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Using Regression Analysis for Predicting Energy Consumption in Dubai Police

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by

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Abstract

The aim of this project is to build a machine learning algorithm to forecast electricity and water consumption for the 27 sites in Dubai Police facilities. This aim is to establish a central database with all the data to monitor the energy consumption in a systematic manner and feed the data in a visualized dashboard. The data was collected from the energy conservation department at Dubai Police for five years from 2017 to 2021 comprising of electricity and water consumption details data. Due to the numerous buildings and facilities any irregular behavior in consumption takes time to be identified using conventional analysis methods, therefore this project will be able to support the organization to find out their energy savings/loss hotspots and facilitate immediate action for the employees to avoid time and monetary loss. Consumption data gathered will be processed through R Programming language to break it down into quarter consumption for each site. The Processed data for 2017 to 2020 will be an input for the multiple regression and ARIMA models to forecast the quarter consumption of year 2021 and to showcase the model. Finally, tableau software will be used to visualize the data and to build the dashboard in the future.

Keywords: Machine learning, Energy consumption prediction, Linear Regression Model, Autoregressive Integrated Moving Average, Energy Forecasting

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Chapter 1

1.1 Introduction

It is evident that Dubai Police has evolved from a conventional policing services provider to a world-leading organization that integrates safety and security with the community's well-being and happiness. And in line with the vision and direction of Dubai Police for utilizing artificial intelligence through integrating software, Apps, and ML programs; implementing best energy practices and measures is crucial at this point. In fact, this study focuses on the water and electricity consumption of the police force across all its owned and occupied buildings/entities, with a main focus of establishing a standard system for monitoring, reporting, as well as providing future consumption predictions.

The current methodology for analyzing and monitoring the energy and water consumption places several obstacles to get accurate results that are instant and allow for immediate action in case of damages or leaks. It is worth mentioning that the consumption data reflects Greenhouse Gases (GHG) emissions increments. Moreover, the first step in analyzing the consumption data is to collect the bills from Dubai Electricity and Water Authority (DEWA) in quarterly basis in one excel sheet containing contract number and consumption detail. The data collection process from all the water and electricity meters under Dubai Police account turned out to be time consuming and questionable due to the lack of a standard inventory system customized for consumption meters and updated on monthly basis. The available excel sheets are numerous, duplicated and contain inconsistent data that gave an alert and concern environmentally and financially.

Nevertheless, with the success of this project two standard ML algorithm will be created to input all the data which will allow for instant analysis for all locations and highlight hotspots (over consumers), to prevent unmonitored expenditures, generate annual comparisons that are credible and accurate and build a forecasting model to predict future consumption. Upon completion, once the project is proved functional and successful, it could be applied across the organization for a better understanding of consumption data and as decision-making tool for the energy conservation department at Dubai Police.

1.2 Project Goals

The Energy Conservation Department at Dubai Police generates quarterly electricity and water consumption reports following the standards and guidelines of ISO 50001: 2018 for energy management systems. Basically, it involves logging the quarterly water and electricity consumption of the Dubai Police facilities, taking into account all the buildings that belong and operate under the organization, and communicate to the head of each building to inform them about their consumption and best practices. Therefore; the purpose is to analyze the consumption data by using IoTs avoiding the use of time-consuming conventional methods, gather all previous and current data in one database, visualize the data to stakeholders in a professional dashboard, monitor consumption loss/savings hotspots sites to find out the causes and solutions based on their frequency, and predict future consumption trends based on seasonal changes and other factors. Additionally, this study will explore and add to previous literature conducted in this sector and will be able to support in identifying the causes of high consumption in organizations.

Research questions

- What factors influence an inaccurate consumption data in any organization?
- What are the benefits of forecasting future consumptions for an organization?
- How does immediate detection of energy savings/loss hotspots impact the organization?

1.3 Aims and Objectives

Dubai Police is considered one of the largest government entities in the Emirate of Dubai employing around 25% of the total of government employees. The Force is distributed among 30 sites in Dubai with more than 400 buildings operating round the clock to provide safety and security for the community as well as achieving the lowest possible carbon footprint via energy and resource efficiency initiatives. Over the years, the electricity and water consumed by Dubai Police facilities to run its operations has proved to constitute the biggest environmental impact. However, the analysis of the electricity and water consumption of Dubai Police facilities is carried out manually using conventional methods which have resulted in generating inaccurate results and consumed time in pinpointing areas of irregular high consumption that are out of the norm.

The main objectives of the project are to:

- Analyze electricity and water consumption data by using ML avoiding the use of time-consuming methods.
- Implement DA tools to gather the data and create a forecasting model to predict electricity and water consumption based on historical data.
- Publish quarter reports to be shared with each building operator showing a comparison between their current and previous consumption including the percentage of savings/loss.

1.4 Research Methodology

For best results, it is recommended to use the CRISP-DM process. The stages are explained in details below.

Stage 1: Business Understanding

Business Objective: The first step is to understand the objective and the problem the organization needs to address.

The clients' concerns are known and included in the problem statement. The organization aims to conserve electricity and water consumption and reduce bills budget and this can be done by building a machine-learning algorithm to monitor and detect hotspots and forecast future consumption. The problem statement was shared with stakeholders and they confirmed that they needed it and the data to be used for the study was provided by them.

Stage 2: Data Understanding

The actions to be done in this phase is to collect initial data, describe data, explore data, and verify data quality. The data is evaluated to know how much it is relevant to the problem. The collection of data will start with identifying Buildings/Facilities, followed by identifying associated accounts/meters, and finally, determining the time period for the consumption data needed. The data collected will contain more than 11 variables including facility name, months, electricity consumption (kWh), and water consumption (Gallons) for five years from the period of 2017 to 2021. The data will be in different excel sheets, each sheet contains consumption details as well as associated meter contract numbers for every year and one sheet mapping the meter contract numbers with each site with the detailed description of every building in each site. The data is fed in the master sheets in respected categories to identify the total number of meters belonging to the study, to compare the consumption pattern over the past five years, and to highlight the accounts that express alarming concerns. For instance, sudden high consumption from a specific meter that usually has a low consumption pattern could indicate an overlooked leak.

Stage 3: Data Preparation

Preprocessing the data is an essential process before inputting the data in ML algorithm. This step will be done using Microsoft Excel and R Studio and it will include discarding excluded/decommissioned accounts to identify concerning accounts, remove null values, zero values, outliers, and duplicated meters. As well as changing the data type of some attributes. Furthermore, merging the tables in consumptions datasheets with facilities table and Capita & Area table. All data will be grouped and summed in quarter basis. The split of 70% trained and 30% tested will be done before run the data in the model.

Stage 4: Modeling

In this stage, the processed data will be an input for the regression model using R programming language to forecast the annual consumption for year 2021. Based on the literature review among the prediction models, ARIMA models are one of the best-known models for time series-based energy consumption prediction. Furthermore, Tableau and R will be used to visualize the data in different plots.

Stage 5: Evaluation

In this final step, the results will be verified for validity and accuracy. The forecasted data for year 2021 will be validated with the actual one. Additionally, the accuracy of the model will be tested in this phase and any errors in its different types will be identified, and finally plots showing the relationship between actual and predicted results will be generated.

1.5 Limitations of the Study

Due to the confidentiality and privacy policies of Dubai police as a policing entity, the dataset was somehow limited. The number of visitors in each police station and department as well as number of prisoners were not accessible that would have given a more accurate insight for the consumption per capita and predicted values if it was added to capita attribute. In addition, due to the lack of time, the area and number of employees data were not provided for all buildings. As a consequence, such facilities were excluded from the study.

Chapter 2 – Literature Review

2.1 Introduction

The literature review conducted highlights important aspects discussed in some of previous research papers and articles. Through this literature review, I was able to identify some minor gaps in the literature that this study might be add to. Also, many variables are considered when deciding which research are considered dropouts.

2.2 Literature Review

(Amasyali and El-Gohary, 2018) summarized data-driven building energy consumption prediction studies. The studies focus on reviewing forecast ranges, data properties and data preprocessing methods used, machine learning algorithms used for forecasting, and performance metrics used for evaluation.

The scope of the study was categorized according to building type, temporal granularity, and expected energy consumption type. Only 19% of these models focus on residential buildings, and the remaining models focus on non-residential buildings, including commercial and educational buildings. Most of these (57%) in these models are designed to predict hourly energy usage, while 12%, 15%, 4%, and 12% of the models Focuses on sub-hourly daily, monthly, and yearly usage. In terms of data types, most of these studies (67%) used real-world data for model training and testing, while 19% and 14% of studies used simulation data and public benchmark data, respectively. However, the majority (56%) of the data sizes in the studies reviewed used records that were one month to one year long, and, 9% used datasets shorter than 1 month. 31% have been using records for over a year.

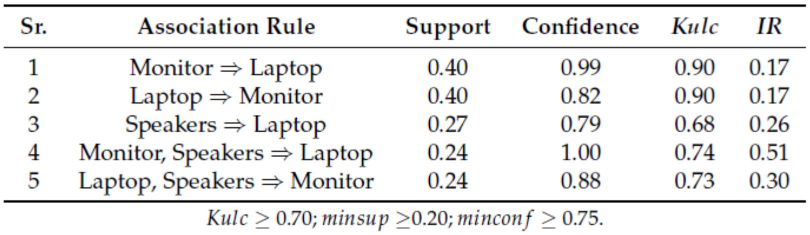
The machine-learning algorithm was used to train the model using ANN and SVM, respectively, in 47% and 25% of the studies. Only 4% of studies used decision trees. Meanwhile, 24% of studies used other statistical algorithms such as MLR, OLS, and ARIMA. To assess overall performance, 41%, 29%, and 16% of the studies reviewed evaluated the model using CV, MAPE, and RMSE, respectively.

Another study done by (Nafil, Bouzi, Anoune and Ettalabi, 2020), the paper contrasts three forecasting methods ARIMA (Autoregressive Integrated Moving Average), Temporal causality modeling, and Exponential smoothing) to calculate the energy demand forecasts of Morocco in 2020.

They found that for the ARIMA model, the mean difference between the predicted and actual values was significant (significance ~ 0). The forecast chart shows the deviation between the predicted and actual values. Therefore, it is a rejected model. For exponential smoothing, the mean difference between the predicted and actual values is not important (significance = 0.782). This means that it is a good candidate model. However, forecast plots show that electricity demand is stable over the next few years, which is not realistic. Therefore, the exponential smoothing model is also rejected. For a temporal causal relationship model, the mean difference between the predicted and actual values for the same year is not that big (significance = 0.404). Therefore, there is no difference between the actual value and the value predicted by the model. The forecast curve is also an accepted model because it shows that electricity demand is increasing and seasonal effects (curve fluctuations) are also known.

(Singh and Yassine, 2018) presented an intelligent data mining model to analyze, forecast and visualize energy time series to energy consumption patterns. Unsupervised data clustering, frequent pattern mining analysis of energy time series, and Bayesian network prediction were used to predict energy consumption. The accuracy results of identifying device usage patterns using the proposed model outperformed Support Vector Machine (SVM) and Multilayer Perceptron (MLP) at each stage, but 25%, 50%, and. Each reached 75% of the training data size. In addition, they achieved prediction accuracy of energy consumption of 81.89% in the short term (hourly) and 75.88%, 79.23%, 74.74%, 72.81% in the long term. Semester; that is, day, week, month, season. I noticed that devices such as laptops, monitors and speakers have associations. And as incremental mining continues, the associations between these devices will be strengthened and new devices such as washing machines, kettles and pedestrians will develop the associations. Residents enjoy working on computers and listening to music while washing clothes, and working on computers and riding trains while cooking, as a result of these interactions. You can deduce the occupants' behavioral preferences.

Table 1: Appliance association rules in 50% training dataset.



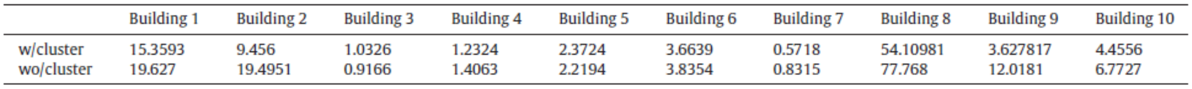
Sr.	Association Rule	Support	Confidence	*Kulc*	*IR*
1	Monitor ⇒ Laptop	0.40	0.99	0.90	0.17
2	Laptop ⇒ Monitor	0.40	0.82	0.90	0.17
3	Speakers ⇒ Laptop	0.27	0.79	0.68	0.26
4	Monitor, Speakers ⇒ Laptop	0.24	1.00	0.74	0.51
5	Laptop, Speakers ⇒ Monitor	0.24	0.88	0.73	0.30

$Kulc \geq 0.70$; $minsup \geq 0.20$; $minconf \geq 0.75$.

Table 1 shows that the decisions made by the resident influence the energy consumption decision pattern, which is directly converted into energy consumption. Therefore, the energy consumption behavior of different residents is affected differently by these parameters depending on their lifestyle. In other words, the behavior of the inhabitants has a direct impact on the energy consumption of the home.

According to (Yang et al., 2017) that apply a new k shape algorithm to detect energy usage patterns at different levels of buildings and further use clustering results to improve the accuracy of predictive models. Ten facility buildings were used as case studies, covering three different types. This white paper further analyzes the range of hourly and weekly energy consumption data. Experimental results show that this proposed method can effectively detect energy consumption patterns of buildings at different temporal particles, and using the results of the proposed clustering method significantly improves the prediction accuracy of the SVR model. It also proves that it will be done. In this study, "dtwclust" is the package used by the R programming language to implement a set of time series clustering algorithms. The table below shows a SVM model that does not cluster the MAPE or 10 building information of the proposed approach. This shows that in 8 of the 10 buildings, if the forecast was supported by the results of kshape clustering, the MAPE of the forecast results was reduced. In the other two buildings (Building 3, Building 5), the results of clustering used a slight increase in MAPE. Improves overall prediction accuracy after applying kshape clustering as shown in Table 2.

Table 2: MAPE of the predicting results for 10 buildings, with/without clustering.



	Building 1	Building 2	Building 3	Building 4	Building 5	Building 6	Building 7	Building 8	Building 9	Building 10
w/cluster	15.3593	9.456	1.0326	1.2324	2.3724	3.6639	0.5718	54.10981	3.627817	4.4556
wo/cluster	19.627	19.4951	0.9166	1.4063	2.2194	3.8354	0.8315	77.768	12.0181	6.7727

(Aranda et al., 2012) Shows a regression analysis of energy consumption in the a Spanish banking sector. The model evaluated the performance on testing the datasets of fifty five banks. Three models were obtained from the analysis. The first proposed model can be used to predict energy consumption across the banking sector, while the remaining models for branches consumptions have low winter climate (model 2) and high winter climate (model 3). Models 2 and 3 differ from the first model in that they require an independent variable that is measured in-situ. Depending on the independent variable, the uncertainty of the response variable is reduced by 56.8% in the first model. In addition, Models 2 and 3 reduce the uncertainty of the response variable as a function of the independent variable by 65.2% and 68.5%, respectively which consider as acceptable uncertainty based on small samples.

Three common predictive modeling techniques used by (Tso and Yau, 2007), multiple regression, neural networks, and decision tree models. The research used to predict the power consumption of the study with an integrated environment to SAS Enterprise Miner. Figure 1 shows a schematic diagram of the data analysis process.

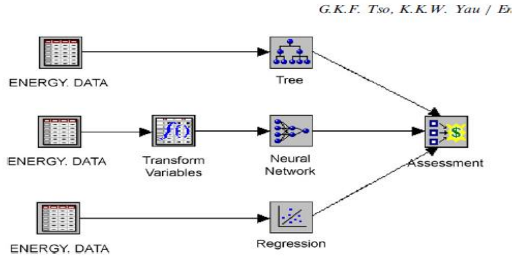
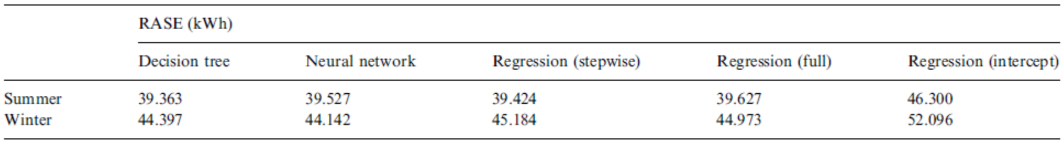


Figure 1: Schematic presentation.

The target value is the total power consumption (kWh) for one week. Home types, home characteristics, and device ownership are considered to be factors that can affect power consumption.

Table 3: RASE of decision tree, neural network and regression models.



	RASE (kWh)				
	Decision tree	Neural network	Regression (stepwise)	Regression (full)	Regression (intercept)
Summer	39.363	39.527	39.424	39.627	46.300
Winter	44.397	44.142	45.184	44.973	52.096

In the summer season, the decision tree model showed a better performance than the other two methods. However, in the winter season, the neural network performed better. For comparison, Table 6 summarizes the key factors identified in these models of energy consumption patterns and energy consumption projections.

(Banihashemi, Ding and Wang, 2017) published a paper representing a hybrid model of a machine learning algorithm that optimizes the energy consumption of houses, considering both continuous energy parameters and discrete energy parameters at the same time. This study shows a hybrid objective function of a machine learning algorithm that optimizes the energy consumption of a house using an artificial neural network as a prediction model, and a classification algorithm (decision tree) is used to create a hybrid function via a cross-training ensemble equation. The model was finally validated via a weighted average of the errors decomposed for performance. This research contributes to this field in various ways. It produces predicted energy consumption data with minimal error and the highest accuracy for the purpose of developing hybrid objective functions. This paves the way for presenting a powerful engine for building energy optimization. The result is an integrated platform that incorporates both qualitative and quantitative variables of building energy consumption without compromising data consistency or requiring data conversion techniques. Due to the many limitations of conducting this study, the study results should be treated with caution. This means that different hybrid models can emphasize different attributes, so the results may not be directly applicable to other types of machine learning algorithms in prediction and classification.

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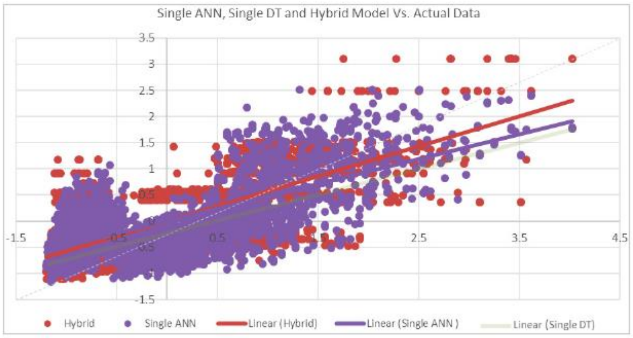


Figure 2: Normalized predictive performance of single ANN, DT and hybrid model vs, normalized actual energy data.

As shown in Figure 2, the approximate linear trend line of the normalized values predicted by the hybrid model is more consistent with the equivalent state compared to that of the individual ANN and DT models. This observation confirms the excellent performance of the hybrid model, which produces predictive data close to baseline and provides a more robust objective function.

(Jamii and Maaroufi, 2021) shows The ARIMA (autoregressive integrated moving average) model (1, 1, 1) is used to model electrical energy consumption during the period 1971-2020. The same data will be used in the 2021-2030 forecasts to validate the model and provide information on Morocco's future energy demand. ARIMA is one of the most well-known models for time series-based energy consumption forecasting.

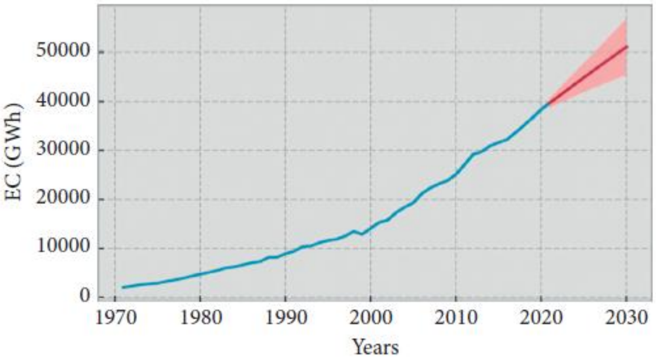


Figure 3: The predictive power of the model.

As shown in the chart above, the predictive power of this model is what drives us to project this study into the next decade, and the main result of this forecast is an upward trend in electricity demand, is expected to increase from 37,741.24 GWh in 2021 to 46,614.04 GWh in 2030. This scenario promises an increase of nearly 34.54% under the conditions of democratic development and increased electrification.

In the (Wang and Meng, 2012) study, a Hybrid Neural Network and ARIMA Model for Energy Consumption Forecasting is used. Because the ARIMA model can't handle nonlinear relationships, and the neural network model can't handle both linear and nonlinear patterns equally well, to take advantage of the distinctive strengths as ARIMA in linear modeling and ANN in nonlinear modeling. The empirical results using energy consumption data from Hebei province in China show that the hybrid model can be a useful tool for improving the accuracy of energy consumption forecasting obtained using either of the models alone. Three statistical measures are used to evaluate each model's predicting performance: RMSE, MAE, and MAPE. The statistical metrics show that the hybrid model can be a useful tool for improving the forecasting accuracy of either of the models when employed alone.

(Sen, Roy and Pal, 2016) Shows an Indian pig iron manufacturing company using ARIMA to predict energy usage and greenhouse gas emissions. The autoregressive integrated moving average (ARIMA) is used for forecasting, and to see which ARIMA model is the best fit model for energy consumption. Selecting the appropriate ARIMA models for these indicators will aid in accurate forecasting. While the ARIMA (0,1,0) (0,1,1) model has an AICC of -8.033 and an SBIC of 8.013 for energy consumption, the ARIMA (0,1,4) (0,1,1) model has an AICC of -8.109 and an SBIC of 8.068. In terms of energy usage, the second [i.e. ARIMA (1,0,0) (0,1,1)] model is unquestionably superior to the first [i.e. ARIMA (0,1,0) (0,1,1)] model, as all key indices show lower values.

A model based on the k-means algorithm was built for this goal in the paper Big Data Analytics for Discovering Electricity Consumption Patterns in Smart Cities (Pérez-Chacón et al., 2018). This research yielded two possible values for the number of clusters, and both cases were subjected to an in-depth investigation of the patterns. The patterns were classified by the type of consumption (high, low, etc.), the season of the year, and the day of the week. Building consumption behavior is mostly determined by their nature (administrative buildings, research centers, schools, or recreational facilities) and the hours of use during the day. Furthermore, it has been established that there is a strong link between temperature and consumption, as well as a significant impact on vacation seasons.

