Advancing Oligopoly Pricing Predictions through Machine Learning within the Indian Telecommunication Industry

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Abstract.

This paper looks at how machine learning can be used to predict revenue in the Indian telecommunication industry, which is mainly controlled by Reliance Jio, Bharti Airtel and Vodafone Idea. Quarterly data on subscriber numbers and average revenue per user was collected from company reports. Three models were tested: Linear Regression, Decision Tree Regression and Random Forest Regression. The data was divided into a training set and a test set using a 70 to 30 ratio. Model accuracy was measured using Mean Squared Error and Mean Absolute Error. The results showed that Random Forest gave the best predictions, followed by Decision Tree and then Linear Regression. The study shows that machine learning can help companies make better pricing and planning decisions in a competitive market. It also suggests that future research could use more advanced models and include outside factors like government policies or economic changes to improve predictions further.

Chapter 1: Introduction

1.1 Research Problem and Market Background

An oligopoly is a form of market structure in which there are a few firms, typically no more than 5, that dominate the market share. In this form of industry, companies rely on each other to make certain decisions that may benefit or harm other players in the market; each action of a company can impact others. This creates a challenging environment for companies trying to make a profit.

An example of an emerging oligopoly market is the Indian telecommunications industry. With a strong focus on digitization, the government has prioritized the widespread use of technology in daily activities. The market is dominated by three major players: Vodafone, Reliance Jio, and Bharti Airtel. As of 2024, these companies hold over 90% of the market share, asserting their dominance within the industry.

This research paper explores how using three different AI regression models can help analyze company revenue data and identify which model is best at predicting future revenue trends. This report aims to find the most reliable forecasting model, so that firms can make better decisions about pricing, production, and marketing strategies while dealing with the uncertainties of a competitive market.

1.2 Objectives and Scope

The primary objective of this study is to advance the predictive accuracy of pricing strategies in the Indian telecommunication sector through the integration of machine learning and game theory.

This paper will use machine learning models trained and tested on data from the investor relations of each of the three companies: Reliance Jio, Bharti Airtel, and Vodafone Idea, on a quarterly granularity. The machine learning models that would be incorporated into this research project include linear regression, decision tree regression, and random forest regression. Overall, regression analysis will play an important role in this aim, as the target variable of the models will be revenue, a real and continuous value.

1.3 Literature Review

The Indian telecommunications sector has shifted from a state-run monopoly to a more competitive oligopoly over the past two decades. This change has been caused by the spread of technologies such as mobile telephony and high-speed broadband, as well as regulatory reforms that opened the market to new players. A significant example of this transformation was the entry of Reliance Jio in 2016, which offered low-cost data services throughout the nation.

In an oligopolistic market, pricing decisions depend heavily on how firms react to one another's actions. Parsheera and Trehan (2023) note that traditional economic models like

Cournot and Bertrand competition continue to be used to understand these interactions. In the Cournot model, companies compete by choosing output levels, while in the Bertrand model, they compete by setting prices. However, these frameworks often rely on simplifying assumptions such as perfect information and marginal costs over a fixed timeframe. They also overlook factors such as product differentiation, marketing influence, and strategic long-term investments that can reshape demand. Combined with the rapidly changing conditions and evolving consumer behaviour, these assumptions mean such models may fail to capture the full complexity of real markets.

Machine learning offers a complementary approach by processing large and diverse datasets, identifying complex non-linear relationships, and adapting to evolving market conditions in real time. This allows for more dynamic and data-driven predictions that can incorporate both quantitative indicators and behavioural insights. Machine learning models are being used to predict how pricing strategies can change in both the short run and long-run. Unlike older statistical methods, these models process large amounts of customer data (e.g., annual revenue and cost) in a shorter time frame to identify trends in the data and make suitable predictions for future paths. For example, TM Forum (2025) explains how certain algorithms let telecom companies forecast demand in real time and adapt their pricing dynamically to stay competitive. Machine learning models can not only process large amounts of customer data but also anticipate consumer preferences and price sensitivity, allowing for more agile and personalized pricing (GhorbanTanhaei et al. 2024).

The use of machine learning in predicting pricing strategies raises important questions about regulation. With more advanced pricing algorithms, there is always a risk that firms could use them to collude (cooperate to gain individual benefits while others are at a loss) or fix prices unfairly. Combining machine learning with game theory could give companies in India’s telecom sector a better way to predict prices and plan their future strategies, but new models must follow nationwide regulations to ensure that competition remains healthy and consumers benefit in the long run.

