SN Computer Science (2023) 4:814
https://doi.org/10.1007/s42979-023-02230-0

ORIGINAL RESEARCH

Optimizing Dynamic Ride Sharing with Multiple Objectives

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Received: 6 March 2023 / Accepted: 6 August 2023 / Published online: 21 October 2023

Abstract

Ride-sharing services, such as those offered by companies like Uber, have gained significant popularity for transporting passengers from one location to another. However, the current model only allows for the provision of a single service at a time. Consequently, if a vehicle is carrying passengers, it cannot simultaneously provide food packet delivery or other services. In this paper, we present an optimized multi-fold service approach, enabling vehicles to carry passengers while also offering additional services like a parcel, medicine box and food packet delivery. To achieve optimal solutions for all four services, we employ a multi-objective algorithm that determines routes balancing and optimizing these services together. Our proposed algorithm provides both analytical and strategic solutions. The analytical solution addresses real-life problems using goal programming, while the strategic solution considers real vehicle situations utilizing set theory concepts. Comparative analysis against other vehicular models demonstrates the superior performance of our proposed model in terms of time and space complexity. Moreover, our model offers a greater number of services compared to the existing system. We evaluate the performance of our model using a randomly self-prepared dataset, and the quick response for each service affirms its potential integration with future vehicles.

Keywords Simplex method · Goal programming · LINGO · Multi goal

List of Symbols

x_1	Number of parcels delivered
x_2	Number of medicine boxes delivered
x_3	Number of food items delivered
x_4	Number of passengers transported
ε_i	Earnings per trip
K	Number of hours limited to working overtime
β_1	Minimum number of parcels to be delivered
β_2	Minimum number of medicine boxes to be delivered
β_3	Minimum number of food items to be delivered
β_4	Minimum number of passengers to be transported
ρ_i	Incentive rate per month
t_i	Average delivery time per trip
c_i	Average cost per trip
T	Total available time (working hours) per month
α	Total earnings target for the month
Y	Total incentive amount received per month
d_i^-	Under achievement of goals or constraints
d_i^+	Over achievement of goals or constraints

This article is part of the topical collection "SWOT to AI-embraced Communication Systems (SWOT-AI)" guest edited by Somnath Mukhopadhyay, Debashis De, Sunita Sarkar and Celia Shahnaz.

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Introduction

The rise of the Platform Economy, helped by the evolution of new digital technologies, has contributed to the immense growth of the food delivery sector in India [1]. Today, the delivery sector has become a multi-billion dollar industry. It has been growing rapidly all over the world, especially during the COVID-19 pandemic period. There are so many companies in the market providing delivery services for different categories of items. Companies like Swiggy and Zomato are on-demand food delivery service providers with having presence in many countries. These companies through their online apps let the customer order food from their favourite restaurants and then deliver the ordered food to their doorstep. In return, they charge delivery fees for this service. The human network is the backbone of delivery service. Delivery executive gets order on their mobile phone and the Global Positioning System (GPS) is used by the organization to coordinate supply and demand in the shortest possible time.

To ease the delivery service and deliver food on time, the service provider divides a city into smaller regions, and a delivery executive has to decide the region he or she wants to work on. The radius of each region is approximately a few kilometres. The pickup and drop-off locations are within the same region. Delivery executives are not allowed to deliver food from one region to another as it will take a lot of time and dissatisfy a customer. The task of choosing a suitable region is a difficult decision-making process because multiple qualitative and quantitative aspects need to be evaluated. A region providing the highest number of orders may not be the right region if it is congested and traffic jam is frequent in that region because the chances of delivering late in this region are comparatively higher. The best regions, for example, are those that provide high incentives, the maximum number of tips from customers and have fewer traffic jams. A suitable model is required to be designed for choosing the region so that the delivery partners can achieve their goals and avoid working extra hours. Region selection requires the evaluation of several regions with a set of common criteria, hence it is regarded as a multiple-criteria decision-making (MCDM) process.