In (Yuan, Liu and Fang, 2016) study a Comparison of China's primary energy consumption forecasting by using the ARIMA model and GM (1,1) model was done. China's primary energy consumption is forecasted using two univariate models: ARIMA and GM (1,1). The two models' findings are in line with the specifications. The fitted values of the ARIMA model respond less to fluctuations since they are restricted by its long-term trend, whereas the fitted values of the GM (1,1) model respond more due to the use of the most recent four data. According to the Wilcoxon signed-rank test, the residues of the two models are statistically opposite. As a result, a hybrid model is created using these two models, with a MAPE (Mean Absolute Percent Error) that is lower than the ARIMA and GM (1,1) models. The three models are then used to forecast China's primary energy consumption.

Accurately estimating energy use in public buildings is an important method for reducing energy demand and increasing energy efficiency. The goal of this research (Liu et al., 2020) was to provide a novel method for predicting energy usage in public buildings. Small samples, high-dimensional, and nonlinear issue forecasts are all good candidates for the SVM approach. The prediction effect of the average relative error is 5.03 percent in the case analysis of daily building energy consumption prediction, and the practicality of the energy vector prediction method based on the SVM method is confirmed. It has been discovered that when the difference between the actual and anticipated values is more than the test set's maximum error, the energy consumption is abnormal.

The algorithm of the prediction model in this study (Shapi, Ramli and Awalin, 2021) is proposed using three methodologies: Support Vector Machine, Artificial Neural Network, and k-Nearest Neighbor. Two tenants from a business building are used as a case study to demonstrate real-life applicability in Malaysia. The energy demand data obtained from June to December 2018 was evaluated and pre-processed for predictive model training and testing. The SVM method yielded the most promising results, as it was the best method for two tenants, with RMSE values of 4.7506789 and 3.5898263, respectively. Furthermore, SVM results show a lower mean absolute error for 12.09 and 43.97, respectively, whereas k-NN results show a lower RMSE for these two tenants. SVM predicted demand also performed better when average consumption was calculated from demand, achieving a lower MAPE than the other methods for all tenants.

In this study (Zhao and Magoulès, 2012), two feature selection methods are used to predict energy consumption, which is then tested on three data sets using support vector regression. The two filter methods used are gradient-guided feature selection and correlation coefficients, which can assign a score to each feature based on its usefulness to the predictor. The experimental results confirm the validity of the chosen subset and demonstrate that the proposed feature selection method guarantees prediction accuracy while reducing computational time for data analysis.

In this paper (de Oliveira and Cyrino Oliveira, 2018), ARIMA methods are used to analyze monthly electric energy consumption time series from various countries. The findings indicate that the proposed methodologies significantly improve the forecast accuracy of demand for energy end-use services in both developed and developing countries. It should be noted that external factors account for a significant portion of the variation in monthly electric energy consumption, which cannot be captured by univariate forecasting methods. Some notable examples include the effects of electric energy generation and, in particular, industrial output in several countries.

(Carrera, Peyrard and Kim, 2021) Shows a three-months-ahead prediction problem for a short-term stacking ensemble model for energy consumption in Songdo, South Korea. To achieve this result, they first designed baseline regressors for prediction, then applied a three-combination of each best model of the baseline regressors, and finally, a weighted meta-regression model was applied using meta-XG Boost. The resulting model is known as the stacking ensemble model. The proposed stacking ensemble model combines the best ensemble networks to improve performance prediction, resulting in an R2 value of 97.89%. The results validate the efficacy of the ensemble networks, which employ Artificial Neural Networks (ANN), Cat Boost, and Gradient Boosting. In terms of R2, MAE, and RSME, the weighted meta-model outperforms several machine learning models, according to this study.

When compared to other statistical models, the linear regression analysis has shown best performance due to its reasonable accuracy and relatively simple implementation. Simple and multiple linear regression analyses, as well as quadratic regression analyses, were performed on hourly and daily data from a research house in this study (Fumo and Rafe Biswas, 2015). The observed data's time interval proved to be an important factor in determining the model's quality. Simple linear regression analysis was performed for time intervals of 5 and 15 minutes, yielding R^2 values of 0.232 and 0.384, respectively, to verify this statement. These additional findings confirm that higher resolution for the analytical time interval leads to lower-quality models.

This paper (Wang, 2022) enhances the combined model I, which directly adds the ARIMA model's projected value with the BP neural network model's anticipated value. The independent variables are the ARIMA model's linear fitting and the BP model's nonlinear fitting, while the dependent variable is the per capita coal consumption sequence. A new combination model II is created using multiple linear regression. The combination model II is used to fit the per capita coal consumption from 2014 to 2018 based on a study of the changing rule of China's per capita coal consumption over time. The fitting errors are 0.62 percent, 0.17 percent, 0.04 percent, 0.04 percent, and 0.07 percent, respectively, according to the results. The combined model II enhances the forecast accuracy over the combined model I. ARIMA model fitting reduces the error of prediction of per capita coal consumption, and BP model fitting predicts the ARIMA model fitting error. The two models together reduce prediction error even further, and the combined model has a greater overall prediction effect.

The annual energy consumption of Iran is estimated in this research (Barak and Sadegh, 2016) utilizing three ARIMA–ANFIS patterns. In the first pattern, the ARIMA model is applied to four input features, and its nonlinear residuals are predicted using six different ANFIS (Adaptive Neuro Fuzzy Inference System) structures, such as sub clustering, and means clustering, and grid partitioning. In the second pattern, ARIMA forecasting is assumed as an input variable for ANFIS prediction, along with four input features. As a result, in addition to ARIMA's output, four more inputs are used in energy prediction with six alternative ANFIS structures. Due to data scarcity, the second pattern is combined with the AdaBoost (Adaptive Boosting) data diversification model in the third pattern, resulting in a novel ensemble methodology. The results show that the third hybrid pattern, which combines the AdaBoost method with the Genfis3 ANFIS structure and the backpropagation training procedure, produces better results, with the model's MSE criterion dropping to 0.026 percent from 0.058 percent in the second hybrid pattern.

2.2 Conclusion

In summary, among the eight papers in the literature review where in each more than one model was used. Eighteen regression models were used with their different types (ARIMA, Multiple Linear Regression, SVM...). However, two researches used Decision Tree, seven researches Artificial Neural Network, and three research K- clustering. Another important point, in the literature covered in this study, all hybrid models showed a better performance than every single model. In general, regression models have proved the best performance comparing with other models. Regarding the performance evaluation metrics, mostly RMSE, MAE, and MAPE were used.

Chapter 3- Project Description

3.1 Introduction

Dubai Police is considered one of the largest government entities in the Emirate of Dubai employing around 25% of the total of government employees. The Force is distributed among 30 sites in Dubai with more than 400 buildings operating round the clock to provide safety and security for the community as well as achieving the lowest possible carbon footprint via energy and resource efficiency initiatives. Over the years, the electricity and water consumed by Dubai Police facilities to run its operations has proved to constitute the biggest environmental impact. However, the analysis of the electricity and water consumption of Dubai Police facilities is carried out manually using conventional methods which have resulted in generating inaccurate results and consumed time in pinpointing areas of irregular high consumption that are out of the norm.

The first step of the project is to gather and collect the data from different sources. Then, data cleaning and preprocessing will take place. The cleaned dataset will be gathered in a quarterly basis and separated to 70:30 ratio to be input in the model. Two models will be run and compared. The first model, a multiple regression model including many independent variables (Year, Quarter, Capita, Area, etc.) to forecast the consumption of electricity and water separately. The second model is univariate ARIMA model for each of electricity and water data. Both models will be done to run the data of year 2017 to 2020 and forecast year 2021 consumption in quarterly basis.

Finally, the model's performance evaluation metrics will be evaluated showing a table compare the actual and predicted consumption.

3.2 Data Source

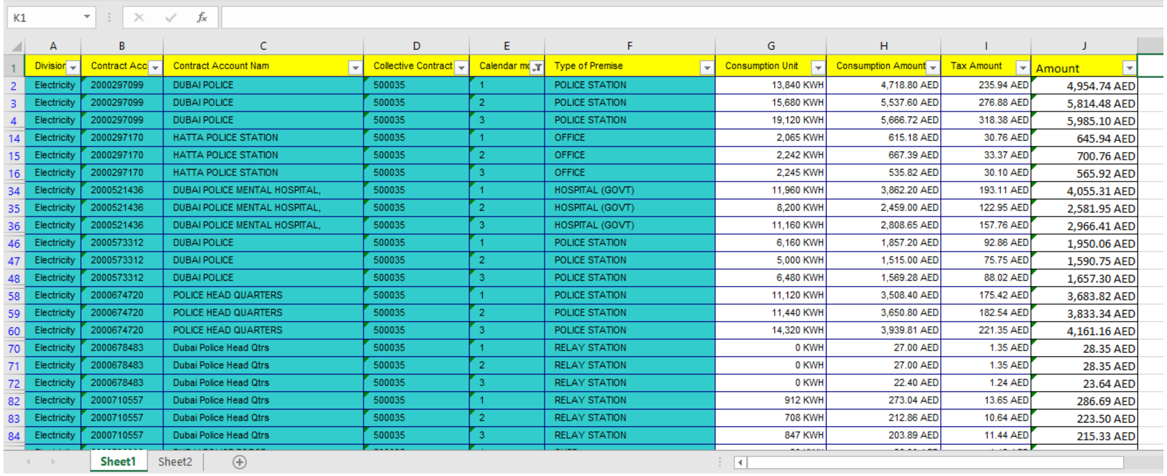
Electricity and water consumption data that will be used is taken from the meter substations provided by DEWA to the organization. The data is then collected from the energy conservation department at Dubai Police consisting of around 10 variables including contract account name, Calendar month, electricity consumption (kWh) and water consumption (Gallons) for five years from the period of 2017 to 2021. Also, to assign each contract number to its department or police station, facilities list assigned to each contract number was collected also from properties department. As well as, data of area and number of employees in each location was collected from maintenance and HR departments. The three datasets will be combined and used for the model. The dataset includes null values, zero values and repetitive values which will be cleaned using techniques that enable us to input the dataset in different machine learning algorithms.

3.3 Data Collection

The energy conservation department in Dubai Police is receiving the monthly bills from Dubai Water and Electricity Authority (DEWA) quarterly. Bills from 2017 to 2021 were combined in one datasheet. In addition, the list of facilities mapped to the contract number is provided by the properties department in Dubai Police. Also, the effect of the number of employees and building areas on electricity and water consumption will be studied. The three datasets need to be combined to create one datasheet and run the model based on it. A sample of each dataset will be shown in the bellow sections.

3.3.1 Electricity and water bills

Table 4: Bills received from DEWA.



K1

	A	B	C	D	E	F	G	H	I	J
1	Divisior	Contract Acc	Contract Account Nam	Collective Contract	Calendar mc	Type of Premise	Consumption Unit	Consumption Amount	Tax Amount	Amount
2	Electricity	2000297099	DUBAI POLICE	500035	1	POLICE STATION	13,840 KWH	4,718.80 AED	235.94 AED	4,954.74 AED
3	Electricity	2000297099	DUBAI POLICE	500035	2	POLICE STATION	15,680 KWH	5,537.60 AED	276.88 AED	5,814.48 AED
4	Electricity	2000297099	DUBAI POLICE	500035	3	POLICE STATION	19,120 KWH	5,666.72 AED	318.38 AED	5,985.10 AED
14	Electricity	2000297170	HATTA POLICE STATION	500035	1	OFFICE	2,065 KWH	615.18 AED	30.76 AED	645.94 AED
15	Electricity	2000297170	HATTA POLICE STATION	500035	2	OFFICE	2,242 KWH	667.39 AED	33.37 AED	700.76 AED
16	Electricity	2000297170	HATTA POLICE STATION	500035	3	OFFICE	2,245 KWH	535.82 AED	30.10 AED	565.92 AED
34	Electricity	2000521436	DUBAI POLICE MENTAL HOSPITAL,	500035	1	HOSPITAL (GOVT)	11,960 KWH	3,862.20 AED	193.11 AED	4,055.31 AED
35	Electricity	2000521436	DUBAI POLICE MENTAL HOSPITAL,	500035	2	HOSPITAL (GOVT)	8,200 KWH	2,459.00 AED	122.95 AED	2,581.95 AED
36	Electricity	2000521436	DUBAI POLICE MENTAL HOSPITAL,	500035	3	HOSPITAL (GOVT)	11,160 KWH	2,808.65 AED	157.76 AED	2,966.41 AED
46	Electricity	2000573312	DUBAI POLICE	500035	1	POLICE STATION	6,160 KWH	1,857.20 AED	92.86 AED	1,950.06 AED
47	Electricity	2000573312	DUBAI POLICE	500035	2	POLICE STATION	5,000 KWH	1,515.00 AED	75.75 AED	1,590.75 AED
48	Electricity	2000573312	DUBAI POLICE	500035	3	POLICE STATION	6,480 KWH	1,569.28 AED	88.02 AED	1,657.30 AED
58	Electricity	2000674720	POLICE HEAD QUARTERS	500035	1	POLICE STATION	11,120 KWH	3,508.40 AED	175.42 AED	3,683.82 AED
59	Electricity	2000674720	POLICE HEAD QUARTERS	500035	2	POLICE STATION	11,440 KWH	3,650.80 AED	182.54 AED	3,833.34 AED
60	Electricity	2000674720	POLICE HEAD QUARTERS	500035	3	POLICE STATION	14,320 KWH	3,939.81 AED	221.35 AED	4,161.16 AED
70	Electricity	2000678483	Dubai Police Head Qtrs	500035	1	RELAY STATION	0 KWH	27.00 AED	1.35 AED	28.35 AED
71	Electricity	2000678483	Dubai Police Head Qtrs	500035	2	RELAY STATION	0 KWH	27.00 AED	1.35 AED	28.35 AED
72	Electricity	2000678483	Dubai Police Head Qtrs	500035	3	RELAY STATION	0 KWH	22.40 AED	1.24 AED	23.64 AED
82	Electricity	2000710557	Dubai Police Head Qtrs	500035	1	RELAY STATION	912 KWH	273.04 AED	13.65 AED	286.69 AED
83	Electricity	2000710557	Dubai Police Head Qtrs	500035	2	RELAY STATION	708 KWH	212.86 AED	10.64 AED	223.50 AED
84	Electricity	2000710557	Dubai Police Head Qtrs	500035	3	RELAY STATION	847 KWH	203.89 AED	11.44 AED	215.33 AED

This excel sheet is a sample of the quarterly bills received from DEWA. It is composed of 10 columns and 17873 rows (for years from 2017 to 2021). The dataset contains many data for private and unneeded accounts and some columns will not be needed for our study, like the "collective contract" column. As the study will be for Dubai Police departments and police stations, any unnecessary or irrelevant facilities will be removed from the data.

3.3.2 Facilities list (The full table is in Appendix 1)

Table 5: Facilities list.

Department Or PS	Contract Account number	GHQ Department	Utility	Unit
GHQ	2008381781	Communication Dept	Electricity	kWh
	2014456402	CID	Electricity	kWh
	2008165620	CID and Anti-Narcotics	Electricity	kWh
	2008381935	CID	Electricity	kWh
	2008422267	GHQ Shared	Electricity	kWh
	2008422410	Health Center	Electricity	kWh
	2008422569	GHQ Shared	Electricity	kWh
	3000778121	GHQ Shared	Electricity	kWh
	3000778132	GHQ Shared	Electricity	kWh
	2008495744	CID	Electricity	kWh
	2008534081	GHQ Shared	Water	GAL
	2009491912	GHQ Shared	Electricity	kWh
	2009816927	Health Center	Electricity	kWh
	2009816960	Communication Dept	Electricity	kWh
	2009943856	AntiNarcotic	Electricity	kWh
	2010094239	HQ BLDG	Electricity	kWh

	2010094980	HQ BLDG	Electricity	kWh
	2010097041	HQ BLDG	Electricity	kWh
	2010097106	HQ BLDG	Electricity	kWh
	2010097130	HQ BLDG	Electricity	kWh
Al Riffa Police Station	2008892646		Electricity	kWh
	2008892875		Electricity	kWh
	2009055420		Water	GAL
	2009222180		Electricity	kWh

The above excel sheet is a sample of the facilities list for each contract number taken from the properties department in Dubai Police. It is composed of 5 columns and 208 rows showcasing the facilities that will be included in the study.

3.3.3. Capita and Area list

Table 6: Capita and Area list.

Facilities	**Capita**	**Area (meter square)**
GHQ Campus	**3072**	**172,397**
Dubai Police Academy	1234	**168,385**
Punitive and Correctional Establishments	5808	**114,040**
Al Wasl Protective Security and Emergency	543	**40,234**
Barsha Police Station	332	**31,624**
Officers Club	264	**28,985**
General Department of Transport and Rescue	898	**32,528**
Naif Police Station	345	**11,887**
K9	85	**10,176**
Nad Alsheba Police Station	988	**11,816**
Al Rashdiyah Police Station	363	**12,895**
Al Riffa Police Station	79	**14,805**
Moraqabat Police Station	350	**21,794**
Port Police Station	483	**11,271**

Traffic Department Deira	642	**11,297**
Barsha Traffic Dept	262	**12,226**
Bur Dubai Police Station	480	**9,278**
Qusais Police Station	344	**9,353**
Airport Security	1985	**7,394**
Awir Horse Stables	130	**6,364**
Hor Al Anz Protective Security and Emergency	124	**4,187**
Lahbab Police station	87	**726**
Hatta Police Station	186	**1,086**
Al Faqqa Police Station	11	**1,406**
Qusais Horse Stables		**1,826**
Qusais Warehouses	4	**3,610**
Jabal Ali Police Station	236	**4,447**
Rowaiyah Shooting Range	51	**2,343**

The number of employees and the area of each facility is described in the above table. The gathered data is for 28 facilities, however, the data for 5 facilities were not provided due to confidentiality reasons. Although that shouldn’t stop us from including these two variables as it will add a good value to the model. This table contains 29 rows and 3 columns.

Chapter 4- Data Analysis

4.1 Data Preparation

First of all, we need to add all bills for all quarters from 2017 to 2021 in one sheet (a total of 17,873 rows). Then, we need to merge all the required data. This was done using the “left_join” function in R. Facilities list will be joined with bills data sheet based on “contract number” and “Division” to get two more columns (DepartmentOrPS and GHQ Department). Then, we will join capita and area based on the DepartmentOrPS column.

4.2 Data Preprocessing

4.2.1 Data Cleaning

The cleaning process was conducted in Microsoft Excel and R Studio. The bills received from DEWA contain many duplicates, zero values, Na’s, unknown locations, and unnecessary accounts. I followed these cleaning steps before we start joining the three datasets together:

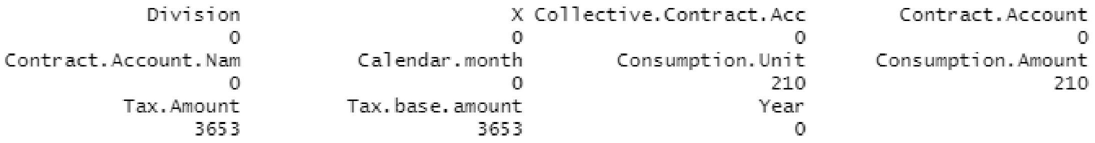
Below are the cleaning steps for the bill’s datasheet:

Microsoft Excel:

- Compile all year’s bills together (monthly basis from January to December)
- Prepare datasheet for locations with their meter numbers (Contract Account)
- Add a new column for years to distinguish which year each consumption is assigned.
- Remove the units from the Consumption unit and Consumption Amount columns. Units are affecting the variable type in R so it's difficult to deal with them as numeric. As we have a column (Division) describing each row if it is assigned to “Electricity” or “Water” keeping the units is useless.

R Studio:

- Removing NAs, blanks, and zero values in Bills dataset.



```
             Division                    X Collective.Contract.Acc        Contract.Account
                    0                    0                       0                       0
 Contract.Account.Nam       Calendar.month        Consumption.Unit      Consumption.Amount
                    0                    0                     210                     210
           Tax.Amount      Tax.base.amount                    Year
                 3653                 3653                       0
```

- Removing NAs and zero values in the “Consumption.Unit” column.

There are 210 NA values and 1160 Zero values in the Consumption.unit. As all the study is based on this variable so it is not logical to keep zero values in this column. As it is impossible to have zero consumption for a working meter unless they closed a building for at least 1 month. And even if it does happen, we will not need this information for the study.

- Replacing NA in Tax.Amount with zero.

Some values in the "Tax.Amount" column are NAs because the tax policy in UAE starts on 2018. So, the data of this column for year 2017 will be NA.

- Replacing NA in Tax.base.amount by Consumption.Amount plus Tax.Amount for year 2017

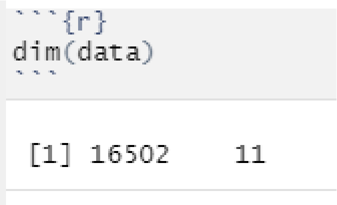
- Changing the type of features

Convert the month column from character to factor.

Convert Consumption.Unit, Consumption.Amount, Tax.Amount, and Tax.base.Amount from character to numeric.

The output of the bill's dataset:

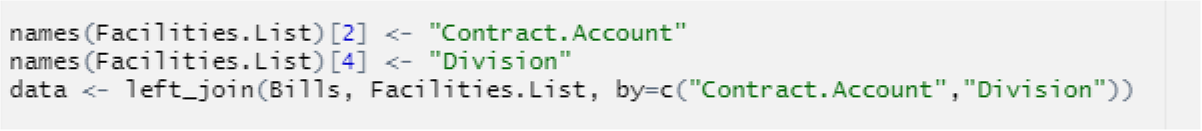
After the cleaning steps, we have 16,502 insights and 11 columns.



