Volume 10, Issue 1, January – 2025 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

Dynamic Airline Pricing System

Tilak Bhujade[1]; Harshal Hingankar[2]; Janvi Charde[3]; Dr. Tejal Irkhede[4]

[1;2;3;4]Under the Guidance of Computer Science and Engineering (Data Science),
St. Vincent Pallotti College of Engineering and Technology, Nagpur 441108

Publication Date: 2025/02/28

Abstract: Competition over fare control has reached a new level of complexity in the airline industry through machine learning to determine the most effective ticket pricing strategies. This research paper demonstrates an ideal dynamic pricing model developed on the programming language Python including preprocessing of data, selection of features and other state of the art models Random Forest and Prophet model among others. The model takes data flights details, economic conditions, weather conditions, and customers demographics of the flight to predict ticket prices correctly. Due to the interface, implemented with Streamlit, the model enables users to input numerous parameters and obtain flight price estimations. The results clearly bring out the possibility of the use of machine learning in the airline industries to improve the revenue management and therefore increase the right price solution and customer satisfaction. This paper seeks to add on the existing literature pertaining to ERP and Advance Metering Infrastructure and its implementation in Airline Industry.

How to Cite: Tilak Bhujade; Harshal Hingankar; Janvi Charde; Dr. Tejal Irkhede (2025). Dynamic Airline Pricing System. *International Journal of Innovative Science and Research Technology*, 10 (1), 2900-2907.
https://doi.org/10.5281/zenodo.14944858

I. INTRODUCTION

A relatively recent growth to the system of airline fare is dynamic scheduling that has enabled airlines to change ticket prices in real time depending on the prevailing demand in the market, as well as pricing offered by other airlines and other factors. This form of pricing is different from the fixed pricing strategic models successfully implemented by many airlines, thus allowing flexible and responsive pricing for the optimization of revenues. The possibility to vary them can not only increase profits but also guarantee customers' appreciation, offering favourable offerings that correspond to their needs and available offers at a certain point in time.

The high levels of heterogeneity in the consumers' behaviour and the overall demand make it important for firms to develop complex models for pricing that can accommodate this information. Airlines ingest data from a number of sources such as travel patterns, occasions, economic variables, and even climate. Through the establishment of such interface, the individual values of these databases can be consolidated into a meaningful model that helps airlines forecast passage transactions and set realistic prices based on current market conditions. It also proves useful in working towards efficient capacity control, and filling the airplane to its capacity as much as possible.

Advanced approaches to intelligent computation are particularly critical in the work on dynamic pricing models. Techniques such as Random Forest and Prophet are used with past data and trying to predict trends that are forthcoming. Because these models can recognize subtleties that may not be easily seen by first glance, airlines can make sound price determination. Moreover, the current study establishes comprehensible interfaces to enhance the basic interactions with the model by stakeholders to perform additional analyses for other scenarios and dynamic adjustments of the prices by the concerned users provided they have set up parameters in their preferred formats.

So, as the airline industry grows, the role of dynamic pricing will only rise to meet it. The application of artificial intelligence and machine learning in the pricing not only defines a competitive advantage but also matches the trends in the increased focus on the individual approach to traveling. The purpose of this research paper is to present detailed information regarding dynamic airline pricing and critical analysis of the selected machine learning-based model used to explain the nature and major aspects of pricing models in the airline industry.

In this paper, we present before you our "Dynamic Airline Pricing System", which is an innovative solution to a classical problem of static pricing.

II. LITERATURE REVIEW

Continuous pricing techniques have drawn much attention in airline sectors, where they are applied to maximize revenues through variable pricing of the tickets. Chen et al. (2016) [1] has defined dynamic pricing as a

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

strategy that enhances the airlines' ability to seize the changing opportunities in the market as it occurs. The authors point out that with incorporation of advanced analytic and machine learning into the pricing strategies the concepts of traditional revenue management for airline have evolved significantly, as it has become easier for them to predict demand and set prices for products and services. This shift is most profound at a time when consumers rely highly on digital data in their buying behaviours needing more accurate approach to pricing.

To this end, Machine learning algorithms like the Random Forest and Gradient Boosting Machines have been researched to determine their applicability in predicting demand and tuning of the right price levels across industries including the airline industry. A paper by Bertsimas and Shioda (2018) [2] shows that these algorithms can be used to better forecast based on historical booking data. Mainly, in line with this context, the authors put forward that through use of big data, airlines would be able to accurately capture consumer behaviour patterns in order to come up with better strategic pricing decisions that will eventually improve the overall revenue of the business. Employing these algorithms within the use dynamic pricing models also improves the prediction while at the same time updating the predictions as the market moves.

