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Demand forecasting and Route Optimization in Supply chain industry using Data Analytics

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***Abstract*— Logistics industry is one of key pillars of the global economy, which involves interdisciplinary domains. Manufacturing companies need to devise strategies in order to deliver best-quality products on time, meeting customers' growing expectations is becoming increasingly important. Demand forecasting and route optimization are key challenges which needs to be solved because it is interdependent on Fleet usage, analyzing the safety stock, and last mile connectivity in large cities where the density of orders to be delivered is high and any miscalculation in the above two aspects will lead to a domino effect in the industry, where the losses are unacceptable. This paper leverages two important algorithms, one is time series analysis i.e. Auto regressive integrated moving average and simulated annealing algorithm for demand forecasting and route optimization respectively. Both the models help in addressing the key problems by formulating a solution by means of simulation and providing the best possible results, that can be directly incorporated in the industry for the benefit.**

Keywords*— *Logistics industry, Auto regressive integrated moving average, simulated annealing, last mile connectivity

I. INTRODUCTION

Demand forecasting plays a crucial role for every organization in terms of their profit, growth, and overall performance. Demand forecasting helps in predicting the future demand based on the previous demand data. Many companies are reliant on demand forecasting to predict their product's future demand and business strategies to make their supply chain run effectively on day-to-day basis[1-2]. Based on the demand of the products, shortest path can be found out using the route optimization technique.

Using the supply chain management technique, we can improve the overall stock management, manufacturing operations to smoothen the operations and deliver all the products as per the schedule. By using these strategies, a solution is created to meet the overall customer demand from time to time. These supply chain strategies help to produce a much better quality product within the stipulated time, which is very important for a manufacturing company. These strategies help manufacturing firms to predict the demand for at least the next 10 years. Each time, second, hour, a millisecond is important for a manufacturing firm to meet the customer demands.

The optimization of the route plan for the supply chain can increase the efficiency of the last mile connectivity of the logistics, simulation of the same can be used to find out the cost reduction and as well find the delivery time for different samples[3-6]. The concept of data analytics in logistics is in an important part in technological evolution, time series analysis provides one of the most accurate results in predictive analytics. ARIMA(Auto Regressive Integrated Moving Average)[7-10] is defined a class of models that explains a given time series by comparing its own past values, such as lagged forecast errors, for the equation to be implemented in the forecast future values. Each component in ARIMA is treated as a parameter with a defined nomenclature. ARIMA with p, d, and q is a notation that is widely accepted for ARIMA models, where integer values replace the parameters to show the type of ARIMA model used. Autoregression is a model in which a changing variable regresses on its own lagged, or prior, values (AR). Integrated (I): signifies the differencing of raw measurements in order for the time series to become stationary, i.e., data values are replaced by the difference between data values and prior values in order for the time series to become stationary. Moving average (MA): When applied to lagged observations, a moving average model incorporates the dependency between an observation and a residual error.

p: the model's lag order, also denoted as the number of lag observations.

d: the degree of differencing, also denoted as the number of times the raw observations are differed.

q: the window size of the moving average, also denoted as the moving average order.

Many python libraries and dependencies such as numpy, pandas, and matplotlib are necessary to execute the program since the company may acquire insights into the data using visualization tools like tableau and other cutting-edge technology like jupyter notebook.

II. LITERATURE SURVEY

The author Subrina Noureen[11] has conducted a seasonal time series forecasting using ARIMA as a model in this paper. An agricultural load dataset is applied to the ARIMA model. It has a performance of 95%. The limitation is that further research can be made using different models for optimum ARIMA model by analysis there Akaiae and Bayesian information.

In the paper [12], author H. Laaroussi has used Keras to establish LSTM and GRU models. A monthly Moroccan tourist arrival dataset is used. The performance is about 80% efficient. The limitation here is that the searched tourist variables in recent times can be used to predict the data accurately.