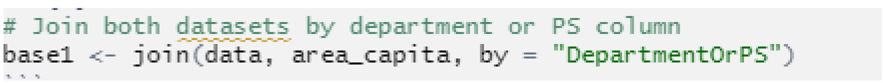
~~~
```{r}
dim(data)
```

 [1] 16502    11
~~~

4.2.2 Data Preparation

First, we need to unify the names of columns that will be joined based on. To join bills with facilities list based on "Contract.Account" and "Division" columns. So, the column name in the Facilities list file should be changed from "contract account number" to "Contract.Account". Same with Area and Capita file, the two files will be joined based on the "DepartmentOrPS" column in the bills file which is the same as "Facilities" in Area and Capita file. The column name has been changed to "DepartmentOrPS" to be easily joined. Also, some facilities' names are not unified in bills and (Area and Capita) files as GHQ is named in GHQ Campus. This is also needed to be fixed before joining the process tale place. Use the left.join() and join() function to merge the three datasheets in one dataset as shown below.



```
names(Facilities.List)[2] <- "Contract.Account"
names(Facilities.List)[4] <- "Division"
data <- left_join(Bills, Facilities.List, by=c("Contract.Account","Division"))
```

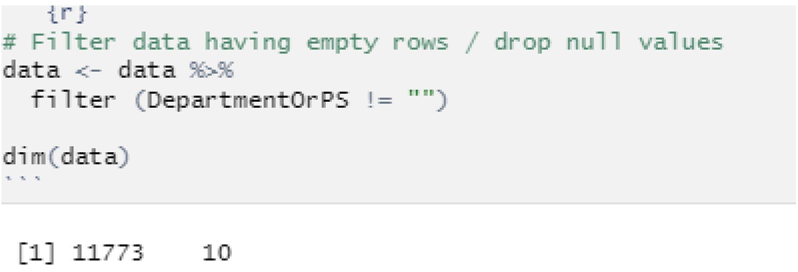


~~~
# Join both datasets by department or PS column
base1 <- join(data, area_capita, by = "DepartmentOrPS")
```
~~~

- Joining the three datasets don to add all of the following columns:

- Add a new column describing which Department or Police Station this contract number is assigned to, this column is called “DepartmentOrPS”.
- Add a new column for the exact location in General Head Quarters called “GHQ.Department”.
- Add a column for the Area of each location called “Area (meter square)”.
- Add a column for Capita number of employees called “Capita”.

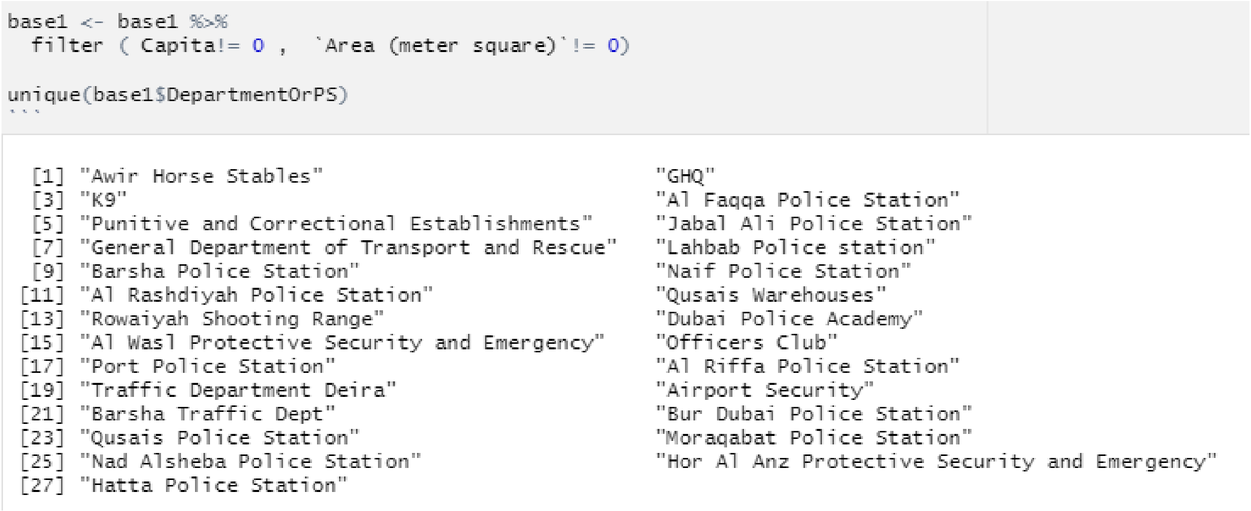
- Remove all rows that are not assigned to any PS or Department (extra account number received in the bill (might be private or excepted from the payment or unneeded for the study).



```
  {r}
# Filter data having empty rows / drop null values
data <- data %>%
  filter (DepartmentOrPS != "")

dim(data)
```
```

 [1] 11773   10
```

- Remove unneeded columns. Like, Collective.Contract.Acc and Contract.Account.Nam columns are not useful factors for our study. This information was added to the bill for payment sakes that will not be affected by our study.

- Remove locations that not have Area and Capita values. We will be left with 27 Departments and Police Stations.

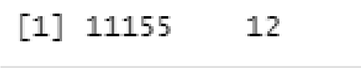


```
base1 <- base1 %>%
  filter (Capita!= 0 , `Area (meter square)`!= 0)

unique(base1$DepartmentOrPS)
```
```

  [1] "Awir Horse Stables"   "GHQ"
  [3] "K9"   "Al Faqqa Police Station"
  [5] "Punitive and Correctional Establishments"   "Jabal Ali Police Station"
  [7] "General Department of Transport and Rescue"   "Lahbab Police station"
  [9] "Barsha Police Station"   "Naif Police Station"
 [11] "Al Rashdiyah Police Station"   "Qusais Warehouses"
 [13] "Rowaiyah Shooting Range"   "Dubai Police Academy"
 [15] "Al Wasl Protective Security and Emergency"   "Officers Club"
 [17] "Port Police Station"   "Al Riffa Police Station"
 [19] "Traffic Department Deira"   "Airport Security"
 [21] "Barsha Traffic Dept"   "Bur Dubai Police Station"
 [23] "Qusais Police Station"   "Moraqabat Police Station"
 [25] "Nad Alsheba Police Station"   "Hor Al Anz Protective Security and Emergency"
 [27] "Hatta Police Station"
```

- Removing duplicated rows:

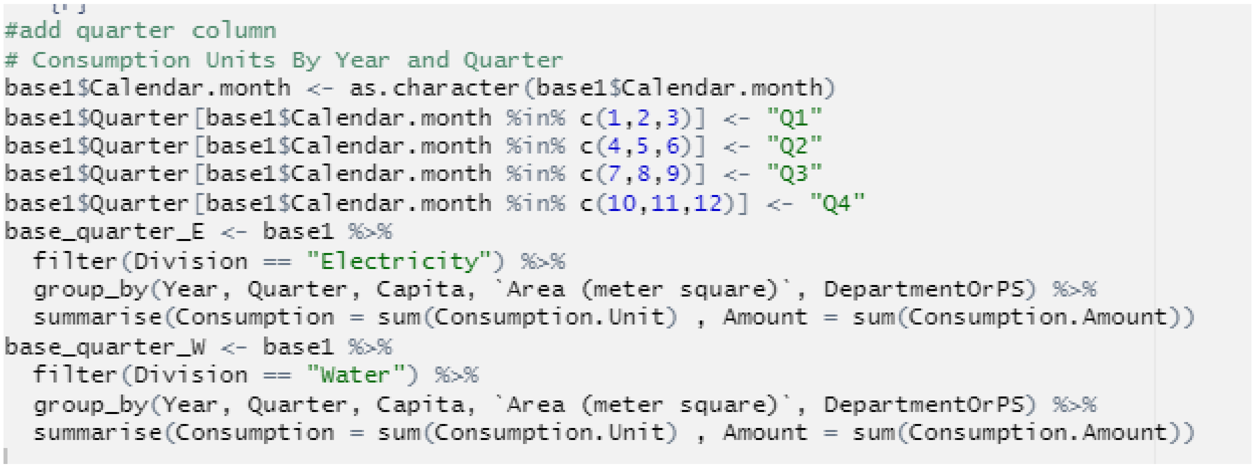
Duplicated rows are not needed in the model so they should be removed from the dataset. There are no duplicated rows as the left_join function was used. When the “join” function was used to join meters and bills datasets, there were 1387 which was removed automatically by using “left_join”.

We will end up having 11,155 rows and 12 columns.



```
[1] 11155    12
```

- Convert the Dataset to be quarterly by assigning each quarter to their month and take the summation of consumption unit and amount. The below code was used to generate the datasheets for electricity and water data.



```
#add quarter column
# Consumption Units By Year and Quarter
base1$Calendar.month <- as.character(base1$Calendar.month)
base1$Quarter[base1$Calendar.month %in% c(1,2,3)] <- "Q1"
base1$Quarter[base1$Calendar.month %in% c(4,5,6)] <- "Q2"
base1$Quarter[base1$Calendar.month %in% c(7,8,9)] <- "Q3"
base1$Quarter[base1$Calendar.month %in% c(10,11,12)] <- "Q4"
base_quarter_E <- base1 %>%
  filter(Division == "Electricity") %>%
  group_by(Year, Quarter, Capita, `Area (meter square)`, DepartmentOrPS) %>%
  summarise(Consumption = sum(Consumption.Unit) , Amount = sum(Consumption.Amount))
base_quarter_W <- base1 %>%
  filter(Division == "Water") %>%
  group_by(Year, Quarter, Capita, `Area (meter square)`, DepartmentOrPS) %>%
  summarise(Consumption = sum(Consumption.Unit) , Amount = sum(Consumption.Amount))
```

4.3 Data Quality Dimensions

To check data quality, we need to look at its six dimensions. The explanation of each is mentioned below:

1. **Completeness:** the dataset has missing values and is set as NA or blanks as well as zero consumption values. Facilities area and capita values are not provided. To overcome any incompleteness in the datasets, we removed these facilities from the model.
2. **Conformity:** The facilities list received from the properties department names the facility different than the table provided for Area and Capita for each facility. This needs to be unified before joining the two datasets together.
3. **Consistency:** To make sure the bill amount (Tax.base.Amount) column received from DEWA is equal to Consumption.amount plus Tax.amount. A new column was created to check if they are consistent. The result was that our dataset is consistent.
4. **Accuracy:** The dataset was taken directly from the concerned department in Dubai Police. This makes us sure that it is accurate. However, the Temperature column added was for the temperature detected in Dubai City not specifying the year. If it has been found for the exact location and each year and quarter it will be more accurate.
5. **Duplicates:** Duplicates can't be applied to each column. As the dataset contains the consumption data for the same "Contract Numbers" repeated for different years and moth. The only duplicates we should avoid is having the same electricity/water consumption duplicated for the same facility "Contract Number" recorded in the same year and month. As this case was checked, the datasets do not contain any duplicates.
6. **Integrity:** The dataset is integrated and connected very well. When we joined the three datasets together based on specific attributes that confirm that all attributes are related and connected.

4.4 Feature Engineering

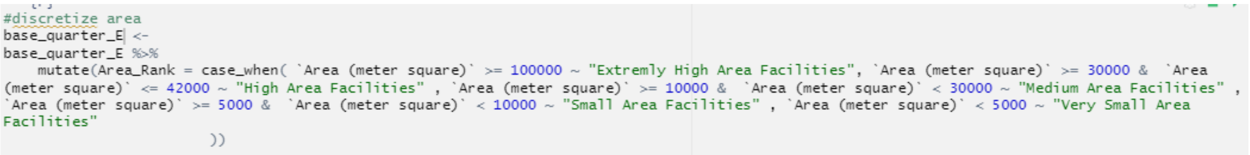
Area Rank (discretization)

To have a good visualization in comparing departments and police stations to each other based on the similar parameter (Area). A new feature was added, "Area Rank" explained in the table below.

Table 7: Area Rank discretization details.

Area_Rank	Area (meter square)	DepartmentOrPS
Extremly High Area Facilities	100,000 meters square - 200,000 meters square	GHQ
		Dubai Police Academy
		Punitive and Correctional Establishments
High Area Facilities	30,000 meters square - 42,000 meters square	Al Wasl Protective Security and Emergency
		Barsha Police Station
		Officers Club
		General Department of Transport and Rescue
Medium Area Facilities	10,000 meters square - 30,000 meters square	Naif Police Station
		K9
		Nad Alsheba Police Station
		Al Rashdiyah Police Station
		Al Riffa Police Station
		Moraqabat Police Station
		Port Police Station
		Traffic Department Deira
		Barsha Traffic Dept
Small Area Facilities	5,000 meters square - 10,000 meters square	Bur Dubai Police Station
		Qusais Police Station
		Airport Security
		Awir Horse Stables
Very Small Area Facilities	0 meters square - 5,000 meters square	Hor Al Anz Protective Security and Emergency
		Lahbab Police station
		Hatta Police Station
		Al Faqqa Police Station
		Qusais Horse Stables
		Qusais Warehouses
		Jabal Ali Police Station
		Rowaiyah Shooting Range

This was done using mutate () function as shown here:



```
#discretize area
base_quarter_E <-
base_quarter_E %>%
    mutate(Area_Rank = case_when( `Area (meter square)` >= 100000 ~ "Extremly High Area Facilities", `Area (meter square)` >= 30000 &  `Area
(meter square)` <= 42000 ~ "High Area Facilities" , `Area (meter square)` >= 10000 &  `Area (meter square)` < 30000 ~ "Medium Area Facilities" ,
`Area (meter square)` >= 5000 &  `Area (meter square)` < 10000 ~ "Small Area Facilities" , `Area (meter square)` < 5000 ~ "Very Small Area
Facilities"
                        ))
```

Consumption per m square

A new attribute was added for each electricity and water consumption which is as below:
Consumption.per.area = Consumption / Area (meter square)
As Consumption is either in kWh or Gallons.
This attribute will give us a better comparison criterion between buildings per building area.

Consumption per Capita

A new attribute was added for each electricity and water consumption which is as below:
Consumption.per.capita = Consumption / Capita (number of employees)
As Consumption is either in kWh or Gallons
This attribute will give us a better comparison criterion between departments as it is per employee number.

Quarter

Add a column that describes each month related to each quarter. As the study is to predict the quarter consumption so the dataset must be built quarterly before input it in the model. The code was shown in the previous section. The column will be described as below:

Table 8: Quarter Column description.

Calendar month	Quarter
1 or 2 or 3	Q1
4 or 5 or 6	Q2
7 or 8 or 9	Q3
10 or 11 or 12	Q4

Temperature

One more column was added to describe the temperature and study the effect of the temperature on the consumption. The temperature of each quarter is "Temperature_Q". The average Temperature in Dubai City was taken for each month as shown below.

Table 9: The average monthly temperature in Dubai (What is weather like in Dubai, Dubai, AE (worldweatheronline.com)).

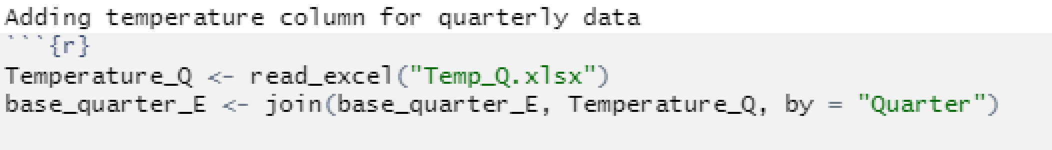
Calendar month	Temperature
1	21
2	22.5
3	25
4	28.5
5	32.5
6	34.5
7	36
8	36
9	34.5
10	31.5
11	27
12	23.5

Then by taking the average of each quarter we calculated the temperature quarterly as shown below:

Table 10: Quarterly temperature column description.

Quarter	Temperature_Q
Q1	22.83
Q2	31.83
Q3	35.50
Q4	27.33

Using the "join" function. This column was joined to our data set based on the "Quarter" Column respectively.



~~~
Adding temperature column for quarterly data
```{r}
Temperature_Q <- read_excel("Temp_Q.xlsx")
base_quarter_E <- join(base_quarter_E, Temperature_Q, by = "Quarter")
~~~

4.5 Correlation between attributes

The Correlogram is a graph of the correlation matrix. This is commonly used to highlight the most connected variables in a data set or data table. We can reorder the correlation matrix based on the degree of relationship between the variables.

Negative correlations are shown by a red scale, whereas positive correlations are represented by a blue scale.

The correlation matrix:

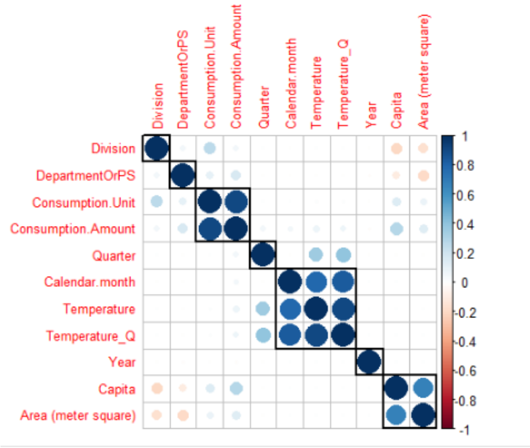


Figure 4: Correlation Matrix.

The tax amount and tax base amount were excluded as they are a function of consumption amount. “Consumption.Unit” is the variable we concerned on. As we can see it is highly correlated with Consumption.amount which is logical as the consumption amount is (consumption unit × tariff rate (constant)). So, it is logical to have them perfectly correlated. It is positively correlated with Division, Capita, DepartmentOrPS, and Area respectively from high to low. It is almost zero correlated with “Year”, “Calendar month”, “Quarter”, “Temperature”, and “Temperature_Q.

4.6 Variable Dictionary

Table 11: Variables Dictionary.

Column	**Data Type**	**Explanation**
Division	Categorical	It is Electricity for electricity consumption and Water for water consumption tuple.
Contract.Account	Character	The electricity and water contract number assigned to each consumption and facility.
Quarter	Categorical	The quarter of the year for the observed consumption. Its “Q1” for the first quarter of the year (month 1,2,3), “Q2” for the second quarter of the year (month 4,5,6), “Q3” for the third quarter of the year (month 7,8,9), “Q4” for the last quarter of the year (month 10,11,12).
Consumption.Unit	Numeric	The quarterly electricity consumption (kwh) for Division “Electricity” and water consumption (gallons) for Division “Water”.
Consumption.Amount	Numeric	The quarterly consumption amount in AED received in the bill. It is equal to consumption unit multiply by tariff rate.
Tax.Amount	Numeric	Tax amount (5%) in AED.
Tax.base.amount	Numeric	The total paid amount, consumption amount plus the tax.
Year	Integer	The year where the consumption detected in (2017,2018,2019,2020,2021).
DepartmentOrPS	Categorical	The names of facilities, departments and police stations (27 unique values).
GHQ.Department	Categorical	The specific department name in General Headquarters.
Capita	Numeric	The number of employees in each facility.
Area (meter square)	Numeric	The area in meter squares for each facility.
Consumption.per.capita	Numeric	The quarterly consumption of electricity and water per number of employees.
Consumption.per.Area	Numeric	The quarterly consumption of electricity and water per meter squares.
Area Rank	Categorical	• The area rank for each facility as the following: • “Extremely High Area Facilities” (100,000 meters square - 200,000 meters square) • “High Area Facilities” (30,000 meters square - 42,000 meters square) • “Medium Area Facilities” (10,000 meters square - 30,000 meters square) • “Small Area Facilities” (5,000 meters square - 10,000 meters square) • “Very Small Area Facilities” (0 meters square - 5,000 meters square)
Temperature_Q	Numeric	The temperature in Dubai city in each quarter (Celsius).

1.7 Data Exploration and Visualization

In this section, a set of graphs have been drawn separately for electricity and water consumption to understand the data better before moving toward the modeling part. The plots were done using R Studio and Tableau. This plot is established to have an overview of what type of questions/information we will try to explore in this section, following is a set of questions that are devised in this case.

- Average consumption units by category overall.
- Total Consumption units by year for electricity and water.
- Month-wise comparison of consumption units for electricity and water.
- The quarter-wise trend of consumption for each year for both water and electricity.
- A trend of consumption units over the past few years.
- Consumption units by GHQ Department and DepartmentOrPS for both water and electricity.
- Consumption per capita and Consumption per area plots.
- A comparison of consumption based on each area rank.
- A sample of quarterly report of one department showing the percentage of saving/loss.
- The temperature affects consumption.

Starting with the analysis part, the pie charts shown below tell us about the overall consumption units and consumption amount by category. It is evident that that the average consumption units for water is much higher as compared to electricity, however, the average consumption amounts for both water and electricity are quite close with the consumption amount for water still higher as compared to electricity.

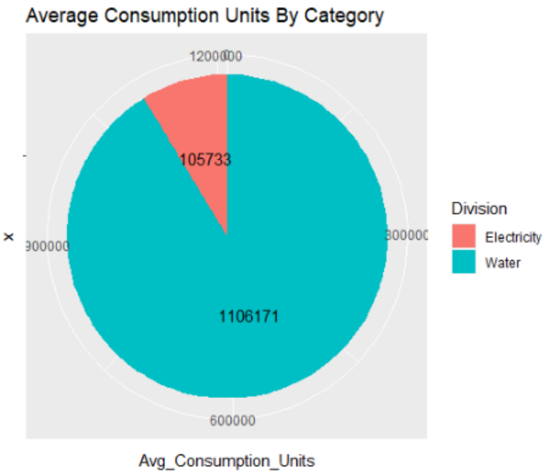


Figure 6: Average Consumption by Division.

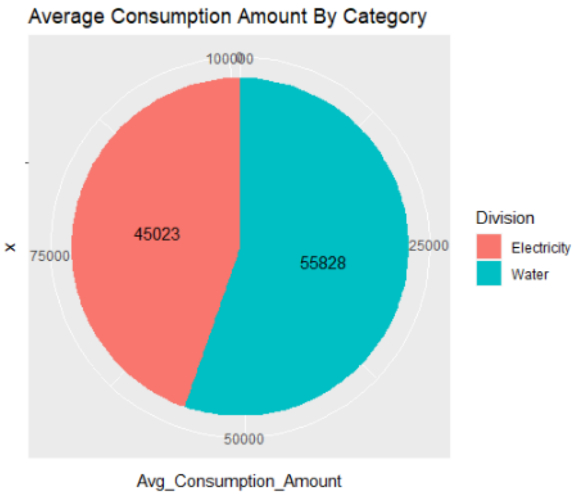


Figure 5: Average Consumption Amount by Division.

The second plot attached below, shows the comparison of total consumption units by year for both water and electricity. Figure 7, shows the consumption units by year for electricity while Figure 8 shows the consumption units by year for water. We can see that the consumption units for electricity are highest in year 2019 among all and lowest in year 2020. This might be due to covid-19 pandemic where most of the departments were closed and employees working remotely from home. Meanwhile the consumption for water is highest in year 2020 and lowest in year 2021. The water consumption units are not affected by the covid-19 pandemic in this case.

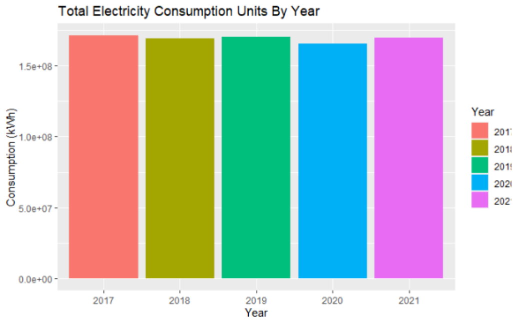


Figure 7: Electricity Consumption by Year.