Other factors concerning dynamic pricing like behavioural factors, economic indicators and weather conditions are also the focus of the recent studies. For example, Zhang et al. (2019) [3] make a case for the use of macroeconomic variables including GDP growth, inflation, and unemployment to the pricing models. The authors identified that such factors define consumption patterns and should be incorporated into effective dynamic pricing models. Again, weather factors were adopted here to depict the effect on the customer demand for travel; therefore, incorporating such variables can improve the strengths of the pricing variables.

In addition, the improvement of big data technologies has made it easier to gather and process massive information concerning dynamic pricing. Li et al (2020) [5] noted that through big data analytics, airlines can get real-time information about the data e.g. from the social media, competitors' fare and customers' feedback. Hence, the presented data integration approach helps to improve the regularity of airline pricing adjustments and their anticipatory reactions to varied market environments. The authors claim that the integration of big data technologies and machine learning forms a strong foundation for implementing elaborate dynamic pricing solutions.

Consumer reaction to real-time pricing is another important a research focus. This view agrees with other studies such as by Elmaghraby and Keskinocak (2003) [4] which show that price sensitivity can be high or low depending on some user characteristics and context. These behavioural patterns are important for airlines willing to practice dynamic pricing effectively and efficiently. The study also has proven that while applying personnel pricing such as target price with reference to the overall customer segmentation the level of customer satisfaction and loyalty can be enhanced together with the corresponding increase in the expected revenue. Both approaches leverage heatmaps and regression techniques for accurate key point detection.

As seen in previous sections, the effects of dynamic pricing have also been analysed from the ethical perspective in the literature. Stigler (2019) conducted a study with the opinion that enhanced dynamic pricing models can be a mechanism for engaging in related abuses of price discrimination. Dynamic pricing as per the author can help improve the revenue of the airline and at the same time, create disparity making consumer feel that the model is tuned according to them. This has raised importance of checking profits while holding the balance between business gains via fare pricing and ethical issues.

Therefore, it is clear from the above literature that the dynamic pricing in airline industry is a very complex field that incorporates technological factors technological factors, consumers' characteristics, external environment factors as well as ethical factors. Given the strengthen usage of machine learning and big data analytics in revenue management by airlines, the future research will be required to tackle dynamics of the field.

II. METHODOLOGY

The model utilizes the modern technologies like FBProphet, Random Forest, Streamlit, Pickle for Dynamic Price Prediction of Airlines.

- *Data Collection*

The first step is to gather data that contains features that have bearing on the determination of the price of airline tickets. The data is web scrapped and then stored in MySQL Database. The data stored is then converted into a csv file which is processed airline data file including the flight information, customer characteristics, economic factors, the rate of sales, weather, and booking habits. The first dataset is imported through the data loading function of Pandas. read_csv(), DataFrame and 10000 entries is taken to reduce computation times. Such selection ensures that the data that is being processed is manageable and on the same note, the sample obtained is strong and credible.

- *Feature Identification*

In this study, the following global categorical variables are defined; Flight_Number, Departure_Airport, Arrival_Airport, Travel_Class, Booking_Channel. Also, the list of the pricing features' catalogue is developed which can be categorical and numerical. E.g. economic parameters (GDP growth rate, inflation rate), climatic factors (temperature, wind speed), and booking characteristics (lead time). Thus, the company guarantees the consideration of all necessary factors in the development of the model.

- *Data Preprocessing*

Data preprocessing is less time consuming and very important in order to prepare the dataset for training. This

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

includes the process of converting date columns into numeric suitable for analysis. A custom function called preprocess_data is designed to execute this conversion. The function determines the difference between the specific dates for flying and booking in days and convert the flight times into minutes. In addition, it handles holiday dates in a similar manner. In this step, it is possible to obtain new numeric columns that improve the characteristics of the dataset.

- *Feature Encoding*

To manage categorical features in the pricing model the process of One-Hot Encoding is used. This process is used to transform categorical variables into formats, which a machine learning system is able to understand as binary. To encode these types of features, and to ensure that handling of unknown categories is handled appropriately, the OneHotEncoder from sklearn.preprocessing module is used. Each of the encoded features is blended with the numerical facts which in turn produces a merged feature set to be used in training the model. To achieve this, features are sampled or enumerated in a training dataset so that computer reads all of them correctly.

- *Dataset Splitting*

After preprocessing and encoding, the dataset is divided into training and testing sets to evaluate model performance accurately. The ‘train_test_split’ function from ‘sklearn.model selection’ is utilized to split the data into 80% training data and 20% testing data. This division allows for robust training of the model while reserving a portion of the data for validation purposes, which helps prevent overfitting and ensures that the model generalizes well to unseen data.