Future research should focus on how to monitor these tools to ensure that markets remain fair for consumers. Governments can also monitor several important key performance indicators that reflect both fair consumer outcomes and healthy financial performance for firms. These indicators may include average consumer expenditure per gigabyte, market concentration indices such as the Herfindahl-Hirschman Index, and subscriber churn rates. Tracking these indicators would help regulators evaluate whether competition remains healthy and whether firms are avoiding anti-competitive practices. This approach would provide an area for future research that combines machine learning based pricing models with policy frameworks to protect both consumers and the industry’s long-term stability.

1.4 Methodology

The following data points will be extracted from each company's quarterly financial report, as presented:

- Subscriber count
- Average Revenue Per Customer (ARPU)

These points will be used to calculate the gross quarterly revenue. These data points will then be applied to the machine learning algorithms, and the results will be thoroughly analyzed. Note: Due to the limitations of publicly available data, there is no fixed period for which the ARPU (Subscription/month) has been extracted. For example, Vodafone has released all required values from 2011 onwards, but this is only available for years after 2017 and 2018 for Reliance and Airtel, respectively.

Year	Quarter	Subscription/month (Rupees)	Subscriber (million)	Quarterly Revenue (Rupees)
2018	1	₹154.00	48.9	₹22,591.80
2018	2	₹145.00	28.3	₹12,310.50
2018	3	₹123.00	36.4	₹13,431.60
2018	4	₹116.00	47.9	₹16,669.20
2019	1	₹105.00	85.7	₹26,995.50
2019	2	₹101.00	65.7	₹19,907.10
2019	3	₹104.00	77.1	₹24,055.20
2019	4	₹123.00	86.8	₹32,029.20
2020	1	₹129.00	95.2	₹36,842.40
2020	2	₹128.00	103.1	₹39,590.40
2020	3	₹135.00	123.8	₹50,139.00
2020	4	₹135.00	136.3	₹55,201.50
2021	1	₹157.00	138.3	₹65,139.30
2021	2	₹162.00	152.7	₹74,212.20
2021	3	₹166.00	165.6	₹82,468.80
2021	4	₹145.00	179.3	₹77,995.50
2022	1	₹146.00	184.4	₹80,767.20
2022	2	₹153.00	192.5	₹88,357.50
2022	3	₹163.00	195.5	₹95,599.50
2022	4	₹178.00	200.8	₹107,227.20
2023	1	₹183.00	205.3	₹112,709.70
2023	2	₹190.00	210.3	₹119,871.00
2023	3	₹193.00	216.7	₹125,469.30
2023	4	₹193.00	224.1	₹129,753.90
2024	1	₹200.00	229.7	₹137,820.00
2024	2	₹203.00	237.5	₹144,637.50
2024	3	₹208.00	244.9	₹152,817.60
2024	4	₹209.00	252.7	₹158,442.90

Analysis of Gross Quarterly Revenue for Airtel

Year	Quarter	Subscription/month (Rupees)	Subscriber (million)	Quarterly Revenue (Rupees, Millions)
2017	3	₹156.40	138.6	₹65,031.12
2017	4	₹154.00	160.1	₹73,966.20
2018	1	₹137.10	186.6	₹76,748.58
2018	2	₹137.10	215.3	₹88,552.89
2018	3	₹134.50	252.3	₹101,803.05
2018	4	₹130.00	280.1	₹109,239.00
2019	1	₹126.20	306.7	₹116,116.62
2019	2	₹122.00	331.3	₹121,255.80
2019	3	₹120.00	355.2	₹127,872.00
2019	4	₹128.40	370	₹142,524.00
2020	1	₹130.60	387.5	₹151,822.50
2020	2	₹140.30	398.3	₹167,644.47
2020	3	₹145.00	405.6	₹176,436.00
2020	4	₹151.00	410.8	₹186,092.40
2021	1	₹138.20	426.2	₹176,702.52
2021	2	₹138.40	440.6	₹182,937.12
2021	3	₹143.60	429.5	₹185,028.60
2021	4	₹151.60	421	₹191,470.80
2022	1	₹167.60	410.2	₹206,248.56
2022	2	₹175.70	419.9	₹221,329.29
2022	3	₹177.20	427.6	₹227,312.16
2022	4	₹151.60	421	₹191,470.80
2023	1	₹175.70	419.9	₹221,329.29
2023	2	₹178.20	432.9	₹231,428.34
2023	3	₹178.20	423.9	₹226,616.94
2023	4	₹178.80	439.3	₹235,640.52
2024	1	₹180.50	448.5	₹242,862.75
2024	2	₹181.70	459.7	₹250,582.47
2024	3	₹181.70	470.9	₹256,687.59
2024	4	₹181.70	481.8	₹262,629.18