The author S. D. Percy[13] has worked on the SGSC dataset using Artificial Neural Network and ABRT algorithm in this paper. It has a performance range of 76-85%. The main drawback is that it could examine the application of a demand model to design a complete microgrid.

The author J. H. Moediahedy[14] has used several techniques such as SVM, DBN etc to work on the Yahoo Finance dataset for forecasting. The limitation is that other data models and algorithms can be used to increase the prediction performance.

The author N. S. Md Salleh[15] has used linear regression, SVM, RBF techniques to work on the electricity dataset. It yields a performance of 75%. The drawback here is that it can still study the significance of machine learning tools used with the model acuuracy produced.

The author M. Karthik[16] uses a wind dataset to which techniques such as RMSE, MAE are applied. The performance is about 74-91%, which can be further improved by using machine learning algorithms and regression model.

The author E. Xing[17] has used Deep Reinforcement learning algorithm technique to work on a traffic dataset. The results show that the effective delivery path optimization can effectively reduce the delivery time and improve customer satisfaction. The drawback is that other machine learning algorithm can be used considering weather condition, time and other external factors.

The author K. Govindan[18] has worked on a food chain dataset using MOGA, NRGA, NSGA-II techniques. The drawback of this paper is that the routing problem can be reduced much more by using other reinforcement learning algorithm, in order to find the shortest path accurately.

The author Techan Bosona[19] uses GID and routing techniques to apply on a warehouse delivery dataset. It yields a performance accuracy of 92-93% routes that were improved. The application can still be improved by adding more map features by showing the shortest path.

The author N. Darapaneni[20] has used linear regression, decision trees, multivariate time forecasting series techniques to work on a transport related dataset. It has a performance accuracy of about 60%. The limitation is, it still require to install hardware and software for tracking the passenger ride across the contry.

The author T. Vantuch[21] has used ANN, RFR, FNT techniques in order to work on an electricity load dataset. Although, its application brought several highly relevant features they did not cover the necessity of use of electric load lagged values in order to improve the forecasting accuracy.

III. ARCHITECTURE

As shown in the dataflow diagram in the figure-1, the initial step in the process is to collect the datasets and read it into the programming environment. The existing data is then analyzed, after which data reformation and data cleansing is done. The cleansed data undergoes visualization for feature extraction for model development. The model is then trained with this data. If the data consists of good accuracy and satisfactory parameters, then we can list the predicted values, otherwise the data is fine-tuned and the process of visualization and feature engineering is repeated. Then the model is validate by testing it with new data.

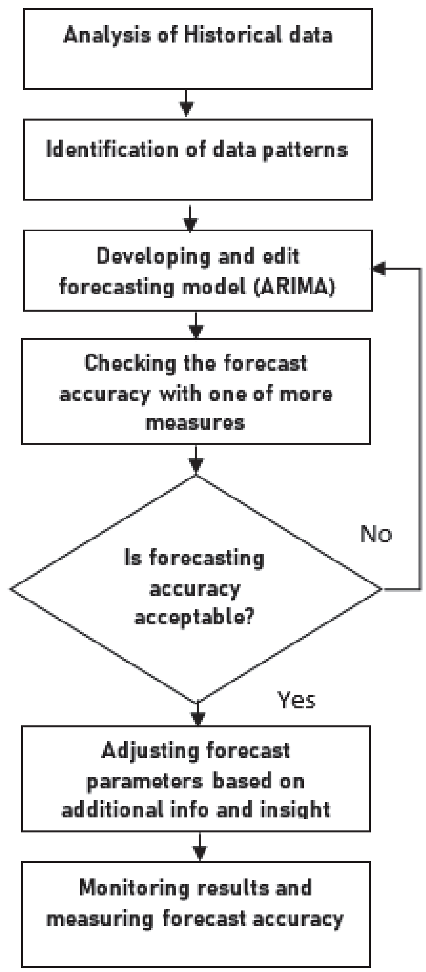

Fig. 1. DATAFLOW DIAGRAM

The figure-2 depicts the architectural diagram of ARIMA model with different components in it. The forecasting is performed on the dataset and the current data is updated with the forecasted values. The actual and predicted values are then reported and the model with better accuracy is chosen.