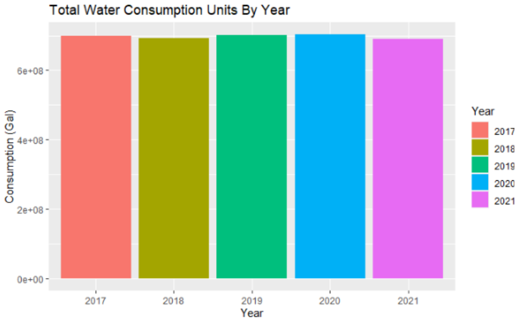


Figure 8: Water Consumption by Year.

Next, we will explore the total consumption units by month to see which month consumes the highest units of electricity and water. We can see from below attached bar graphs that the consumption units for electricity are recorded lowest in 2nd and 3rd month of each year respectively. The highest consumption is recorded in 8th and 9th month which is August and September, the peaks of summer season. Same trend is seen for water as well, the consumption is highest in 8th month and lowest in 3rd month. This shows us that the time of year has a strong effect on consumption of units.

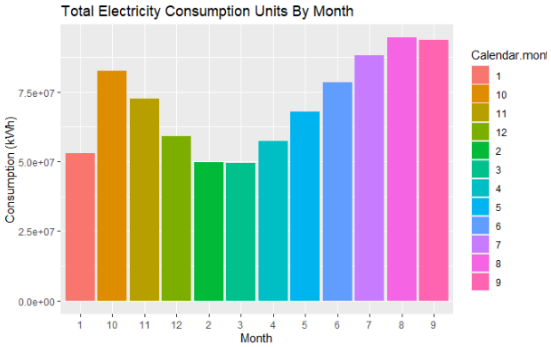


Figure 9: Electriciy Consumption by Month.

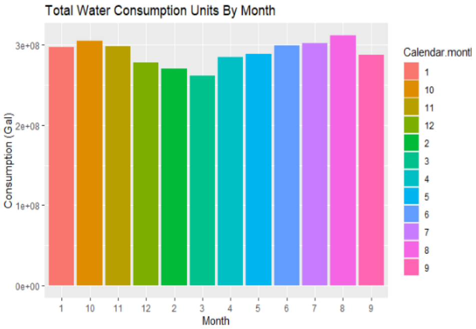


Figure 10: Water Consumption by Month.

While looking at the quarter-wise comparison of consumption units for each year for electricity, we can see that in almost all the years except 2019, the third quarter of the year records the highest consumption of electricity. This information could be seen in the graphs attached below:

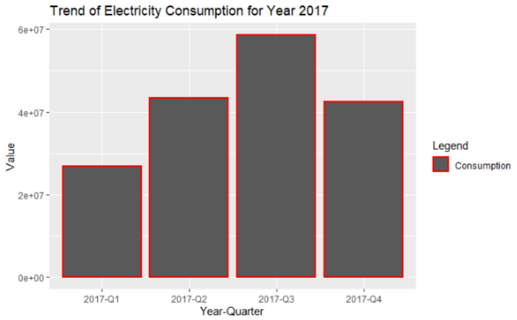


Figure 11: Electricity consumption quarterly for year 2017.

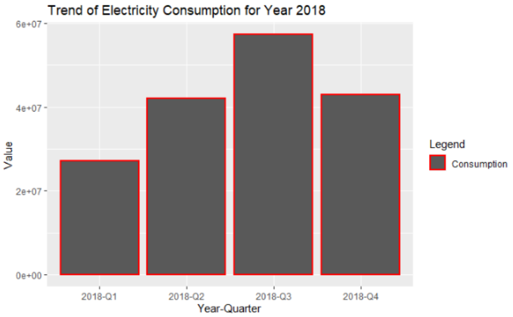


Figure 12: Electricity consumption quarterly for year 2018.

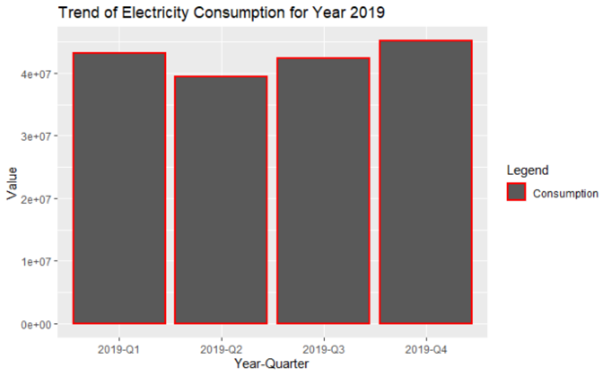


Figure 13: Electricity consumption quarterly for year 2019.

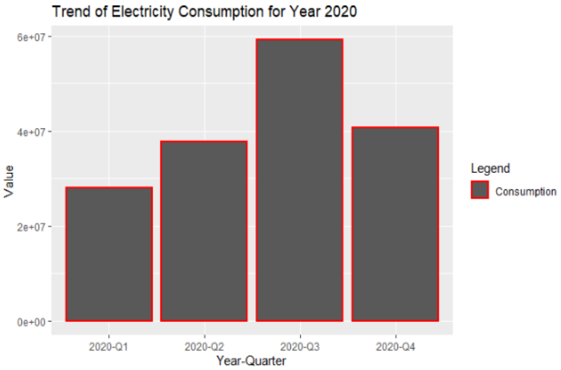


Figure 14: Electricity consumption quarterly for year 2020.

Same graphs are generated for water consumption as well and are attached below. Same trend as observed above could be seen here as well except for year 2019. For 2019, the consumptions are abrupt.

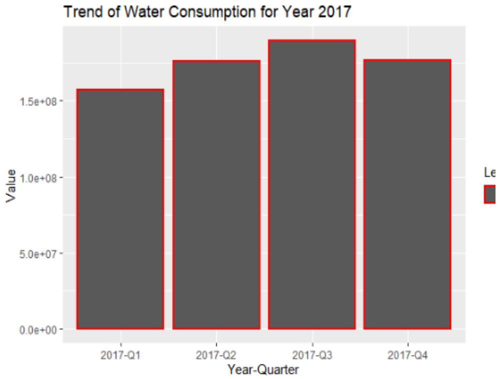


Figure 15: Water consumption quarterly for year 2017.

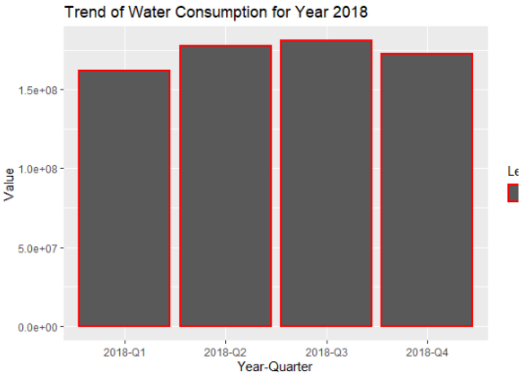


Figure 16: Water consumption quarterly for year 2018.

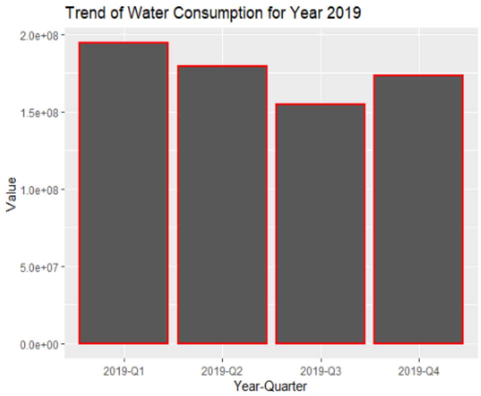


Figure 17: Water consumption quarterly for year 2019.

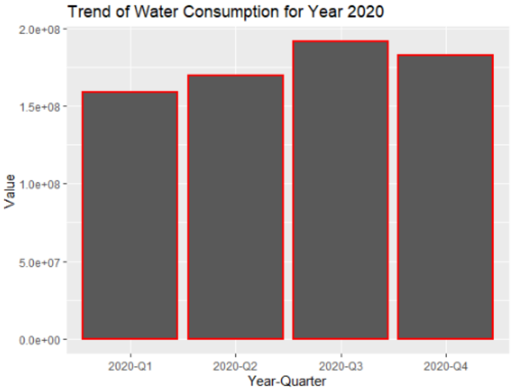


Figure 18: Water consumption quarterly for year 2020.

A graph showing the overall trend from 2017-2021 is attached below for both the categories which are electricity and water consumption. From the trend for electricity consumption, we can see that the lowest consumptions are recorded in first quarter of 2017 and the highest is recorded in quarter 3rd of year 2020. Same for the consumption units of water, the highest consumption for water is recorded in 1st quarter 2019 and lowest in 3rd quarter in 2019.

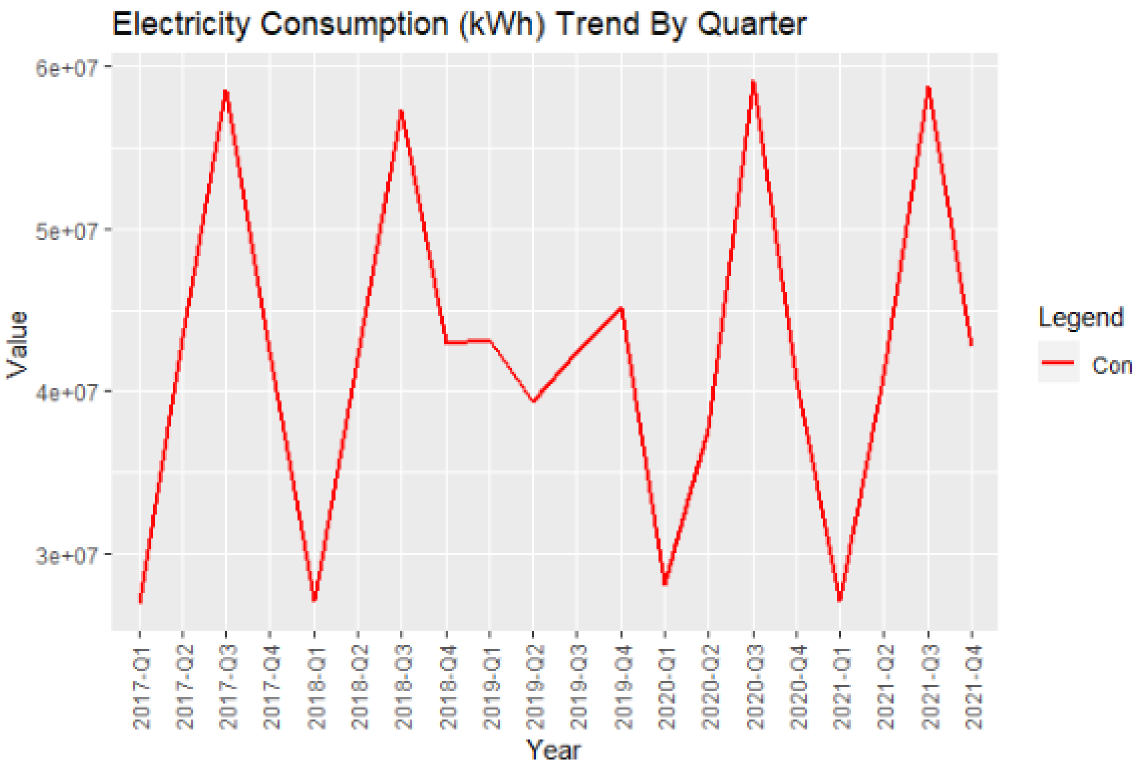


Figure 19: Electricity Consumption trend.

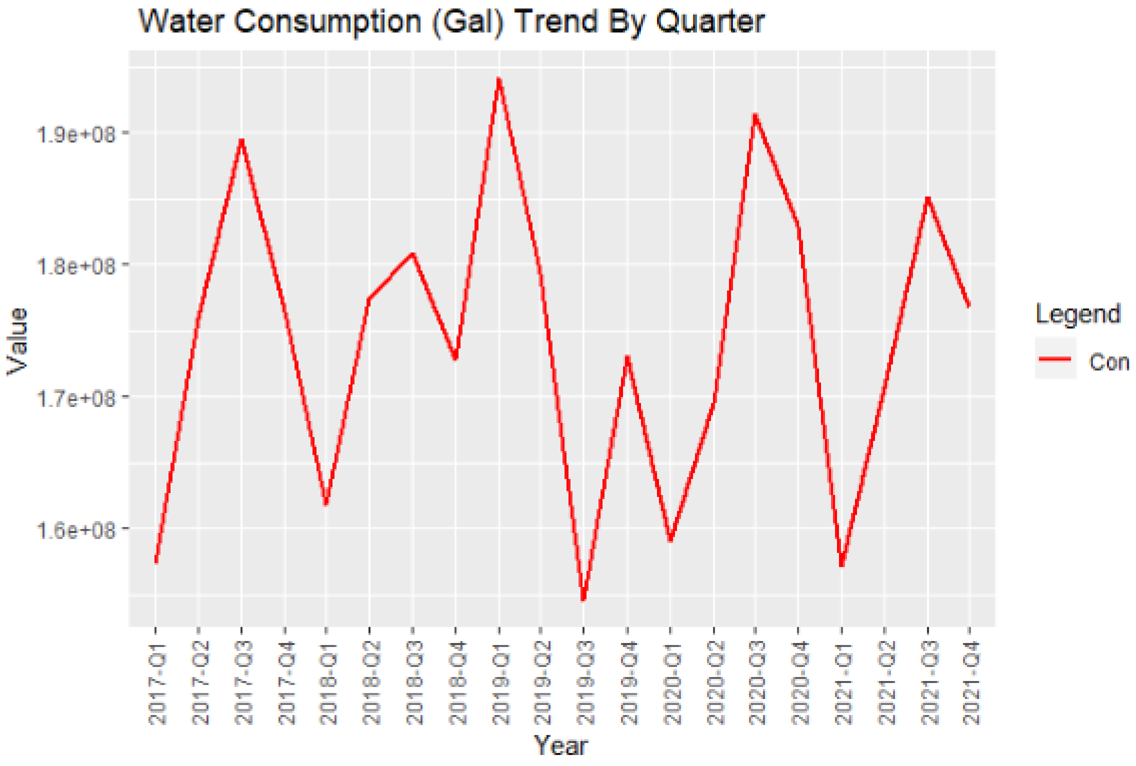


Figure 20: Water Consumption trend.

Below, two other bar graphs are created to show the department wise consumption for water and electricity which are attached below. It can be seen that the consumption of electricity for Forensic department and HQ building is highest while it is lowest for Decision making new department. Similarly, the consumption of water is highest in GHQ shared and lowest in explosive department.

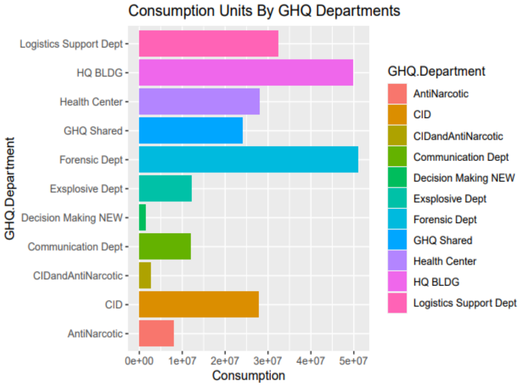


Figure 21: Electricity Consumption for each GHQ Department.

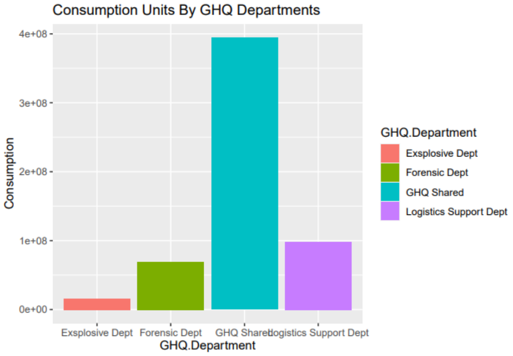
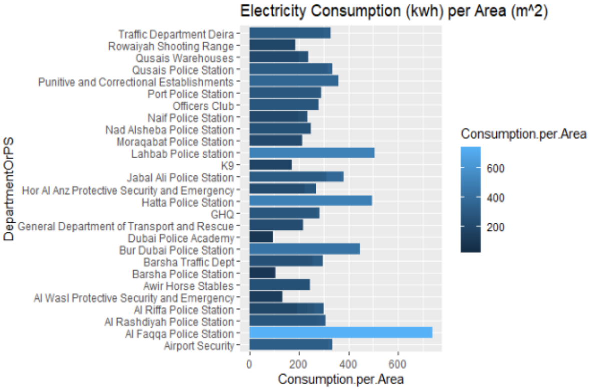


Figure 22: Water Consumption for each GHQ Department.

In the below plots, the total electricity consumption per area and capita based on departments or police stations for the total period of study (2017-2021) is shown. As we can see the highest consumption per area is conducted for Al Faqqa Police Station and the lowest for Dubai Police Academy. On the other hand, the highest consumption per capita was detected for Qusias Warehouses and the lowest for Airport Security.



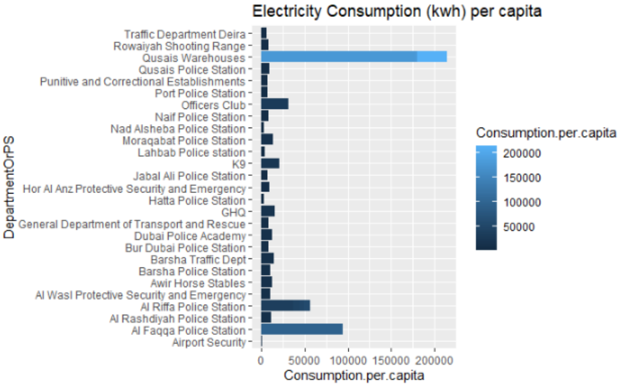


Figure 23: Electricity Consumption per Area for all departments and PSs.

Figure 24: Electricity Consumption per Capita for all departments and PSs.

Same for water consumption, as we can see the highest consumption per area is conducted for Rawiyah Shooting Range, however the lowest for Al Riffa Police Station. In the other hand, the highest consumption per capita was detected for Qusias Warehouses again and the lowest for Airport Security, General Department of Transport and Rescue, and Lehbab Police Station.

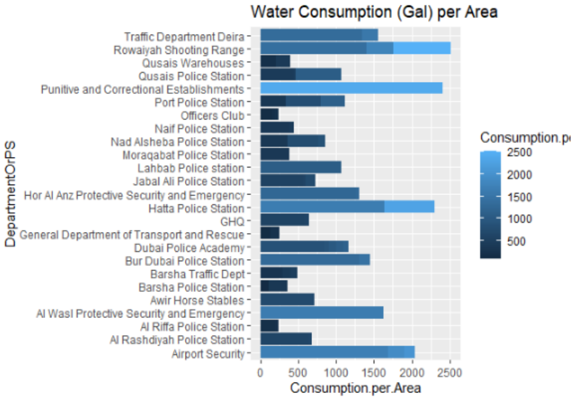


Figure 25: Water Consumption per Area for all departments and PSs.

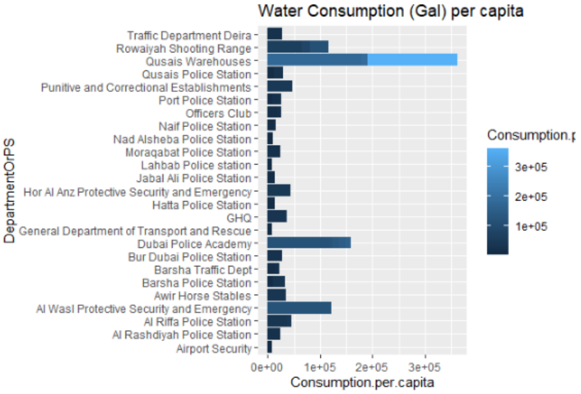


Figure 26: Water Consumption per Capita for all departments and PSs.

Moreover, the below plots showing electricity and water consumption for each department based on their area ranks. For electricity plot, GHQ campus showed the highest consumption in extremely high area facilities section, General Department of Transport and Rescue in high area facilities, Officers Club in medium area facilities, Bur Dubai Police Station in small area facilities, and Jabal Ali Police Station in very small area facilities. However, for water consumption Punitive and Correctional Establishments showed the highest consumption in extremely high area facilities section, Al Wasl Protective Security and Emergency in high area facilities, Traffic Department Deira in medium area facilities, Airport Security in small area facilities, and Hor Al Anz Protective Security and Emergency in very small area facilities. This concludes that these facilities need to be focused on, to detect the reasons of their high consumptions compared with the other locations in the same rank.

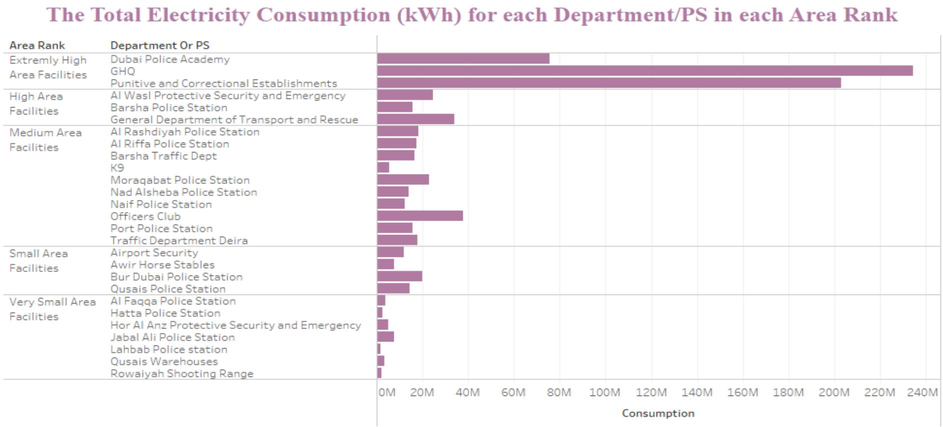


Figure 27: Electricity Consumption of Departments and PSs based on their Area Rank.

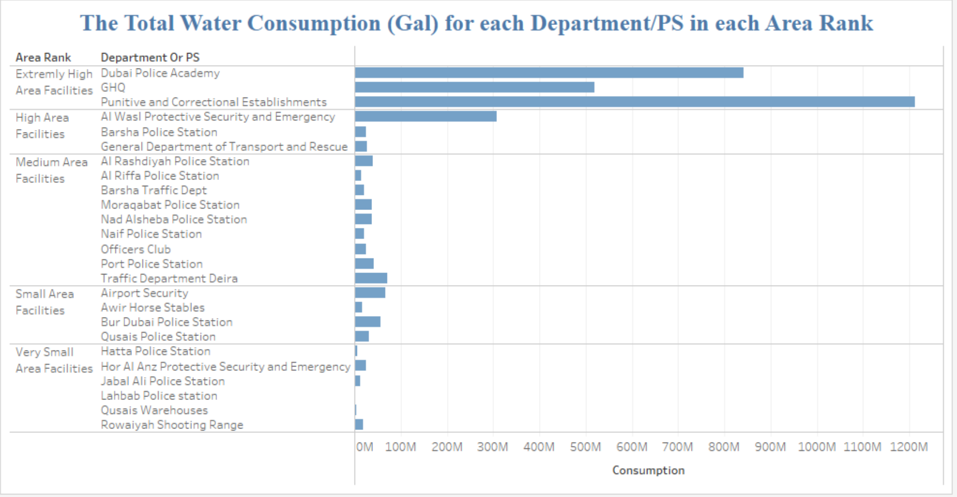


Figure 28: Water Consumption of Departments and PSs based on their Area Rank.