Analysis of Gross Quarterly Revenue for Reliance

Year	Quarter	Subscription/month (Rupees)	Subscriber (million)	Quarterly Revenue (Rupees)
2011	1	₹182.00	68.9	₹37,619.40
2011	2	₹167.00	74.2	₹37,174.20
2011	3	₹168.00	81.8	₹41,227.20
2011	4	₹161.00	89.5	₹43,228.50
2012	1	₹160.00	95.1	₹45,648.00
2012	2	₹155.00	100.2	₹46,593.00
2012	3	₹159.00	106.4	₹50,752.80
2012	4	₹160.00	112.7	₹54,096.00
2013	1	₹156.00	117.2	₹54,849.60
2013	2	₹148.00	115.5	₹51,282.00
2013	3	₹158.00	113.9	₹53,988.60
2013	4	₹167.00	121.6	₹60,921.60
2014	1	₹174.00	125	₹65,250.00
2014	2	₹164.00	127.2	₹62,582.40
2014	3	₹169.00	128.7	₹65,250.90
2014	4	₹173.00	135.8	₹70,480.20
2015	1	₹181.00	139	₹75,477.00
2015	2	₹176.00	143.6	₹75,820.80
2015	3	₹179.00	150.5	₹80,818.50
2015	4	₹179.00	157.8	₹84,738.60
2016	1	₹182.00	162.1	₹88,506.60
2016	2	₹175.00	166.6	₹87,465.00
2016	3	₹176.00	171.9	₹90,763.20
2016	4	₹179.00	175.1	₹94,028.70
2017	1	₹181.00	176.2	₹95,676.60
2017	2	₹173.00	178.8	₹92,797.20
2017	3	₹157.00	185.2	₹87,229.20
2017	4	₹142.00	189.5	₹80,727.00
2018	1	₹141.00	189	₹79,947.00
2018	2	₹132.00	₹182.40	₹72,230.40
2018	3	₹114.00	188.5	₹64,467.00
2018	4	₹105.00	194.5	₹61,267.50
2019	1	₹92.00	435.4	₹120,170.40

Analysis of Gross Quarterly Revenue for Vodafone

Three machine learning algorithms were selected for this study: Linear Regression, Decision Tree Regression, and Random Forest Regression. Linear Regression was chosen as a baseline model due to its simplicity, interpretability, and effectiveness in forecasting continuous variables, making it a standard starting point in predictive modelling (Teradata, n.d.; Academic Oxford, 2023). Decision Tree Regression was selected because it can capture complex, non-linear relationships in the data without requiring strict statistical assumptions, while remaining easy to visualise (Viswanathan, 2023; GeeksforGeeks, 2024). Random Forest Regression, a technique that makes predictions from multiple decision trees, was included for its ability to handle high-dimensional datasets effectively (Wikipedia, 2024; UTEP ScholarWorks, 2020). Together, these models provide a balanced range of complexity and interpretability.

To evaluate how well the models performed, the dataset for each company was split into a training set and a test set using a 70 to 30 ratio. This means 70 percent of the data was used to train the model, and 30 percent was used to test how accurately the model could predict new values. A 70:30 train-test split was chosen to balance training robustness with reliable evaluation. Such ratios are commonly employed in practice for datasets of this size, as noted in Machine Learning Mastery (Jason Brownlee, 2020), and supported by its widespread application in empirical studies.

Simple hyperparameter tuning was done to keep the models efficient and easy to interpret. For the decision tree model, the maximum depth was set to 4, which prevents the model from becoming too complex and overfitting the training data. The squared error criterion was used to make the splits by minimizing the difference between actual and predicted revenue. For the random forest model, 15 trees were used with a maximum depth of 5. This setup helped the model capture patterns in the data while still avoiding overfitting and staying computationally fast.

These hyperparameters were selected heuristically to prevent overfitting while keeping the models computationally efficient and interpretable, rather than through exhaustive tuning; the choices were guided by aiming for a reasonable trade-off between model accuracy (based on MAE) and simplicity.