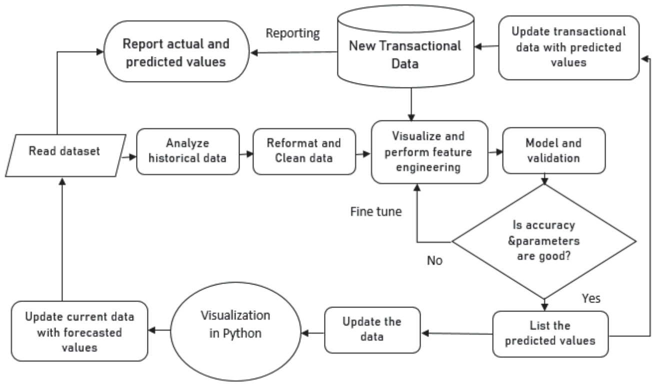

Fig. 2. ARCHITECTURE DIAGRAM

IV. DATAFLOW DIGRAM

In dataflow diagram, the first step is to analyze the historical data for identification of data patterns, then a forecasting model pertinent to the data pattern is built called as ARIMA model. The forecasting accuracy is checked with one or more measures to see if the accuracy of the forecasting model is satisfactory and acceptable, we move on with the process, otherwise a different forecasting model is selected. Further, the forecast is adjusted using certain parameters based on the qualitative information and insight. Finally, the forecasted results are monitored and the forecasting accuracy is measured.

V. METHODOLOGY

Based on the literature survey, the problem statement requires a mixed approach, which includes both qualitative as well as quantitative methodologies for the implementation. So implementation is done using case studies, inductive and deductive methods with suitable techniques and procedures. The heart of the project lies in two important algorithms i.e., Time series algorithm (ARIMA) and the simulated annealing algorithm for acceptable accuracy and results. The chosen algorithm is appropriate to the problem statement and data. Both the algorithms follow industry required error free results and it can be used to find irregular patterns in the data such as seasonality, trend or random data. The maintainability of the code is easy and bugs can be easily removed in the code. The parameters like Historical sales data, coordinates of the warehouse, cost of transportation and demand at each warehouse are certain data sets which are used for the analysis. The analysis and simulation is conducted using Jupyter notebook and spyder IDE (integrated development environment) respectively, python libraries such as pandas, numpy, matplotlib, pmdarima etc. are used for mathematical calculation and interpretation of the data. Series of steps are involved in cleaning of the data, training the model and suitable methods are incorporated to fill the missing values in the dataset. A separate dataset is used for training and testing of the data. The results are plotted on the graphs, for the forecasted and the real world demand.

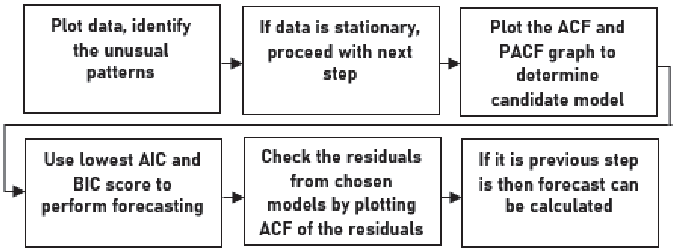

Fig. 3. Process of forecasting the demand

The process of forecasting the demand is shown in figure-3, which involves a series of steps for analyzing the performance metrics on the data, are discussed are as follows:

Step 1: Plotting the graph for the given data and to find if there are any abnormal behavior in the data. Then choose the type of forecasting model that is needed i.e., univariate time series or multivariate time series. The dataset is checked for any missing values and corrective measures are taken for the same.

Step 2: Test for a stationary data is done in this step. The mean, variance and covariance should not be a function of time. If it is a function of time, the curve should be smoothened by adding few lags to the data. The least differencing required to obtain a near-stationary series roams around a defined mean. If the autocorrelations are positive for a large number of lags (ie. 10 or more), the series should be differentiated further else if the lag-1 autocorrelation is too negative, the series is most likely to be over-differenced.

