EE4211
Project Report
Global Maxima

Final Submission by Global Maxima

Question 2:

A.

The natural gas consumption by the customer is not deterministic with time. The usage pattern of the day may not be similar to previous days. This would lead do aggregate consumption requirements which might not have been foreseen by the distribution companies leading to difficulty in operations.

Natural gas is extracted from the oil wells and processed by the generation companies and further handled by the transmission utilities which transport large quantities of gas through interstate lines. The Local Distribution Companies (LDCs) buy natural gas from the transmission utility through Gate stations. The pressure of gas is reduced at these stations to further deliver to individual households through pipelines of smaller diameter. The LDCs are duty bound to ensure sufficient delivery of natural gas to its customers despite unexpected variations in the consumption values.

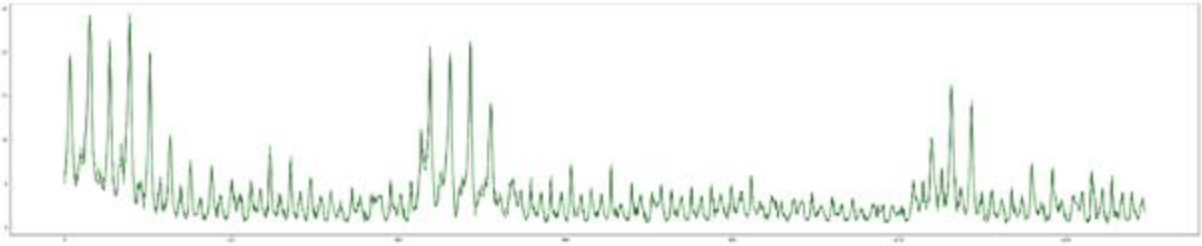
The rate of flow of gas is determined by the pressure maintained in the pipelines. Thus, the pressure has to be altered by the utilities to manage the fluctuating demands at the consumer end. Additionally, since the generation and consumption do not exactly get balanced everytime, it requires storage of gas when excess and retrieval of the stored gas when deficit. The above operations cannot be done instantly and would require some latency of time. Eventually, this implies that if the distribution companies have the gas consumption predictions for the next hour or day, they can, in conjunction with the utilities decide the quantum of storage or retrieval and also the optimum pressure to be maintained in the lines for the next hour.

With a good forecasting model, the distribution utilities can avoid excessive gas storage which are unproductive assets in a business case and thus reduce the operational margins. The pressure control can also be smoothly done to have an optimal operation and dispatch. Additionally, the predicted data can also be used to create tariff models such as demand response programs (detailed in our proposal) to reduce the stress during the peak period and also make market strategies to increase customer base with attractive pricing methods by exploiting the existing lines and compressor stations to its fullest capacity.

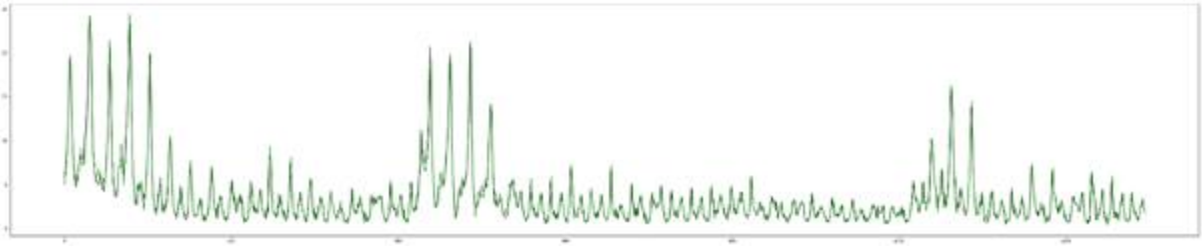
B. Linear Regression Model for Hourly Prediction

Hourly readings estimated from the raw measurement records have been used as the training dataset. For each prediction, the feature space consists of the hourly readings from the previous 24 hours. Since the overall goal for the prediction model is to help the system operators to make better decisions for the entire natural gas grid, we focused on the gas usage from the entire town. The overall usage has been estimated by calculating the average hourly usage. To ensure the average being representative, the data from the first day and the last day has been abandoned since they did not have adequate households to represent the entire town. Two models have been built using linear regression and support vector regression method respectively.

The predicted results versus the actual readings for the two models have been plotted in Figure 1.