The below plots show the trend of temperature in each Quarter with electricity and water consumption. For electricity, we can see that the trend of consumption is same as temperature for year 2017. However, the consumption is the highest in all years except year 2019 in quarter 3 where the temperature is the highest as well. Same for water consumption plot.

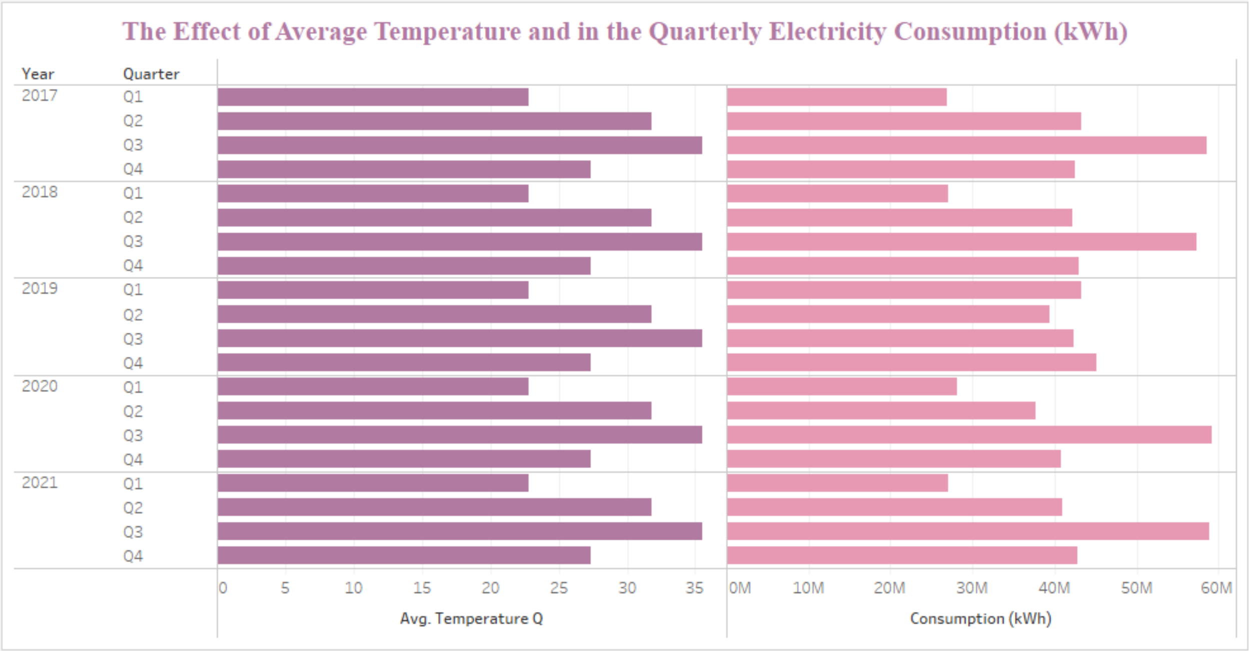


Figure 29: The trend of temperature and electricity consumption each quarter.

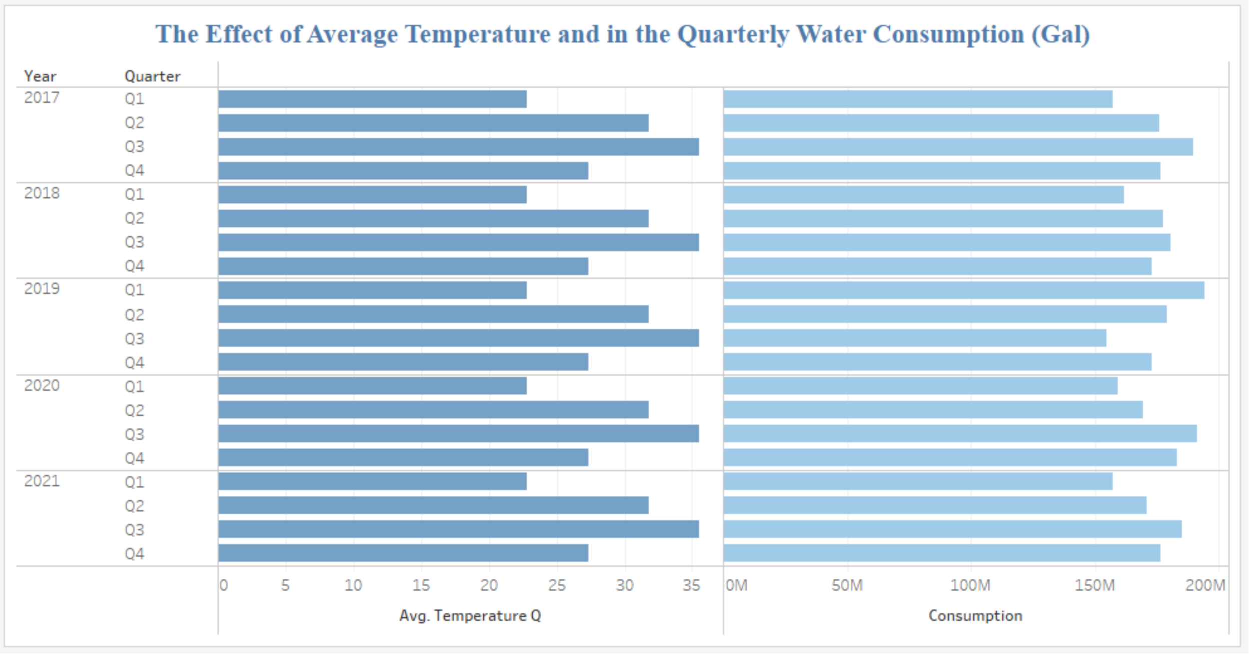


Figure 30: The trend of temperature and water consumption each quarter.

The plots here show a sample for logical comparison per a specific Quarter (Q1) and a facility (Al Riffa Police Station. In electricity consumption, first quarter of year 2019 got the highest and 2021 got the lowest electricity consumption. In the other hand, for water consumption in Q1, year 2020 detected the highest water consumption and 2018 the lowest.

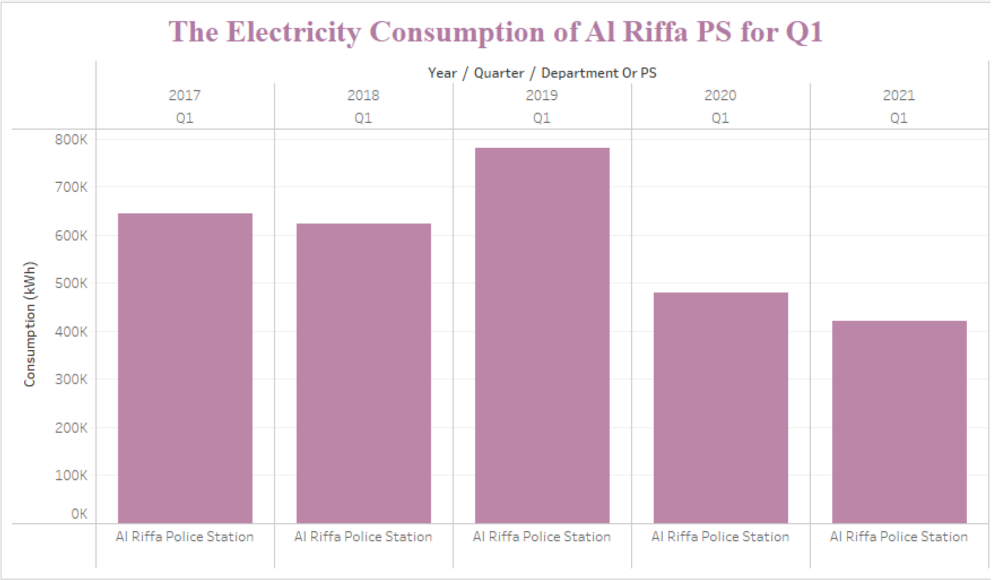


Figure 31: A quarterly report of electricity consumption for Al Riffa PS for the first Quarter.

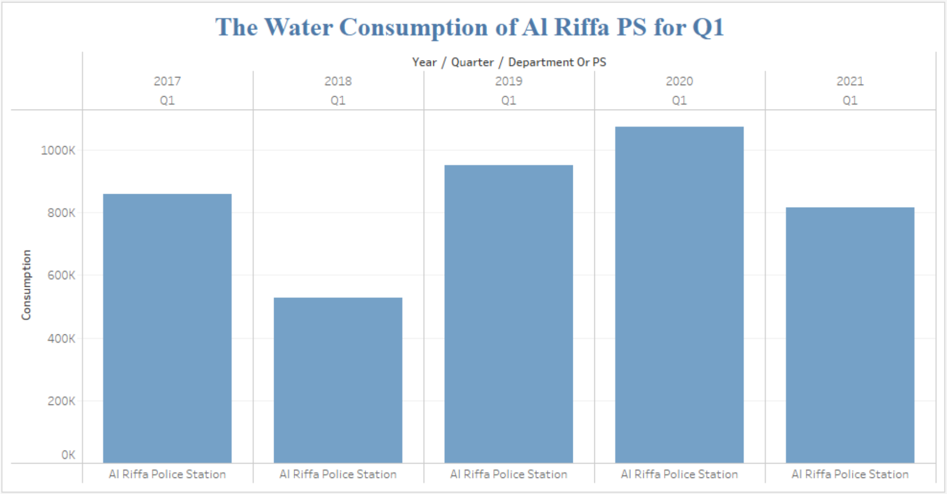


Figure 32: A quarterly report of water consumption for Al Riffa PS for the first Quarter.

This plot below represents the quarterly report that should be published for each department and police station (here is a sample for Airport Security) showing the percentage of saving and loss.

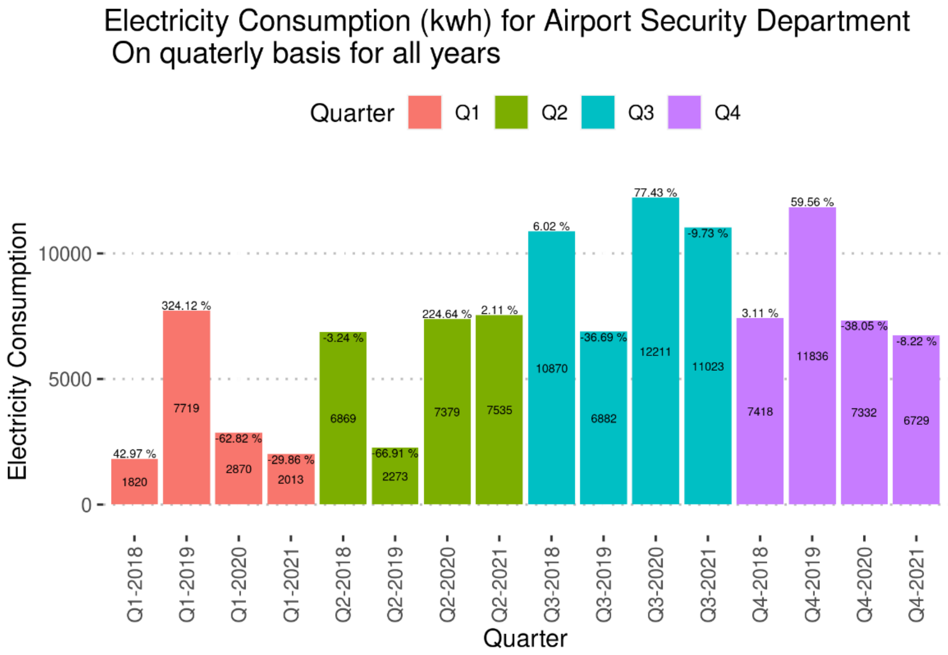


Figure 33: Electricity Consumption for Airport Security Department for each quarter.

The below plots show the total electricity consumption quarterly based on area rank. We can see the high difference in the consumption of extremely high area facilities compared with other ranks. This means if we need to see a noticeable saving in electricity bills. It is enough to concentrate on reducing consumption in extremely high area facilities.

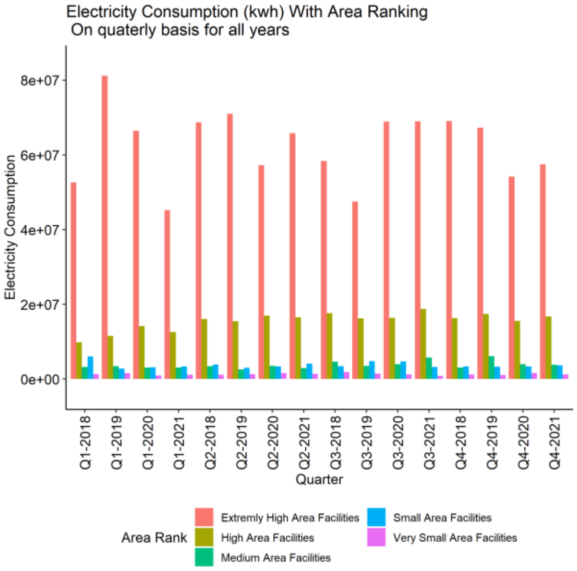


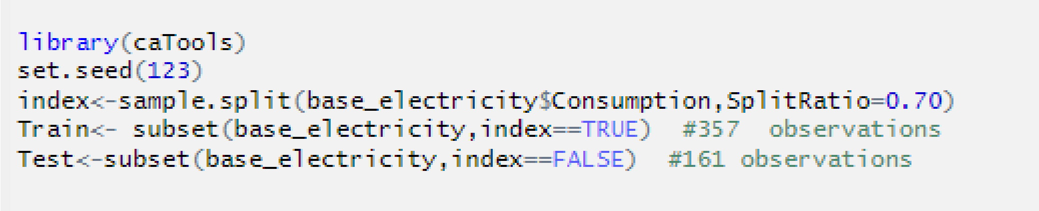
Figure 34: Quarterly Electricity Consumption based on Area Ranking.

4.8 Data Separation

The train-test split procedure is used to evaluate the performance of machine learning algorithms that make predictions on data that was not used to train the model. It's a fast and easy way for comparing the performance of various machine learning algorithms for your predictive modeling task.

We end up testing and training our model on the same data if we don't divide the dataset into training and testing sets. When we test on the same data that we used to train our model, we usually receive decent results. However, this does not imply that the model will perform as well on data that has not been observed. In the domain of machine learning, this is known as overfitting.

As our dataset is ready now it’s ready to run the model. However, before that, data separation is needed. The dataset will be splatted in a split ratio of 70:30 which means 70% of the data will be training set and 30% of the dataset will be testing set. The following code is used for this process:



```
library(caTools)
set.seed(123)
index<-sample.split(base_electricity$Consumption,SplitRatio=0.70)
Train<- subset(base_electricity,index==TRUE)   #357  observations
Test<-subset(base_electricity,index==FALSE)  #161 observations
```

4.9 Data Modeling

This project will study the dataset in Multiple linear regression model and ARIMA model. The two models will be discussed based on the following performance evaluation metrics:

- ME:

The mean error (ME) is calculated by adding the variances and dividing the result by n.

Equation 1: Mean Error

$$ME = \frac{Sum\ of\ All\ Errors}{Number\ of\ Observations}$$

- RMSE:

The Root Mean Squared Error (RMSE) is an unusual measurement, but extremely useful one. it is calculated by taking the square root of the average of summation of all squared error.

Equation 2: Root Mean Squared Error.

$$\text{RMSE}= \sqrt{\frac{1}{n}\sum e_t^2}$$

- MAE:

The Mean Absolute Error (MAE) is an excellent metric for determining forecast accuracy. It is calculated by finding the mean of the absolute error.

Equation 3: Mean Absolute Error.

$$\text{MAE} = \frac{1}{n}\sum |e_t|$$

- MPE:

This metric refers to the Mean Percentage Error which is equal to the average of percentage errors by which model projections differ from actual values of the quantity being forecasted in statistics.

Equation 4: Mean Percentage Error

$$\text{MPE} = \frac{100\%}{n}\sum_{t-1}^{n}\frac{a_t - f_t}{a_t}$$

a_t is the actual value, f_t is the forecasted value, and n is the number of times the variable will be forecasted.

- MAPE:

One of the most prominent methods for determining forecast accuracy is the Mean Absolute Percentage Error (MAPE). MAPE is the total of all absolute errors divided by the demand (each period separately).

Equation 5: Mean Absolute Percentage Error

$$\text{MAPE} = \frac{1}{n}\sum\frac{|e_t|}{d_t}$$

- MASE:

The (one-period-ahead) forecast error divided by the average forecast error of the naive method yields the mean absolute scaled error (MASE) of a single data point. The MASE can be used to assess forecast methods on a single series as well as between series to compare forecast accuracy.

Equation 6: Mean Absolute Scaled Error

$$\text{MASE} = \frac{1}{n}\sum_{t=1}^{n}|q(t)|$$

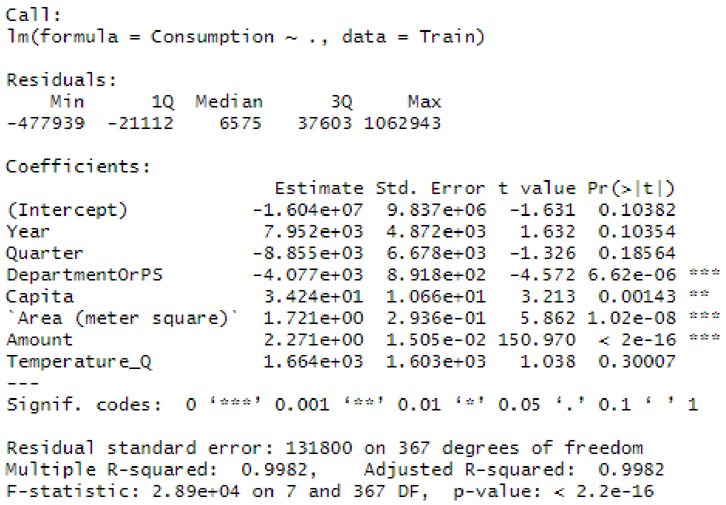
4.9.1 Multiple Linear Regression Model

Multiple linear regression (MLR) is a statistical technique that predicts the result of an independent variable by combining numerous dependent variables. The linear relationship between explanatory (independent) and response (dependent) variables is proposed to be represented using multiple linear regression.

In this step, I have used a regression model to build a machine learning model which will predict the consumption units based on the input data for electricity. As I'm trying to predict a continuous value in this case, hence linear regression model is one of the best choices in this case. The model is a multiple regression model as it will involve multiple predictors to predict a response variable. The summary of the model couldn't be pasted in this case here because our predictors are large in number and we made two models, one for electricity and one for water. However, I will discuss the significance of the model and the performance of our model. Two models will be done, one using the electricity dataset and the other using the water dataset. As combing them together will be not logical because the unit of the out dependent variable (Consumption) is not identical.

4.9.1.1 Electricity

In this step, we have used a regression model to build a machine learning model which will predict the consumption units based on the input data for electricity. For electricity, we got a huge number of significant variables which have a value less than the significance level alpha = 0.05. The R square of our model is 99.82%, which means that the model was able to predict 99.82% variability in the dataset. Moreover, in simple terms, we can say that the regression model was able to cover 98.9% data points in the dataset. The overall p-value (less than 2.2×10^{-16}) of the model is less than significance level alpha = 0.05, hence we can say that the overall model is significant. The AIC (9915.891) and the residuals of the model (131800) are high.



```
Call:
lm(formula = Consumption ~ ., data = Train)

Residuals:
    Min      1Q  Median      3Q     Max 
-477939  -21112    6575   37603 1062943 

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)    
(Intercept)           -1.604e+07  9.837e+06  -1.631  0.10382    
Year                   7.952e+03  4.872e+03   1.632  0.10354    
Quarter               -8.855e+03  6.678e+03  -1.326  0.18564    
DepartmentOrPS        -4.077e+03  8.918e+02  -4.572 6.62e-06 ***
Capita                 3.424e+01  1.066e+01   3.213  0.00143 ** 
`Area (meter square)`  1.721e+00  2.936e-01   5.862 1.02e-08 ***
Amount                 2.271e+00  1.505e-02 150.970  < 2e-16 ***
Temperature_Q          1.664e+03  1.603e+03   1.038  0.30007    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 131800 on 367 degrees of freedom
Multiple R-squared:  0.9982,	Adjusted R-squared:  0.9982 
F-statistic: 2.89e+04 on 7 and 367 DF,  p-value: < 2.2e-16
```

The multiple linear equation is:

Equation 7: Electricity Linear Regression

$$Consumption = -1.604\times10^{7} + 7.952\times10^{3}\ Year - 8.855\times10^{3}\ Quarter - 4.077\ \times10^{3}\ DepartmentOrPS + 3.424\times10^{1}\ Capita + 1.721\ Area + 2.271\ Amount + 1.664\times10^{3} Temperature\_Q$$

The residuals show a linear trend, the points deviate at the tails, indicating that the data were not normally distributed, the condition of equal variance is not violated because the scale location line is straight enough, and a few of influential observations have been identified. Concluding this section of modeling, the model is a better-fitted model when it comes to the R Square as the predictors were able to explain almost 98.9% variability in the dataset.

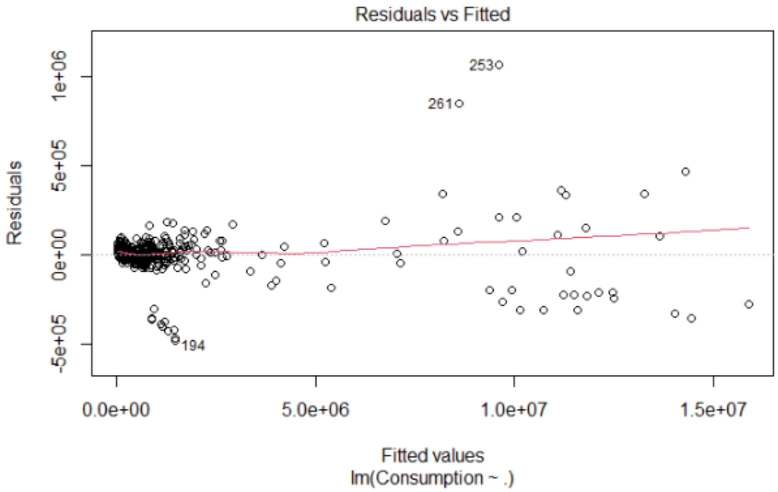


Figure 35 : Residuals versus fitted values for electricity linear regression model.

