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An Effective Resource Allocation and Revenue Generation for Rental Vehicles

Hrushikesava Raju Sangaraju[1,2*], Sivaneasan Balakrishnan[2], Siva Shankar Subramanian[3], Tulika Chakrabarti[4], Prasun Chakrabarti[4], Martin Margala[5]

[1] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Guntur 522502, India
[2] Singapore Institute of Technology, Singapore 138683, Singapore
[3] Department of Computer Science and Engineering, KG Reddy College of Engineering and Technology, Hyderabad 501504, India
[4] Department of Computer Science and Engineering, Sir Padampat Singhania University, Udaipur 313601, India
[5] School of Computing and Informatics, University of Louisiana at Lafayette, Lafayette 70503, USA

Corresponding Author Email: hkesavaraju@gmail.com

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ABSTRACT

Dynamic pricing on seat selection contributes good revenue during demand, and forecasting of income using events occupancy is lagging are to be addressed by novel methods. The passengers, who may not have the purchasing capability of a 4 wheeler must prefer to share the facility for savings. The crucial aspects are customer comfort and knowing price drops in advance. The proposed system is a hybrid upfront that consists of modified ARIMA, and GBM to accurately forecast income based on filled events occupancy. This system not only provides integrated features such as applying discounts on specific scenarios, a dynamic seat selection, individual track of the vehicle, and predicting income of future days. The Firsts Come First Serve (FCFS) and seat ranking have been integrated into the evolution of a hybrid method that also outputs good revenue. The evaluation is compared against existing approaches. The outcome is an effective way of selecting the seat as per their choice, and the event occupancy cut-off is reached. This feature guides the driver community to raise seat prices or drop prices would generate revenue as well as maximize passenger comfort.

1. INTRODUCTION

There are many scenarios that demand customer comfort while opting for transport apps and related services. Although there are local apps, national apps like OLA, Uber, and many others serve the transport service by means of renting for their journey. In all these, two features need to be incorporated such as one focuses and elevates on seat selection as per customer choice and to pay for that seat selection. The second is optimal revenue generation using dynamic pricing based on demand. These two may enhance customer satisfaction. This also helps to generate profitable revenue for the vehicle owner as well as the application owner. In the studies available, many algorithms are proposed for seat selection and few algorithms are proposed for variable fare imposition for the customer choice of selection that results the comfort.

In today's travel-oriented world, ensuring passenger comfort is paramount for rental vehicle companies. Seat selection, a seemingly minor aspect of the rental process, can significantly impact travelers' overall experience. However, existing seat selection methods often fall short of catering to individual preferences, leading to discomfort and dissatisfaction. To address this challenge, a novel and efficient algorithm for personalized seat selection in rental vehicle apps has been proposed. This algorithm leverages a multi-criteria decision-making (MCDM) approach, meticulously evaluating seat options based on various factors, including seat characteristics, passenger profiles, and vehicle types.

At the heart of this algorithm lies a user-friendly interface within the rental vehicle app. This interface empowers travelers to articulate their desired seat characteristics, passenger profile information, and vehicle type preferences. These preferences are then fed into the algorithm, enabling it to make personalized seat recommendations tailored to each traveler's unique needs. The efficacy of this algorithm was rigorously evaluated using a comprehensive dataset of rental vehicle bookings and passenger preferences. The evaluation revealed that the algorithm's seat selection recommendations consistently outperformed those made by human experts, demonstrating its ability to optimize passenger comfort and satisfaction.

There exists variety of methods for seat selection, advantages and demerits of those methods are highlighted in Table 1.

Table 1. Pros and cons of methods used for revenue generation

Algorithm	Pros	Cons
Linear Regression	Simple to understand and interpret, fast to train, works well for linear relationships	Limited to linear relationships
Lasso regression and Ridge regression	Regularization techniques that address over-fitting in linear regression, good for feature selection (Lasso)	Less interpretable than standard linear regression
Random Forests and Gradient Boosting Machines	Powerful ensemble methods for both regression and classification, handle non-linear relationships, robust to outliers	Can be computationally expensive to train
ARIMA	Effective for time series forecasting, captures seasonality and trends	Limited to stationary time series data
Recurrent neural Networks (RNN)	Can handle sequential data, good for tasks like language translation or machine translation	Complex architecture
LSTM	Special type of RNN designed to handle long-term dependencies in sequential data	Complex architecture

