the Introduction, the training data set changed within the model training process. We will explain further details of this training process in Section V.

IV. Performance Metrics

In this research, we considered several performance metrics for evaluating a model's performance. Specifically, we used the conventional performance metric, Mean Absolute Percentage Error (MAPE), which is quite common in estimation or forecasting models [22] and the Total Absolute Error Percentage metrics developed by the project team in the first phase of the project.

A. Mean Absolute Percentage Error

The mean absolute percentage error (MAPE) metric measures the average absolute error percentage between the predicted and the actual value. Equation 4 shows the calculation of the MAPE.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|Y_i - \hat{Y}_i|}{|Y_i|} \tag{4}$$

B. Total Absolute Error Percentage (TAEP)

Apart from MAPE, the project team developed a new metric to measure a model's forecasting accuracy. This metric considers the ratio between the total absolute error and the total usage over the testing period. It is suitable for evaluating the performance of models built for forecasting in the utility industry. In this research, we used it as a primary metric for model comparison. The TAEP metric is calculated as follows.

$$TAEP = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y_i}|}{\sum_{i=1}^{n} Y_i} \quad (5)$$

Based on previous research [22], we recognized that the challenge in the model development process is in the selection of a model that can perform well in forecasting usage in peak periods, which is critical for the planning of utility provisioning and supply. To compare the performance of models in this context, we also calculated the MAPE (Equation 4) and the TAEP metric (Equation 5) using only the top 10%, 5%, and 1% of the highest usage periods in the testing data set and their forecasts. In so doing, we can compare the models' performance in forecasting usage in peak periods.

V. Forecasting Models

As mentioned, several studies used statistical models, such as traditional time series models, to forecast energy consumption [23]–[26]. Other studies considered that past energy usage is not the only factor in predicting future usage. Several environmental factors, like temperature, should also be considered [27], [28]. In these cases, a regression model or a machine learning algorithm is a practical alternative and preferred as these factors could easily be included in the modelling process.

For this research, the machine learning models are trained and re-trained using eighteen months of "rolling" data. In essence, an initial model was trained using the training data set (from June 16th, 2018, to February 08th, 2020) to produce hourly forecasts for February 09th, 2020. For the computation of performance metrics, we also recorded the forecasts and actuals for the day. In simulating the use of the model in an actual operating environment, we re-trained the model with the same set of features and hyper-parameters using a new training data set. This new data set consisted of the initial training data set but with the dropping of observations from June 16th, 2019, and the addition of observations from February 09th, 2021. In other words, we removed one day's data from the beginning of the original training time series and added another day's to the end using the data from the testing time series. Again, we recorded the forecasts and actuals for the second day to compute performance metrics later on in the process. We repeated this re-training process until the end of the testing time series was reached.

Given that we have one year of testing data, we would need to perform the above re-training process 364 times. This re-training process was computationally costly. Instead, we modified this process to complete the re-training process every week, using training data sets with one-week drops and one-week adds. The re-trained model would produce hourly usage forecasts every day for the following week. The re-training process for each model was run 52 times instead, thereby easing the computational burden. In other words, the model was trained to produce daily forecasts but was evaluated only on a weekly basis.

Different machine learning algorithms for forecasting energy usage have been used in the past. In the artificial neural nets (ANN) arena, a "Multiple Layer Perceptron" (MLP) algorithm was used in the study by McManamin and Moon [32], [33]. Other research used a Long-Short term memory (LSTM) algorithm [25], [34]. Apart from ANN, the Support Vector Regression (SVR) algorithm has also been used to estimate electricity consumption by residential customers [29]. Together with two other algorithms, they were candidates in the development of forecasting model in our study:

- Multiple Layer Perceptron (MLP)
- Long-Short Term Memory (LSTM)
- Support Vector Regression (SVR)
- Random Forest Regression (RFR)
- XGBoost

As usual, we experimented with different combinations of features and hyper-parameters for each algorithm to optimize performance and reduce prediction error.

VI. Results

Tables I and II show the results for the best models (in terms of performance metrics) developed for each type of algorithm. All models in the tables, except the LSTM model, were built using standardized data (Equation 2). Normalized data (Equation 3) were used to build the best LSTM model.

TABLE I
MAPE of the Best Forecasting Models

Model	MAPE			
	Overall	Top 10%	Top 5%	Top 1%
XGBoost (Estimator: 100, Max. Depth: 100)	6.40%	4.17%	3.68%	4.15%
RFR (Trees: 100, Max. Depth: 100)	6.93%	4.42%	3.94%	3.79%
SVR (Kernel: rbf, Gamma: 0.1 , C: 10)	6.43%	4.01%	3.52%	3.23%
MLP (1 Hidden Layer: 100, relu, Dropout: 0.25)	5.91%	3.85%	3.4%	3.05%
LSTM (1 Hidden Layer: 300, Dropout: 0.05)	8.25%	5.82%	4.14%	2.79%

TABLE II
TAEP Metric of the Best Forecasting Models

Model	TAEP Metric			
	Overall	Top 10%	Top 5%	Top 1%
XGBoost (Estimator: 100, Max. Depth: 100)	6.00	4.14	3.70	4.18
RFR (Trees: 100, Max. Depth: 100)	6.52	4.38	3.93	3.80
SVR (Kernel: rbf, Gamma: 0.1 , C: 10)	6.04	3.97	3.51	3.24
MLP (1 Hidden Layer: 100, relu, Dropout: 0.25)	5.56	3.84	3.33	3.05
LSTM (1 Hidden Layer: 300, Dropout: 0.05)	7.89	5.69	4.08	2.79