1.5 Assumptions and Limitations

This study assumes that quarterly revenue can be accurately predicted using only three main inputs: ARPU, subscriber count, and time-based variables like year and quarter. While this approach simplifies the model, it also leaves out other possible factors such as government regulations, inflation, consumer preferences, and competitive actions like price wars. These were not included due to time and data limitations, but they could be explored in future work. Another limitation is the uneven data availability across companies. Vodafone's data starts from 2011, while Airtel and Reliance only began in 2017 and 2018; Reliance entered the market much later than Vodafone, while Airtel only publicly released data from 2017 onwards. This could affect how well the models perform for each company, since a longer dataset often allows for better learning. The 70:30 split for training and testing was chosen based on common practices for small datasets, but using methods like k-fold cross-validation could offer more reliable results. Future studies could explore more sophisticated algorithms such as Multiple Linear Regression with interaction terms, Gradient Boosting Regressors (GBM), or Support Vector Regression (SVR). These methods may capture subtler patterns in the data, handle non-linear relationships more effectively, and improve overall prediction accuracy, especially when trained on larger and wider datasets.

Chapter 2: Machine Learning Models

2.1 Linear Regression

A linear regression (LR) model was used to estimate the total revenue generated. The model uses ordinary least squares (OLS) estimation, which fits a linear equation in the form $y = mx + c$ to the data by minimizing the sum of squared residuals between the actual and predicted revenue values.

The independent variables include:

- Year: to capture time-related trends
- ARPU (Average Revenue Per User): a direct measure of income per subscriber.
- Number of Subscribers: representing the market size.
- Quarter: encoded as categorical dummy variables to reflect seasonal effects.

The output of this model will display three main features, including:

1. A correlation heatmap, which is a color-coded table that shows how strongly your input variables are related to each other and to the target variable (the quarterly revenue). The values in the table will range between -1 and 1 inclusive, with -1 indicating a negative correlation (inversely proportional), and 1 indicating a positive correlation (directly proportional).
2. A line of best fit, which compares the model's predicted revenue to the actual revenue. The red dashed line represents a perfect prediction, and points closer to the red line represent an accurate model.
3. An OLS regression summary, which shows the estimated effect of each predictor on quarterly revenue, the overall model fit (R-squared), and tests of statistical significance to evaluate how well the model explains the variation in revenue.

2.2 Decision Tree Regression

A DTR model generates an estimate by learning simple decision rules from the input variables. Unlike linear regression, the decision tree does not assume a linear relationship but instead splits the data into smaller groups using a tree-like structure of nodes and branches.

The independent variables include:

- Year
- ARPU (Average Revenue Per User)
- Number of Subscribers
- Quarters

The outputs include:

1. A decision tree, which shows how the data is split at each decision node based on subscriber numbers and other predictors to estimate quarterly revenue.
2. A line of best fit, which compares the model's predicted revenue to the actual revenue values in the dataset; points closer to the red dashed line indicate a more accurate prediction.
3. Basic error metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE), which measure how far the predictions are from the actual revenue on average.

2.3 Random Forest Regression

A Random Forest Regressor estimates the total quarterly revenue by combining the results of multiple decision trees trained on different parts of the dataset. This approach reduces the risk of overfitting compared to using a single tree and helps capture complex patterns in the data.

The independent variables include:

- Year
- ARPU (Average Revenue Per User)
- Number of Subscribers
- Quarter

The output of this model includes two features:

- A scatter plot (line of best fit), which compares the Random Forest's predicted revenue to the actual revenue values.

- Error metrics, such as Mean Squared Error (MSE) and Mean Absolute Error (MAE), show how close the model's predictions are to the true revenue figures on average.

Chapter 3: Data Analysis

3.1 Linear Regression

<u>Correlation Heatmap</u>

The correlation heatmaps for Airtel, Reliance, and Vodafone show how each company's key variables relate to one another. The main features considered are ARPU, subscriber count, revenue, year, and one-hot encoded quarterly values.

In Airtel's heatmap, revenue has a strong positive correlation with both subscriber count (0.98) and ARPU (0.93). This suggests that revenue increases are driven by both a growing user base and higher per-user value. ARPU and subscribers are also positively correlated (0.86), meaning Airtel has been able to add users without reducing ARPU. Revenue also increases over time, shown by the 0.98 correlation with the year.

Reliance exhibits a similar pattern in terms of year–to–revenue (0.98) and subscriber–to–revenue (0.93). However, its ARPU is less connected. The ARPU–revenue correlation is 0.77, and ARPU–subscriber correlation is 0.48. This shows that revenue is mostly coming from more users rather than from a higher revenue per user. The relatively low correlation between ARPU and subscriber count might be due to pricing models that attract a wide range of users.