Various models have been developed for region or location selection by researchers. Tzeng et al. have developed a mathematical model for restaurant location selection [2]. Vasant and Bhattacharya developed a multiple-criteria decision-making model for plant site location problems [3]. Ho et al. developed a model for the selection of location using an analytic hierarchy process and multi-choice goal programming [4]. Traditionally, there is a separate vehicle to carry passengers, food packets and parcels. There was no provision to carry passengers, food packets, parcels etc. altogether by the same vehicle through the same or nearby route. Few ride-sharing applications such as Uber [5, 6] are available that provide passenger service (such as UberGo) as well as Food delivery service (such as Uber Eats) but not by using the same vehicle for the purpose at the same time. UberGo is a 4-seater luxury sedan that offers peer-to-peer ride-sharing services. UberGo is operated in a maximum number of cities with reasonable pricing by maintaining good service quality. Uber Eats supplies food from local restaurants to the doorstep at a fast rate. Uber performs better compared to other ride-sharing services such as Lyft, Ola etc. in terms of price, availability, coverage and service quality. Also, there are online food delivery services [7] such as Zomato, Swiggy etc. which supply only food and do not carry passengers. Parcel delivery services [8] are also available such as DTDC, DHL Express etc. Each of the service approaches has the potential to meet customer service requirements as well as to earn profit for the organization. Each organization uses their own resources such as employees, software, vehicle, other third-party service etc. to ensure their service. But often a user expects multiple services from the same service provider, which can reduce users' complications to make orders and payments, and tracking and collecting individually. So, from a customer's point of view, multiple services from a single entity will simplify their job. On the other hand, multiple service provider uses multiple resources which could be reduced in a few cases such as when the same user wants multiple services from a single vendor at the same time, or multiple users want multiple services at the same time where the route is common. Merging multiple services into one service, drastically reduce the cost of the service which facilitates both consumer and service provider. In such scenarios, a customer gets the service at a low cost and the service provider gains more profit as costing reduces. The proposed method includes mainly four categories of services: passenger service, Food packet delivery service, Parcel delivery service and Medicine box delivery.

Wherever the same consumer with multiple services is found or multiple consumers for multiple services but a common route is found, the same vehicle is utilized for multiple purposes to reduce cost. A consumer can make a request either in non-shared or shared mode. In the case of non-shared mode, a vehicle is dedicated only to that service. In shared mode, a vehicle is shared based on the availability of seats and space. In a vehicle, provision for Passengers, Food packets and Parcel is available. Considering the food safety criteria, Food packets are assigned to separate seats only, not in the luggage area. Two-seater bikes are obtained only in non-shared mode, so only one service can be availed at a time. In a four-seater vehicle, only the front seat is utilized for the Food packet and in the six-seater vehicle, only the last two seats are utilized for the Food packet. The external removable plastic jacket is used to carry Food packets. In case, all the seats in the vehicle are filled up with Passengers, plastic jackets are eliminated from the respective seat. For Parcel, the only luggage area is utilized, considering the available space has already been utilized by the luggage of the Passenger. While the vehicle carrying Parcels, the request from the consumer is confirmed considering the size of the luggage of the consumer could be placed on the remaining space of the luggage area. Ridesharing or carpooling concept with parcel [9] is already in use where multiple services from a single vehicle at the same time are possible. By sharing a ride, the cost is minimized, profit is maximized and also it leads to an increase in urban mobility as well as helps to alleviate urban congestion and environmental pollution. The model used for ride-sharing did not consider issues such as track conditions, environmental impacts etc. Few existing models can merge only two types of services, not more than that.

Strategic planning is formulated for region selection using a zero–one-goal programming approach. Zero–one goal programming is a special type of Goal Programming (GP) method and can be applied to solve multi-objective problems. In this method, the values of the decision variable can either result in zero or one. This method has been used in many fields of study. However, to the best of our knowledge, zero–one goal programming has not been applied for region selection in delivery service so far.

Delivery services have increased rapidly in the last few years. Apps like Zomato, Swiggy, and Uber have become important tools during lockdowns due to the Covid-19 pandemic. These platforms connect the customers to delivery executives (drivers) to carry out the delivery of products from one location to another within a specific region. Data shows, the average distance of a trip is between 3 and 5 km and usually takes time between 30 and 60 min. Based on the number of trips and distance travelled the delivery executives are given salaries and incentives by the companies. But due to improper strategic planning, it is often seen that delivery executives are not able to meet their targets at the end of the month. So, we have come up with a Goal Programming model for Delivery Executives to optimize monthly earnings, reduce overtime working hours, increase incentives etc. The goals of our proposed model are prioritized. The priorities can be rearranged as per their importance to the decision-maker.