Another method to test the stationary data is by using augmented dickey fuller test, which examines whether or not a unit root exists in an autoregressive model. Depending on the version of the test chosen, the alternative hypothesis is usually stationary or trend-stationary. The test consists of many parameters such as p-value, test statistic value, the number lags for the test, critical value cut-off with confidence values of 1%, 5%, 10%. The p-value should be less than 0.05 for the curve to be stationary.

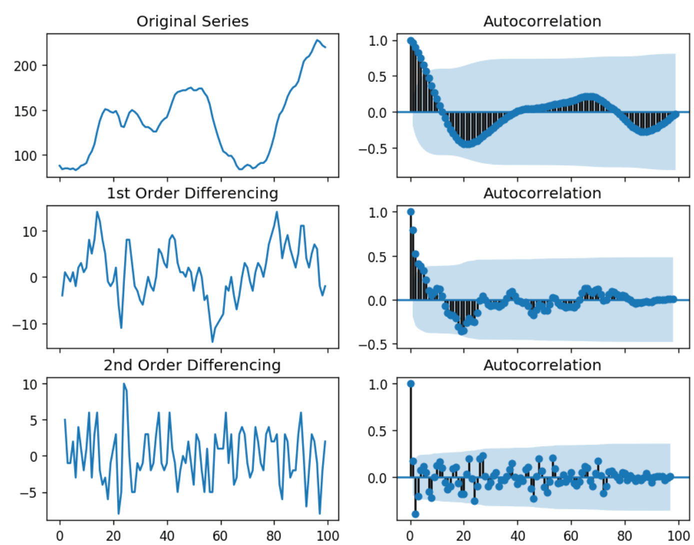

Fig. 4. Order of Differencing

Step 3: In this step, ACF and the PACF graphs are plotted. The next step is to define whether or not, the model requires any AR terms. The necessary number of AR terms can be assessed by looking at partial autocorrelation (PACF) diagram. After removing the contributions from the intermediate lags. Partial autocorrelation can be understood as the correlation between the series and its lag. As a result, PACF condense the pure correlation between series and lags. In this manner, you will understand the requirements of lags in the AR term. By introducing enough AR terms in a stationarized series, autocorrelation can be corrected. As a result, we set the AR term's order equal to number of delays that pass the PACF plot's significance limit. A graph is plot for 1st order and 2nd order differencing of the PACF to check if the data is stationary.

The next step is to see the ACF plot for the number of MA terms which is very much similar to looking PACF plot for AR terms. The error in the lagged forecast is referred to as an MA term. The ACF directs the proportion of MA terms required to be remove any autocorrelation from both the stationarized series. If the series is slightly under differed, adding one or more additional AR terms generally corrects the problem as indicated in the figure-5a. Similarly, if it's slightly over-differentiated, we try adding another MA term as show in the figure-5b.