In the first plot "Residuals vs Fitted", the red line (which is a scatterplot smoother, displaying the average value of the residuals at each value of the fitted value) is almost flat. This indicates that the residuals have a detectable linear tendency. Furthermore, across the whole range of fitted values, the residuals appear to be unequally varied. There's evidence of non-constant variation.

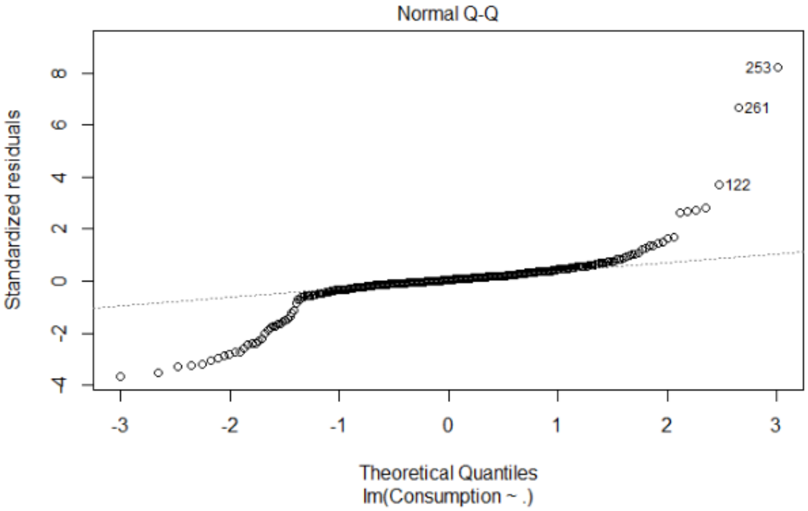


Figure 36: QQ plot for electricity linear regression model.

A standard QQ plot is good if the residuals are properly lined up on the straight dashed line. In both the higher and lower tails of the QQ plot, the residuals depart from the diagonal line. We can see that the tails are 'heavier' (have higher values) than we would predict based on the typical modeling assumptions. This is represented by the points making a "steeper" line than the diagonal.

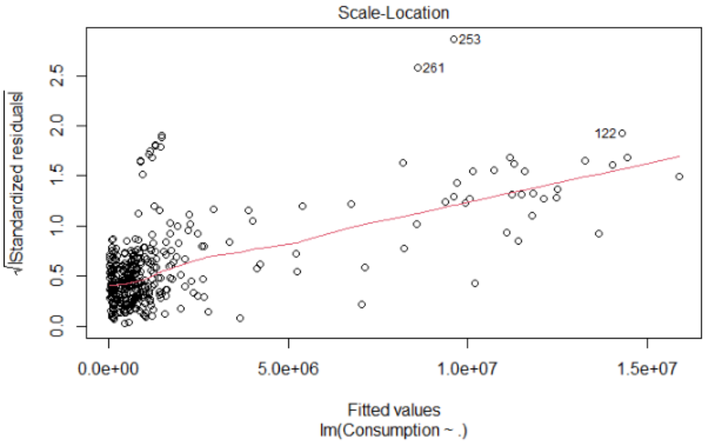


Figure 37: Spread-Location graph for electricity linear regression model.

The Spread-Location graph reveals if residuals are distributed evenly across predictor ranges. This is how you can test the equal variance assumption (homoscedasticity). If you notice a horizontal line with evenly (randomly) spaced points, that's a positive sign. The scale location plot indicates some non-linearity, although the dispersion of magnitudes appears to be greatest in the fitted values close to 0 and less than 3×10^6, lower in the fitted values greater.

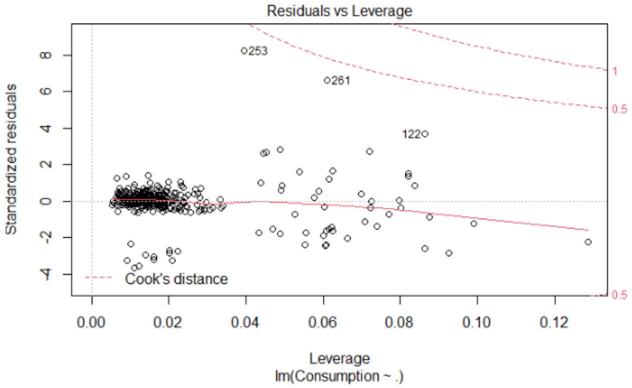
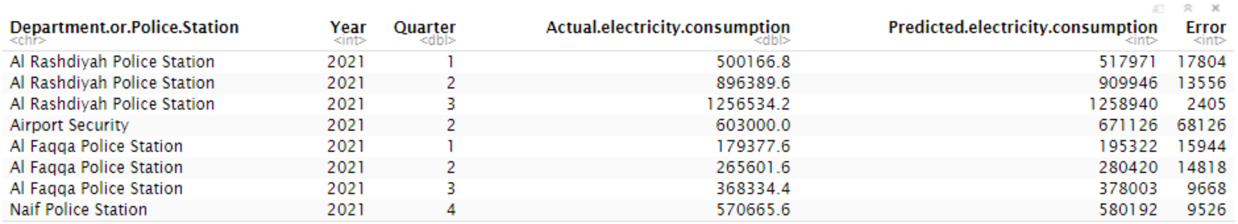


Figure 38: Residuals versus leverage plot for electricity linear regression model.

Residuals versus leverage plot is unlike the others as patterns are irrelevant. Outlying values in the upper or lower right corner should be avoided. Cases can have an impact on a regression line at such points. Outside of a dashed line, Cook's distance. When cases go outside of the Cook's distance, the regression findings are influenced. If we exclude certain instances, the regression results will improve ("Understanding Diagnostic Plots for Linear Regression Analysis”, 2015). In this model, the residuals appear to be concentrated on the left. #253 and #261 could be recognized as the influential observation by the plot as it's neat to cook distance but still it is fine as it's in the acceptable range. Although, if I exclude these two observations from the analysis, the slope coefficient and R2 will change positively.

Error Table:

Table 12 : Error table for electricity linear regression model.



Department.or.Police.Station <chr>	Year <int>	Quarter <dbl>	Actual.electricity.consumption <dbl>	Predicted.electricity.consumption <int>	Error <int>
Al Rashdiyah Police Station	2021	1	500166.8	517971	17804
Al Rashdiyah Police Station	2021	2	896389.6	909946	13556
Al Rashdiyah Police Station	2021	3	1256534.2	1258940	2405
Airport Security	2021	2	603000.0	671126	68126
Al Faqqa Police Station	2021	1	179377.6	195322	15944
Al Faqqa Police Station	2021	2	265601.6	280420	14818
Al Faqqa Police Station	2021	3	368334.4	378003	9668
Naif Police Station	2021	4	570665.6	580192	9526

Table 11 shows the actual and predicted electricity consumption (Quarterly) as well as the error. It shows a good result as the error is not that high compared with consumption values.

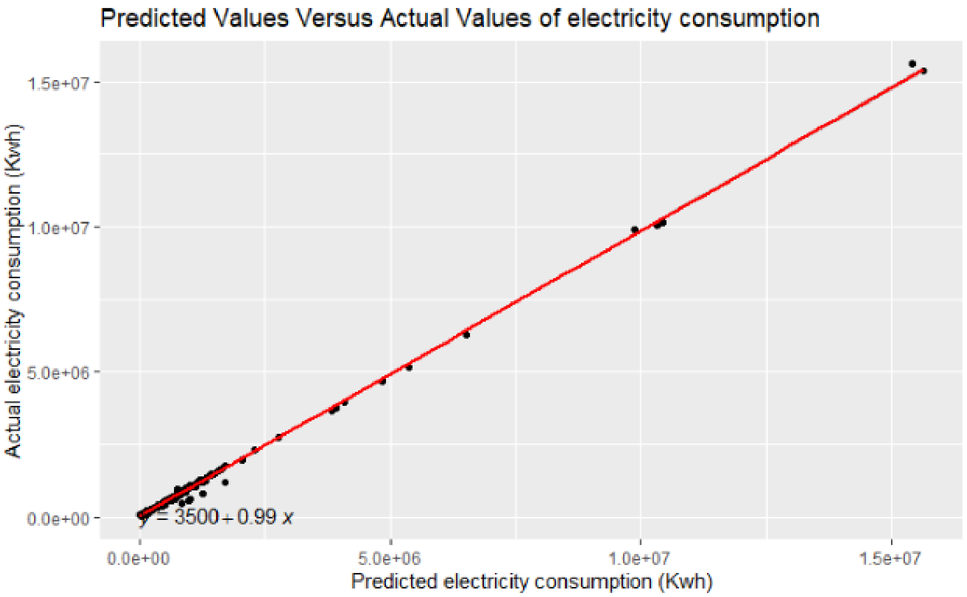
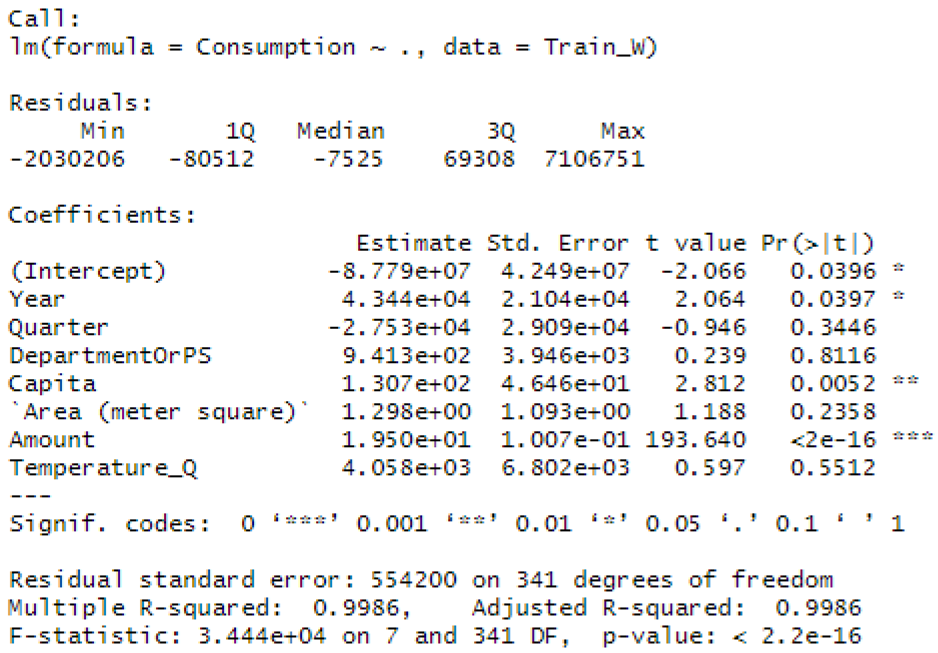


Figure 39: Predicted versus actual values for electricity linear regression model.

The model was used to verify the accuracy of the proposed multiple linear regression model in examining the link between predicted and actual consumption. As shown almost all the actual values are fitted in the predicted line which gives us a good result for the model.

4.9.1.2 Water

The same was done for water consumption prediction, we got a huge number of significant variables which have a value less than the significance level alpha = 0.05. The R square of our model is 99.86%, which means that the model was able to predict 99.86% variability in the dataset. Moreover, in simple terms, we can say that the regression model was able to cover 98.9% data points in the dataset. The overall p-value (is less than 2.2×10^{-16}) of the model is less than significance level alpha = 0.05, hence we can say that the overall model is significant. The AIC (10231.53) and the residuals of the model (554200) are high.



```
Call:
lm(formula = Consumption ~ ., data = Train_W)

Residuals:
     Min       1Q   Median       3Q      Max 
-2030206   -80512    -7525    69308  7106751 

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)          -8.779e+07  4.249e+07  -2.066   0.0396 *  
Year                  4.344e+04  2.104e+04   2.064   0.0397 *  
Quarter              -2.753e+04  2.909e+04  -0.946   0.3446    
DepartmentOrPS        9.413e+02  3.946e+03   0.239   0.8116    
Capita                1.307e+02  4.646e+01   2.812   0.0052 ** 
`Area (meter square)` 1.298e+00  1.093e+00   1.188   0.2358    
Amount                1.950e+01  1.007e-01 193.640   <2e-16 ***
Temperature_Q         4.058e+03  6.802e+03   0.597   0.5512    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 554200 on 341 degrees of freedom
Multiple R-squared:  0.9986,	Adjusted R-squared:  0.9986 
F-statistic: 3.444e+04 on 7 and 341 DF,  p-value: < 2.2e-16
```

The multiple linear equation is:

Equation 8: Water Linear Regression

$$Consumption = -8.779\times10^{7} + 4.344\times10^{4}\ Year - 2.753\times10^{4}\ Quarter + 9.413\times10^{2}\ DepartmentOrPS + 1.307\times10^{2}\ Capita + 1.298\ Area + 19.5\ Amount + 4.058\times10^{3}\ Temperature\_Q$$

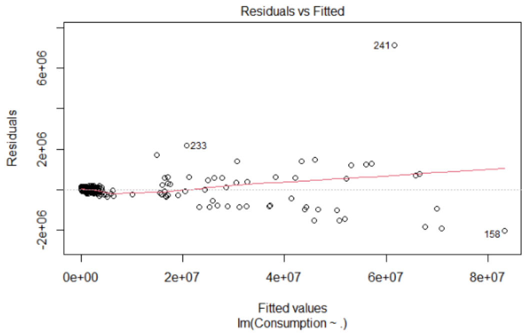


Figure 40: Residuals versus fitted values for water linear regression model.

We can see that residuals appear to be unequally varied as in electricity consumption. There's evidence of non-constant variation.

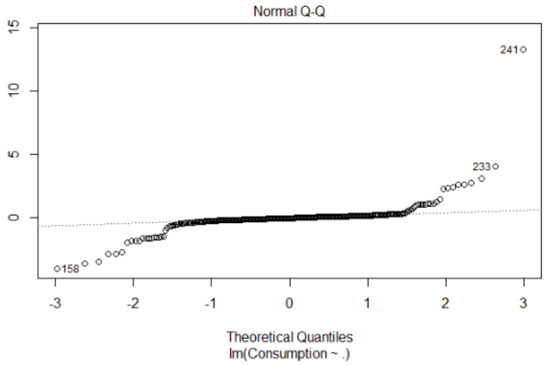


Figure 41: QQ plot for water linear regression model.

We can see that the tails are 'heavier' than we would predict based on the typical modeling assumptions. This is represented by the points making a "steeper" line than the diagonal.

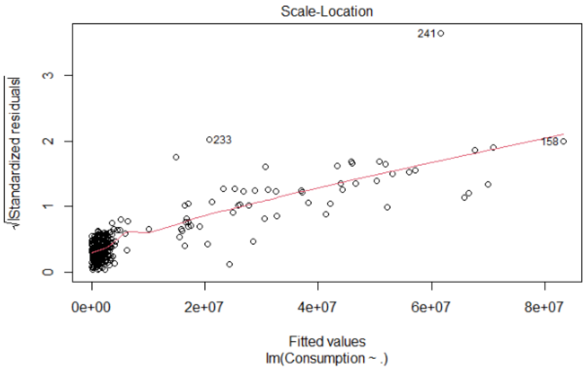


Figure 42: Spread-Location graph for water linear regression model.

The scale location plot indicates non-linearity, although the dispersion of magnitudes appears to be greatest in the lowest fitted values and almost nothing for higher values. As it shows a steep angle which means it’s not horizontal at all.

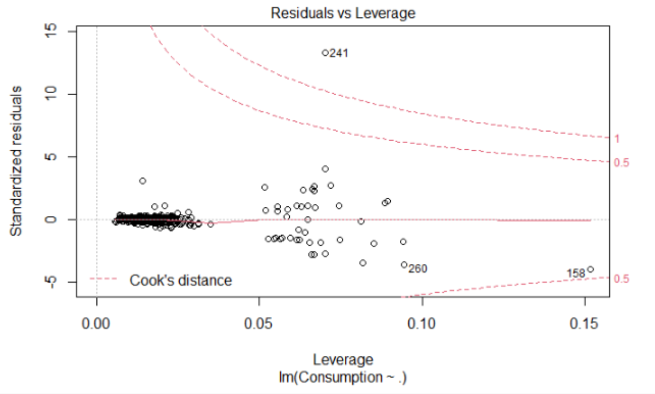
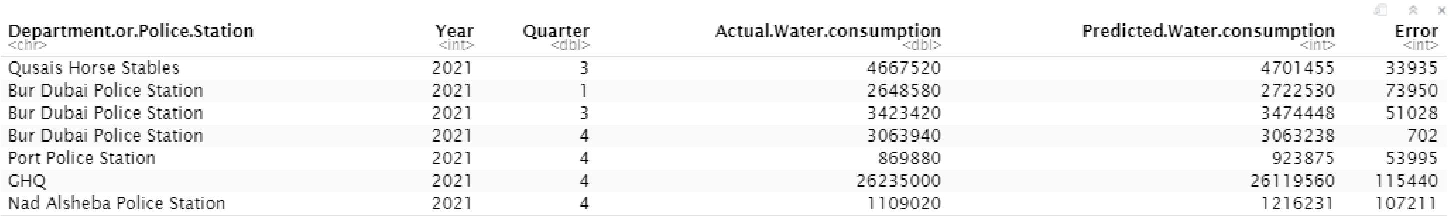


Figure 43: Residuals versus leverage plot for water linear regression model.

In this model, the residuals appear to be concentrated from leverage 0.01 to almost 0.04 was recognized as an influential observation by the plot. Observation 241 is an outlying value in this model.

Error Table:

Table 13: Error table for water linear regression model.



Department.or.Police.Station <chr>	Year <int>	Quarter <dbl>	Actual.Water.consumption <dbl>	Predicted.Water.consumption <int>	Error <int>
Qusais Horse Stables	2021	3	4667520	4701455	33935
Bur Dubai Police Station	2021	1	2648580	2722530	73950
Bur Dubai Police Station	2021	3	3423420	3474448	51028
Bur Dubai Police Station	2021	4	3063940	3063238	702
Port Police Station	2021	4	869880	923875	53995
GHQ	2021	4	26235000	26119560	115440
Nad Alsheba Police Station	2021	4	1109020	1216231	107211

A table was built to show the (Quarterly) actual and predicted water consumption as well as the error. A sample of the water consumption data is presented in Table 13. It doesn’t show bad results as the error is not that high compared with consumption values.

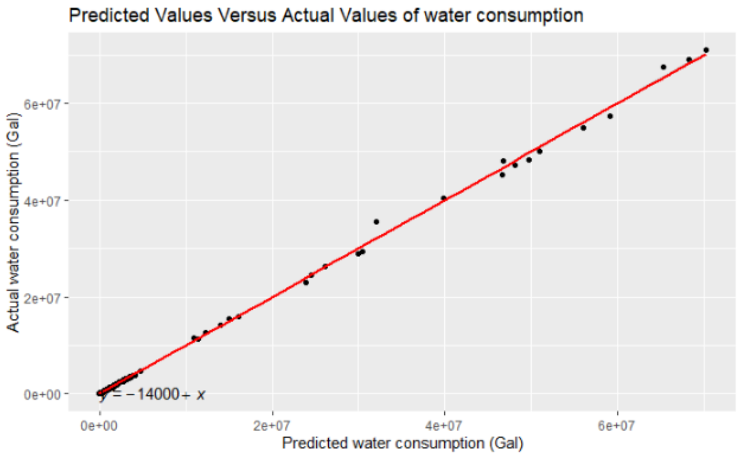
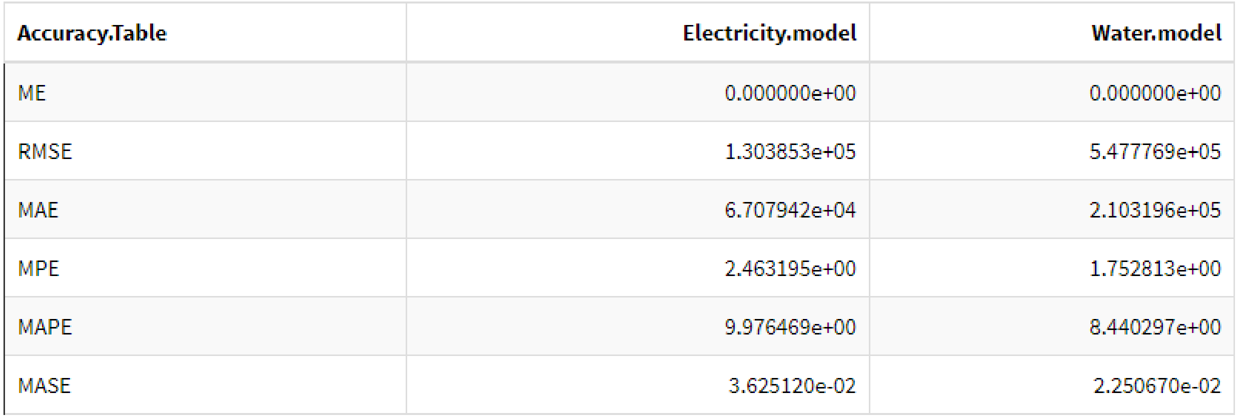


Figure 44: Predicted versus actual values for water linear regression model.

Here as well it showed almost all the actual water consumption values are fitted in the predicted line which gives us a good result for the model.

4.9.1.4 Accuracy Table

Table 14: Accuracy Table for electricity and water models.



Accuracy.Table	Electricity.model	Water.model
ME	0.000000e+00	0.000000e+00
RMSE	1.303853e+05	5.477769e+05
MAE	6.707942e+04	2.103196e+05
MPE	2.463195e+00	1.752813e+00
MAPE	9.976469e+00	8.440297e+00
MASE	3.625120e-02	2.250670e-02

The accuracy parameters was calculated using accuracy() function in R for both models based on the test dataset. The table above shows a summary of the two models results of the six measurements. I will discuss here the RMSE and MAPE values. For the electricity regression model the RMSE and MAPE are 130385.3 kWh and 11.89% respectively. In the other hand, for the water model they are equal to 547776.9 Gallons and 9.53% respectively. both models gave us a good result.

All of these outputs provide information about your model and data. The existing model may not be the most effective approach to comprehend the information we have. That’s why I build a time series model to check if we will get a better result.