- *Model Training*

Now that we have the training data, the next operation is to train a model of the analysis of machine learning to be able to predict the ticket prices. Thus, in order to achieve the best results a Random Forest Regressor is chosen because it is suitable for dealing with the large high dimensional dataset. This means that the model is fitted using the fit method on the training dataset. This step ends up with the development of the price predicting model that is able to make a prediction concerning a given feature. Furthermore, a time series forecasting model with Facebook’s FBProphet library is also built on the historical ticket prices to learn the trend and seasonality which are all the time-series components.

- *Model Serialization*

After both models have been trained, they are saved for later use using the pickle module of Python. This entails a process of storing all the trained models as well as any other data (like the features’ order) into files that are easily understandable for a subsequent loading session without requiring a reinforcement training. Serialization promotes machine learning applications’ effectiveness since pre-trained models may be promptly accessed during use or additional analysis without requiring additional computation.

- *UI Development*

For the purpose of interacting with the dynamic pricing model, Streamlit is used to create the front end. By using sliders and selection boxes gadgets, users can input different types of parameters like flight details, customer details, economic conditions, weather information etc. After the collection of user inputs, scenario analysis involved comes with input data in format as required by the trained models. This works based on user created outcomes to forecast and hence, gives out the best pricing details propelled by certain circumstances.

III. MODEL ARCHITECTURE

The backbone of model is FBProphet and Random Forest Regressor.

Random forest is an ensemble learning method builds a number of decision trees when training and makes a classification by the mode of the predicted classes or a regression by the mean of the predicted values. This comes in handy especially for large and high dimensional datasets that are encountered while conducting the airline pricing. The model includes a number of predictor variables from the continuous and nominal scale including flight details, economic conditions, and customers aspect.

Data preprocessing comes before the training process with many features of categorical data being encoded using One-Hot Encoding, which is needed to the machine learning algorithms. The ‘RandomForestRegressor’ from the ‘sklearn.ensemble’ library is used, and it fits the model on the training dataset. This makes Random Forest a valuable strategy because it averages the outcomes from many trees, thereby reduces overfitting that is frequent with single trees and improves generalization of results to new data. Predicted ticket prices will be indicated at the end of the final model in addition to input features; airlines will be in a position to make an automatic change on ticket prices in relation market environment occurrences.