Here, we have considered a new platform wherein the delivery executives can deliver various products like parcels, medicines boxes, and food items as well as provide ride service to commuters. The model aims to optimize the monthly goals of delivery executives.

Primary objectives are mentioned below which are met by our proposed model.

1. To propose a goal programming model for delivery executives in a multi-service platform, considering the delivery of various products such as parcels and food items, as well as providing ride services to commuters.
2. To optimize the monthly earnings of delivery executives, reducing overtime working hours, and increasing incentives.
3. To present analytical and strategic solutions for the multi-goal problem.

The organization of the following sections are explained below. This article aims to provide a literature review on various techniques of ride-sharing systems and their optimal solution in "Literature Survey". "Formulation of the Problem" introduces the formulation of the problem where the goal programming model is defined. This section also describes the analytical and strategic solution to the multi-goal problem.

Literature Survey

The ride-sharing system gained popularity because of its efficient transportation. This literature review aims to provide an overview of the existing research and findings related to the ride-sharing system. A**.** Charnes, W. W. Cooper and R. O. Ferguson [10] were the pioneers of Goal Programming. In 1955, they presented a paper in which they have shown how, by appropriate adaptations, the methods of linear programming may be used to get estimates of parameters when more usual methods like the "least squares method" are hard or impossible to apply. But the actual name 'Goal Programming" first appeared in a 1961 text by Charnes and Cooper. Thereafter, it was developed by Ijiri in the 1960s. The first books dedicated to Goal Programming written by Lee [11] and Ignizio [12] appeared during the early to mid-1970s. In the 1970s, Goal Programming and its variants were extensively applied to many subject areas such as academic resources planning, media scheduling, portfolio management, agricultural planning, water resource planning, library management and accounting.

Applications of goal programming in various fields are explained by many authors. Stinnett and Paltiel [13] demonstrated a general mathematical framework that can accommodate complex information by using optimization techniques. Wood et al. [14] have presented several designing and financial issues of arranging, working and controlling force age and transmission frameworks in electric utilities. Miller et al. [15] used a mathematical approach to optimize the scheduling of physicians in a hospital. Their approach generated better schedules than those made by the experts. Tridvei [16] developed a mixed-integer goal programming model to optimize the expense budgeting of the nursing department in a hospital. The results indicate the model is practical and reliable for budgeting in a hospital nursing department. Deckro and Hebert [17] reviewed various goal programming applications to the linear decision rule formulation of production planning problems and then presented extensions using polynomial goal programming. The solutions of various models have been shown using linear programming software. Keown and Martin [18] presented a model for capital budgeting in hospitals and solved it using zero–one-goal programming. Baker et al. [19] developed a non-linear mathematical model for the allocation of emergency medical service (EMS) ambulances within a county to meet a government-mandated criterion. In addition, their model included budget and workload. The model is solved using the non-linear goal programming method. The solution of the model provided the ambulance allocations to sectors within the county, the probability of an ambulance exceeding a predefined response time and the utilization factor for ambulances per sector. Jia et al. [20] proposed a model of the two-sided ridesharing markets. In their work, they investigated a highly generalised model for the taxi and delivery services in the market economy that can be widely used in two sided-markets. Hao [21] proposed a model for Dynamic Taxi-Sharing. Their model matches taxi drivers and user pairs in certain sequences with the goal of maximizing taxi providers' profit. Azevedo and Weyl [22] provided a broad discussion of sharing economics and two-sided markets. Jagtap and Kawale [23] developed a model wherein they optimized the transportation problem (TP) involving multiple objectives by hierarchical orders using the GP model. Ahmadpour and Chitgar [24] developed a goal programming model for Transportation planning Decision Problems. Gur and Eren's [25] work examined the studies associated with scheduling and planning with goal programming methods in service systems. Hassan and Ayob [26] developed a goal programming model for a Small and Medium Enterprise (SME), a company that produces and sell five different products and distributes them to three locations. In their work, they try to maximize the total distribution of products, their second goal was to maximize the total profits of the company and the last goal was to minimize the total manufacturing cost. Choudhary and Shankar [27] proposed a model for joint decision-making of inventory lot-sizing, supplier selection and carrier selection problems. The purpose of their model was to determine the timings, lot size to be obtained, and supply and carrier to be selected in each replenishment period. DARP [28] is an automated ride service model. DARP provides a door-to-door pick-up and drop facility and designs minimum-cost routes with an optimum number of passengers. The model imposes a time window on departure and arrival times to make it more convenient for passengers. In DARP, a group of users for the same vehicle are identified and sequenced along the route. Groups are formed considering nearby co-location. The optimal route is selected based on minimum route duration by satisfying the time window property. A dynamic programming algorithm is used using heuristic methods. But the model is lacking behind to consider many issues. The maximum amount of time a driver can serve is not considered. The maximum coverage area a driver will be allowed to move or wish to move to pick up a passenger is not considered. The model has also considered the earliest feasible pick-up time as a parameter to be considered to select a passenger. But, to maximize profit, a passenger needs to be selected where journey time or journey distance is more. Another model SARP [29] which is the extension of DARP, has considered a few missing parameters and made the model efficient. SARP and FIP [29] both have considered many constraints to dealing with automated passenger service along with parcel carrying service. The model has considered a sufficient number of constraints to deal with the problem. It has considered both services separately, so passengers and parcels will be treated differently. Considering these services individually made this model more accurate but at the same time, it made it more complex. Therefore, the model has higher complexity in terms of time and space. To perform these kinds of services in an automated manner, quick response is one of the main criteria, which is lacking in this model. Another paper [30] discussed customer experience with Online Food Delivery services, where structural relations between the customer and influential factors related to online food are studied. A novel deep learning-based solution is proposed for the RedPacketBike, a bike-sharing system, with the objective of effectively balancing bike availability across city-wide stations, where the proposed solution aims to address the crucial challenge of maintaining a consistent supply of bikes throughout the network [8]. A recent study introduced a mobility-on-demand system for vehicles aimed at meeting customers' shared transportation needs, with a particular focus on addressing mobility demands in smart cities. This innovative solution holds significant potential for implementing effective transportation strategies [31].