4.9.2 ARIMA Model

ARIMA stands for autoregressive integrated moving average, and it's a statistical analysis model that employs time series data to better understand the data set or anticipate future trends.

An autoregressive integrated moving average model determines how powerful one dependent variable is in contrast to other variables associated. The model's goal is to predict future value of the independent variable by analyzing differences between values in a series rather than actual values.

Components of the ARIMA model:

- Autoregression AR: A model that displays a changing variable regressing on its own lagged.
- Integrated (I): denotes the differencing of raw observations to allow the time series to stabilize.
- Moving average (MA): A moving average model applied to lagged observations incorporates the dependency between an observation and a residual error.

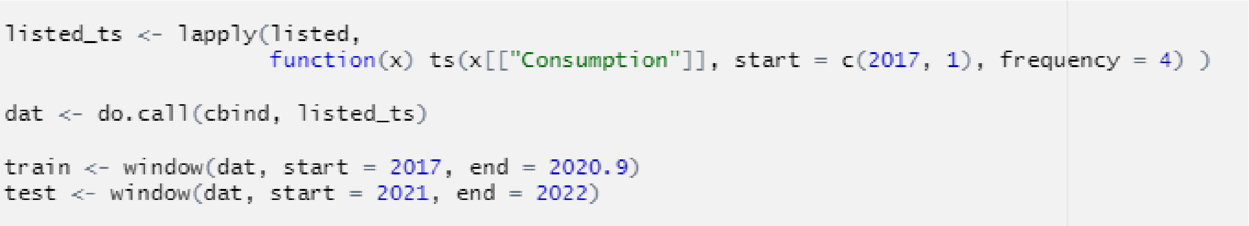
A univariate ARIMA time series model for water and electricity consumption was done. As we have chosen to forecast each department forecast, it is wiser to only consider a single variable-based ARIMA model.

The steps to prepare data for the ARIMA model:

As I'm considering groups, I prepared data differently than a single ARIMA model. The first step is to convert data to time series, for which I have used the (ts) function. As data is collected from 2017 to 2022, and data is aggregated quarterly, I only need to provide frequency and year to create a date column.

As for turning data into a time series format, there are many ways to create time series from data. However, the most convenient way is to use the ts() function in R. The ts function is like this:

ts(data, start_date, end_date, frequency)

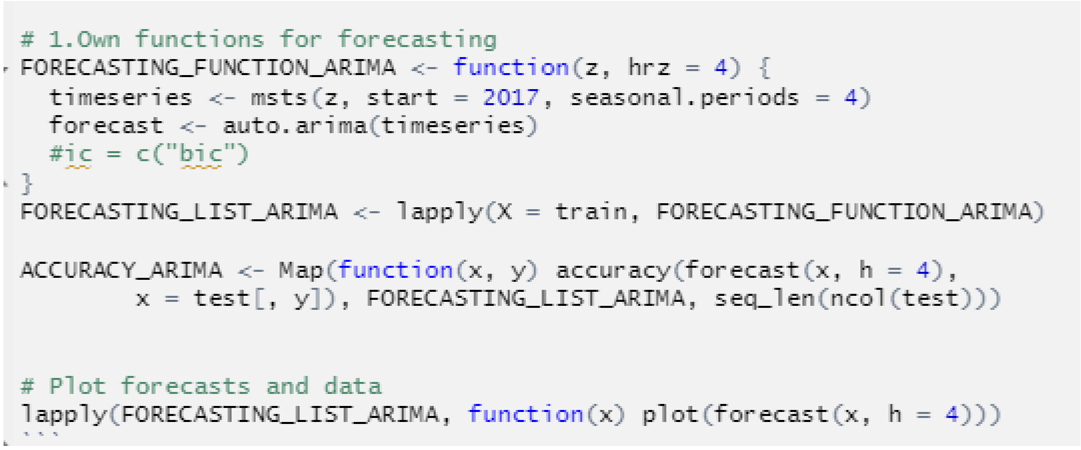


```
listed_ts <- lapply(listed,
                    function(x) ts(x[["Consumption"]], start = c(2017, 1), frequency = 4) )

dat <- do.call(cbind, listed_ts)

train <- window(dat, start = 2017, end = 2020.9)
test <- window(dat, start = 2021, end = 2022)
```

As you can see, in this format, we can create time-series data easily.

For quarterly data, we will do this:

ts(data, start_date, end_date, freq=4), which indicates that there will be 4 observations for each year. After converting to time series, now I need to concatenate all-time series row-wise, so I can apply time series more efficiently and fast way. Then, Split data into train and test. Train data contains data from year 2017 to 2020 data and test data is 2022 data. All as shown in the screenshot above.



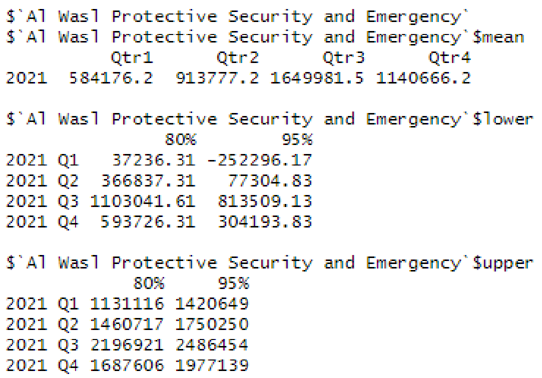
```
# 1.Own functions for forecasting
FORECASTING_FUNCTION_ARIMA <- function(z, hrz = 4) {
  timeseries <- msts(z, start = 2017, seasonal.periods = 4)
  forecast <- auto.arima(timeseries)
  #ic = c("bic")
}
FORECASTING_LIST_ARIMA <- lapply(X = train, FORECASTING_FUNCTION_ARIMA)

ACCURACY_ARIMA <- Map(function(x, y) accuracy(forecast(x, h = 4),
        x = test[, y]), FORECASTING_LIST_ARIMA, seq_len(ncol(test)))


# Plot forecasts and data
lapply(FORECASTING_LIST_ARIMA, function(x) plot(forecast(x, h = 4)))
```

After this step, I create my function, which first considers seasonality in data (msts function) and then passes the series to auto.arima() function, which is a time series model. The benefit of using auto.arima is that it will automatically infer the auto-regressive and moving average part of a series and we don't need to find specific order for every series, which is impractical when considering different groups. Then, apply ARIMA function to all our groups. For that, I use the lapply() function, which splits data into groups and then applies the required function. Now that the ARIMA model is built, we can forecast future values and then look at the accuracy table for each group.

4.9.2.1 Results

4.9.2.1.1 Electricity Consumption ARIMA Model

When we forecast with time series models, we receive three values for each observation: Mean, Low, and high. The Mean value is the actual forecast. The low is the confidence interval of that forecast doing a downward trend, and the high is the confidence interval of that forecast going upward. We got a result for each department and police station. As shown for example in protective security emergency department electricity consumption model.



```
$`Al Wasl Protective Security and Emergency`
$`Al Wasl Protective Security and Emergency`$mean
          Qtr1      Qtr2      Qtr3      Qtr4
2021  584176.2  913777.2 1649981.5 1140666.2

$`Al Wasl Protective Security and Emergency`$lower
               80%         95%
2021 Q1   37236.31 -252296.17
2021 Q2  366837.31   77304.83
2021 Q3 1103041.61  813509.13
2021 Q4  593726.31  304193.83

$`Al Wasl Protective Security and Emergency`$upper
            80%     95%
2021 Q1 1131116 1420649
2021 Q2 1460717 1750250
2021 Q3 2196921 2486454
2021 Q4 1687606 1977139
```

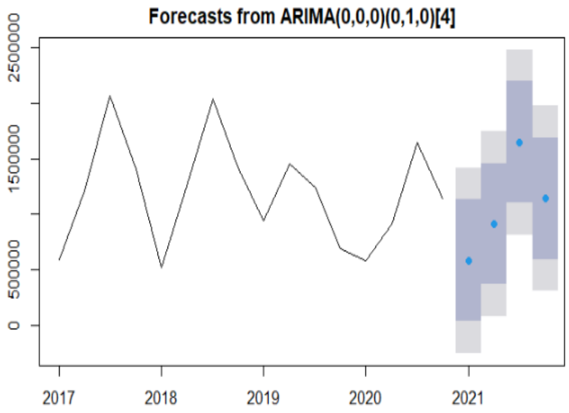
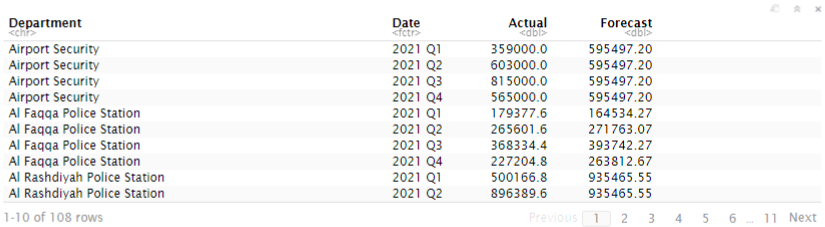


Figure 45: Protective Security Emergency Department Electricity Consumption ARIMA Model forecast output.

The forecast shows that for most of the groups, there is no clear seasonality or trend, which results in constant mean predictions for these groups (as ARIMA models are mean models). However, some groups average changes each quarter, so we can also see predictions accommodate that seasonality. The forecasts accuracy depends on past values as its essence of time series model). In plots, we can see that some locations have cyclical pattern and some locations have no clear trend. This can also be seen in forecasts. When ARIMA found clear trend plus seasonality. the forecasts are good. But when observations have no pattern, the predictions follow same mean for all forecasts. The visualizations with no seasonal pattern and no clear trend, results in poor predictions.

The below table shows a sample for some location of the output of actual 2021 electricity consumption versus forecasted one. (The full table in Appendix 2)

Table 15: Actual and Forecasted Electricity Consumption of each department.



Department <chr>	Date <fctr>	Actual <dbl>	Forecast <dbl>
Airport Security	2021 Q1	359000.0	595497.20
Airport Security	2021 Q2	603000.0	595497.20
Airport Security	2021 Q3	815000.0	595497.20
Airport Security	2021 Q4	565000.0	595497.20
Al Faqqa Police Station	2021 Q1	179377.6	164534.27
Al Faqqa Police Station	2021 Q2	265601.6	271763.07
Al Faqqa Police Station	2021 Q3	368334.4	393742.27
Al Faqqa Police Station	2021 Q4	227204.8	263812.67
Al Rashdiyah Police Station	2021 Q1	500166.8	935465.55
Al Rashdiyah Police Station	2021 Q2	896389.6	935465.55

1-10 of 108 rows

The accuracy table (test dataset):

Table 16: Accuracy table for ARIMA Model using Electricity dataset.

X1	ME	RMSE	MAE	MPE	MAPE	MASE
Airport Security	-9997.2	162094.7	123500	-10.7743	24.86287	0.692621
Al Faqqa Police Station	-13333.5	23685.35	20755.13	-4.26381	8.401261	0.397936
Al Rashdiyah Police Station	-62174.5	275316.5	222708.8	-19.2983	32.07427	0.946821
Al Riffa Police Station	122374.3	130350.3	122374.3	18.62394	18.62394	0.607273
Al Wasl Protective Security and Emergency	257388.9	302571.3	257832.8	16.49376	16.56988	0.761672
Awir Horse Stables	18513.6	196850.4	162481.2	-35.8172	65.30971	0.648833
Barsha Police Station	116626.9	139544.5	116626.9	10.8076	10.8076	0.800051
Barsha Traffic Dept	-47175	94098.79	72075	-6.2182	9.614732	0.507183
Bur Dubai Police Station	4789.175	315711.5	239366	-11.4122	28.58718	0.785473
Dubai Police Academy	17524.7	242972.2	210626.5	-1.05575	7.078043	0.4416
General Department of Transport and Rescue	90213.56	633711.2	483849.2	-10.5519	33.64712	0.891438
GHQ	317897.7	488301.4	437258.9	2.279393	3.644494	0.280705
Hatta Police Station	28103	29708.24	28103	11.37193	11.37193	2.290601
Hor Al Anz Protective Security and Emergency	28559.7	34924.25	28559.7	14.17428	14.17428	1.070166
Jabal Ali Police Station	-65999.4	107802.8	97301.57	-28.3468	35.15951	1.12214
Lahbab Police station	7435	41055.75	35060	-15.6129	46.87774	0.79047
Moraqabat Police Station	-47860.5	447211.6	372934.4	-15.2408	31.63697	0.647359
Nad Alsheba Police Station	37809.2	53501.88	37809.2	4.184984	4.184984	0.160408
Naif Police Station	14976	67744.99	62477.6	4.029646	11.59976	0.720109
Officers Club	105389.9	552249.2	442396.6	-3.23456	24.88511	0.794511
Port Police Station	13641.6	36492.87	24116.4	2.005363	2.904569	0.335214
Punitive and Correctional Establishments	183877.2	595027.1	515411.6	2.395666	4.710647	0.307627
Qusais Police Station	-47518.5	233881.8	194878.9	-19.8144	34.03138	0.871139
Qusais Warehouses	98834.9	118602	98834.9	33.81088	33.81088	1.378979
Rowaiyah Shooting Range	6323.45	17986.7	14392.7	3.447398	16.24954	0.367868
Traffic Department Deira	-65116	128666.2	90818.75	-6.85111	9.807892	0.298014

I will discuss 3 Metrics which are considered standard: MSE, RMSE, and MAPE. The metrics are difference between actual and predicted values in terms of Mean Square Error and Mean percentage error (MAPE).

If I take Al Faqqa Police Station as example (Electricity consumption prediction)

```
                       ME     RMSE      MAE          MPE       MAPE      MASE      ACF1     Theil's U
Training set     22.76526 54413.77  38256.25  -8.627517 22.754437 0.7334835 0.2834065        NA
Test set     -13333.46667 23685.35 20755.13  -4.263807  8.401261 0.3979362 0.2586741 0.1957359
```

The RMSE metrics shows that for training set, error margin was 54413.77 units (predictions can be off with this difference (+/-), and for test set, this metric is 23685.35 which is much better.

Same is true for MSE, which is similar to RMSE. As for MAPE it shows percentage difference between predictions and actual values. In this case the training set has larger MAPE (22.75) than test set (8.4).

So, it means that predictions are not that bad this will be considered small error margin. Some will be larger and others will be even smaller than this. The actual and prediction values was shown in previous section. The average MAPE calculated for all location in the model to be 20.02.

4.9.2.1.2 Water Consumption ARIMA Model

Same steps were done for water consumption dataset. The actual and forecasted consumption table is in Appendix 3. Here is the accuracy table (Average MAPE = 36.9164):

Table 17: Accuracy table for ARIMA Model using Water dataset.

X1	ME	RMSE	MAE	MPE	MAPE	MASE
Airport Security	-157433.65	1373734.99	1044350.91	-13.51	34.72	0.65
Al Rashdiyah Police Station	-10419.94	190278.19	183865.00	-1.43	9.29	0.25
Al Riffa Police Station	-36019.19	83591.94	72710.00	-6.21	10.75	0.30
Al Wasl Protective Security and Emergency	1179090.00	1589061.35	1378190.00	7.53	8.77	1.23
Awir Horse Stables	302445.00	321598.71	302445.00	25.68	25.68	2.04
Barsha Police Station	-485430.00	514676.49	485430.00	-31.11	31.11	0.33
Barsha Traffic Dept	-278048.60	500714.55	416059.82	-69.43	80.12	0.95
Bur Dubai Police Station	403865.00	488301.47	403865.00	12.57	12.57	0.99
Dubai Police Academy	-5200525.00	6521624.80	5200525.00	-15.94	15.94	0.78
General Department of Transport and Rescue	-355657.69	385046.18	355657.69	-39.46	39.46	0.54
GHQ	901197.08	1453849.07	1149841.04	3.10	4.18	0.84
Hatta Police Station	-1035705.00	1165528.98	1035705.00	-201.02	201.02	3.64
Hor Al Anz Protective Security and Emergency	-310475.00	324684.62	310475.00	-21.07	21.07	0.78
Jabal Ali Police Station	1919.06	217190.55	179660.47	-9.99	28.36	0.80
Lahbab Police station	90426.25	112106.57	90426.25	37.21	37.21	1.80
Moraqabat Police Station	105700.33	159805.05	144168.19	3.98	5.64	0.18
Nad Alsheba Police Station	-895588.76	903911.37	895588.76	-83.82	83.82	1.12
Naif Police Station	314270.00	340678.26	314270.00	27.93	27.93	1.24
Officers Club	-331760.00	340243.18	331760.00	-35.53	35.53	1.07
Port Police Station	618915.00	985050.12	823075.00	72.59	91.19	1.09
Punitive and Correctional Establishments	-362340.00	1787738.65	1584110.00	-0.59	2.30	0.14
Qusais Police Station	10010.00	88093.04	81400.00	0.26	7.98	0.11
Qusais Warehouses	-81309.00	83120.20	81309.00	-30.81	30.81	0.37
Rowaiyah Shooting Range	85690.00	95336.06	85690.00	10.24	10.24	0.27
Traffic Department Deira	-2378860.00	2456183.11	2378860.00	-67.22	67.22	3.15

Chapter 5- Conclusion

5.1 Summary

The summary of the two models. Showing some model accuracy measures. All measures show a lower value in MLR model comparing with ARIMA model. This proves that the performance of Linear Regression model is better.

Table 18: Summary table of MLR and ARIMA model.

Measures	Electricity		Water	
	MLR	ARIMA	MLR	ARIMA
RMSE	130385.3	202594.9	547776.9	899285.9
MAE	67079.42	167131.5	210319.6	773177.5
MPE	2.46	-2.4025	1.753	-17.042
MAPE	9.98	20.0232	8.44	36.9164
MASE	0.03625	0.7006	0.02251	0.9864

5.2 Conclusion

Annually, the electricity and water bills cost Dubai Police over 100 million dirhams which is a critical issue that needs to be monitored and resolved. In fact, savings achieved in the utility's bills will add extra money to other budgets allocated for other various operations. Analyzing consumption data using Machine learning algorithms will help in reducing the consumption in the future. I have used two different regression models to predict electricity and water consumption and they are Multiple Linear Regression and ARIMA model. As appeared in the actual and predicted consumption tables in both models, MLR model resulted in a better value which are very close the actual values. Moving to the accuracy measurements, using electricity data, the MAPE result is 11.88 for MLR and 20.79 in ARIMA model. However, using water data, the value of MAPE is 9.53 for MLR and 36.92 for ARIMA model. To conclude, Multiple Linear Regression model results in a lower MAPE which means higher prediction performance. The poorer performance of the ARIMA model is due to the fact that external factors account for a considerable amount of the fluctuation in monthly electric energy use, which univariate forecasting approaches cannot capture.

5.3 Recommendations

This study can be used by Dubai Police, specifically the energy conservation department, to place remedial measures to reduce the consumption of the highest consuming facilities that have been identified. In addition, factoring in the temperature parameter in the model, Dubai Police should focus on spreading more awareness with regards to the consumer behavior during the summer season as the consumption peaks. Finally, this study findings can facilitate a baseline for Dubai Police to adopt clean solar energy into its facilities, starting with the highest consuming facilities.

5.4 Future Works

Although for this research work the dataset was somehow limited due to confidentiality reasons as stated earlier, being an employee at the energy conservation department in Dubai Police, I will be able to access the full dataset and make a detailed study containing all operational, capita, and area data. As well as, to add a multivariant ARIMA model to the study and compare it with the existing models.

References

1. Understanding Diagnostic Plots for Linear Regression Analysis | University of Virginia Library Research Data Services + Sciences. (2015). Retrieved 20 April 2022.

2. Amasyali, K. and El-Gohary, N., 2018. A review of data-driven building energy consumption prediction studies. *Renewable and Sustainable Energy Reviews*, 81, pp.1192-1205.

3. Nafil, A., Bouzi, M., Anoune, K. and Ettalabi, N., 2020. Comparative study of forecasting methods for energy demand in Morocco. *Energy Reports*, 6, pp.523-536.

4. Singh, S. and Yassine, A., 2018. Big Data Mining of Energy Time Series for Behavioral Analytics and Energy Consumption Forecasting. *Energies*, 11(2), p.452.

5. Yang, J., Ning, C., Deb, C., Zhang, F., Cheong, D., Lee, S., Sekhar, C. and Tham, K., 2017. k-Shape clustering algorithm for building energy usage patterns analysis and forecasting model accuracy improvement. *Energy and Buildings*, 146, pp.27-37.

6. Aranda, A., Ferreira, G., Mainar-Toledo, M., Scarpellini, S. and Llera Sastresa, E., 2012. Multiple regression models to predict the annual energy consumption in the Spanish banking sector. *Energy and Buildings*, 49, pp.380-387.

7. Tso, G. and Yau, K., 2007. Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, 32(9), pp.1761-1768.

8. Banihashemi, S., Ding, G. and Wang, J., 2017. Developing a Hybrid Model of Prediction and Classification Algorithms for Building Energy Consumption. *Energy Procedia*, 110, pp.371-376.

9. Jamii, M. and Maaroufi, M., 2021. The Forecasting of Electrical Energy Consumption in Morocco with an Autoregressive Integrated Moving Average Approach. *Mathematical Problems in Engineering*, 2021, pp.1-9.

10. Wang, X. and Meng, M., 2012. A Hybrid Neural Network and ARIMA Model for Energy Consumption Forcasting. *Journal of Computers*, 7(5).

11. Sen, P., Roy, M. and Pal, P., 2016. Application of ARIMA for forecasting energy consumption and GHG emission: A case study of an Indian pig iron manufacturing organization. *Energy*, 116, pp.1031-1038.

12. Pérez-Chacón, R., Luna-Romera, J., Troncoso, A., Martínez-Álvarez, F. and Riquelme, J., 2018. Big Data Analytics for Discovering Electricity Consumption Patterns in Smart Cities. *Energies*, 11(3), p.683.

13. Yuan, C., Liu, S. and Fang, Z., 2016. Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM(1,1) model. *Energy*, 100, pp.384-390.

14. Liu, Y., Chen, H., Zhang, L., Wu, X. and Wang, X., 2020. Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: A case study in China. *Journal of Cleaner Production*, 272, p.122542.

15. Shapi, M., Ramli, N. and Awalin, L., 2021. Energy consumption prediction by using machine learning for smart building: Case study in Malaysia. *Developments in the Built Environment*, 5, p.100037.

16. Zhao, H. and Magoulès, F., 2012. Feature Selection for Predicting Building Energy Consumption Based on Statistical Learning Method. *Journal of Algorithms &amp; Computational Technology*, 6(1), pp.59-77.

17. de Oliveira, E. and Cyrino Oliveira, F., 2018. Forecasting mid-long term electric energy consumption through bagging ARIMA and exponential smoothing methods. *Energy*, 144, pp.776-788.

