2020

Prediction of Natural Gas Consumption in Bahçeşehir Using Machine Learning Models

Suhaib Ahmed
Istanbul Sehir University, suhaidahmed@gmail.com

Samaneh Madanian
Auckland University of Technology, Sam.madanian@aut.ac.nz

Farhaan Mirza
Auckland University of Technology, New Zealand, farhaan.mirza@aut.ac.nz

Selim Zain
Istanbul Sehir University, selimzain@sehir.edu.tr

Prediction of Natural Gas Consumption in Bahçeşehir Using Machine Learning Models

Completed research paper

Suhaib Ahmed
School of Natural and Applied Sciences
Istanbul Şehir University
Istanbul, Turkey
Email: suhaidahmed@gmail.com

Samaneh Madanian
School of Engineering, Computer and Mathematical Sciences
Auckland University of Technology
Auckland, New Zealand
Email: sam.madanian@aut.ac.nz

Farhaan Mirza
School of Engineering, Computer and Mathematical Sciences
Auckland University of Technology
Auckland, New Zealand
Email: farhaan.mirza@aut.ac.nz

Selim Zaim
School of Engineering and Natural Sciences
Istanbul Şehir University
Istanbul, Turkey
Email: selimzaim@sehir.edu.tr

Abstract

Accurate prediction of natural gas consumption is of great importance for supply-demand balances and investments. This paper aims to utilize and compare the performance of multiple powerful machine learning algorithms to accurately predict the consumption of natural gas in Bahçeşehir, Istanbul. The utilized algorithms include Linear Regression, Random Forest Regression, Multilayer perceptron with back propagation (MLP) and gradient boosting (XGBoost). The algorithms were evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R Squared to ensure consistency. The final results indicated that XGBoost outperformed MLP by 0.02, Forest Regression and Linear Regression by 0.04 Mean Absolute Error. XGBoost is highly scalable, efficiently reduces compute time and makes optimal use of memory which makes it a more suitable model for prediction. Accurate predictions reduce loss to the economy and ensure a balance between supply and demand.

Keywords Forecasting, Machine learning, XGBoost, MLP, Natural gas consumption

1 Introduction

Many countries around the world resort to natural gas as a primary source of energy due to its environmentally friendly nature which lead to an enormous increase in demand. Energy is considered a significant factor in improving the quality of life and social development (Esen and Bayrak 2017).

Turkey relies on natural gas for its industrial and residential power generation with significant imports from Russia, Iran and Azerbaijan. In 2018 Turkey imported more than 6 billion cubic meters of natural gas with a total consumption of 49.3 billion standard cubic meters (Sm3) by the end of the year (Ministry of Energy and Natural Resources 2020), reaching a record of 245 million cubic meters in a day on 8th January 2019. Natural gas accounted for 15.2% of electricity production in the first half of 2019 (Ministry of Energy and Natural Resource 2020). Economic and population growth are attributed to the increasing demand for energy in Turkey. Amongst the OECD countries, Turkey recorded the highest and fastest demand for electricity with a 5.5% progress rate from 2002. In early 2019 Turkey exceeded 88 GW of its installed capacity which is highest in more than a decade. The rising demand and insufficient natural gas storage facilities in Turkey (Asian Infrastructure Investment Bank 2018) makes the prediction of natural gas consumption very significant. Accurate prediction of natural gas has the following benefits:

- Ensures the balance between supply-demand and prevents natural gas crisis.
- Provides a solid base for investment
- Prevents future loses both to the economy and natural gas distributors.
- Can prevent Take or Pay (ToP) penalties

The impact of wrong or no prediction could be severe. An example is the oil crisis recorded on the 20th April 2020 in the USA where oil prices fell below zero dollar, which resulted due to high production and less demand (The Guardian n.d. 2020).

This paper aims to utilize and compare the performance of multiple machine learning algorithms to accurately predict the consumption of natural gas in Bahçeşehir, Istanbul. The utilized algorithms include Linear Regression, Random Forest Regression, Multilayer perceptron with back propagation and Extreme gradient boosting (XGBoost) techniques.

The main contributions of this paper are:

- Comparison of four powerful machine learning models for prediction of natural gas and identifying the model with the least prediction error and lowest compute time.
- Experimentally determining the variables that most affect the consumption of natural gas.
- Evaluating the models using four different indices to ensure consistency
- Predicting natural gas consumption of Bahçeşehir, Istanbul.
- This paper can be used as a benchmark by future researchers on this subject.