Our proposed model addresses the limitations of existing models, such as the absence of sufficient constraints in the DARP and the overwhelming number of constraints in the SARP. Our model ensures equal treatment of multiple services by not favouring any particular service over others. Instead, each service is given equal consideration, making the model simpler and more comprehensive. The proposed approach guarantees equal treatment for all four types of services, without any preference or bias towards a specific service.

Formulation of the Problem

In our model, we have considered a delivery executive who works under an on-demand food delivery company. The company operates in a big metropolitan city and has multiple regions within the same city. The company allows delivery executives to choose the desired regions where they want to work within. Once a region is selected by a delivery executive the pickup and drop-off locations of all the orders will be within that specific region. In this model, we will use Zero–One Goal Programming to select the best region. Table 1 shows the sample data for the regions.

The six criteria used in selecting the best region are as follows:

1. Average net income of each delivery partner per month
2. Average rating of each delivery partner

Table 1 Data of regions

	Region 1	Region 2	Region 3	Region 4	Region 5
Net income (Rs)	15,500	16,000	15,300	16,200	15,800
Rating (out of 5)	4.4	4.0	4.5	3.9	4.3
Congestion level	40%	48%	36%	50%	43%
Probability of tips above Rs 3000/month	0.78	0.80	0.88	0.70	0.80
Orders delayed	20%	16%	12%	23%	14%
Incentive of Rs 1000/day	255	250	254	240	248

3. Congestion level in per cent (%)
4. Probability of getting tips above Rs 3000 per month
5. Orders delayed due to traffic jam
6. Daily income of delivery partners (full-timer) from incentive on earning Rs 1000 per day. The company gives incentives for achieving the daily target.

Now, using the data from Table 1, we will formulate a zero–one-goal programming problem.

Decision Variables

X1: Region 1, X2: Region 2, X3: Region 3, X4: Region 4, X5: Region 5.