Vodafone's data is significantly different from the other two companies. ARPU and subscriber count have a strong negative correlation of minus 0.84, which means that as more users are added ARPU tends to decrease. ARPU and revenue also show a negative correlation of minus 0.51. This indicates that increasing ARPU is associated with lower total revenue. A possible explanation is that higher paying users are not replacing the volume lost from lower paying users.

ARPU and revenue also show a negative correlation of −0.51. This suggests that increasing ARPU is associated with lower total revenue. A hypothesis for this is that Vodafone may be losing a larger volume of price-sensitive customers when it raises ARPU. In attempting to defend its market share against aggressive pricing from competitors, the company might attract higher-paying users at the cost of losing a significant number of low-ARPU subscribers. This trade-off may result in an overall decline in revenue despite an increase in ARPU.

<u>OLS Regression Summary</u>

In Airtel's model, the coefficient for ARPU is ₹281.37, and for Subscribers, it is ₹393.97 million. This means that for every ₹1 increase in ARPU per month, quarterly revenue increases by ₹281.37 million. For every one million additional subscribers, revenue increases by ₹393.97 million.

In Reliance's model, the coefficient for ARPU is ₹893.51, and for Subscribers, it is ₹361.66 million. This indicates that Reliance's quarterly revenue is more sensitive to changes in ARPU than in subscriber count. A ₹1 increase in ARPU is associated with an increase of ₹893.51 million in revenue, while each million additional subscribers adds ₹361.66 million.

In Vodafone's model, the ARPU coefficient is ₹558.51, and the Subscribers coefficient is ₹254.13 million. Vodafone shows a moderate increase in revenue with rising ARPU and a smaller increase per million new subscribers compared to Airtel and Reliance.

3.2 Decision Tree Regression

The decision tree models for Airtel, Reliance, and Vodafone are evaluated based on how accurately they predict quarterly revenue using input features such as ARPU, subscriber count, and quarterly indicators. The models are assessed using Mean Absolute Error (MAE) and Mean Squared Error (MSE) as the primary evaluation metrics.

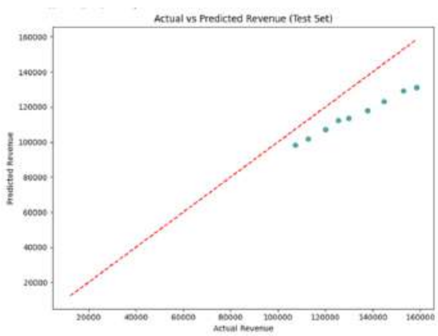
Vodafone's model produces the lowest MAE at ₹5,689.22 million. On average, the predicted revenue is within roughly ₹5.7 billion of the actual revenue per quarter. The predicted vs actual scatter plot shows that most points fall close to the ideal prediction line, though some deviations occur in the middle revenue range. Overall, the model performs well, especially in capturing smaller changes in revenue. The decision tree structure shows that ARPU is consistently used as the top-level split, followed by subscriber count and quarterly features.

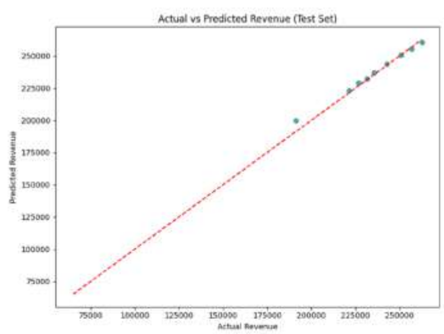
Airtel's model has a higher MAE of ₹9,113.77 million. Predictions are generally close to actual values, but some lower-revenue data points show noticeable underprediction. Despite the higher error compared to Vodafone, the overall trend is still captured. Like Vodafone, Airtel's tree relies heavily on ARPU and subscriber count for its main splits.

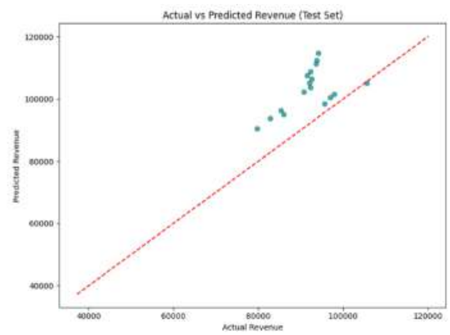
Reliance shows the highest MAE at ₹9,638.02 million; its predictions deviate more on average than the other two models. The scatter plot reflects a wider spread, particularly at mid and high revenue levels. Although the model still follows the overall revenue trend, its accuracy is weaker compared to Vodafone. The decision tree also prioritizes ARPU and subscriber count at the top levels.