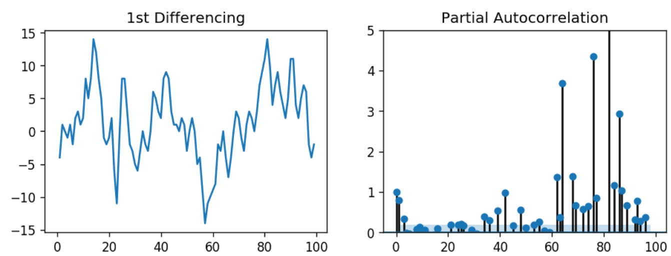

Fig. 5. (a). Order of AR term

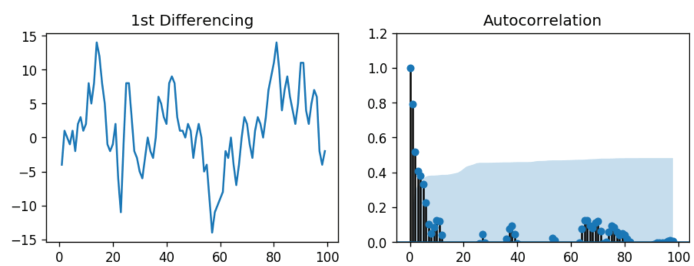

Fig. 5. (b). Order of MA term

Step 4: The next step is to design an ARIMA model to find the best possible AIC (Akaike's Information Criteria) and BIC (Bayesian Information Criteria) score. Now everything is available that is needed to fit the ARIMA model after establishing values for p, d, and q. We will utilize the stats model package's ARIMA() function for implementation. The coefficient table is in the middle and the values under 'coef' represent the weights of the various terms. The MA2 term's coefficient is closer to zero, and the P-Value in the 'P>|z|' column is inconsequential. For the relevant X to be significant, it should be less than 0.05. The model evaluates details such as coefficient, standard error, AIC score, BIC score, log likelihood and the p value. The lowest values of AIC and BIC scores are chosen as a criteria to select the forecasting model. There are some distinctions between the two approaches to model selection. The AIC is a measure of the quality of fit of any statistical model that has been estimated. The BIC approach is a method of selecting a model from a group of parametric models with varying amounts of parameters. In general, Akaike's Information Criteria seeks out an unknown model with a high dimensional realism. In AIC, this suggests the models aren't real models. The Bayesian Information Criteria, on the other hand, exclusively finds true models.

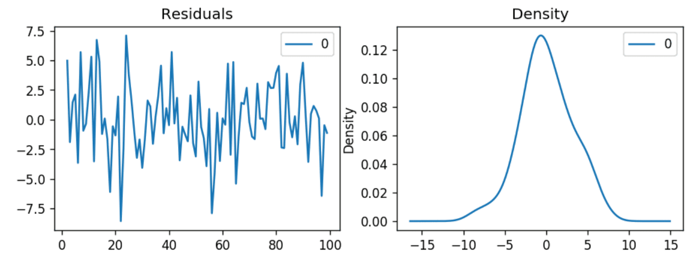

Fig. 6. (a). Residuals Density

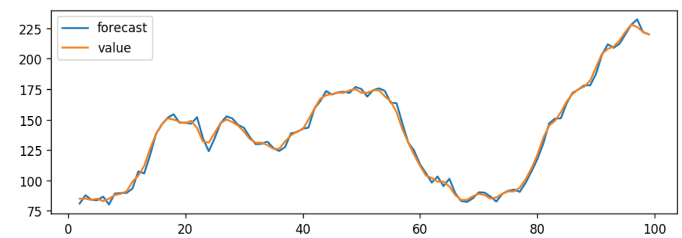

Fig. 6. (b). Actual vs Fitted

Step 5: Once the parameters are corrected, the rolling mean and the standard deviation for the data is plotted on the graph and after this we fit the model. The model is trained by using 75% of the training dataset and 25% of dataset is used for testing the model after verification of the residuals (as shown in figure-6a). It was evident that it has zero mean and uniform variance. To create next prediction, the model is trained until the previous value. This can make the fitted forecast and actuals values appear overly optimistic (as shown in the figure-6b). The cross-validation involves taking few steps back in time and forecasting it into the future. The forecast is then compared to the actuals as shown in the figure-7. To perform out-of-time cross-validation, divide the time series into two contiguous portions in a 75:25 ratio or an acceptable fraction dependent on the series' time frequency.