Hard Constraints

These are the constraints that must be fulfilled in this study. The delivery partner aims for the congestion level of the region must be a maximum of 50%. Each region has a different congestion level depending on various aspects. The congestion level constraint is as follows:

$$0.40 \times X_1 + 0.48 \times X_2 + 0.36 \times X_3 + 0.53 \times X_4 + 0.43 \times X_5 \leq 0.50. \tag{1}$$

To choose the best region, the constraint is as follows:

$$X_1 + X_2 + X_3 + X_4 + X_5 \leq 1. \tag{2}$$

Soft Constraints

Unlike hard constraints, soft constraints possess deviational variables where d_i^- denotes the amount by which the target (goal) is underachieved and d_i^+ denotes the amount by which the goal is overachieved. In goal programming, the achievement function contains these deviational variables. In this model, the delivery partner wants to work in a region that has a minimum Net Income of Rs 16,000, then the constraint is as follows:

$$15500 \times X_1 + 16000 \times X_2 + 161000 \times X_3 + 16200 \times X_4 + d_1^- - d_1^+ = 16000. \tag{3}$$

The delivery partner wants that the minimum incentive amount of Rs 1000/day should not be less than Rs 250. The constraint is as follows:

$$255 \times X_1 + 250 \times X_2 + 254 \times X_3 + 240 \times X_4 + 248 \times X_5 + d_2^- + d_2^+ = 250. \tag{4}$$

Since the income earned through Tips is directly credited to the delivery partners' accounts. The delivery partner aims to work in a favourable region to supplement the total monthly income. In this case, the delivery partner aims to work in the region in which the probability of getting Tips above Rs. 3000/month is achievable. The constraint is as follows:

$$0.78 \times X_1 + 0.80 \times X_2 + 0.88 \times X_3 + 0.70 \times X_4 + 0.80 \times X_5 + d_3^- - d_3^+ = 1. \tag{5}$$

The food delivery companies offer extra incentives to their partners for maintaining a good rating level. Higher ratings from the customers also help them to build a good portfolio for the future. In addition, it helps them to get a maximum number of orders. In our model, the delivery partner aims to maintain a rating level of 4.5. The rating constraint is as follows:

$$4.4 \times X_1 + 4.6 \times X_2 + 4.5 \times X_3 + 3.9 \times X_4 + 4.3 \times X_5 + d_5^- - d_5^+ = 4.5. \tag{6}$$

Delivering food on time is important to get good feedback from customers. In some cases, the companies impose penalties and deprive executives of incentives. The delivery partner prefers to work in a region in which delivery delay is minimum. The constraint is as follows:

$$0.20 \times X_1 + 0.10 \times X_2 + 0.12 \times X_3 + 0.23 \times X_4 + 0.14 \times X_5 + d_6^- - d_6^+ = 0. \quad (7)$$

Discussions About the Problem Formulation

The above-considered problem has been analysed and explained in two ways.

1. Analytic solution and its numerical verification
2. Strategic solution

Analytic Solution and Discussion

Analytically we have examined the real-life problem using a goal programming problem.

Goal and Priority

In this model, there are five goals that have been arranged according to the importance and priority of each goal. The priority orders of the goals can be arranged as per their importance to the decision-maker.

Priority 1: maximize the net income per month

$$15500 \times X_1 + 16000 \times X_2 + 161100 \times X_3 + 16200 \times X_4 + d_1^- - d_1^+ = 16000. \quad (8)$$

Priority 2: maximize the incentive amount

$$255 \times X_1 + 250 \times X_2 + 254 \times X_3 + 240 \times X_4 + 248 \times X_5 + d_2^- - d_2^+ = 250. \quad (9)$$

Priority 3: maximize the probability of getting tips

$$0.78 \times X_1 + 0.80 \times X_2 + 0.88 \times X_3 + 0.70 \times X_4 + 0.80 \times X_5 + d_3^- - d_3^+ = 1. \quad (10)$$

Priority 4: maximize the rating

$$4.4 \times X_1 + 4.6 \times X_2 + 4.5 \times X_3 + 3.9 \times X_4 + 4.3 \times X_5 + d_4^- - d_4^+ = 4.5. \quad (11)$$

Priority 5: minimize the delivery delay as much as possible

$$0.20 \times X_1 + 0.10 \times X_2 + 0.12 \times X_3 + 0.23 \times X_4 + 0.14 \times X_5 + d_5^- - d_5^+ = 0. \quad (12)$$

Objective Function

The achievement function for this model is as follows:

$$\text{Min}Z = P_1 \times d_1^- + P_2 \times d_2^- + P_3 \times d_3^- + P_4 \times d_4^- + P_5 \times d_5^+,$$

where P_i is the priority and $P_i > P_{i+1}$.