The above approaches demand for efficient allocation based on user interface, policies incorporated, and automatic discount applied on not filling seats by our hybrid optimal approach. The hybrid optimal approach seeks for the allocation of all seats to be filled, which generates revenue. The hybrid optimal approach involves steps like as follows:

Step1: Better User interface design with seat details

Step2: Auto collection of events using calendar feature

Step3: Design of hybrid optimal approach works for each user, and for driver

Step4: Apply user preferences over the seat selection to the user

Step5: Confirming and proceed further

Step6: Driver may use discount price on seats to fill the seats on less demand times

Step7: Driver uses Predicting of income based on events occupancy reached

Step8: Exit with feedback

Among these steps, step3 to be defined in the proposed methodology in which many inputs are considered like fare, seat details like beside window, free boot space, discount amount on rare seats, dynamic policy injection based on seats filling to complete all seats to be filled, and ambiance quality.

Although there are many approaches in the context of data structures, the specific application decides which approach is to be suitable for handling the scenario efficiently. The drawback of FCFS is that some seats never fill up due to their proximity and user preferences. The drawback of the best-fit approach is searching takes more time, and results in unused memory because of fragmentation. The drawback of the greedy approach is provides always local optimal solution but does not guarantee a global optimal solution. The drawbacks of using optimal approaches are computationally expensive which would be minimized. In order to avoid these issues, a hybrid optimal approach is required and that would be customized as per application-specific yields far better results.

Here, there is a scope to know specific features that present applications used for rental vehicles. The status of such applications was quoted against specific features that are summarized in Table 2. The five columns in which each column denotes the specific feature. These features helped to design a hybrid optimal system.

From Table 2, the first column feature denotes driver has the option to increase or decrease fares based on real-time scenarios, users would see details on that driver dashboard, the second feature denotes occupancy of events of a day notification to the driver, to take decision to increase or decrease fares, the third feature denotes income to be earned based on occupancy of events of a city where their vehicle is in locality, the fourth feature denotes fare of a seat to be displayed to the user when selects the seat as per their comfort, and fifth feature denotes fares to be adjusted based on guidance of AI and based on events occupancy of a specific day.

Table 2. Existing applications status on specific metrics

Application	Discount Customization by Driver Itself	Auto Event Occupancy Calendar Notification	Forecasting of Income	Personal Seat Selection	Dynamic Pricing
Meru	X	X	X	In Process	X
Ola	X	X	In Process	In Process	X
Uber	X	X	In Process	In Process	X
Rapido	X	X	X	X	X
Mega	X	X	X	X	X

2. BACKGROUND WORK

There are various studies on seat selection in the traveling mode in which the majority were on seat bookings in the flights (airlines). Among them, specific studies focus on per descriptions of references listed. From Guerriero and Olivito [1], the discussion is on applying one method such as dynamic programming and logistic operator in the car rental zone is framed as a policy. In various scenarios, the specific criteria are addressed in overcoming the challenges faced during this scenario. In regard to Haensel et al. [2], the usage of capacity controls and fleet distribution forms a novel method called stochastic program at rental stations. The result is analyzed over a small network management over a set of scenarios.

In the view of the study [3], the analysis is done from 2019 to 2027 that involves the evolution of technology in which self-driving cars and autonomous features would dominate as per prediction and usage of vehicles. This leads to a reduction in rental prices. The graph also demonstrated showing technology usage and price drops. From the study of Oliveira et al. [4], the profit computed using pricing and capacity integration and biased random key generation method against a hierarchical approach is compared and discussed. It makes use of initial prices, fitness calculation, decomposition, and relaxation concepts, and even uses constraints. From Yang et al. [5], it compares a proposed model called the hybrid approach that consists of Holt-Winters as linear and backpropagation as nonlinear models. The bias errors, effectiveness, and feasibility are addressed, and are satisfied with the results obtained.

In the context of Fiig et al. [6], discussion on methods such as single leg model and multiple airline network models experienced that increase or decrease price elasticity parameter bias. This would result in a revenue reduction of 1% or 4%. This work is oriented towards airline revenue.

From Wang et al. [7], the invented approach implemented in two modes which first mode works based on decision tree induction for decision making, and the second mode finishes analysis using Shapley additive prediction (SHAP) using important influencing factors (such as the price of the ticket, preferences of the user, and duration of journey) that results in better interpretation. In the regard of Rouncivell et al. [8], the demonstration of bi-variant analysis for seat selection results in either of negatively (price of seats) or positive (reputation and frequency of takeoffs) correlation. The efficiency of this study depends on past experience of seat selection, fares, frequency of take-offs and results of ancillary returns.