2 Background Literature

Different techniques have been implemented by previous studies to predict natural gas consumption during varying time frames, datasets and in different locations/countries as shown in Appendix A. These techniques include the following models: time series, machine learning, econometric and Grey prediction. Regardless of the model type, the main aim is to decrease prediction errors while maintaining high efficiency.

In (Mirjalili and Lewis 2016) the Whale Optimization Algorithm (WOA) is proposed. WOA promised great results however the algorithm was completely dependent on randomness (Qiao et al. 2020) and had a permutation flow shop scheduling problem (Abdel-Basset et al. 2018).

(Qiao et al. 2020) developed a prediction model based on Volterra adaptive filter and improved whale optimization algorithm (IWOA). They completed the study in the following four steps; (a) a time series was reconstructed using the C-C and Gauss smoothing methods. (b) the spiral position and jumping behaviour together with adaptive search-surround mechanism was implemented to improve the performance of the algorithm (c) the improved whale optimization algorithm was used to optimize the parameters and natural gas consumption was predicted using the Voltera adaptive filter. (d) the performance of the model was tested with an actual example. The results indicated that IWOA performed better than WOA and other benchmark models in terms of prediction however IWOA exceeded the average execution time compared to other benchmark models and it proved to be less efficient.

Polynomial Curve model was used by (Šebalj et al. 2017), this model was efficiently implemented and used due its low cost and small data requirements. This method is specifically more accurate if projection been done is on a small location. Historical input values define the characteristics of this method. The consumption of natural gas was expressed by an ascending curve minus the additive seasonality. In (Boran 2015) the author forecasted natural gas consumption for the years 2014-2018, using grey prediction with rolling mechanism (GPRM), according to Boran GP has 3 basics processes: accumulated generating operator (AGO), inverse accumulating operator (IAGO) and grey model (GM).

The authors (Beyca et al. 2019; Boran 2015; Demirel et al. 2012; Kizilaslan and Karlik 2009; Kumar et al. 2017; Szoplik 2015) modelled an artificial neural network model with an input layer, hidden layer and output layer and applied the sigmoid function for activation to the hidden layer and linear function to the output layer. The weights of the neurons were calculated using the Levenberg-Marquardt optimization algorithm. (Szoplik 2015) compared fuzzy neural networks with temperature clusterization model and single neural network model.(Taşpinar et al. 2013) used two neural networks: ANN-MLP, ANN-RBF and compared it with time series.

Support Vector machines (SVM) and support vector regressor (SVR) are among other commonly used techniques for prediction of natural gas. (Beyca et al. 2019) proposed an SVR model with polynomial cubic function. The regression model resulted in an excellent fit with the data (F=393.7, p b 0.01) and explained 94% of the variations in the consumption of natural gas. The error in the test data set was reduced using regularization parameters c=1 and e=0.001. (Beyca et al. 2019) implemented a time series method called seasonal autoregressive moving average (SARIMA).

Several research studies have been done in this area to predict natural gas consumption in different countries including Turkey. Research studies in Turkey were mostly limited to the Istanbul region. There has been no research at the suburb level neither in Istanbul nor any other part of Turkey. Some research studies implemented basic methods such as time series i.e. ARIMA or SARIMA, these primitive methods do not produce good prediction results. Studies that used more complex methods like Whale optimization algorithm and powerful machine learning models, were limited by one or more problems such as (a) permutation flow shop scheduling problem (b) Higher execution time (c) overfitting (d) scalability and (e) low convergence speed.

Extreme Gradient Boost (XGBoost) on the other hand is a new and powerful technique. To the best of our knowledge, there has been no study implementing and comparing the results of XGBoost to other power machine learning models specific to the prediction of natural gas consumption. XGBoost significantly reduces execution time, efficiently solves the problem of overfitting, scalability and has better convergence in comparison with the other ML models. XGBoost due to its inbuilt capabilities is easier and faster to implement with a better prediction accuracy and performance than linear regression, MLP and forest regression. XGBoost is also more efficient while handling missing data, when a missing value is encountered at any node it learns the route that will lead to a higher loss for each node by attempting both the left- and right-hand split.

We implemented four best machine learning models for prediction of natural gas consumption in Bahçeşehir. To the best of our knowledge, there are no studies specific to Bahçeşehir. These models were chosen after careful study of similar works and due to their ability of estimating missing values while still maintaining accuracy and efficiency. The parameters of these models except linear regression have the capability of hyper tuning resulting in a better performance. The proposed XGBoost technique is a new and powerful prediction technique with inbuilt regularization, which enables the model to prevent overfitting by default, it has the capability of handling missing values internally and hence increasing the efficiency of the model. XGBoost has the fastest compute time compared to other machine learning models due to its ability of parallel processing. The monthly natural gas consumption of Bahçeşehir is shown in Figure 1.