Formation of Constraints of the Goals

Priority 1: to avoid underutilization of working hours T

$$\sum_{i=1}^{4} t_i \times x_i + d_1^- - d_1^+ = T.$$

Priority 2: to limit the overtime to K hours.

Priority 3: the desired total earnings is α per month

$$\sum_{i=1}^{4} \varepsilon_i \times x_i + d_2^- - d_2^+ = \alpha$$

Priority 4: to deliver at least β_1 parcels, β_2 medicine boxes, β_3 food items and transport β_4 passengers.

$$x_1 + d_3^- - d_3^+ = \beta_1$$

$$x_2 + d_4^- - d_4^+ = \beta_2$$

$$x_3 + d_5^- - d_5^+ = \beta_3$$

$$x_4 + d_6^- - d_6^+ = \beta_4$$

Priority 5: to minimize the overtime as much as possible

$$d_1^+ + d_{11}^- - d_{12}^+ = K$$

Priority 6: maximize the amount of the incentive

$$\sum_{i=1}^{4} \rho_i \times \varepsilon_i \times x_i + d_7^- - d_7^+ = Y$$

Priority 7: to minimize the cost

$$\sum_{i=1}^{4} c_i \times x_i + d_8^- - d_8^+ = 0$$

ıwhere P_i are the priorities set and defined as $P_i > P_{i+1}$.

Achievement Function

$$\begin{aligned}\mathrm{Min}Z = & P_1 \times d_1^- + P_2 \times d_{12}^+ + P_3 \times d_2^- \\ & + P_4 \times (d_3^- + d_4^- + d_5^- + d_6^-) \\ & + P_5 \times d_1^+ + P_6 \times d_7^- + P_7 \times d_8^+.\end{aligned}$$

Analysis

The above model is illustrated through an example below. First, we solved the model using the Simplex method and then validated the result using LINGO Software. Here we have taken only three goals to solve the model manually using the simplex algorithm.

Please find below the formulation of the multi-objective problem.

Step-1: consider a model wherein a delivery executive delivers three types of items namely parcels (X_1), medicine boxes (X_2) and food items (X_3) alongside ride service to passengers (X_4).

Step-2: assume the average delivery time per trip is 36 min and the total available time for the entire month is 300 h. Also, assume the earnings per trip are Rs 50 for the parcel, Rs 45 for medicine, Rs 30 for food and Rs 60 for the passenger.

Step-3: solve the problem using the GP model assuming the cost as Rs 20 per trip for any of the four services.

The delivery partner has set the following goals:

- To avoid underutilization of available time (working hours)
- To earn Rs 28,500 per month
- To minimize the total cost as much as possible

Formulation of GP Model

$$\text{Minimize } Z = P_1 \times d_1^- + P_2 \times d_2^- + P_3 \times d_3^- + P_4 \times d_1^+.$$

Subject to,

$$0.6 \times X_1 + 0.6 \times X_2 + 0.6 \times X_3 + 0.6 \times X_4 + d_1^- - d_1^+ = 300,$$

$$50 \times X_1 + 45 \times X_2 + 30 \times X_3 + 60 \times X_4 + d_2^- - d_2^+ = 28500,$$

$$20 \times X_1 + 20X_2 + 20 \times X_3 + 20 \times X_4 + d_3^- - d_3^+ = 0,$$

$X_i \geq 0, \forall i$ and $d_i^-, d_i^+ \geq 0$.

In Table 2, the first three rows of the table are set up in the same way as for the linear programming model, with coefficients of the associated variables placed in the appropriate entries. At the bottom, there are 4 rows and each row represents a priority goal level.

The optimal criterion ($Z_j - C_j$) is a 4×10 matrix because there are 4 priority factors and 10 variables. The pre-emptive priority goals are written in the basic variable column B at the bottom of the table from the lowest at the top to the highest at the bottom.

Selection of key column: in $Z_j - C_j$, we have taken the largest positive element at the P_1 level (avoid b_o column). If there is a tie in the most positive Δ_j value of a given priority level, then we consider the corresponding Δ_j values in the next priority level and select the variable which has a greater numerical value of Δ_j.