From the study of Ivanov [9], demonstrates the logic of to whom seat selection is to be disabled, and to whom, the seat selection to be enabled could be evaluated by the seat selection algorithm. In this, the lock is imposed on selected stations, before the starting station, and after the target station, the lock is released that allows to book of the tickets if there are seats. The study of Boyar and Larsen [10], demonstrates an algorithm called FFBF which stands for First Fit Best Fit approach (based on FCFS), allows to book for long length duration stations than short length. The internal algorithm used to confirm the seats is a randomized method. From the study [11], it demonstrates the various levels of booking tickets using VIP, ladies, impaired level, and old citizen. The preference is to be given to the passengers who are of type single women, old couples, newly married couples, children, and handicapped people but there is no existence of selection of seats before tatkal and at the tatkal time.

From the study [12], it elevates how to log into the railway system, search for a train, enter passenger details, and make payment. One payment is made, and tickets to be confirmed if there are vacancies are there. The description is elaborated using ER, DFD, activity, and sequence diagrams. The study [13] demonstrates the Java code for movie ticket booking, in which seat is the two-dimensional array that keeps track of filled and not filled seats. Deshpande et al. [14] demonstrate the car rental app for users who are traveling to high rates places, and many other characteristics are taken into focus such as vehicle type, location, history, and rental patterns. The analysis of the application allows to use its services effectively.

From the study [15], it shows various policies set for customers, drivers, and owners of the app, and imposes feedback on those to evaluate, and monitor the progress of the app, and its services. Chen et al. [16] demonstrate student choice of seating environment, which helps the student to involve in the course delivery and activities. The environment builds student learning experience, and strategies, and facilities are available that nurture all-round fusion gamified scenarios. This environment addresses and overcomes various competencies, and provides a holistic atmosphere that is suitable to do practicals, activities, and multi-modalities.

From Losonczy-Marshall and Marshall [17], demonstration of the bifurcation of students' mindset and their performance, other factors would be influenced by the selection of seats. The student seat selection is assessed by a set of questionnaires. According to their answers, these questionnaires were grouped into five categories. The seat sitting may be among first, back, sides, middle, corner, etc. Zhao and Zhao [18] demonstrate an increase in earnings especially in the HSR route by booking tickets using nonlinear programming. The various factors are taken into consideration such as preferences, specific timing, number of stops, and different segments of the compartments, etc. This exercise and practice would increase the revenue management of railways. Ko et al. [19] demonstrate re-assigning the seats when an aircraft was canceled and assigned another aircraft for traveling in which seat allotment to be taken place. The mathematical-based allocation is used which assigns intelligently when there is grouping of seats are there. In the airways, the seat selection taken place in advance as per availability and customer choice. From the study [20], it demonstrates the variety of layouts that event planners are supposed to apply for the events and may experience the customer feedback. It leads to innovative styles of arrangements of the seating patterns and allows registering the customers by group or individual as per their preferences.

Milne et al. [21] demonstrate a staged procedure that takes the passengers based on their luggage in the first phase, and weighted slack times to be maximized using a mixed integer programming concept. The outputs demonstrated using this approach would be better using this proposed model. Zhou et al. [22] demonstrate the increase of revenue using the logit model and annealing approach by applying various pricing based on passenger demand divisions. The results obtained would guarantee better service and more revenue than present models on the route from Beijing to Shanghai in China. Hales and García [23] demonstrate the seating arrangement of political parties in assembly sessions and in congress meetings using the mathematical approach in which the heuristic model works efficiently and produces good results than other existing methods.

From Fabro [24], demonstration of strategies, and policies for booking seats for the restaurant system. During which, double booking is to be avoided. Have to welcome and assign the seat during their arrival who already booked the table or seat which is trending in the restaurants. Deng et al. [25] present the use of a mathematical optimization model over the Wuhan route to increase revenue. The imposition of dynamic pricing rates based on the demand of passengers, and price fixes more over short-distance trains than long-distance trains, and also based on the point where more passengers are there, again dynamic pricing and seat selection to be applied. Weicker [26] demonstrates minimizing the distance between the trains when there is transferring the seats, uses an optimization model, and handles NP-hard problems present in the scenarios.