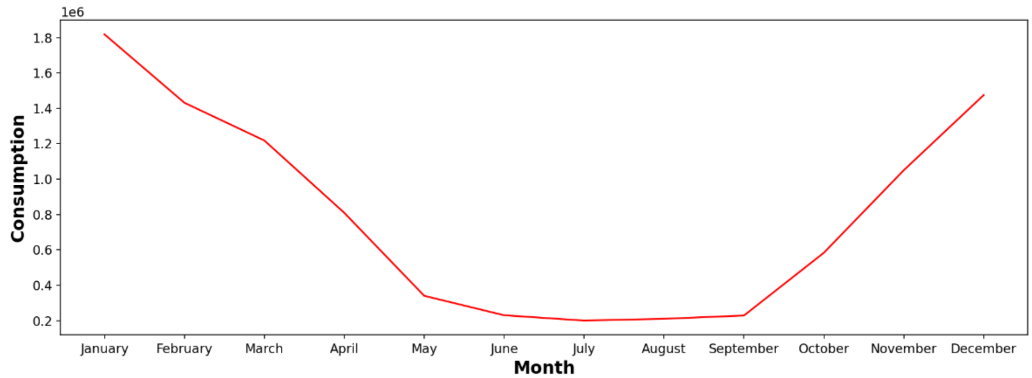

Figure 1: Monthly Natural Gas Consumption of Bahçeşehir

2.1 Input and Output Variables Used for Modelling

The type of variables used in addition to past natural gas consumption data varied from study to study. Metrological data such as temperature (Beyca et al. 2019; Demirel et al. 2012; Kumar et al. 2017; Szoplik 2015; Viet and Mańdziuk 2003), squared temperature (Demirel et al. 2012), wind speed (Taşpinar et al. 2013), humidity (Kumar et al. 2017; Taşpinar et al. 2013), moisture (Szoplik 2015), rainfall data (Kumar et al. 2017) and average cloud cover (Taşpinar et al. 2013) was commonly used in addition to variable such as subscriber price (Demirel et al. 2012) and population (Beyca et al. 2019). Some studies also considered calendar data such as day of the week and month (Szoplik 2015). Temperature is one of the most important variables to consider as demonstrated by many studies, this is because temperature has a negative correlation with natural gas consumption.

3 Proposed Methodology

The steps followed in this paper are illustrated in Figure 2. The purpose of these procedures is to find and use the best machine learning technique to Predict the monthly Natural gas consumption in Bahçeşehir and also the best criteria for evaluation is determined to improve performance.

3.1 Data Collection

This is an essential stage as it takes care of determining the attributes which are relevant in a dataset. The average monthly natural gas consumption data is obtained from Istanbul Gas Distribution Company (IGDAS), monthly average temperature was obtained from the National Weather Forecasting Institute of Turkey, monthly GDP/USD-B and Inflation in percentage was obtained from online sources (The World Bank Group, 2019). The data collected is structured, combined and recorded into a single excel spreadsheet for further analysis.

3.2 Data Exploration

The success of a machine learning algorithm will depend on the quality of data provided to it. This is the step where we check for any inaccurate data which can skew our model's findings. It Is imperative to carefully observe the data for trends, missing values, incomplete values, outliers and skewed information after gathering the data. This was done using Python functions and Python graph libraries to visualize data in the form of histograms and scatter plots. In this research, five numerical columns (Year, Monthly

Consumption, Temperature, GDP/USD-B, Inflation) and one categorical column (Month) in the data set were used. The columns with numeric data are plotted as histograms to check for data skew-ness and the categorical column is one-hot encoded.