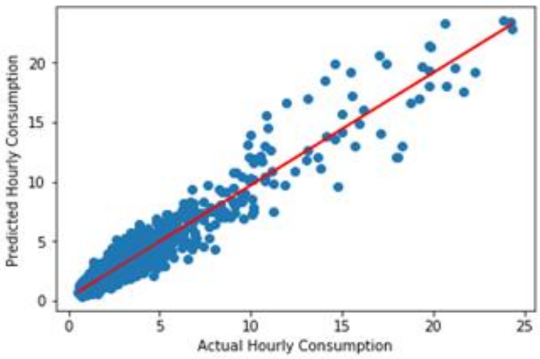
1a. Linear Regression Model

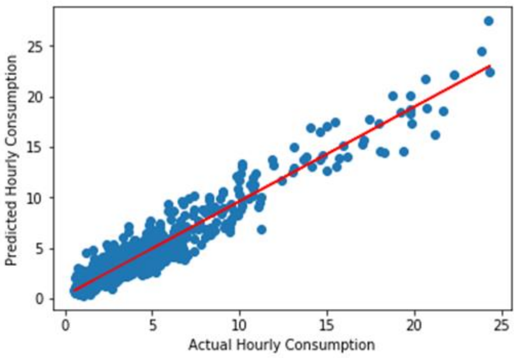


1b. SVR Model

Figure 1. Time series plot for the actual (black) versus the predicted (green)

Figure 2 has shown the scatter plots between the predictive value versus the actual value with the line of best fit.





2a. Linear Regression Model

2b. SVR Model

Figure 2. Predicted value versus actual value with the line of best fit.

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Question 3: Day-Ahead Hourly Gas Consumption Prediction for Natural Gas Demand Response Program

1.0 Introduction

1.1 Motivation

In electricity market, demand response program is a common practice to reduce the stress on the grid and high electricity prices. It is usually implemented with dynamic pricing or other forms of financial incentives to encourage consumers to change consumption behavior, either reducing or shifting the electricity during peak period where the cost of electricity is the highest. Viewing success of demand response program in electricity market, interest is gained to implement demand response program for the natural gas market (Hamel, 2019). The benefits brought by demand response program is multiple as the Department of Energy is conducting a study to address “the costs and benefits associated with those savings, including avoided energy costs, reduced market price volatility, improved electric and gas system reliability, deferred or avoided pipeline or utility capital investment, and air emissions reductions.” (Nera Economic Consulting, 2019)

1.2 Envisioning Natural Gas Demand Response Program

Using the natural gas hourly consumption data, the day-ahead hourly demand can be predicted from the historical demand and the recent hourly demand based on demand response actions. These predicted day-ahead quantities would be used as demand bids submitted to the natural gas local distribution companies. Using these demand bids and the price bids submitted by the natural gas suppliers, the system operator obtains a day-hour schedule for the gate stations. These constitutes the day-ahead consumption operations in the demand response program for natural gas, which is modelled after the electricity counterpart (Subramanian, Das, Kwon, & Gosavi, 2019).

1.3 Objective

Given the limited information from the provided dataset, the dynamic pricing component is not explored. Hence, the team is unable to create a full demand response program with real-time pricing adjustments.The primary focus for this project is on the first part of the demand response program: to predict the day-ahead hourly gas consumption (gas consumption for each hour for the future 24 hours) for a potential natural gas demand response program to be implemented for the Mueller Neighbourhood.

2.0 Methodology

2.1 Features

Hourly Gas Consumption

Hourly gas consumption data of 80 households is created from the given Pecan Street dataset for Muller neighbourhood. For any hourly gas consumption prediction in the 24-hour prediction time frame, the past 144-hour historical gas consumption data of that hour is used to train the model.

Weather

Daily weather data including precipitation and average temperature is acquired from the closest weather station from the U.S. National Centers for Environmental Information website. It is suspected that weather conditions have an impact on households' activities, which are related to natural gas consumption.

- **Temperature**: More energy is required to heat up colder air to the same desired temperature than warmer air. Households would have a higher natural gas consumption on a cold day than a warmer day given the same operation time. In addition, according to a survey by the Energy Saving Trust, 52% of the surveyees responded to that they turn the thermostat up when it's cold outside.
- **Precipitation**: Precipitation could have potential relationships with households' gas consumption pattern. For example, people might decide to stay at home or stay at home for a longer period of time if it is raining heavily outside.