Ricky et al. [27] demonstrate challenges, and issues raised in ranking algorithms such as repetitive data, and multi-dimensional classes. It also addresses pair-wise, types of two bipartite methods, and their working themes. Regarding Efimov [28], it demonstrates three optimal ranking approaches such as pair-wise, point-wise, and list-wise, and discusses their working procedure along with benefits and difficulties. Hrushikesava et al. [29] provide demonstrations on specific places based on the mass visit that, automatically raises the feedback of the customer. The accumulation of reviews of many such visitors is computed and makes that place more popular. The higher number of visitors of the place would mark a high rank for that place. This study did not describe optimality but focused on ranking of the places. From Bulum et al. [30], the focus done on revenue generation by using ticket booking system in which buckets assigned for each booking, proved some raise tickets purchase. This study went on rails, as shift from airways. There is still significant increase of the revenue to be expected, which also motivates for proposed system to design. Most of these studies have not dealt with the optimality of the service and are not aimed at revenue generation for the rental vehicles.

3. METHODOLOGY

This involves ER model, flow diagram, and pseudo procedures of few modules, and main module.

The objective of a hybrid optimal system for efficient revenue generation would involve activities such as registering as a specific role, browsing the application for services, selecting the pickup (source station), a number of dropping points, selecting the destination (dropping place), driver number and profile, Vehicle penalty details, seat availability details, pricing tag on seats with possible discounts, rating based on feedback, and feedback of the journey. In this context, only necessary specific details would be used and discussed. Based on these activities, the modules are taken up as customer, driver, vehicle, services, and reviews and ratings. These 5 modules integration is the combined effort of all modules in which very specific activities were considered for more exploration such as fare fixing or price fixing for available seats, forecasting and notifying the driver on demand based on events occupied in a city, selection of seats as per customer choice, and follow up review and rating, which is optional due to reduce the storage complexity of the model. Here, the focus is only on how to alert the driver, as well as customers on the high-demand days based on occupancy of events on that day.

Figure 1 dictates the flow of interaction among the modules of this work.

The details of Figure 1 would be explored through the below ER model in Figure 2 where attributes of each entity are shown.

In Figure 2, the customer, driver, app owner, services are the significant modules in which app owner provides particular services to the passenger and driver. Among these, % of commission expected by the application owner, customer pays the amount for their usage of the travel over a vehicle, Driver pays the % of commission for service used, and earns money by providing travelling service to the customer. The services module in the rental application like User Interface where source, destination, displaying of vacant vehicles, displaying of inner details of seats of the vehicle, allows interaction over the seats to select with specific fare (optional), provides communication once passenger books the seat. Among these four modules, the significant activity taken for exploration in this study is optimal manner of selection of seats by the passenger and discount rising by the driver for profit generation. The objective to be achieved is good revenue generation to the driver, as well as aware of demand for vehicles on specific days based on events occupied.

PS1:
Pseudo_Procedure
Hybrid_Optimal_revenue_generation(Passenger_IDs[], Driver_ID[],Vehicle_ID[],Events[][], Constraints[], Meta_Details[][]):
Input: Passenger, Driver, Vehicle, Events, Constraints, Meta_datails arrays
Output: Accuracy, Performance, cost_charged

Step1: Application is designed to allow the passengers, drivers of vehicles to register. Both passengers and Drivers would be mapped based on passenger search location like **source, and destination**.
Step2: Once driver chooses the passenger, passenger can view **vehicle inner view like dashboard, alerts, and seat details.**
Step3: Define constraints like dividing areas in to clusters
Cluster1= Hotels region
Cluster2= Movies region
Cluster3= Shopping region
..
ClusterN-2 = Railway station
ClusterN-1 = Temples Region
ClusterN= Bus Stand
Case1: Based on week ends, ClusterN, and ClusterN-2 may experience more revenue
Case2: Based on Festivals, ClusterN-1 may experience more revenue
..
CaseN: Based on meetings or marriage events, Cluster1 would may experience more revenue
The customers and drivers who wanted interests on cluster, may get alerts and notifications by the application
Call Hybrid_ARIMA_GBM(Events[][], Constraints[][], Passengers[][], Drivers[][])