$Z_j - C_j$ = elements in C_i column $\times$ corresponding element in X_j columns – priority factor to a deviational variable.

e.g. $Z_1 - C_1$ = elements in C_B column $\times$ corresponding elements in x_1 column $- 0 = P_1 \times \frac{3}{5} + P_2 \times 50 + P_3 \times 20 - 0 = \frac{3}{5} P_1 + 50P_2 + 20P_3$.

Similarly, other $Z_j - C_j$ values can be obtained.

Selection of key row: θ for 1st row $= \frac{300}{3/5} = 500$, for 2nd $= \frac{28500}{60} = 475$, for 3rd $= \frac{0}{20} = 0$.

The least is the element of the 3rd row. Hence, this is the key row and obviously, 20 is the key element. In case of a tie, select the row that has the variable with the highest priority factor.

By following the usual simplex procedure, Tables 3, 4, and 5 are obtained.

Table 2 does not give the optimal solution. In Table 2, d_3^+ is the key column and d_2^- is the key row. The number encircled in red is the key element. This solution can be improved if d_3^+ is driven out and the decision variable d_2^- enters into the solution.

Table 2 Solution using Simplex method

C_j			0	0	0	0	P_1	P_2	P_3	P_4	0	0
C_i	B	b_0	X_1	X_2	X_3	X_4	d_1^-	d_2^-	d_3^-	d_1^+	d_2^+	d_3^+
P_1	d_1^-	300	3/5	3/5	3/5	3/5	1	0	0	− 1	0	0
P_2	d_2^-	28,500	50	45	30	60	0	1	0	0	− 1	0
P_3	d_3^-	0	20	20	20	20	0	0	1	0	0	− 1
Z_j–C_j	P_4	0	0	0	0	0	0	0	0	− 1	0	0
	P_3	0	20	20	20	20	0	0	0	0	0	− 1
	P_2	28,500	50	45	30	60	0	0	0	0	− 1	0
	P_1	300	3/5	3/5	3/5	3/5	0	0	0	− 1	0	0

Table 3 Solution using the Simplex method

C_j			0	0	0	0	P_1	P_2	P_3	P_4	0	0
C_i	B	b_0	X_1	X_2	X_3	X_4	d_1^-	d_2^-	d_3^-	d_1^+	d_2^+	d_3^+
P_1	d_1^-	300	0	0	0	0	1	0	− 3/100	− 1	0	3/100
P_2	d_2^-	28,500	− 10	− 15	− 30	0	0	1	− 3	0	− 1	3
0	d_3^-	0	1	1	1	1	0	0	1/20	0	0	− 1/20
$Z_j - C_j$	P_4	0	0	0	0	0	0	0	0	− 1	0	0
	P_3	0	0	0	0	0	0	0	− 1	0	0	0
	P_2	28,500	− 10	− 15	− 30	0	0	0	− 3	0	− 1	3
	P_1	300	0	0	0	0	0	0	− 3/10	− 1	0	3/100

Table 4 Solution using the Simplex method

C_j			0	0	0	0	P_1	P_2	P_3	P_4	0	0
C_i	B	b_0	X_1	X_2	X_3	X_4	d_1^-	d_2^-	d_3^-	d_1^+	d_2^+	d_3^+
P_1	d_1^-	15	1/10	3/20	3/10	0	1	− 1/100	0	− 1	1/100	0
0	d_3^+	9500	− 10/3	− 5	− 10	0	0	1/3	− 1	0	− 1/3	1
0	X_4	475	5/6	3/4	1/2	1	0	1/60	0	0	− 1/60	0
$Z_j - C_j$	P_4	0	0	0	0	0	0	0	0	− 1	0	0
	P_3	0	0	0	0	0	0	0	− 1	0	0	0
	P_2	0	0	0	0	0	0	− 1	0	0	0	0
	P_1	15	1/10	3/20	3/10	0	0	− 1/100	0	− 1	1/100	0