2.2 Algorithms

Data Preprocessing

Similar to the processing method in Question 2, we used shifted window to collect the feature. However, we assumed that including more input data would be needed for a further prediction. Therefore, in this part of the project, we used the data from the previous six days (6×24 features) to predict the next day (24 outputs) for every prediction.

Linear Regression

Although neural network is one of the most popular methods for machine learning, it often requires a lot of computing power. In the previous one-hour prediction model, we have observed a promising result from the linear regression model. Therefore, we chose to try with linear regression method to see the performance for the next-day prediction.

Neural Network

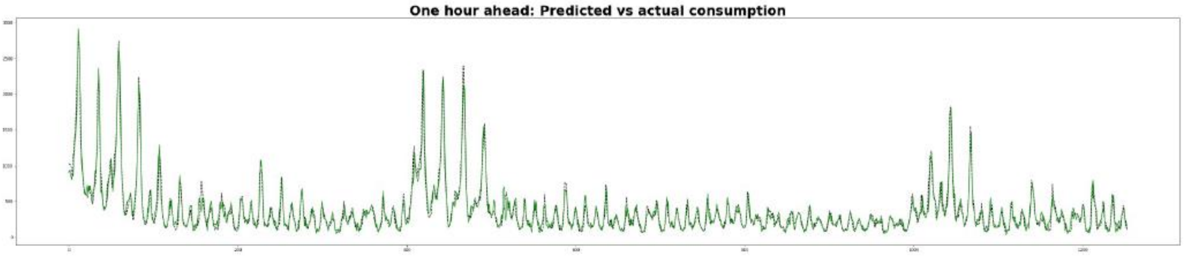
To keep the model structure simple, two-layer neural network has been used with four and three neurons implemented respectively. Rectify Linear Unit (ReLU) has been used for activation function and the optimizer chosen was "Adam". ReLU has been proven to have better computational efficiency and tends to show a better convergence performance than sigmoid function (Krizhevsky, Sutskever& Hinton, 2017). Adam is

Mean squared error (MSE) has been chosen as the loss function since the gas system operator would care about the larger magnitude of prediction error more than some small deviations.

3.0 Model Results

Model 0: Linear Regression

Model 0 is a linear regression model with only historical gas meter data as features.