Step4: For seat_no=1 to n # FCFS (Optimal seat selection)
For preference=1 to n #RANKING
If(seat matches and preferences_all matches)
Fare= Price1;
else if(seat matches and 50% of preferences matches)
Fare = Price2;
else if(seat matches and only one preference matches)
Fare = price3;
else # no seat number matched, and no preference matched
Raises discount by the driver
Step5: Accuracy = Timing followed by the timer mentioned in the app vs gap created(difference of time) for dropping
Step6: Performance = Effectiveness of service response to the passenger and driver
Step7: Cost1, Cost2 are the two identifiers created for each driver, in which
Cost1= % of commission to the app owner
Cost2 = ∑ fare – Cost1 = Driver effort price
Step8: Call for feedback one each passenger completes their dropping by app automatically
Step9: Provides tags, rating to both driver, passenger, and vehicle

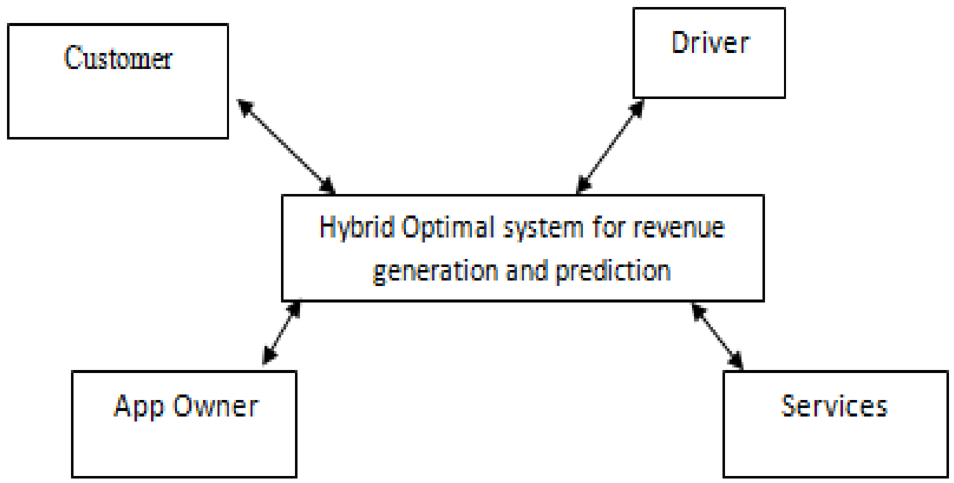

Figure 1. Modules interaction of rental vehicle application

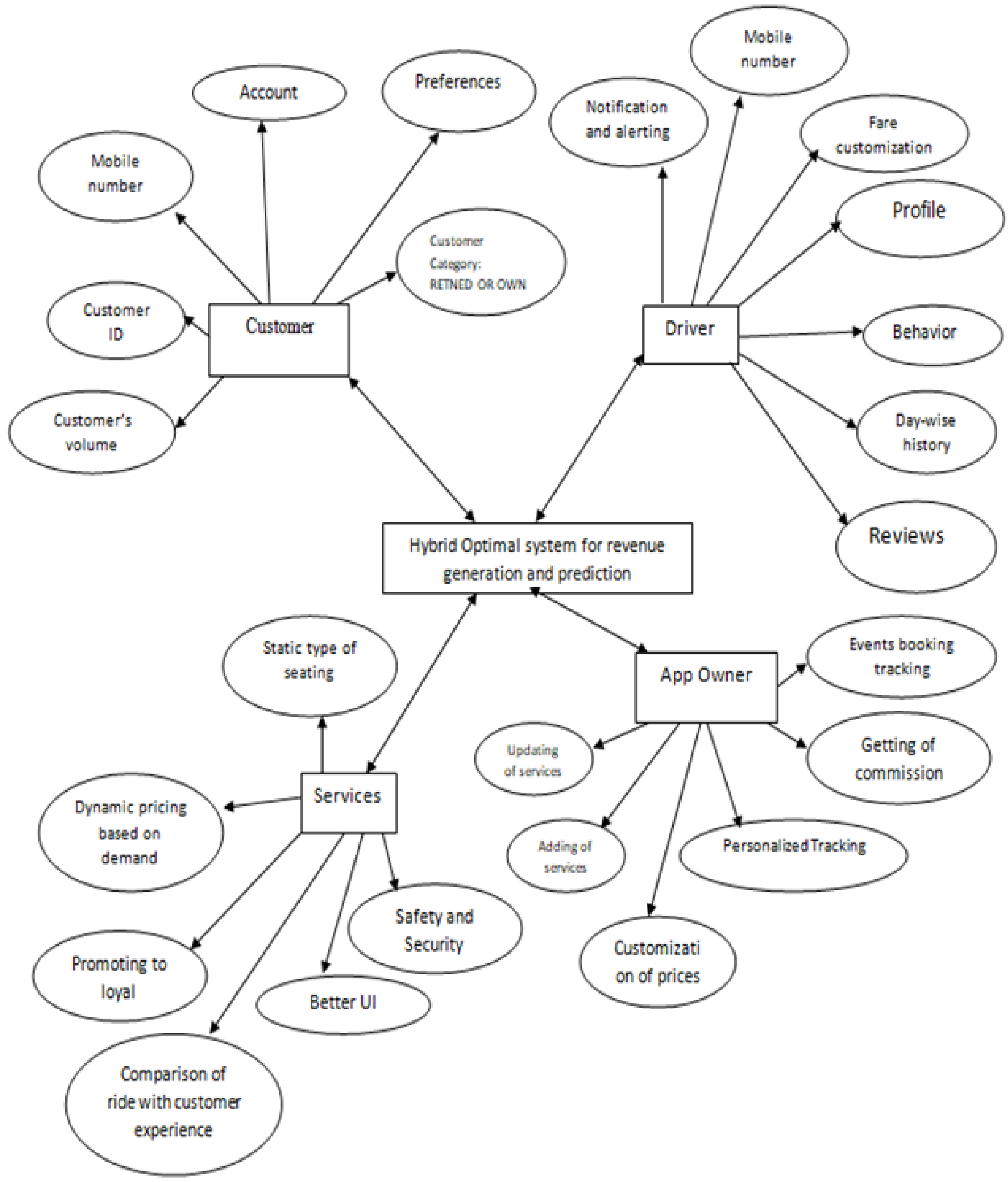

Figure 2. ER model of proposed model

In above procedure, Areas are clustered based on their type, and number of events registered suppose exceed predeifned threshold, would generate alert. This module use the combination of FCFS, and Ranking are applied for dynamic selection of seats,and dynamic pricing is applied. The user framed policies were added to make more efficient way of choosing the seats, price fixing based on fast fill up, events ae cassified as festival seasons, local big events, NGO events, and others. The application policies, Ranking, FCFS makes the system more accurate, efficient, and cost effective in fixing dynamic prices only at the time of demanding contexts.

PS2: Pseudo_procedure **Hybrid_ARIMA_GBM(Events[][], Constraints[][], Passengers[][], Drivers[][]):**
Input: Events[][], Constraints[][], Passengers[][], Drivers[][] arrays
Output: Alerting and Notifications