Scatter Plots

1. Linear Regression



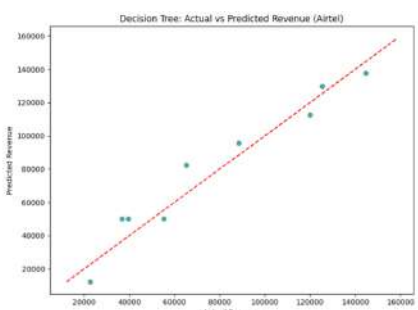


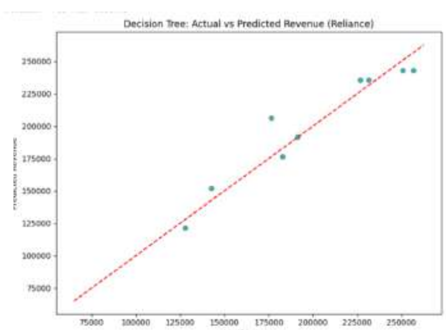


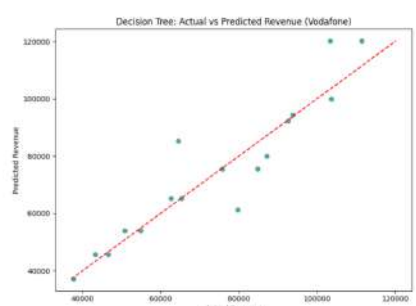
Airtel Reliance

Vodafone

2. Decision Tree Regression



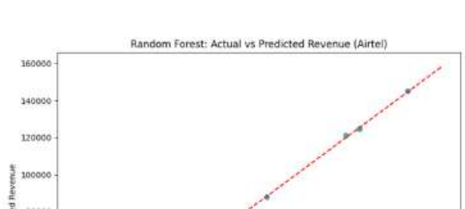


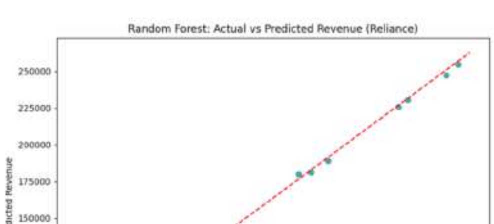


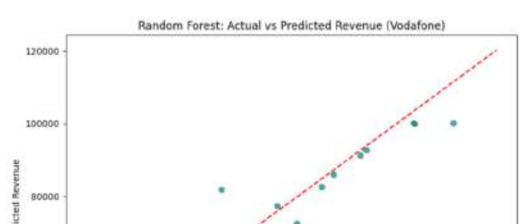
Airtel

Reliance Vodafone

3. Random Forest Regression

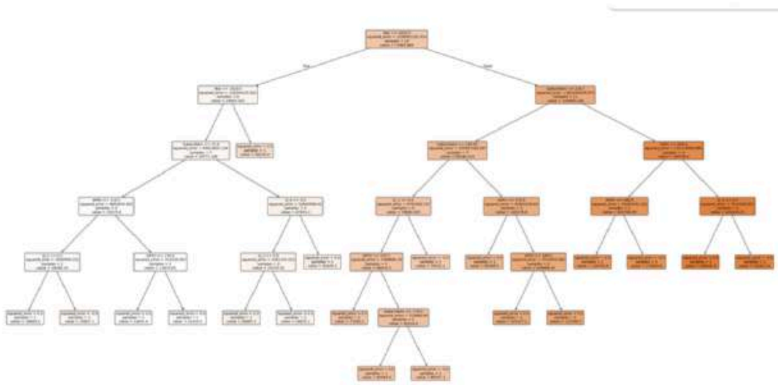




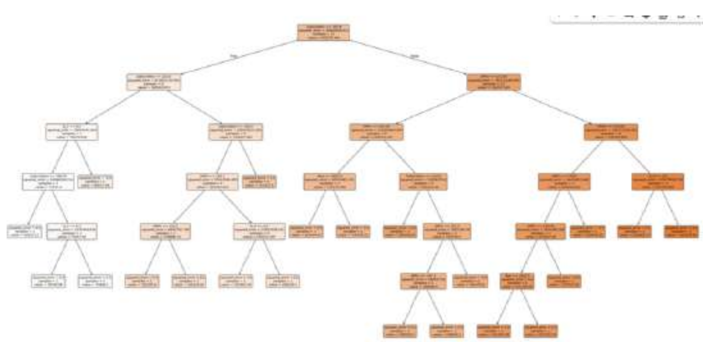


Airtel Reliance Vodafone

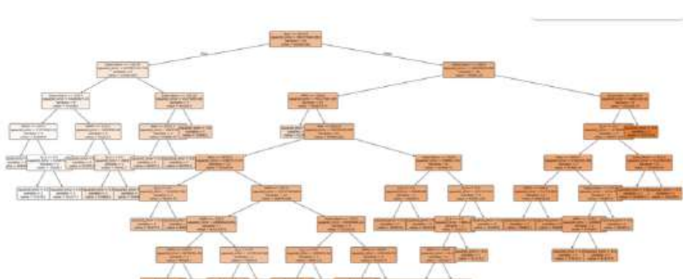
Decision Trees



Airtel



Reliance



Vodafone

3.3 Random Forest Regression

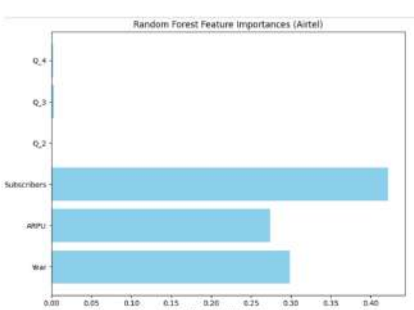
In the Random Forest models for Reliance, Vodafone, and Airtel, subscriber count emerges as the most important variable across all three cases. The model for Reliance assigns the highest weight to subscribers, at around 0.68, while ARPU has a much lower importance score, slightly below 0.10.