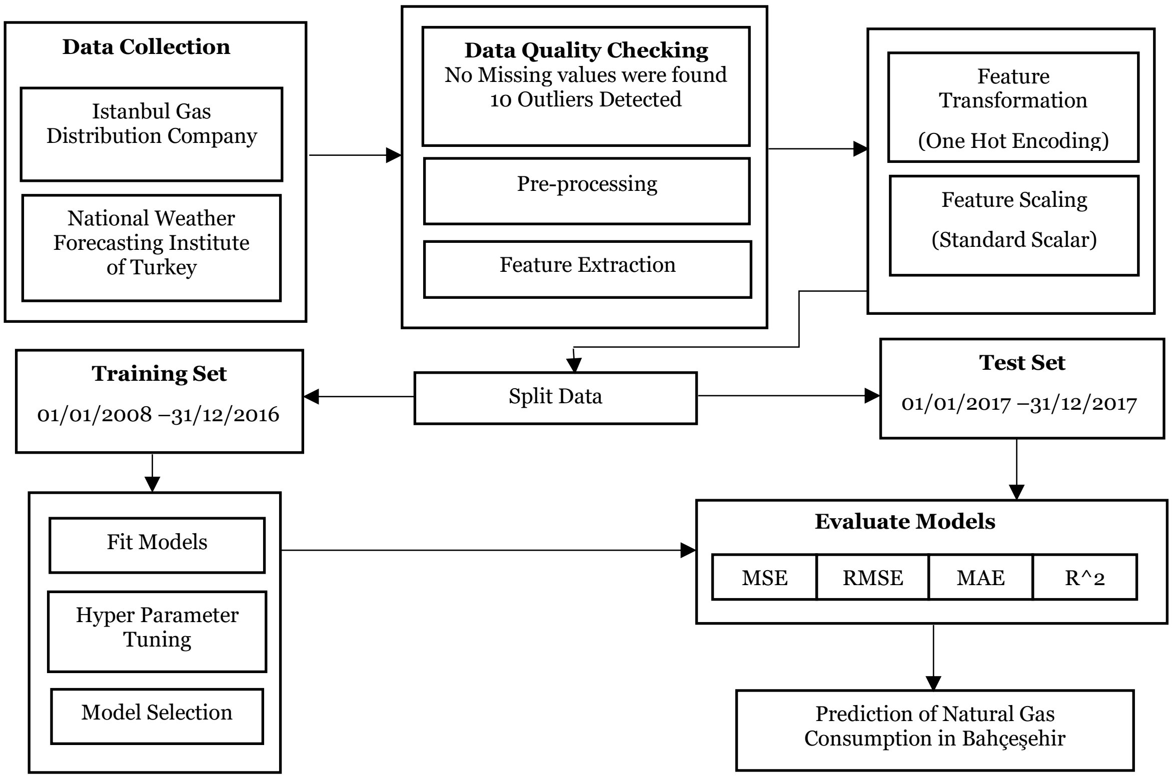

Figure 2: Proposed Prediction Steps

3.3 Data Preparation

Discussing with experts, academicians with relevant knowledge and thoroughly examining articles and journals, average monthly temperature, GDP/$USD, the inflation rate of Turkey and seasonal index were identified as initial variables to be used for prediction of natural gas consumption of Bahçeşehir. Time series plot was used to check for seasonality of the natural gas consumption. The time series plot for natural gas consumption is shown in Figure 3. The relationship between average monthly consumption and temperature can be seen in Figure 4. It is noticeable from Figure 4 that a negative association exists between the average monthly consumption and temperature values. A linear relationship can be seen up to 20 °C and then the demand for natural gas is no longer affected by temperature. There exists a negative correlation (-0.852) between temperature and consumption as seen in Table 1, this indicates that the demand for natural gas decreases with rising temperatures and vice versa this can be attributed to the use of heaters during the winter season. No missing or Not a Number (NaN) values were detected in the dataset.