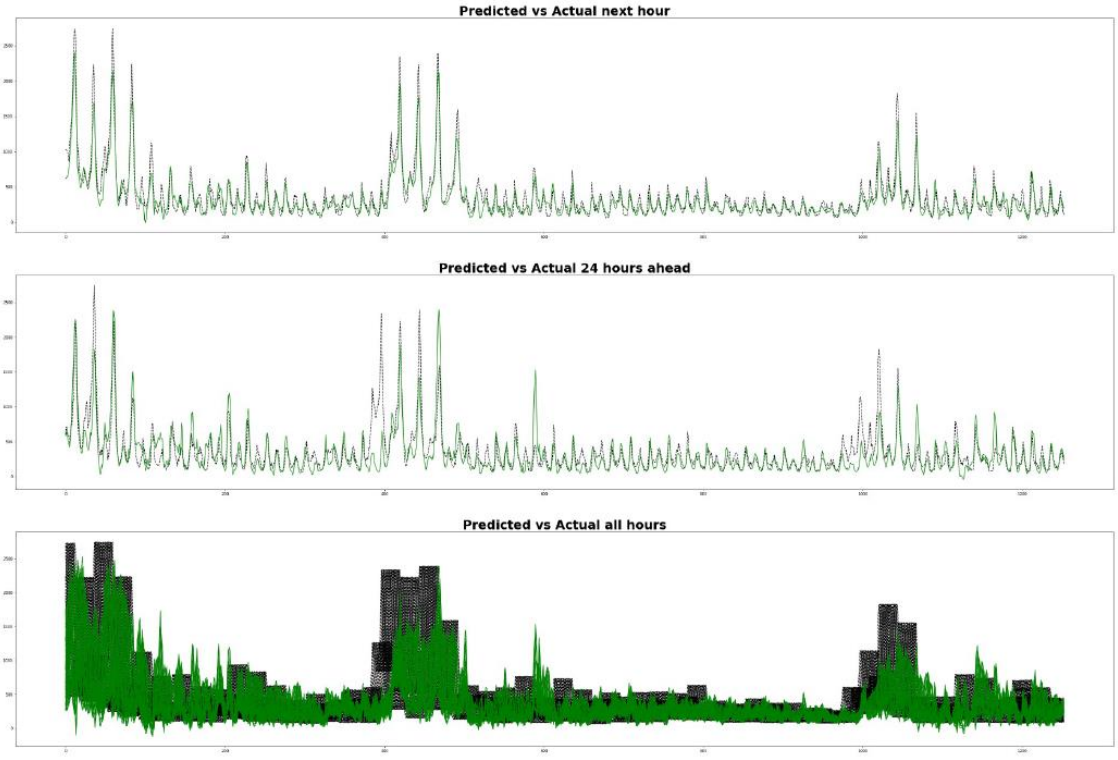


One-hour ahead actual (black) vs predicted with linear regression model (green)

MSE (overall): 48,530
MSE (next hour forecast): 9,488
MSE (24 hour ahead forecast): 54,471

Model 1: Neural Network

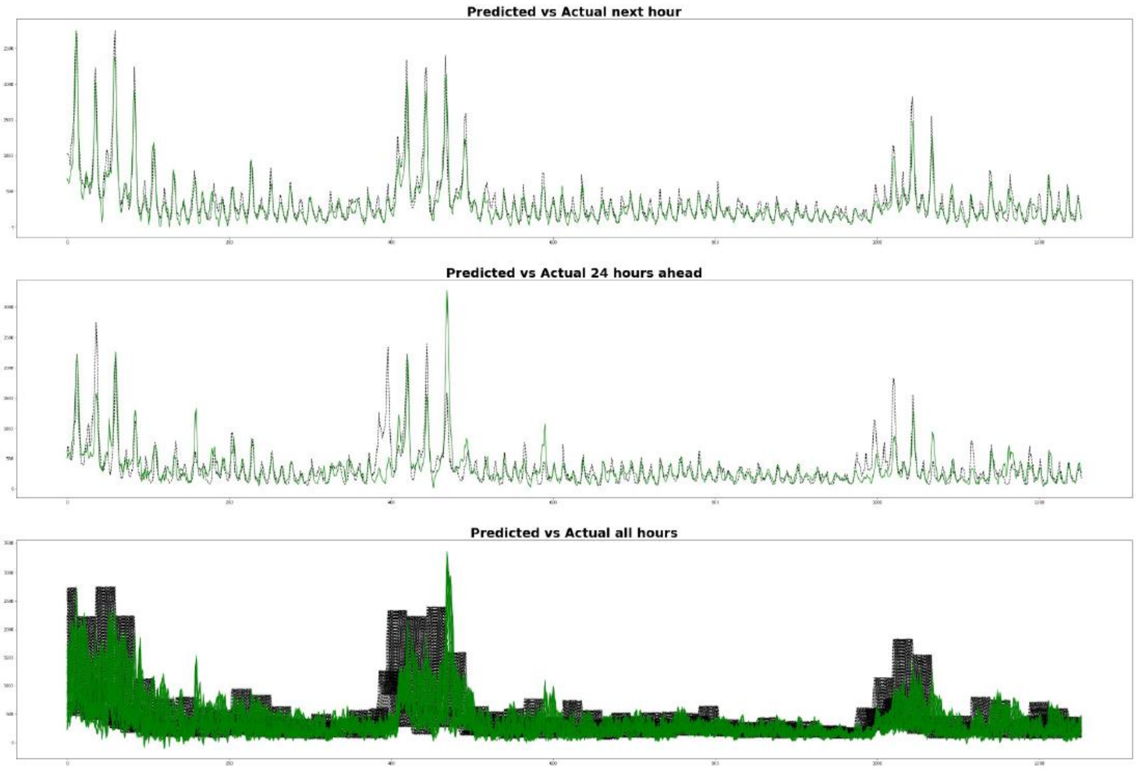
Model 1 is a neural network with only historical gas meter data as features.