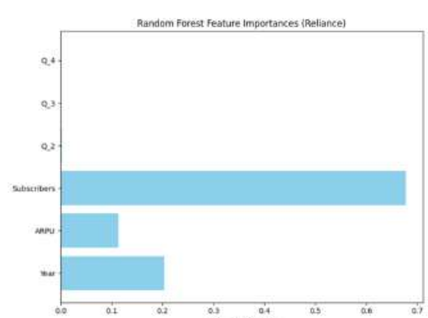
Vodafone's model shows a similar pattern, with subscriber count accounting for roughly 0.66 of the total importance and ARPU contributing only slightly above 0.05. This indicates that the number of users explains most of the variation in Vodafone's revenue, while ARPU has very little effect on the output.

Airtel's model is more balanced. Subscriber count remains the top factor at around 0.41, but ARPU contributes meaningfully at about 0.28. Compared to Reliance and Vodafone, Airtel's model gives greater weight to ARPU, suggesting that both market size and per-user revenue are significant drivers of its total revenue.

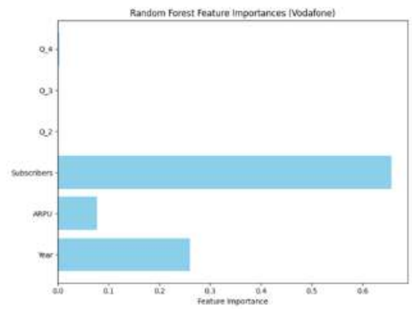
In all three Random Forest models, quarter-based features contribute almost nothing, while the year variable has some importance but remains lower than subscribers and ARPU. Feature importance charts are presented below.