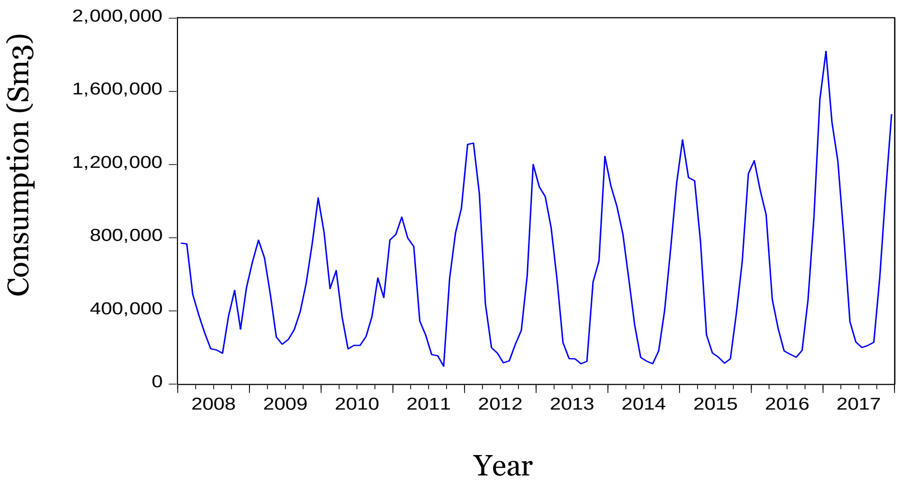

Figure 3: Time Series Plot for Consumption

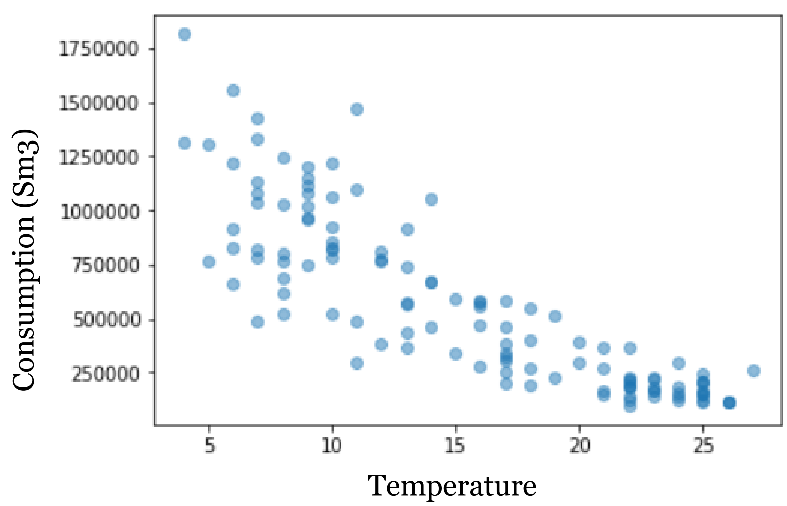

Figure 4: Scatter Plot of Consumption vs Temperature

	Year	Consumption	Temperature	GDP/USD-B	Inflation %
Year	1	0.217	0.0405	0.521	0.0587
Consumption	0.217	1	-0.852	0.0544	0.293
Temperature	0.0405	-0.852	1	0.0293	-0.295
GDP/USD-B	0.521	0.0544	0.0293	1	0.0324
Inflation %	0.0587	0.293	-0.295	0.0324	1

Table 1: Correlation Matrix

The values of raw data vary widely and hence it is important to scale and transform the data. Some machine learning models may not work properly without normalization. The categorical column is one hot encoded and all numeric columns are scaled using the standard scalar library in python with equation 1.

$$z = \frac{x - \mu}{\delta} \qquad (1)$$

Where $\mu = 0$ and $\delta = 1$

Outliers might cause errors and incorrect results and should be eliminated, ten outliers were detected and deleted during data cleaning. When deleting outliers care is taken in order not to skew the data so much it no longer represents real world-situations. Relevant features in a data set are the foundation of an accurate model, The Random Forest regressor with Min-Max scalar was used to visualize the important features in the dataset as presented in Figure 5. Features in the data set are important to the model been used for prediction, a good prediction can only be expected if the model is fed with data both in quantity and quality. Better results can be expected with a model fed with better features, such a model will be flexible and simpler.

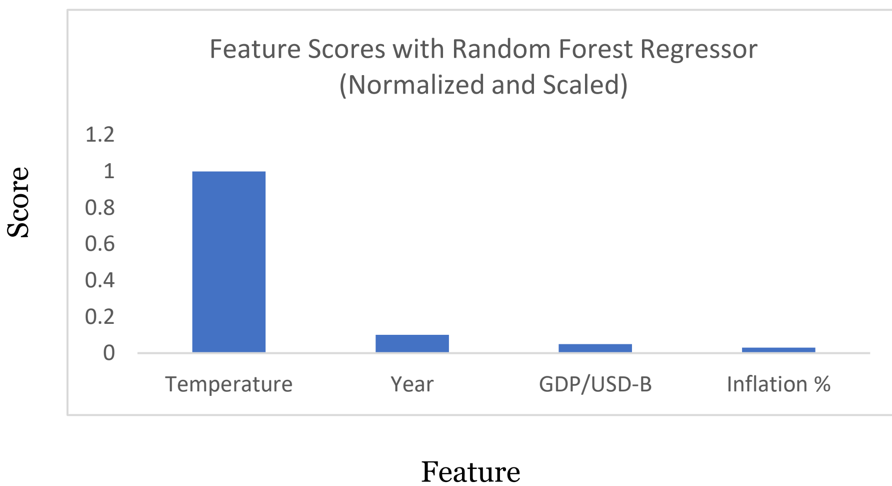

Figure 5: Feature Importance

3.4 Data Splitting

The data used is from January 2008 to December 2017. As mentioned earlier the data includes historical seasonal data, historic temperature data, GDP in $USD, inflation of Turkey and monthly natural gas consumption of Bahçeşehir. The data is divided into train and test sets which are used for training and evaluation of models respectively. The data from the period 01/01/2008 to 31/12/2016 was used for training the models and the data from 01/01/2017 to 31/12/2017 was utilized to evaluate the performance of the models on new instances.