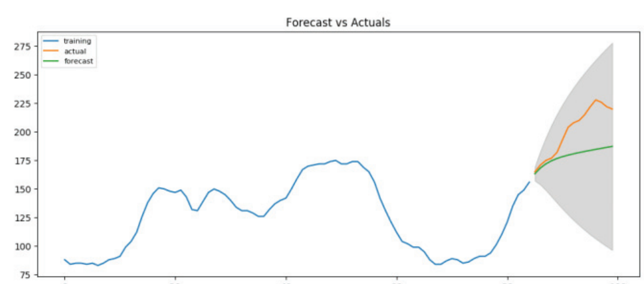

Fig. 7. Forecast vs Actual

Step 6: The ARIMA (1,1,1) model appears to provide correct forecast based on the graph show in the figure-8. The actuals observed values are also within the 95% confidence interval that appears to be satisfactory. However, each of the forecasts values is consistently lower than the actuals. As a result, there is a room for improvement. The AIC has dropped from 515 to 440 and the X terms' P-values are less than 0.05, which is excellent. We perform the 8 different accuracy metrics to check the measure of error and the performance of the model. In industrial usage, the accuracy monitoring is automated so that the firm can choose the model based on accuracy they obtained, in order make this project industry ready we can use automated ARIMA concept. It employs a stepwise technique to find the optimal model with the lowest AIC by searching numerous combinations of p, d and q parameters.

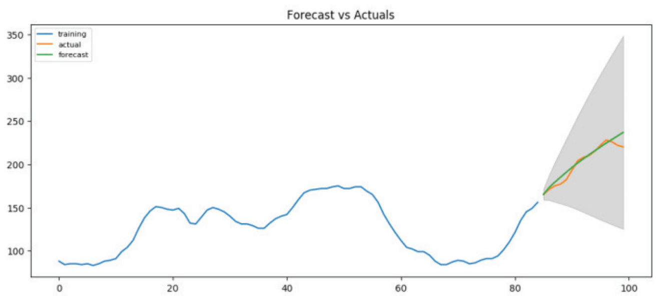

Fig. 8. Revised Forecast vs Actual

The process of Route optimization:

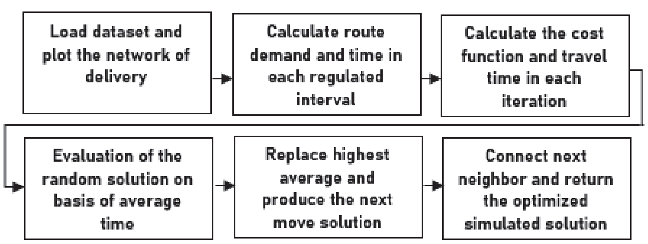

Fig. 9. Process of route optimization

The 2nd step is to optimize the route to deliver the products to the warehouses. So the process of route optimizations is shown in the figure-9. The steps are discussed below.

Step 1: The simulated annealing algorithm for route optimization involves series of steps to generate the best possible optimized solution. We load the three different data sets, which includes the demand at each warehouse, the travel time and the location of each warehouse. Compiled list of the network's routes are further analysis for the optimal route. Store names are visited in order on the routes, before returning to the warehouse. The route begins at the any designated warehouse and concludes at the last warehouse.

Step 2: The next step is to calculate the route demand, the demand that needs to be fulfilled in each delivery cycle, by keeping the route time in a fixed variable i.e., the time in seconds it takes to traverse a route and deliver its demand.

Step 3: Calculation of the cost in each iteration of the delivery is a crucial phase and it returns the delivery time of entire set of routes, and also calculating the travel time from previous node to the indexed node.

Step 4: Generation of random solution as shown in the figure-10 and figure-11, can be on the basis of average time required to travel to and from the store. The random solution is necessary to enhance the efficiency of the algorithm, the random solution is one of the possible solution and keeping it as a base model simulation model is constructed for improved connectivity, reduced travel time and reduced operation cost. Figure-12 and figure-13 shows improved solution and accuracy of improved solution.

Step 5: In this step, we replace the highest average and produce the next move solution. This selects the four stores with the highest average input and output timings from all of the routes and removes them from their corresponding routes. The resultant paths are then computed for all possible insertions of these four stores. The route with the shortest travel time is then accepted for each removed store, and it is inserted as needed. A deterministic technique was used for this transform because it is unlikely that global optimum within the neighborhood of solutions. The final solution is then double-checked to ensure that it accesses all of the relevant stores, which should be guaranteed based on the first solution.