Actual (black) vs predicted (green) with a neural network for one-hour ahead, twenty-four hours ahead and all together (top to bottom)

MSE (overall): 46,040
MSE (next hour forecast): 18,413
MSE (24 hour ahead forecast): 50,566

Model 2: Neural Network with Weather [Temperature and precipitation] Features
Model 2 is a neural network with historical gas meter data and next-day average temperature and total precipitation as features.



Actual (black) vs predicted (green) with a Neural Network trained with weather data as well for one-hour ahead, twenty-four hours ahead and all together (top to bottom)

MSE (overall): 47,855
MSE (next hour forecast): 16,555
MSE (24 hour ahead forecast): 55,566

It should be noted that the unit for MSE is ft^3/hr for the entire town.

4.0 Limitations

The main assumption for this project is that the demand response program mechanism for natural gas is similar to the electricity demand response program and hence can be modeled after the electricity counterpart. It is worthwhile to investigate the differences in the operating schemes and distribution systems in depth to create a more realistic and meaningful program. For example, demand response programs' impact on gas resource costs could take longer to observe than it does for electricity demand response programs due to the gas supply long planning process undertaken by gas distributor (Nera Economic Consulting, 2019).

Limitation introduced by the models include the lack of fine tuning for the loss function. We chose the simple MSE as the metrics. However, to match with the realistic situation, the negative predictions should be heavily penalized to create a boundary for prediction. We also should have consult with the real system operators to see if the overestimation or underestimation of the gas demand should be treated differently.

Oscillations of the MSE value have also been observed, the reason for which was deemed to be random initialization of the weights. The model may not have been converged within the 150 epochs. However, to ensure the model being trained in a timely fashion, we decided to limit the epoch value for this project.

Only a single train-test split has been used and to ensure the test set not being polluted, the split was made based on the time sequence (i.e. not random split). However, to make the prediction model more robust, we would love to have a larger dataset so that the model could be tested and trained on several contiguous and sufficiently large train-test splits. The model is also limited by not having any data during spring and summer seasons. It is safe to assume that the gas usage pattern in the residential household would be different in especially summer.

As for using the climate data, we still have faith in it. Daily data was used in this project and we did not see a better performance in prediction. We assume hourly weather data would be more helpful.

5.0 Conclusion

From the evaluation performed, it appears that the neural network trained without weather data was the best performing model overall. The linear model performed significantly better than both neural networks in forecasting the next hour ahead, with an MSE value of around half of the neural network's corresponding value, but had a much quicker decrease in performance when predicting further into the future.

For this reason, we would recommend that a combination of a linear regression model for forecasting one hour ahead consumption and a neural network trained on historical consumption data for forecasting the next 23 hours. Further exploration into whether more precise weather data would improve the forecasts should also be carried out as this could provide more insight than the daily data that was available for this investigation.

6.0 Future Study Recommendations

Full Scale Review of Natural Gas Consumption Contributing Factors
With more available data and resources, the next step is to study and include other factors related to natural gas consumption pattern to the model through literature review. For example, besides temperature and precipitation, there are other possible weather characteristics might affect heating requirements including angle and intensity of sunlight, humidity, and wind speed. This could increase the performance of the model predictions.

Dynamic Pricing Prediction

For electricity demand response program with dynamic pricing, the system operator obtains dynamic prices using two inputs: the day-ahead electricity price and the previous day's dynamic price for the current hour (Subramanian, Das, Kwon, & Gosavi, 2019). Any deviation in load consumption for the current hour from the day-ahead demand bid / prediction is settled using another price called real-time prices submitted by the electricity generators (Subramanian, Das, Kwon, & Gosavi, 2019). Then the system operator settles the market to pay the generators for the hour using day-ahead and real-time prices, determining the cost for satisfying the demands. If natural gas pricing data is available, a demand response program with dynamic pricing can be modelled after the electricity dynamic pricing with adjustment to the regional natural gas network operation.

Consumer Behavior Change Prediction and Sensitivity to Pricing Adjustments

For any new program, it is important to estimate its effectiveness and impact to make a successful business case. If pre-demand-response electricity consumption pattern and the consumption pattern with demand response program implemented are available, the consumers’ potential behavior change for natural gas consumption can be modeled after the electricity counterpart.

In addition, It is also worth investigating the elasticity of dynamic pricing such as how sensitive consumers are to different level of pricing incentives or penalties from the electricity demand response program, which will help natural gas distribution companies to maximize the potential of demand response program.

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