3.5 Hyperparameter Tuning

The Grid Search and Random search with cross-validation was implemented with for and while loops to iterate through multiple parameters. This was done to find the best parameters for training the machine learning models. These parameters were used to regulate the learning process. Tuning these parameters significantly improved the performance of the models.

4 Results and Analysis

The results and analysis are obtained by training Linear Regression, Forest Regression, Multilayer Perceptron and XGBoost models with the best parameters possible to obtain the best prediction. The performance of the models was measured using 5-fold cross-validation technique. The prediction performance of each model was assessed using different performance criteria's such as the Mean Absolute Error (MAE), Mean Squared Error, Root Mean Squared Error (RMSE) and R-Squared.

4.1 Comparison of Models

Four machine learning algorithms were compared in terms of prediction performance. The performance of the models was measured using four different error measures, the MAE, MSE, R squared and RMSE. Table 2 compares the values of MAE, MSE, RMSE and R-Squared of models before hyper parameter tuning and Table 3 compares the results after tuning. Figure 6 compares the results of each model's prediction against actual values.

Metrics/Models	Linear Regression		Random Forest Regressor		MLP Regressor		XGBoost	
	Train	Test	Train	Test	Train	Test	Train	Test
MAE	0.2602	0.1019	0.0894	0.1553	0.0013	0.1682	0.0666	0.1307
MSE	0.1141	0.0150	0.0169	0.0806	0.0000	0.0481	0.0077	0.0330
RMSE	0.3377	0.1224	0.1300	0.2839	0.0000	0.2193	0.0877	0.1816
R^2	0.8843	0.9849	0.9828	0.9193	0.9999	0.9519	0.9922	0.9669

Table 2: Performance Indices for Models Before Tuning

Metrics/Models	Linear Regression		Random Forest Regressor		MLP Regressor		XGBoost	
	Train	Test	Train	Test	Train	Test	Train	Test
MAE	0.2602	0.1019	0.0936	0.1098	0.2925	0.0867	0.0567	0.0607
MSE	0.1141	0.0150	0.0178	0.0259	0.1278	0.0139	0.0054	0.0117
RMSE	0.3377	0.1224	0.1334	0.1609	0.3574	0.1178	0.0734	0.1081
R^2	0.8843	0.9849	0.9821	0.9740	0.8721	0.9860	0.9945	0.9882

Table 3:Performance Indices of Models after Hyper Parameter Tuning

As can be seen in Figure 6, Linear Regression, MLP, Forest regression and XGBoost predicted very well the monthly natural gas consumption in Bahçeşehir. However, XGBoost has the lowest MAE, MSE and RMSE value as compared to Linear Regression, MLP and Forest Regression and the highest value for Rsquared. The XGBoost regressor performed better than all other models. The Multilayer perceptron model outperformed the Forest Regressor and Linear Regressor. The Random Forest regression model performed quite well in predicting the monthly Natural gas consumption as can be seen in Figure 6 but was outperformed by XGBoost, MLP and Linear regression in all evaluation metrics used. Figure 7 shows the prediction of XGBoost against actual values, it is clear from Figure 7 that XGBoost predicted very accurately from 2.3 onwards with very slight difference at 4. However, XGBoost did not predict well from 0 to 2.2, which results in the small RMSE, MSE and MAE values as seen in Table 3.

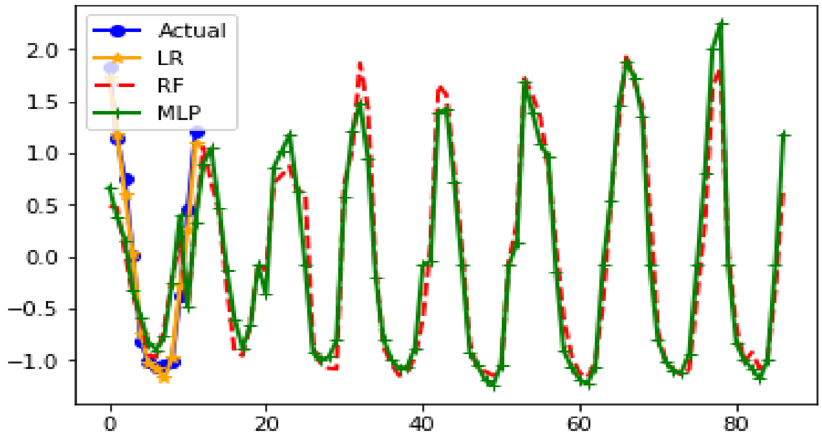

Figure 6: Prediction of Machine Learning models vs Actual Consumption Values (Normalized and Scaled)