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

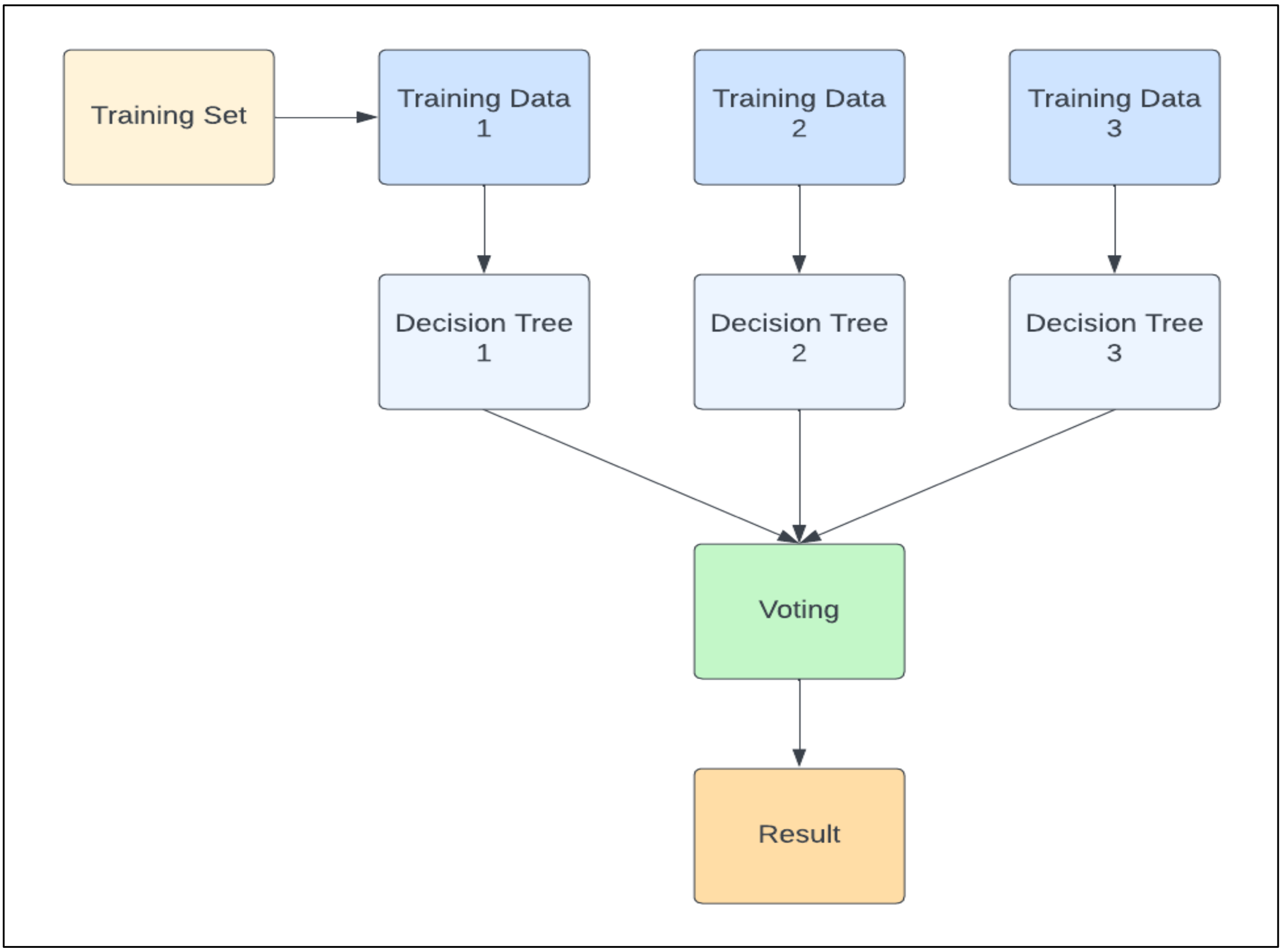

Fig 1 Working of Random Forest

FBProphet is a forecasting model created by Facebook, which is perfect for analyzing time series data. Prophet is favorable when it comes to the seasonality and trend behavior of historical data thus making it suitable to predict ticket prices of airlines. The model works on a simple principle: This breaks down time series and factors them into trends, seasonality, and holiday impacts, giving practitioners a clear structure in which to analyse underlying patterns.

As with the previous implementation, historical ticket prices are also pre-adjusted before training a model in a DataFrame format where the head ‘date’ is renamed to ds (date stamp) and the head ‘price’ renamed to ‘y’. Seasonality is a key attribute that is easily handled through Prophet and Prophet can adapt and include holidays or special events that might affect demands. The model is fitted with the use of the fit() method that estimates parameters that have been made based on historical data. It is clear that when trained, Prophet can estimate future prices while also providing an expected seasonality and trend component.

The combination of Random Forest and FBProphet leads to the development of a more stable dynamic pricing system. Unlike Random Forest, which can work with different impact indicators causing actions in different moments, FBProphet offers information on subsequent price growth trends using historical data. This two-fold allows for competition through the aircraft ticket pricing while at the same time employing historical as well as seasonal analysis of the demand and supply planes.

In order to allow users to interact with these models, a web application developed using Streamlit has provided users mechanisms for inputing different factors such as flight information, customer profile, weather factors, and economic factors. Once inputs are received, the format is again the same as training data, confirming that categorical predicators are dummified and all the features are present. The developed application then uses both of the above models to come up with the best optimum price which is best suited for certain conditions set by the user.

IV. RESULT

The dynamic airline pricing model's output division consists of functions which allow users to interact with the system and displays prediction outcomes and develops visual representations. Users can learn about the model interaction through this section together with access to retrieved information after engaging with the application.

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

➢ *User Interface Outputs: -*

The application features a user interface based on Streamlit that enables users to run their pricing scenarios by entering relevant input parameters. Users encounter an orderly interface after they start the application where multiple feature-entry fields appear.