Step 6: In the final step, the data frame involving different solutions for the same problem is then fed to the annealing algorithm. To find the solution which has a least cost function and good global solution, there is clear distinction between the random and the improvised solution from the implications produced by cost for delivery. The algorithm returns the best route for delivery and entire cost for delivery.

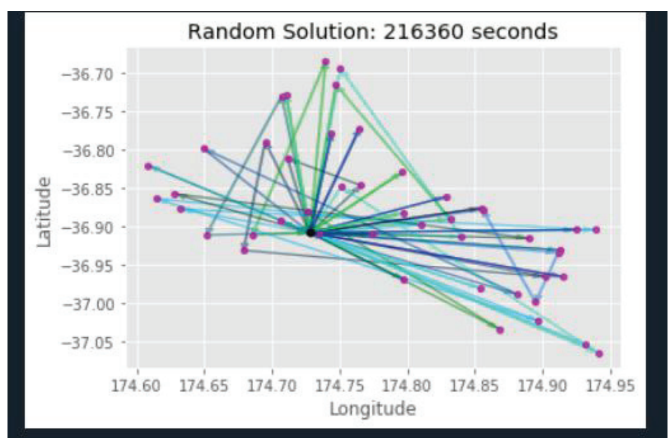

Fig. 10. Random solution routes

```
Random solution:  [['Warehouse', 'Four Square Lancaster', 'New World Green Bay', 'Four Square Botany
Junction'], ['Warehouse', "Pak 'n Save Albany", 'Four Square Glen Eden'], ['Warehouse', 'New World
Long Bay', 'New World New Lynn'], ['Warehouse', "Pak 'n Save Sylvia Park", 'Four Square BKs Torbay'],
['Warehouse', 'New World Stonefields', 'New World Browns Bay'], ['Warehouse', 'New World Southmall',
'Four Square Fair Price Henderson', 'Four Square Ellerslie'], ['Warehouse', "Pak 'n Save Henderson",
'Four Square Cockle Bay'], ['Warehouse', 'New World Metro Queen St', 'New World Birkenhead'],
['Warehouse', "Pak 'n Save Lincoln Road", 'Four Square Pakuranga Heights'], ['Warehouse', 'New World
Papakura', 'New World Victoria Park'], ['Warehouse', 'New World Botany', 'Four Square Everglade',
'Four Square Great Eastern'], ['Warehouse', "Pak 'n Save Manukau", 'Four Square Hobsonville'],
['Warehouse', "Pak 'n Save Clendon", 'Fresh Collective Alberton'], ['Warehouse', "Pak 'n Save
Papakura"], ['Warehouse', "Pak 'n Save Mt Albert"], ['Warehouse', "Pak 'n Save Botany"],
['Warehouse', "Pak 'n Save Royal Oak"], ['Warehouse', 'New World Albany'], ['Warehouse', "Pak 'n Save
Wairau Road"], ['Warehouse', 'New World Eastridge'], ['Warehouse', 'New World Mt Roskill'],
['Warehouse', "Pak 'n Save Glen Innes"], ['Warehouse', "Pak 'n Save Westgate"], ['Warehouse', 'New
World Milford'], ['Warehouse', 'New World Devonport'], ['Warehouse', 'New World Remuera'],
['Warehouse', 'New World Howick'], ['Warehouse', 'New World Papatoetoe'], ['Warehouse', "Pak 'n Save
Mangere"], ['Warehouse', "Pak 'n Save Ormiston"]]
Random cost:  216360
Running SA
Current temperature: 0.001, Explored cost (No wetlease): $7717.84Minutes to imporve:
0.059381596247355145
```