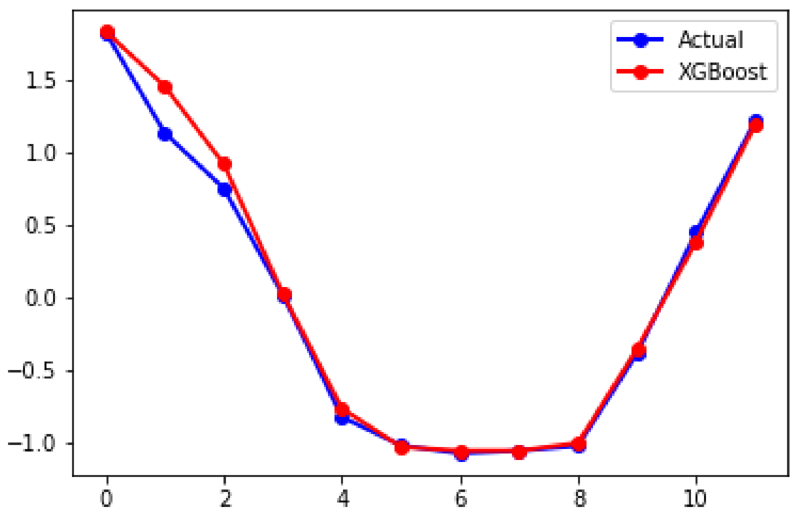

Figure 7: XGBoost Prediction vs Actual Values (Normalized and Scaled)

5 Discussion and Conclusion

Turkey's natural gas demand has been increasing exponentially over the past decade. Turkey's natural gas consumption peaked on 8th January 2019 to a record of 245 Million Cubic Meters. Turkey depends heavily on imports from Iran, Russia and Azerbaijan to fulfil its natural gas supply while suffering from insufficient storage infrastructure. Turkey pays its suppliers a fixed amount of money regardless of whether natural gas is imported or not, technically referred to as Take or Pay penalties. This makes forecasting very essential to meet supply, demand and make the necessary investments. Investments of such nature needs a lot of planning and good management to reduce loses to the economy, this can only be achieved by implementing the most powerful machine learning models to predict accurately the natural gas consumption. This paper was aimed at using powerful machine learning models like Linear Regression, MLP, Random Forest Regression and XGBoost to predict the natural gas consumption in Bahçeşehir, Istanbul. The ML models were compared to each other to find the model with the best performance. This paper revealed that XGBoost with 60 trees with maximum depth of 2 and dart booster outperformed MLP, Random Forest and Linear regression models for predicting the monthly natural gas consumption using the following input variables:

Seasonal data, temperature, GDP, Inflation and monthly natural gas consumption. XGBoost outperformed other ML Models due to its flexibility, versatility, effectiveness in utilizing memory and hardware resources, built in regularization and ability to handle missing values, parallel processing and effective tree pruning. XGBoost also has a reduced compute time as compared to the other ML models. The proposed XGBoost model can be implemented as a significant decision- making tool for prediction of natural gas consumption.

The study was limited by the availability of data. The dataset used to train and evaluate the machine learning models were limited to a span of 10 years with just 6 variables even though we had an excellent result we believe a larger dataset with additional variables like price of natural gas, average income of consumers will give us a better prediction.

6 References

Abdel-Basset, M., Manogaran, G., El-Shahat, D., and Mirjalili, S. 2018. "A Hybrid Whale Optimization Algorithm Based on Local Search Strategy for the Permutation Flow Shop Scheduling Problem," *Future Generation Computer Systems*. (https://doi.org/10.1016/j.future.2018.03.020).

Asian Infrastructure Investment Bank. 2018. "Turkey Gas Storage Expansion Project."

Beyca, O. F., Ervural, B. C., Tatoglu, E., Ozuyar, P. G., and Zaim, S. 2019. "Using Machine Learning Tools for Forecasting Natural Gas Consumption in the Province of Istanbul," *Energy Economics*. (https://doi.org/10.1016/j.eneco.2019.03.006).

Boran, F. E. 2015. "Forecasting Natural Gas Consumption in Turkey Using Grey Prediction," *Energy Sources, Part B: Economics, Planning and Policy*. (https://doi.org/10.1080/15567249.2014.893040).

Demirel, Ö. F., Zaim, S., Çališkan, A., and Özuyar, P. 2012. "Forecasting Natural Gas Consumption in Istanbul Using Neural Networks and Multivariate Time Series Methods," *Turkish Journal of Electrical Engineering and Computer Sciences*. (https://doi.org/10.3906/elk-1101-1029).