Feature Importances





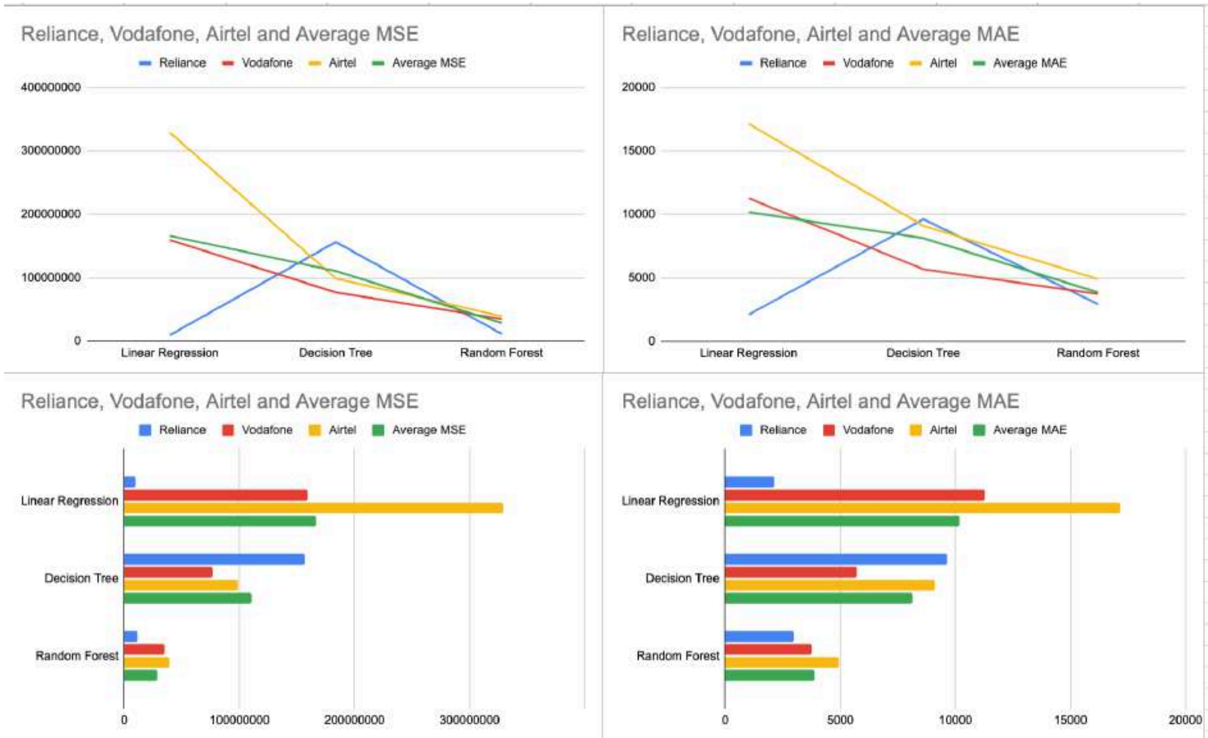
Airtel Reliance



Vodafone

3.4 MAE vs MSE Values

The Mean Squared Error (MSE) and Mean Absolute Error (MAE) were used to evaluate the performance of three models: Linear Regression, Decision Tree, and Random Forest. The models were tested across Reliance, Vodafone, and Airtel using the same set of input features. Both MSE and MAE are expressed in millions. MSE is measured in rupees squared since it squares the errors, which makes large errors more noticeable. MAE is measured in rupees and shows the average size of the error in a more direct way. Using both gives a clearer picture of the model's performance.



The Linear Regression model has the highest average MSE at ₹166,091,375.10 and the highest average MAE at ₹10,182.98. This shows that the model is not reliable. Its predictions have large errors on average, and the squared errors are even more significant, indicating that some predictions are far from the actual values.

The Decision Tree model performs better than Linear Regression, with an average MSE of ₹110,703,108.90 and an average MAE of ₹8,147.00. The model still makes large errors, but both metrics are lower, meaning the predictions are closer to actual values.

The Random Forest model has the best results. Its average MSE is 28,765,956.16, and its average MAE is 3,868.85. These are the lowest values across all models. The predictions are consistently close to actual revenue, and the model avoids large deviations. Random Forest performs well for all three companies.

Chapter 4: Conclusion & Recommendations

Based on both MSE and MAE, Random Forest is the most accurate and reliable model. Decision Tree is second. Linear Regression has the weakest performance. The results show that Random Forest should be used when the goal is to minimise error and improve prediction quality for future revenue.

For future research, one promising direction is to experiment with different artificial intelligence models, such as linear optimization, support vector regression, or gradient boosting methods. These models may capture nonlinear relationships more effectively and adapt better to complex patterns in telecom revenue data. It would also be useful to test different ensemble techniques that combine the predictions of multiple models to reduce error further and improve stability. Applying these approaches on a larger dataset could offer better generalization and more robust conclusions.

Another possible extension of this research would be to calculate the price elasticity of demand. This means checking how sensitive the predicted revenue is when ARPU or subscriber numbers change. For example, by inputting a series of slightly higher or lower ARPU values into the Random Forest model, we could observe how much revenue is expected to rise or fall. This would help companies understand how price changes may impact customer behavior and overall revenue, and could lead to more accurate pricing strategies.

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