The MLP model developed has the lowest overall, top 10%, and top 5% TAEP Metric, which is 5.56, 3.84, and 3.33 respectively. However, for the forecasts with the top 1% of

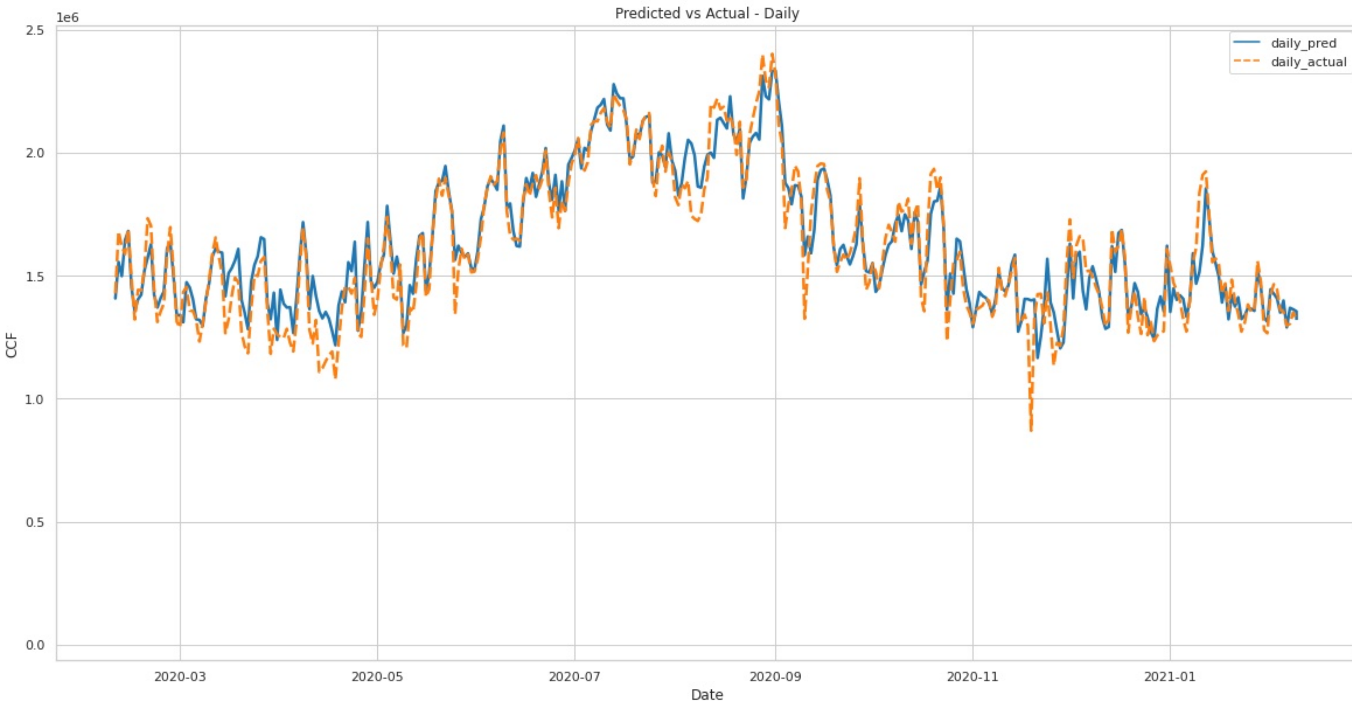

Fig. 1. Actual versus Forecasting Summarized by Day Under the MLP Model

usage, the LSTM model has the lowest TAEP Metric (2.79). The same pattern is observed in the MAPE results (Table I). We can conclude that for forecasts with top 1% usage, the LSTM model performs better. On the other hand, the MLP model has better performance in most situations. We suspect that the MLP model developed is the best model overall for forecasting the hourly usage of electricity in this case.

Figure 1 displays the daily forecasting result (summation of 24 hours' usage within a day) of the MLP model on the testing data set. The usage forecasts (blue line) track the actual use (orange dashed line) closely most of the time. The figure also shows that the models underestimate the energy usage in the majority of peak periods.

The above results show that machine learning algorithms, especially the MLP and LSTM models, could help create accurate forecasts for utility usage. Moreover, the results also show that when we focus on different levels of peak usage (top 10%, top 5%, or top 1%), other models could be used to minimize the prediction error. Using our research result as an example, if the top 1% of usage is the focus, the LSTM model is a good alternative. This example also shows the importance of selecting the appropriate metric for comparing model performance in utility usage forecasting.

VII. Conclusion and Future Work

Overall, this paper demonstrates the possibility of utilizing machine learning algorithms to produce daily forecasts of utility usage on an hourly basis. It also shows the advantage of this approach is the incorporation of related environmental factors and calendar effects into the modelling process. Furthermore, feature engineering techniques, such as using a trimmed mean of temperature in the previous periods, could also be easily incorporated for the time lags involved in changes in utility usage patterns.

This research shows the importance of choosing a proper performance metric in evaluating forecasting models. The TAEP metrics used in the study are worthwhile candidates if the performance of the forecasts at peak periods is the primary concern.

From a practical perspective, the cost of underestimating at peak periods could be higher than that of overestimation in forecasting utility usage. Most models developed under this research are produced in many peak periods, and therefore the improvements in this regard will be a worthwhile pursuit.

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