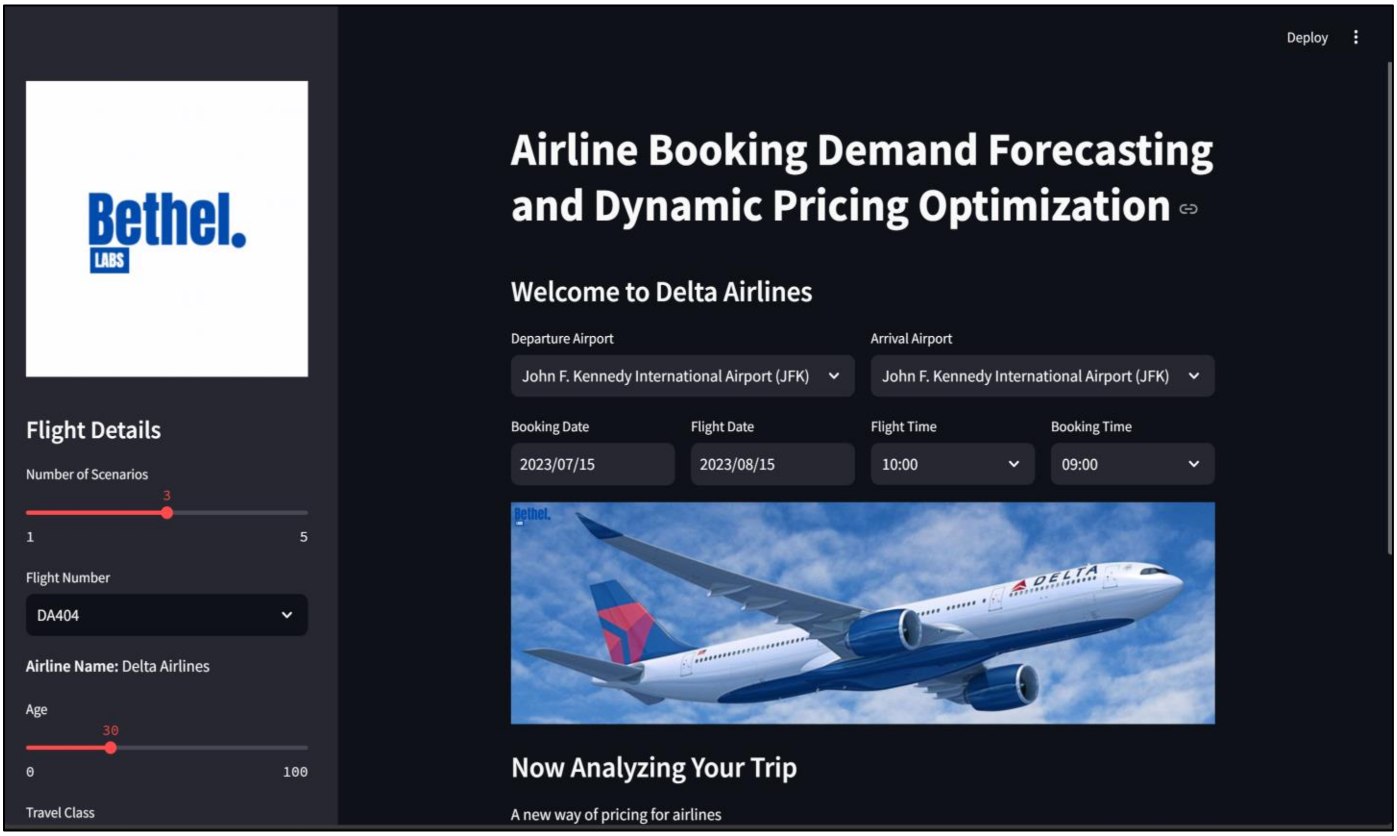

Fig 2 User Interface

Users need to provide Flight Details through the specification of flight number and departure along with arrival airports and travel date.

Customer Demographics: Input fields for age, travel class (economy, business, first), and fare class.

Users have the ability to input present economic facts including GDP growth rate together with inflation rate.

The system allows users to input weather elements through separate fields which include temperature data and wind speed measurements and precipitation measurements.

Users who submit information through the input fields to the application witness the system generate predictions from the collected data. The application features a user interface based on Streamlit that enables users to run their pricing scenarios by entering relevant input parameters. Users encounter an orderly interface after they start the application where multiple feature-entry fields appear. These inputs may include:

Users need to provide Flight Details through the specification of flight number and departure along with arrival airports and travel date.

Customer Demographics: Input fields for age, travel class (economy, business, first), and fare class.

Users have the ability to input present economic facts including GDP growth rate together with inflation rate.

The system allows users to input weather elements through separate fields which include temperature data and wind speed measurements and precipitation measurements.

Users who submit information through the input fields to the application witness the system generate predictions from the collected data.