Step1: Identify occupancy of events based on clusters.
For cluster1 to ClusterN
If(%_EVENTS_OCCUPIED >= Cluster_thhreshold[i])
Alert members of the cluster like customers, and drivers to simply the complexity
Step2: Compute p, q, and d in parallel with Step1, where p denote autocorrelation, q denote partial, and d denote difference
Step3: If they are near identical, compute Accuracy
Step4: Include hyper parameters such as cluster thresholds, based on number of events occupied
Step5: Compute grid operator
Step6: Compute Mean Squared Error (MSE)

$$MSE = \sum \frac{(Y_i - P_i)^2}{\mathrm{n}}$$

where, y_i is the ith observed value; p_i is the corresponding predicted value for y_i; n is the number of observations.

From above pseudo procedure, two metrics such as accuracy and MSE are evaluated. In these, accuracy to be more, and error rate should be less. The projected incomes suppose earned by the driver, and feedback filled by the driver, would be the success of the model.

PS3: Pseudo_Procedure **Passenger(Passenger_IDs[]):**
Input: Passenger_IDs array
Output: Reversation_status

Step1: Register in the rental app
Step2: Login and search for vehicle
Step3: Once List of Vehicles is ready that provide passengers comfort like seating selection, allows to choose the random vehicle.
Step4: Display interface of the seats view, allows the passenger to select the seat based on provided details like window seat, foot space, aisle seat ,and other parameters.
For preference 1 to Preference N
Fare=∑ Fare $_i$
Step5: Once passenger interested over a specific seat, locks that seat for that journey.
Step6: Allows to choose payment method, and alerts the passenger as well a Driver of the vehicle.
Step6: Call Driver module
Step7: Provides feedback of the journey

In above procedure, passenger allows choosing the seat as per their preferences, the fare to be fixed based on more preferences. If the preferences are more, more fare to be fixed as per competitive apps.