18. Carrera, B., Peyrard, S. and Kim, K., 2021. Meta-regression framework for energy consumption prediction in a smart city: A case study of Songdo in South Korea. *Sustainable Cities and Society*, 72, p.103025.

19. Fumo, N. and Rafe Biswas, M., 2015. Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews*, 47, pp.332-343.

20. Wang, X., 2022. Research on the prediction of per capita coal consumption based on the ARIMA–BP combined model. *Energy Reports*, 8, pp.285-294.

21. Barak, S. and Sadegh, S., 2016. Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm. *International Journal of Electrical Power &amp; Energy Systems*, 82, pp.92-104.

Appendix 1: Facilities List

Facility	Contract Account	**Location**	**Utility**	**Unit**
Traffic Department Deira	2008422127		Electricity	kWh
	2009123344		Electricity	kWh
	2008258289		Water	GAL
	2000967329		Water	GAL
	2001348495		Water	GAL
GHQ	2000730906	GHQ Shared	Electricity	kWh
	2000739210	GHQ Shared	Water	GAL
	2000891217	GHQ Shared	Water	GAL
	3004102288	GHQ Shared	Electricity	kwh
	2008177947	GHQ Shared	Water	GAL
	2008206564	GHQ Shared	Water	GAL
	2008344720	GHQ Shared	Water	GAL
	2008381781	Communication Dept	Electricity	kWh
	2014456402	CID	Electricity	kWh
	2008165620	CIDandAntiNarcotic	Electricity	kWh
	2008381935	CID	Electricity	kWh
	2008422267	GHQ Shared	Electricity	kWh
	2008422410	Health Center	Electricity	kWh
	2008422569	GHQ Shared	Electricity	kWh
	3000778121	GHQ Shared	Electricity	kWh
	3000778132	GHQ Shared	Electricity	kWh
	3003928609	Decision Making NEW	Electricity	kWh
	3003928611	Decision Making NEW	Electricity	kWh
	3003928621	Decision Making NEW	Electricity	kWh
	3005618221	GHQ Shared	Electricity	kWh
	2008435474	Logistics Support Dept	Electricity	kWh
	2008495302	GHQ Shared	Electricity	kWh
	2008495442	Logistics Support Dept	Electricity	kWh
	2008495442	Logistics Support Dept	Water	GAL
	2008495604	Logistics Support Dept	Electricity	kWh
	2008495744	CID	Electricity	kWh

	2008534081	GHQ Shared	Water	GAL
	2009491912	GHQ Shared	Electricity	kWh
	2009816927	Health Center	Electricity	kWh
	2009816960	Communication Dept	Electricity	kWh
	2009943856	AntiNarcotic	Electricity	kWh
	2010094239	HQ BLDG	Electricity	kWh
	2010094980	HQ BLDG	Electricity	kWh
	2010097041	HQ BLDG	Electricity	kWh
	2010097106	HQ BLDG	Electricity	kWh
	2010097130	HQ BLDG	Electricity	kWh
	2010097181	HQ BLDG	Electricity	kWh
	2010097211	HQ BLDG	Electricity	kWh
	2010097246	HQ BLDG	Electricity	kWh
	2010097300	HQ BLDG	Electricity	kWh
	2014956103	GHQ Shared	Electricity	kWh
	2016164379	GHQ Shared	Water	GAL
	2016589701	Exsplosive Dept	Electricity	kWh
	2016589701	Exsplosive Dept	Water	GAL
	3000520413	Forensic Dept	Electricity	kWh
	3000520424	Forensic Dept	Electricity	kWh
	3000520435	Forensic Dept	Electricity	kWh
	3000520446	Forensic Dept	Electricity	kWh
	3000520457	Forensic Dept	Electricity	kWh
	3000520468	Forensic Dept	Electricity	kWh
	3000520479	Forensic Dept	Electricity	kWh
	3000520481	Forensic Dept	Electricity	kWh
	3000841131	Forensic Dept	Water	GAL
Airport Security	2008350827		Water	GAL
	2009043529		Electricity	kWh
Punitive and Correctional Establishments	2008525686		Water	GAL
	2009912039		Electricity	kWh
	2009922859		Electricity	kWh
	2009922883		Electricity	kWh
	2009926587		Electricity	kWh
	2009960246		Electricity	kWh
	2009964810		Electricity	kWh
	2009964845		Electricity	kWh
	2009969537		Electricity	kWh
	2009969561		Electricity	kWh
	2009969596		Electricity	kWh

	2009969626		Electricity	kWh
	2009977513		Electricity	kWh
	2010034074		Electricity	kWh
	3000268799		Electricity	kWh
	3000268799		Water	GAL
	3000598481		Electricity	kWh
	3000613331		Electricity	kWh
Awir Horse Stables	2020372649		Water	GAL
	3006065337		Electricity	kWh
	2020372657		Electricity	kWh
Rowaiyah Shooting Range	2008465942		Electricity	kWh
	2009816323		Electricity	kWh
	2008541681		Water	GAL
General Department of Transport and Rescue	2008849929		Water	GAL
	2010331281		Electricity	kWh
	2010331303		Electricity	kWh
	2010331320		Electricity	kWh
	2010331354		Electricity	kWh
	2015925570		Electricity	kWh
	2015925589		Electricity	kWh
	2016979267		Electricity	kWh
	2016979275		Electricity	kWh
Dubai Police Academy	2002192219		Water	GAL
	2002255792		Water	GAL
	2002255881		Water	GAL
	2008195619		Water	GAL
	2008234835		Water	GAL
	2008277623		Water	GAL
	2008399818		Electricity	kWh
	2008408388		Electricity	kWh
	2008413853		Electricity	kWh
	2008644553		Electricity	kWh
	2008644693		Electricity	kWh
	2008644839		Electricity	kWh
	2008686493		Electricity	kWh
	2008791459		Electricity	kWh
	2008798160		Electricity	kWh
	2008822273		Electricity	kWh
	2009465857		Electricity	kWh
	2009700015		Electricity	kWh
	2009787056		Electricity	kWh

	2009811755		Electricity	kWh
Barsha Police Station	2015841393		Water	GAL
	2015841393		Electricity	kWh
	2015841407		Electricity	kWh
Barsha Traffic Dept	2008453243		Water	GAL
	2008640302		Electricity	kWh
Bur Dubai Police Station	2008280187		Water	GAL
	2008359280		Electricity	kWh
	2008359352		Electricity	kWh
	2008613607		Electricity	kWh
	2001927282		Electricity	kWh
Officers Club	2008325393		Electricity	kWh
	2008334333		Water	GAL
	2008325466		Electricity	kWh
	2009577922		Electricity	kWh
Al Faqqa Police Station	2000573312		Electricity	kWh
	3002582616		Electricity	kWh
	2002028230		Electricity	kWh
Hatta Police Station	2000297099		Electricity	kWh
	2000297099		Water	GAL
	2000297170		Electricity	kWh
	2000297170		Water	GAL
	2000297250		Water	GAL
	2003410686		Electricity	kWh
Jabal Ali Police Station	3000073472		Electricity	kWh
	3000073483		Electricity	kWh
	3000229001		Water	GAL
Lahbab Police station	2000674720		Electricity	kWh
	2016240032		Water	GAL
Moraqabat Police Station	2005947121		Electricity	kWh
	2005947253		Electricity	kWh
	2006241800		Electricity	kWh
	2006241800		Water	GAL
	2008507050		Water	GAL
Nad Alsheba Police Station	2001125488		Water	GAL
	2008450660		Electricity	kWh
	2008456072		Electricity	kWh
	2008456927		Electricity	kWh
Naif Police Station	2001467010		Water	GAL
	2004124580		Electricity	kWh
	2015722335		Electricity	kWh

	2004129182		Water	GAL
	2008559033		Electricity	kWh
Port Police Station	2008438945		Water	GAL
	2009352432		Electricity	kWh
	2009352467		Electricity	kWh
Coast Guard-Pollution Control	2008444899		Electricity	kWh
Al Wasl Protective Security and Emergency	2008396770		Electricity	kWh
	2008631974		Electricity	kWh
	2008650855		Electricity	kWh
	2008650910		Electricity	kWh
	2008690814		Electricity	kWh
	2008246051		Water	GAL
	2009556097		Water	GAL
	2009750608		Electricity	kWh
Hor Al Anz Protective Security and Emergency	2007891662		Electricity	kWh
	2007891662		Water	GAL
	2007942232		Electricity	kWh
	2007989948		Electricity	kWh
	2008385809		Water	GAL
Qusais Police Station	2002965617		Water	GAL
	2002965749		Electricity	kWh
	2008206637		Water	GAL
	2008595722		Electricity	kWh
Qusais Warehouses	2000428762		Water	GAL
	2009836839		Water	GAL
	2009836839		Electricity	kWh
Qusais Horse Stables	2005872652		Electricity	kWh
	2005872652		Water	GAL
	2007025817		Water	GAL
	2013325231		Electricity	kWh
Qusais Barracks	2009264061		Electricity	kWh
	2009264061		Water	GAL
	2009314328		Electricity	kWh
Al Rashdiyah Police Station	2008607674		Electricity	kWh
	2008607828		Electricity	kWh
	2008671445		Water	GAL
	2009296281		Electricity	kWh
	2009296303		Water	GAL
	2009322002		Electricity	kWh
	2009487214		Water	GAL
	2009922077		Water	GAL

	2010002610		Electricity	kWh
Al Riffa Police Station	2008892646		Electricity	kWh
	2008892875		Electricity	kWh
	2009055420		Water	GAL
	2009222180		Electricity	kWh
K9	3003551419		Electricity	kWh
Bur Dubai Detention	3004123782		Electricity	kWh
	3004123771		Electricity	kWh
	3004123771		Water	GAL
Lost and Found department	3006175414		Electricity	kWh
			Water	GAL
Al Khawaneej Police Station	3004604086		Electricity	kWh
	3004604086		Water	GAL

Appendix 2: MLR output for electricity

Department	Date	Actual	Forecast
Airport Security	2021 Q1	7332	6498.438
Airport Security	2021 Q2	2013	6498.438
Airport Security	2021 Q3	7535	6498.438
Airport Security	2021 Q4	11023	6498.438
Al Faqqa Police Station	2021 Q1	38372	42019
Al Faqqa Police Station	2021 Q2	35476	42019
Al Faqqa Police Station	2021 Q3	30313	42019
Al Faqqa Police Station	2021 Q4	43311	42019
Al Rashdiyah Police Station	2021 Q1	58374	51150.19
Al Rashdiyah Police Station	2021 Q2	61141	51150.19
Al Rashdiyah Police Station	2021 Q3	55929	51150.19
Al Rashdiyah Police Station	2021 Q4	33389	51150.19
Al Riffa Police Station	2021 Q1	44846	33285.06
Al Riffa Police Station	2021 Q2	48544	33285.06
Al Riffa Police Station	2021 Q3	40892	33285.06
Al Riffa Police Station	2021 Q4	35175	33285.06
Al Wasl Protective Security and Emergency	2021 Q1	82206	69988
Al Wasl Protective Security and Emergency	2021 Q2	55798	69988
Al Wasl Protective Security and Emergency	2021 Q3	79862	69988
Al Wasl Protective Security and Emergency	2021 Q4	73236	69988
Awir Horse Stables	2021 Q1	17192	18141.26
Awir Horse Stables	2021 Q2	21341	15726.09
Awir Horse Stables	2021 Q3	17014	25130.57
Awir Horse Stables	2021 Q4	18544	13056.04
Barsha Police Station	2021 Q1	37566	25341.34
Barsha Police Station	2021 Q2	36941	26277.79
Barsha Police Station	2021 Q3	37623	29729.71
Barsha Police Station	2021 Q4	17996	23508.98
Barsha Traffic Dept	2021 Q1	10126	7635
Barsha Traffic Dept	2021 Q2	5125	6460
Barsha Traffic Dept	2021 Q3	9804	8973
Barsha Traffic Dept	2021 Q4	12841	14570
Bur Dubai Police Station	2021 Q1	42992	51556.23
Bur Dubai Police Station	2021 Q2	42900	49947.88
Bur Dubai Police Station	2021 Q3	52824	47424.25
Bur Dubai Police Station	2021 Q4	39487	46215.07
Dubai Police Academy	2021 Q1	184260	158159.9
Dubai Police Academy	2021 Q2	137285	158159.9

Dubai Police Academy	2021 Q3	182045	158159.9
Dubai Police Academy	2021 Q4	168054	158159.9
General Department of Transport and Rescue	2021 Q1	114615	98841.5
General Department of Transport and Rescue	2021 Q2	117698	98841.5
General Department of Transport and Rescue	2021 Q3	102168	98841.5
General Department of Transport and Rescue	2021 Q4	71957	98841.5
GHQ	2021 Q1	593584	521511.4
GHQ	2021 Q2	713147	521511.4
GHQ	2021 Q3	575332	521511.4
GHQ	2021 Q4	498503	521511.4
Hatta Police Station	2021 Q1	47811	53819
Hatta Police Station	2021 Q2	31863	27681
Hatta Police Station	2021 Q3	66683	65613
Hatta Police Station	2021 Q4	80847	80451
Hor Al Anz Protective Security and Emergency	2021 Q1	53294	58767
Hor Al Anz Protective Security and Emergency	2021 Q2	23063	28627
Hor Al Anz Protective Security and Emergency	2021 Q3	51809	43224
Hor Al Anz Protective Security and Emergency	2021 Q4	76044	76082
Jabal Ali Police Station	2021 Q1	34574	37763.06
Jabal Ali Police Station	2021 Q2	27660	37763.06
Jabal Ali Police Station	2021 Q3	35175	37763.06
Jabal Ali Police Station	2021 Q4	44200	37763.06
K9	2021 Q1	NA	17362
K9	2021 Q2	NA	4121
K9	2021 Q3	NA	9499
K9	2021 Q4	NA	11848
Lahbab Police station	2021 Q1	8429	9581.125
Lahbab Police station	2021 Q2	3142	9581.125
Lahbab Police station	2021 Q3	13301	9581.125
Lahbab Police station	2021 Q4	17523	9581.125
Moraqabat Police Station	2021 Q1	55626	52442.38
Moraqabat Police Station	2021 Q2	83390	52442.38
Moraqabat Police Station	2021 Q3	51770	52442.38
Moraqabat Police Station	2021 Q4	21833	52442.38

Nad Alsheba Police Station	2021 Q1	29693	33704.81
Nad Alsheba Police Station	2021 Q2	51222	33704.81
Nad Alsheba Police Station	2021 Q3	43013	33704.81
Nad Alsheba Police Station	2021 Q4	24824	33704.81
Naif Police Station	2021 Q1	35673	45178.63
Naif Police Station	2021 Q2	48648	45178.63
Naif Police Station	2021 Q3	25706	45178.63
Naif Police Station	2021 Q4	46212	45178.63
Officers Club	2021 Q1	30285	35371.25
Officers Club	2021 Q2	39482	35371.25
Officers Club	2021 Q3	30701	35371.25
Officers Club	2021 Q4	44323	35371.25
Port Police Station	2021 Q1	21009	20326.69
Port Police Station	2021 Q2	34715	20326.69
Port Police Station	2021 Q3	21429	20326.69
Port Police Station	2021 Q4	14334	20326.69
Punitive and Correctional Establishments	2021 Q1	168864	186655.7
Punitive and Correctional Establishments	2021 Q2	176292	186655.7
Punitive and Correctional Establishments	2021 Q3	164948	186655.7
Punitive and Correctional Establishments	2021 Q4	202530	186655.7
Qusais Police Station	2021 Q1	17525	19705.06
Qusais Police Station	2021 Q2	11559	19705.06
Qusais Police Station	2021 Q3	15145	19705.06
Qusais Police Station	2021 Q4	23227	19705.06
Qusais Warehouses	2021 Q1	33626	34353.38
Qusais Warehouses	2021 Q2	16490	34353.38
Qusais Warehouses	2021 Q3	38298	34353.38
Qusais Warehouses	2021 Q4	46136	34353.38
Rowaiyah Shooting Range	2021 Q1	18217	21833.06
Rowaiyah Shooting Range	2021 Q2	20338	21833.06
Rowaiyah Shooting Range	2021 Q3	17800	21833.06
Rowaiyah Shooting Range	2021 Q4	19775	21833.06
Traffic Department Deira	2021 Q1	24315	21627
Traffic Department Deira	2021 Q2	14218	21627
Traffic Department Deira	2021 Q3	24875	21627
Traffic Department Deira	2021 Q4	32022	21627

Appendix 3: MLR output for water

Department	Date	Actual	Forecast
Airport Security	2021 Q1	22834	9749.438
Airport Security	2021 Q2	8122	9749.438
Airport Security	2021 Q3	11854	9749.438
Airport Security	2021 Q4	7182	9749.438
Al Rashdiyah Police Station	2021 Q1	55468	68205.06
Al Rashdiyah Police Station	2021 Q2	62391	68205.06
Al Rashdiyah Police Station	2021 Q3	68393	68205.06
Al Rashdiyah Police Station	2021 Q4	65340	68205.06
Al Riffa Police Station	2021 Q1	10933	10642.81
Al Riffa Police Station	2021 Q2	8456	10642.81
Al Riffa Police Station	2021 Q3	10151	10642.81
Al Riffa Police Station	2021 Q4	8327	10642.81
Al Wasl Protective Security and Emergency	2021 Q1	23873	22200.69
Al Wasl Protective Security and Emergency	2021 Q2	24532	22200.69
Al Wasl Protective Security and Emergency	2021 Q3	24503	22200.69
Al Wasl Protective Security and Emergency	2021 Q4	26017	22200.69
Awir Horse Stables	2021 Q1	14955	19883
Awir Horse Stables	2021 Q2	29292	32746
Awir Horse Stables	2021 Q3	37578	36280
Awir Horse Stables	2021 Q4	34001	36687
Barsha Police Station	2021 Q1	24784	23082.38
Barsha Police Station	2021 Q2	20560	23082.38
Barsha Police Station	2021 Q3	18920	23082.38
Barsha Police Station	2021 Q4	23478	23082.38
Barsha Traffic Dept	2021 Q1	15917	14395.41
Barsha Traffic Dept	2021 Q2	15897	14577.41
Barsha Traffic Dept	2021 Q3	12346	14577.41
Barsha Traffic Dept	2021 Q4	4096	14577.41
Bur Dubai Police Station	2021 Q1	23745	23741
Bur Dubai Police Station	2021 Q2	16909	23741
Bur Dubai Police Station	2021 Q3	1469	23741
Bur Dubai Police Station	2021 Q4	8706	23741
Dubai Police Academy	2021 Q1	84392	88544.25
Dubai Police Academy	2021 Q2	74442	80402.67
Dubai Police Academy	2021 Q3	82872	83871.43
Dubai Police Academy	2021 Q4	65802	82393.55
General Department of Transport and Rescue	2021 Q1	11562	12677.9

General Department of Transport and Rescue	2021 Q2	11630	13948.16
General Department of Transport and Rescue	2021 Q3	12433	15415.67
General Department of Transport and Rescue	2021 Q4	12294	16503.61
GHQ	2021 Q1	184806	168209
GHQ	2021 Q2	170151	168209
GHQ	2021 Q3	141400	168209
GHQ	2021 Q4	168153	168209
Hatta Police Station	2021 Q1	44767	69356.56
Hatta Police Station	2021 Q2	67403	69356.56
Hatta Police Station	2021 Q3	72996	69356.56
Hatta Police Station	2021 Q4	60082	69356.56
Hor Al Anz Protective Security and Emergency	2021 Q1	58888	51626.31
Hor Al Anz Protective Security and Emergency	2021 Q2	42595	60399.62
Hor Al Anz Protective Security and Emergency	2021 Q3	47642	53633.35
Hor Al Anz Protective Security and Emergency	2021 Q4	50795	58851.72
Jabal Ali Police Station	2021 Q1	4640	7209.625
Jabal Ali Police Station	2021 Q2	4524	7209.625
Jabal Ali Police Station	2021 Q3	7729	7209.625
Jabal Ali Police Station	2021 Q4	13041	7209.625
Lahbab Police station	2021 Q1	16271	15155.56
Lahbab Police station	2021 Q2	19959	15155.56
Lahbab Police station	2021 Q3	16984	15155.56
Lahbab Police station	2021 Q4	NA	15155.56
Moraqabat Police Station	2021 Q1	29276	29485.44
Moraqabat Police Station	2021 Q2	27525	29485.44
Moraqabat Police Station	2021 Q3	26493	29485.44
Moraqabat Police Station	2021 Q4	31122	29485.44
Nad Alsheba Police Station	2021 Q1	13145	17896
Nad Alsheba Police Station	2021 Q2	14131	17896
Nad Alsheba Police Station	2021 Q3	14063	17896
Nad Alsheba Police Station	2021 Q4	14423	17896
Naif Police Station	2021 Q1	12594	13625.56
Naif Police Station	2021 Q2	12862	13625.56
Naif Police Station	2021 Q3	11983	13625.56
Naif Police Station	2021 Q4	7542	13625.56

Officers Club	2021 Q1	11234	15869
Officers Club	2021 Q2	13161	15869
Officers Club	2021 Q3	13067	15869
Officers Club	2021 Q4	13568	15869
Port Police Station	2021 Q1	14258	15564.22
Port Police Station	2021 Q2	12637	16179.45
Port Police Station	2021 Q3	11622	16179.45
Port Police Station	2021 Q4	11740	16179.45
Punitive and Correctional Establishments	2021 Q1	22439	21330
Punitive and Correctional Establishments	2021 Q2	28150	21330
Punitive and Correctional Establishments	2021 Q3	35538	21330
Punitive and Correctional Establishments	2021 Q4	35615	21330
Qusais Police Station	2021 Q1	32015	35337.81
Qusais Police Station	2021 Q2	31535	35337.81
Qusais Police Station	2021 Q3	33160	35337.81
Qusais Police Station	2021 Q4	34182	35337.81
Qusais Warehouses	2021 Q1	29589	36435.65
Qusais Warehouses	2021 Q2	37417	36252.5
Qusais Warehouses	2021 Q3	37999	33897.76
Qusais Warehouses	2021 Q4	37575	33954.73
Rowaiyah Shooting Range	2021 Q1	10193	9806
Rowaiyah Shooting Range	2021 Q2	11238	9806
Rowaiyah Shooting Range	2021 Q3	10883	9806
Rowaiyah Shooting Range	2021 Q4	11811	9806
Traffic Department Deira	2021 Q1	34925	28726.42
Traffic Department Deira	2021 Q2	30947	38389.42
Traffic Department Deira	2021 Q3	33282	25927.42
Traffic Department Deira	2021 Q4	29943	22588.42