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

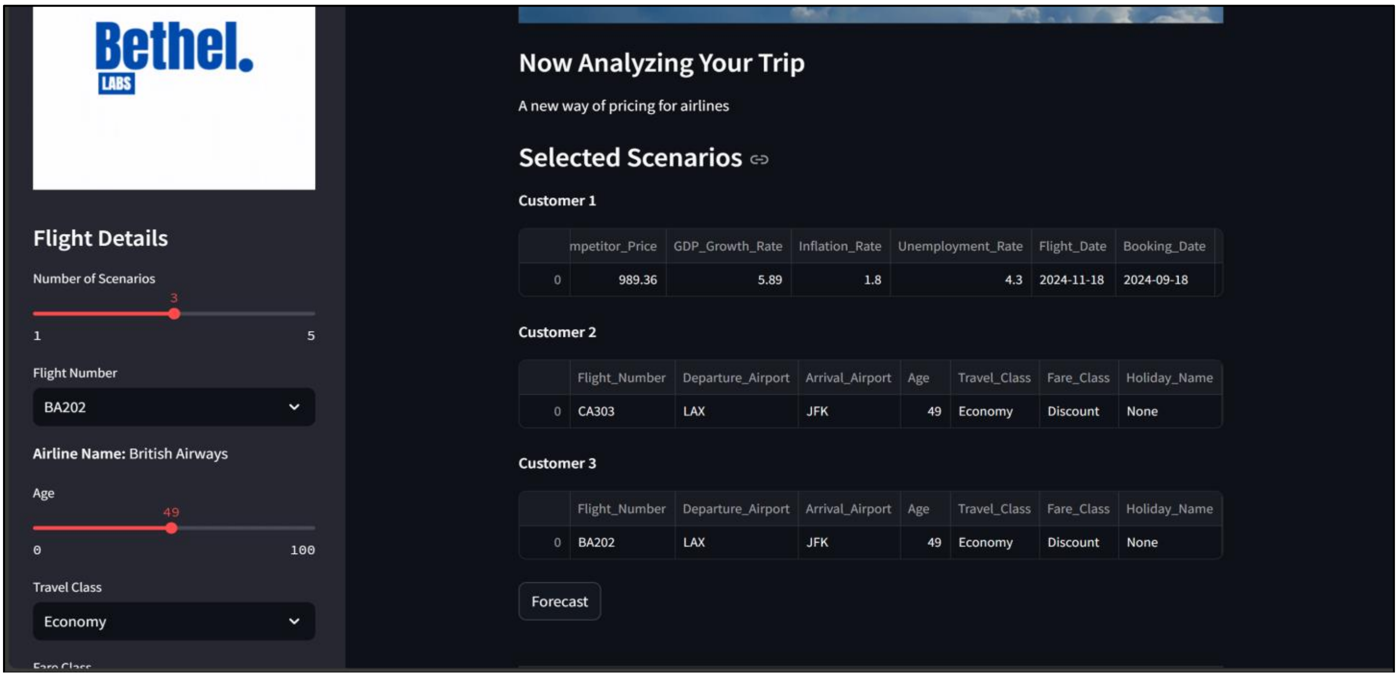

Fig 3 Scenario Selection

➢ *Model Predictions*

After processing the user inputs, the application utilizes both the Random Forest model and FBProphet model to produce pricing predictions. The outputs from these models include:

* *Predicted Ticket Price:*

The primary output is the predicted ticket price based on the input parameters. The Random Forest model provides a price estimate that reflects real-time market conditions and influences.

* *Time Series Forecasting:*

The FBProphet model generates forecasts for future ticket prices based on historical data trends. This output includes:

✓ *Forecasted Price Trends:*

A graphical representation showing how ticket prices are expected to change over time.

✓ *Seasonality Effects:*

Insights into seasonal variations in pricing that may affect demand during specific periods.