Fig. 11. Accuracy for random solution

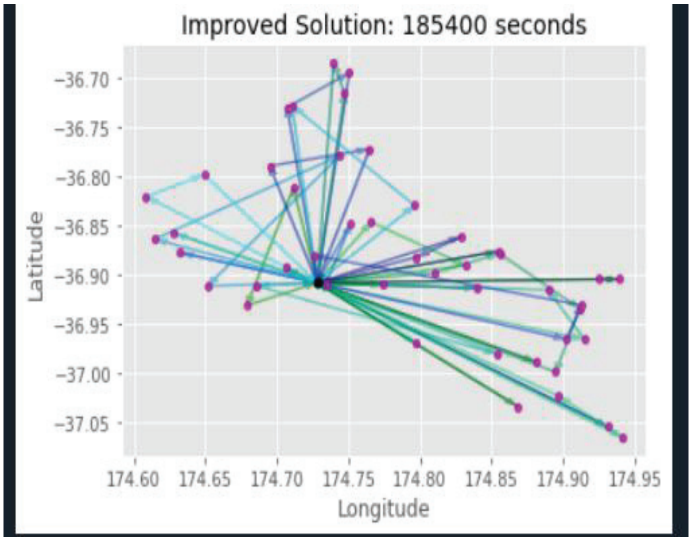

Fig. 12. Improved solution

```
Improved solution:  [['Warehouse', 'New World Birkenhead', 'New World Green Bay'], ['Wareho
'n Save Mangere"], ['Warehouse', 'New World New Lynn', 'New World Papatoetoe'], ['Warehouse
['Warehouse', "Pak 'n Save Henderson"], ['Warehouse', "Pak 'n Save Albany", 'Four Square BK
Torbay'], ['Warehouse', "Pak 'n Save Manukau"], ['Warehouse', 'New World Mt Roskill', 'New
Victoria Park'], ['Warehouse', "Pak 'n Save Sylvia Park"], ['Warehouse', 'New World Browns
World Long Bay'], ['Warehouse', "Pak 'n Save Royal Oak"], ['Warehouse', 'New World Metro Qu
'New World Stonefields'], ['Warehouse', "Pak 'n Save Mt Albert"], ['Warehouse', 'Four Squar
Price Henderson', "Pak 'n Save Wairau Road", 'Four Square Glen Eden'], ['Warehouse', "Pak '
Glen Innes"], ['Warehouse', 'Four Square Lancaster', 'New World Milford'], ['Warehouse', 'N
Devonport', 'New World Albany'], ['Warehouse', "Pak 'n Save Ormiston", 'Four Square Pakuran
Heights'], ['Warehouse'], ['Warehouse', "Pak 'n Save Lincoln Road"], ['Warehouse', 'New Wor
Eastridge', 'New World Remuera'], ['Warehouse'], ['Warehouse'], ['Warehouse', 'Four Square
Ellerslie', 'Four Square Great Eastern', 'New World Botany', 'Four Square Everglade'], ['Wa
"Pak 'n Save Papakura"], ['Warehouse', 'New World Papakura', 'New World Southmall'], ['Ware
"Pak 'n Save Clendon"], ['Warehouse', 'Four Square Botany Junction', "Pak 'n Save Botany",
Collective Alberton'], ['Warehouse', 'Four Square Cockle Bay', 'New World Howick'], ['Wareh
"Pak 'n Save Westgate", 'Four Square Hobsonville']]
Improved cost:  185400
```

Fig. 13. Accuracy of improved solution

VI. CONCLUSION

Demand forecasting and route optimization play an important role in supply chain management across warehouses and manufacturing firms. In this paper, two algorithms are implemented namely ARIMA algorithm for forecasting the demand for the warehouse products is implemented and time series analysis is done and second algorithm called Simulated annealing is implemented for route optimization.

After performing AIC, BIC approximation and MAPE error, ARIMA model is used to forecast the actual demand of the product in the warehouse. The route optimization algorithm helped us to find the shortest path of last-mile delivery by considering the demand of the product in the warehouse. Both of this algorithms will help the startup and manufacturing firms in the supply chain industry to make proper decision about their product delivery, customer needs, customer behavior analysis and scope of the product. The supply chain firms can have proper idea about the demand of the product and where it should be delivered at any point of time. This work is continued to develop other models that combine qualitative and quantitative techniques to improve forecast accuracy.

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