Esen, Ö., and Bayrak, M. 2017. "Does More Energy Consumption Support Economic Growth in Net Energy-Importing Countries?," *Journal of Economics, Finance and Administrative Science*. (https://doi.org/10.1108/JEFAS-01-2017-0015).

Kizilaslan, R., and Karlik, B. 2009. "Combination of Neural Networks Forecasters for Monthly Natural Gas Consumption Prediction," *Neural Network World*.

Kumar, P., Dhal, S., and Kumar, N. 2017. "Neural Network Based Forecasting Model for Natural Gas Consumption," *Communications on Applied Electronics* (7:11), pp. 1–8. (https://doi.org/10.5120/cae2017652727).

Mirjalili, S., and Lewis, A. 2016. "The Whale Optimization Algorithm," *Advances in Engineering Software*. (https://doi.org/10.1016/j.advengsoft.2016.01.008).

Qiao, W., Yang, Z., Kang, Z., and Pan, Z. 2020. "Short-Term Natural Gas Consumption Prediction Based on Volterra Adaptive Filter and Improved Whale Optimization Algorithm," *Engineering Applications of Artificial Intelligence*. (https://doi.org/10.1016/j.engappai.2019.103323).

"Republic of Turkey Ministry of Energy and Natural Resources - Electricity." (n.d.). (https://enerji.gov.tr/Electricity-infobank, accessed May 4, 2020).

Šebalj, D., Mesarić, J., and Dujak, D. 2017. "Predicting Natural Gas Consumption – A Literature Review," *Central European Conference on Information and Intelligent Systems 2017* (180), pp. 293–300. (https://www.alberta.ca/climate-methane-emissions.aspx).

Szoplik, J. 2015. "Forecasting of Natural Gas Consumption with Artificial Neural Networks," *Energy*. (https://doi.org/10.1016/j.energy.2015.03.084).

Taşpinar, F., Çelebi, N., and Tutkun, N. 2013. "Forecasting of Daily Natural Gas Consumption on Regional Basis in Turkey Using Various Computational Methods," *Energy and Buildings*. (https://doi.org/10.1016/j.enbuild.2012.10.023).

The Guardian. (n.d.). "Oil Prices Dip below Zero as Producers Forced to Pay to Dispose of Excess | Business | The Guardian." (https://www.theguardian.com/world/2020/apr/20/oil-prices-sink-to-20-year-low-as-un-sounds-alarm-on-to-covid-19-relief-fund, accessed May 10, 2020).

Viet, N. H., and Mańdziuk, J. 2003. "Prediction of Natural Gas Consumption with Feed-Forward and Fuzzy Neural Networks," in *Artificial Neural Nets and Genetic Algorithms*. (https://doi.org/10.1007/978-3-7091-0646-4_21).

World Bank Group. 2015. "Turkey | Data," *World Bank Group*. (http://data.worldbank.org/country/turkey, accessed May 5, 2019).

APPENDIX A

Year	Country/Area	Data Source	Evaluation Metric	Method Implemented
2009	Turkey/Istanbul	IGDAS	Absolute Relative Error (ARE)	Neural network (NN)
2010	China	-	Chinese Statistics Year Book from 1996- 2009 And 2007 - 2008	Polynomial Curve, PCMACP
2011	Turkey/Istanbul	IGDAS	RMSE, MAD, MAPE	Artificial Neural Network, Time Series
2012	Turkey/Sakara	Sakara Gas Dist. Company	MAPE, RMSE, R^2	SARIMAX, ANN-MLP, ANN-RBF, Time Series
2014	Turkey/Istanbul	Energy Information Administration	MAPE	Grey prediction with rolling mechanism
2015	Poland/Szczecin	Network Weather meteorological	MAPE/ RMSE	Artificial Neural Network (ANN)
2016	Australia	-	Mathematical Benchmarks	Whale Optimization Algorithm (WOA)
2017	India/Bhubaneswa	-	RMSE	Neural network
2018	Colombia/Medellín	Sistema Unico de Informacion	RMSE, MAE	ARIMA, Support Vector Machine (SVM)
2019	Slovenia/Ljubljana	Slovenian Environment Agency	MAE, MAPE	ANN
2019	Turkey/Istanbul	IGDAS	MAPE	NN, SVM, Time Series
2019	China/Anhui	-	5 Benchmark Algorithms	Improved whale swarm algorithm
2020	China/ Hefei	Natural gas gate station	Griewank function, Schaffer function (SF), Rastrigin function (RF), and Ackley function (AF)	Volterra adaptive filter and an improved whale optimization algorithm
2020	US	-	5 Benchmark models, MAPE	Improved kernel-based nonlinear extension of the Arps decline model (KNEA)