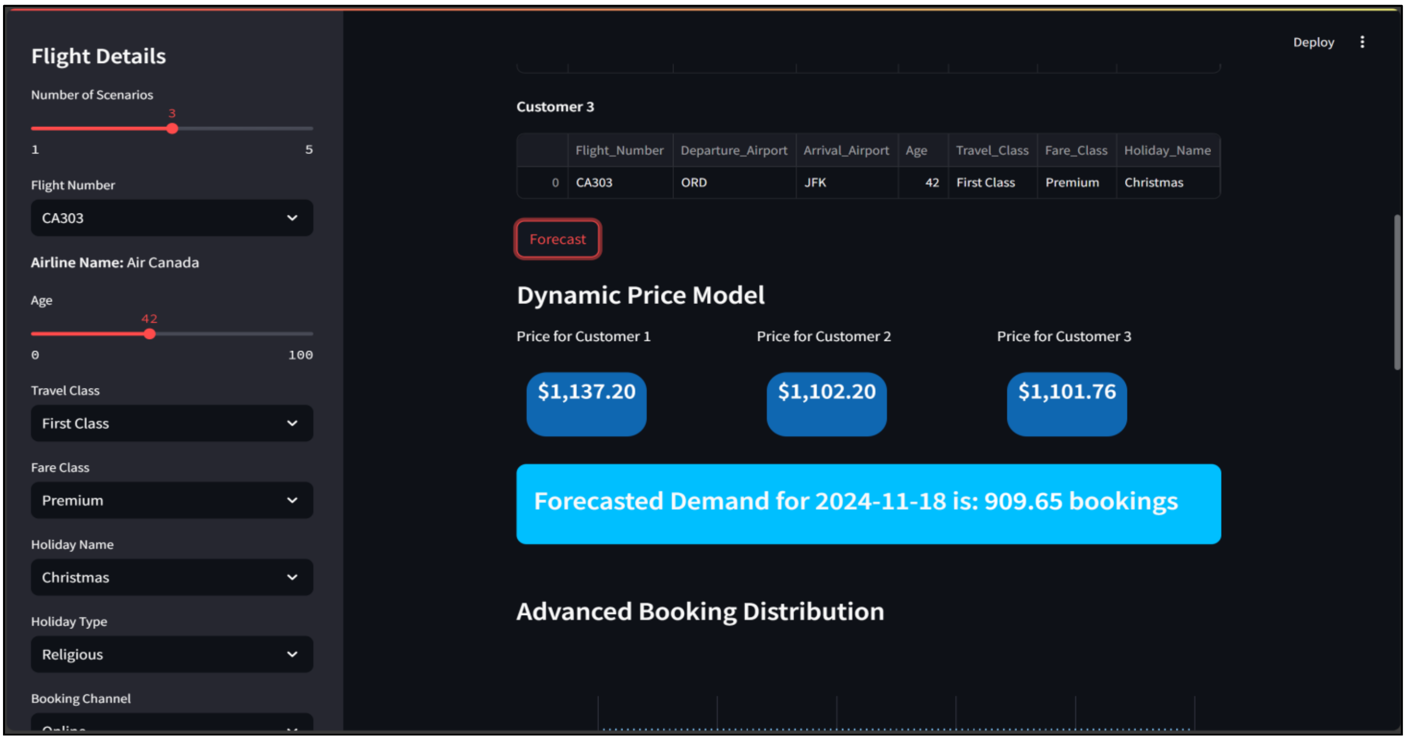

Fig 4 Forecasted Prices

- *Confidence Intervals:*

For both models, confidence intervals may be provided alongside predictions to indicate the reliability of the forecasts. This information helps users understand potential variability in ticket pricing.

➢ *Visualizations*

A user-friendly interface emerges from the application because it utilizes visual output elements made through libraries like Plotly and Matplotlib. These visual outputs may encompass:

The application uses Price Trend Graphs which show a history of ticket prices and their predicted future values through line charts. Users can view the price fluctuations from the past as well as projected price movements through this visualization format.