PS4: Pseudo_Procedure **Driver(Driver_ID[])**
Input: Driver_ID array
Output: Drops the passengers

Step1: Calls the passenger and follow up the pick up point
Step2: Allows the passenger to take their blocked seat (temporary reserved seat)
Step3: For each dropping point, collects the fare from the passengers
Step4: If any seat is not filling, driver set up discount using discount module from the app
Call Discount module
Step5: Calculates the amounts once trip is completed.

In above Driver module, monitoring of the all seats are filling very fast or slowly. In case of slow filling, get discount module service from the app.

PS5: Pseudo_Procedure **Discount(price_drop[])**
Input: Price_drop array
Output: Reduced fare

Step1: Opt for Discount service from app
Step2: Choose one item from price_drop[], and apply
Step3: Displays updated Seat details to the passengers

In above discount module, price amount to be reduced based of selection of driver decision. It would be 10%, 25%, 50% or %N as per driver input.

The below module demonstrates the review and rating concept where each user input is considered over the service provided, and accumulated passengers average is the final rating to the driver and vehicle. This reviews and rating may the updated based on new passengers and their preferences.

4. RESULTS

The proposed approach derives its capability over accuracy, performance, and cost metrics. In Table 3, the purpose and advantage of each module is highlighted. The comparison of the hybrid optimal (novel) approach against existing approaches is demonstrated in Tables 4-8.

The analysis of existing applications if they would import this kind of efficient model, they can forecast or predict future days income to auto-calendar notification feature enabled. The future scope would be environmental consequences which may also drop the income that needs to be incorporated in this model.

The comparison of existing methods versus proposed method hybrid optimal approach are demonstrated in the below Table 4.

The accuracies of novel optimal against existing approaches are demonstrated in Table 5, and depicted in Figure 3. Accuracy is defined as correctly predicted instances by total instances. Among these approaches, novel optimal approach is observed having high accuracy than others.

Accuracy = Instances correctly computed / Total instance cases

Table 3. The advantages of listed modules

Name of the Module	Theme	Advantage
Passenger	Make an attempt and use the facilities offered for choice of seat selection.	Generates income, and experiences the comfort.
Driver	Follow up the passenger, and provide best service during their interaction.	Experiences income, and opt for Discount module.
Vehicle	Provides accommodation to the driver as well as passengers.	Better condition results good rating.
App Owner	Provides innovative services, creative services that helps to the passengers because are passengers are real stakeholders.	Better UI, and load balancing would benefit more appreciations and public talk.
Services	Basic services, novel services to be incorporated and useful to the stakeholders.	Allows to do analysis and to make reliable decisions.

Table 4. Metrics comparison of hybrid optimal against existing

Approach	Accuracy	Performance	Cost
Linear Regression	Good for linear relationships	Good for linear relationships	Good for linear relationships
Lasso regression and Ridge regression	Good for feature selection (Lasso)	Good for feature selection (Lasso)	Good for feature selection (Lasso)
Random Forests and Gradient Boosting Machines	High for complex problems	High for complex problems	High for complex problems
ARIMA	Effective for time series forecasting	Effective for time series forecasting	Effective for time series forecasting
Recurrent neural Networks (RNN)	High for sequential data	High for sequential data	High for sequential data
LSTM	High for long	term dependencies in sequential data	High for long
Hybrid optimal	High for high dimensional data, and time series data	High for nonlinear relationships	Moderate for initial usage, and later low cost

Table 5. Accuracy of hybrid optimal against existing

Approach	Accuracy (%)
Linear Regression	85
Lasso Regression and Ridge Regression	88
Random Forests and Gradient Boosting Machines	95
ARIMA	93
Recurrent Neural Networks (RNN)	95
LSTM	95
Hybrid Optimal	99

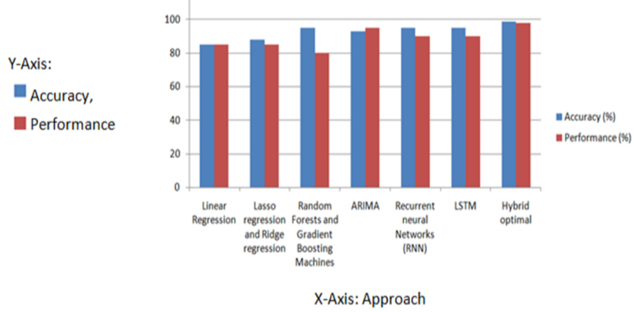

Figure 3. Accuracies, performances of hybrid optimal system against existing approaches

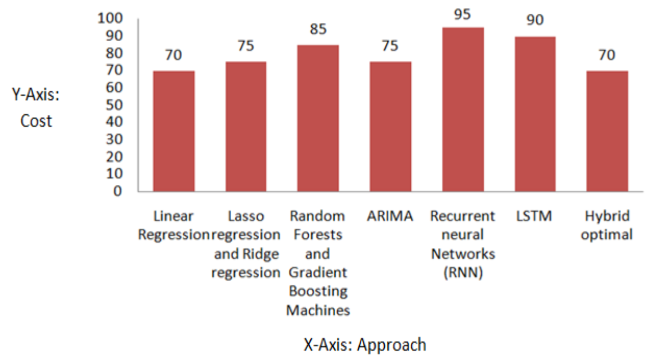

Figure 4. Cost of optimal against existing

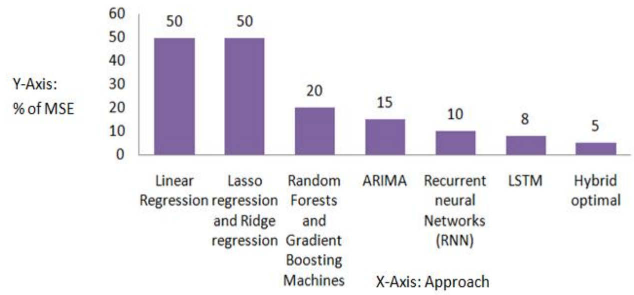

Figure 5. Error rate (MSE) of hybrid optimal against existing approaches

The efficiency of novel optimal against existing approaches are demonstrated in Table 6, and depicted in Figure 3. Efficiency is defined as achieved performance to be looking good even though the number of instances is to be increased. Among these approaches, novel optimal approach is observed having high performance than others due to simple number of constraints, and their conjunctions.

The computation cost of novel optimal against existing approaches are demonstrated in Table 7, and depicted in Figure 4. The computation cost is defined as the amount spent to achieve the task to be done effectively. Among these approaches, novel optimal approach is observed having medium computational overhead which is accepted than others. The MSE of hybrid optimal against existing approaches are demonstrated in Table 8, and depicted in Figure 5. The MSE's of existing approaches, against hybrid optimal approach is observed having less impact which is extremely accepted than others.

Table 6. Performance of hybrid optimal against existing

Approach	Performance (%)
Linear Regression	85
Lasso Regression and Ridge Regression	85
Random Forests and Gradient Boosting Machines	80
ARIMA	95
Recurrent Neural Networks (RNN)	90
LSTM	90
Hybrid Optimal	98

Table 7. Cost of hybrid optimal against existing approaches

Approach	Cost
Linear Regression	Low
Lasso Regression and Ridge Regression	Low
Random Forests and Gradient Boosting Machines	Moderate
ARIMA	Low
Recurrent Neural Networks (RNN)	High
LSTM	High
Hybrid Optimal	Low

Table 8. Error rate of hybrid optimal against existing approaches

Approach	MSE(%)
Linear Regression	50
Lasso Regression and Ridge Regression	50
Random Forests and Gradient Boosting Machines	20
ARIMA	15
Recurrent Neural Networks (RNN)	10
LSTM	8
Hybrid Optimal	5

5. CONCLUSIONS

Due to customized constraints, and their conjunctions in the hybrid optimal system, the accuracy, and performance are computed more than expected and the cost is moderately accepted, involving cost as fair terms as well as with considerably lesser error rates. The modules involved such as passenger, driver, app owner, services, and Vehicle are ordered systematically and appeal to better User interface, and satisfactory services for increasing the revenue of the trip by activating the discount module by the driver. The existing methods are compared against the proposed approach, and their results are visualized in graphs. The highlights of the hybrid optimal are fare fixing based on preferences justification, injection of discount over unfilled seats, and forecasting of income on a specific day when events are filled than their cluster thresholds. The better UI, and adaption of notification service when more events occupancy is reached over clusters, would influence the further level of recognition, and withstand in the competitive rental vehicle environments.

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