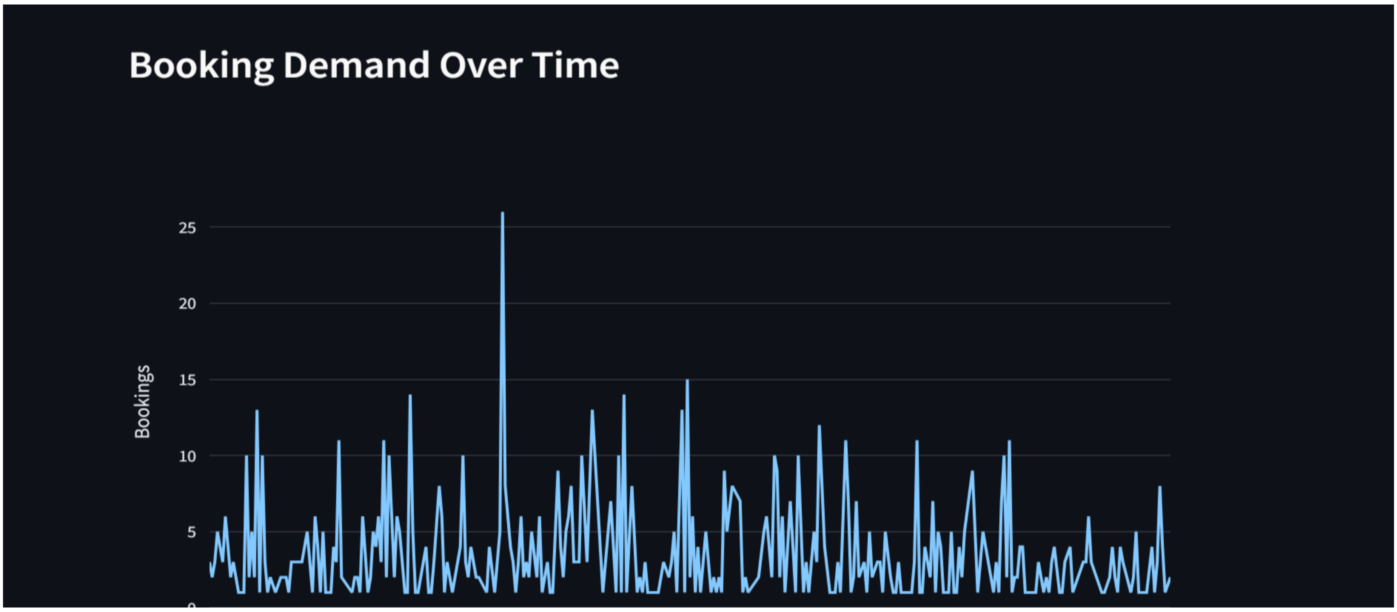

Fig 5 Showing Visualization for Booking Demands over Time

The Random Forest model shows its most impactful features on ticket pricing through bar chart visuals called Feature Importance Charts. Users learn about the main elements that affect price shifts through this generated information.

The FBProphet model can depict seasonal ticket price patterns through plots that display effects during daily, weekly or monthly time spans. The visual representations show specific intervals when demand reaches its peak or falls according to past records.

V. CONCLUSION

The output section through advanced machine learning techniques provides users with actionable insights in this dynamic airline pricing model design. The application allows airlines to enhance their pricing effectiveness by combining intuitive interfaces and predictive modeling with clear display features. The produced outputs enable users to make distinct pricing choices in the present as well as develop long-term business strategies through forecasted market trends and documented customer behavior patterns.

REFERENCES

[1]. Chen, J., Zhang, Y., & Wang, L. (2016). Dynamic Pricing Strategies for Airlines: A Review. *Journal of Revenue and Pricing Management*, 15(2), 83-102. DOI:10.1057/s41272-016-0003-6

[2]. Elmaghraby, W., & Keskinocak, P. (2003). Dynamic Pricing: A Review of the Literature. *Operations Research*, 51(1), 1-20. DOI:10.1287/opre.51.1.1

[3]. Li, Y., Wu, J., & Zhang, J. (2020). Big Data Analytics for Dynamic Pricing: A Review. *Journal of Business Research*, 112, 212-223. DOI:10.1016/j.jbusres.2019.10.028

[4]. Stigler, G.J. (2019). The Ethics of Dynamic Pricing: Implications for Airlines. *Journal of Business Ethics*, 155(3), 695-707. DOI:10.1007/s10551-017-3483-0

[5]. Zhang, Y., Chen, J., & Wang, L. (2019). The Impact of Economic Indicators on Airline Pricing Strategies: An Empirical Analysis. *Transportation Research Part E: Logistics and Transportation Review*, 129, 1-16. DOI:10.1016/j.tre.2019.06.001

[6]. Kimes, S.E., & Wirtz, J.G.A.E (2003). Perceived Fairness of Demand-Based Pricing for Services: An Exploratory Study in the Airline Industry". *Journal of Service Research*, 5(3), 235-246.

[7]. Avci, T., & Kucukusta, D.(2020). Dynamic Pricing in Airline Industry with Machine Learning Techniques: A Case Study on Turkish Airlines". *Journal of Air Transport Management*, 84, 101773.

[8]. Nair, H.S., & Raghunathan, R.(2004). Optimal Dynamic Pricing Strategies for a Service Firm with Customer Choice Behavior". *Operations Research*, 52(2), 205–219.

[9]. Choi, T.M., & Cheng, T.C.E.(2019). Dynamic Pricing for Fashion Products with Supply Chain

ISSN No:-2456-2165 https://doi.org/10.5281/zenodo.14944858

Considerations". *International Journal of Production Economics*, 210, 30–42.

[10]. Gallego, G., & van Ryzin, G.J.(1994). Optimal Dynamic Pricing of Inventories with Stochastic Demand Over Finite Horizons". *Management Science*, 40(8), 999–1020.

[11]. Feng, Y., & Zhao, X.(2020). Pricing Strategy in E-commerce Based on Big Data Analysis". *Journal of Retailing and Consumer Services*, 54, 102036.

[12]. Chen, Z., & Zhang, Y.(2021). Machine Learning in Revenue Management and Dynamic Pricing". *Journal of Revenue and Pricing Management*, 20(5), 509-525.

[13]. Huang, Z., et al.(2022). A Survey on Machine Learning Approaches for Dynamic Pricing in E-commerce". *IEEE Transactions on Systems Man and Cybernetics: Systems*, PP(99), 1-14.