Table 5 Solution using the Simplex method

C_j			0	0	0	0	P_1	P_2	P_3	P_4	0	0
C_i	B	b_0	X_1	X_2	X_3	X_4	d_1^-	d_2^-	d_3^-	d_1^+	d_2^+	d_3^+
0	X_3	50	1/3	½	1	0	10/3	− 1/30	0	− 10/3	1/30	0
0	d_3^+	10,000	0	0	0	0	100/3	0	− 1	− 100/3	0	1
0	X_4	450	2/3	1/2	0	1	− 5/3	1/30	0	5/3	− 1/30	0
$Z_j - C_j$	P_4	0	0	0	0	0	0	0	0	− 1	0	0
	P_3	0	0	0	0	0	0	0	− 1	0	0	0
	P_2	0	0	0	0	0	0	− 1	0	0	0	0
	P_1	0	0	0	0	0	− 1	0	0	0	0	0

Table 6 The decision variables' value

Decision variable	Region	Value
X_1	Region 1	0
X_2	Region 2	0
X_3	Region 3	1
X_4	Region 4	0
X_5	Region 5	0

Table 7 Summary of deviation values for each priority

Goal priority	d_i^-	d_i^+	Goal achievement
P_1	0.000000	100.0000	Achieved
P_2	0.000000	4.000000	Achieved
P_3	0.120000	0.000000	Not achieved
P_4	0.000000	0.000000	Achieved
P_5	0.000000	0.120000	Not achieved

Proceeding as above, we get Table 3.

X_3 is the key column and d_1^- is the key row. This solution can be improved if d_1^- is driven out and decision variable x_3 enters into the solution.

The optimal solution is $X_3 = 50$, $X_4 = 450$, $d_3^+ = 10{,}000$. That is the delivery executive should deliver 50 food items and transport 450 passengers to meet his monthly goals.

Since all the rows in $Z_j - C_j$ are having either zero or negative values we can say that all four goals are completely achieved.

Table 8 Values of variables on LINGO software

Variable	Value
d_1^-	0.000000
d_2^-	0.000000
d_3^-	0.000000
d_1^+	0.000000
X_1	0.000000
X_2	0.000000
X_3	50.00000
X_4	450.0000
d_2^+	0.000000
d_3^+	10,000.00

Table 9 Vehicle and consumer optimal combination

Vehicle	Passenger	Food-Packets	Parcel + luggage
Two-wheeler	1	0	0
Two-wheeler	0	2	0
Two-wheeler	0	1	1
Four-wheeler Small	4	0	4
Four-wheeler Small	3	2	4
Four-wheeler Large	6	0	6
Four-wheeler Large	4	4	6

Numerical Verification

The above problem is solved using LINGO Software. The solution to the problem is as follows (shown in Table 6):

In Table 6, the value of decision variable X_3 is 1 while the value of the other four variables, X_1, X_2, X_4 and X_5 are zero. Thus, the best region is Region 3.

Table 7 shown the summary of deviation values for each priority and Table 8 shows the values of the variables obtained from the LINGO software.

As can be seen from Table 8, LINGO software produces the same results as the simplex method computed earlier. Both methods show that the delivery partner should deliver 50 food items and provide ride service to 450 passengers. Hence, the simplex used earlier is validated.

Strategic Solution

In the beginning, the driver shows interest to provide riding service and sharing location with the server. Shared information contains the driver identity number, vehicle identity number, latitude, longitude and radius of the coverage area.

$$\text{Location}_{\text{Driver}}\left(D_{\text{ID}};V_{\text{ID}};\text{Latitude};\text{Longitude};\text{Radius}\right)$$

where D_{ID}: driver identification, V_{ID}: vehicle identification. On the other side, consumer requests vehicle in shared or non-shared mode. Consumer means either Passenger or food packet or parcel. In the case of non-shared mode, a vehicle is availed only by the consumer who made the request.

In the case of shared mode, the vehicle is shared among multiple consumers as per seat or/and space availability of the vehicle. Vehicles are also categorized as per the carrying capacity of the consumer. Numerous combinations of the consumer with varying categories of vehicles are discussed in Table 9.

It has been assumed that the maximum size for each Food packet/Parcel is (30×30) sq. cm. In Four-wheeler small vehicle, one seat is reserved for the Food Packet which can hold a maximum of two Food packets. In a Four- wheeler Large vehicle, two seats are reserved for the Food Packet which can hold a maximum of four Food packets. Parcels will be occupied in the luggage area, so the presence of a Passenger or Food Packet will not affect Parcel's number (or number). But Passenger with extra luggage affects the Parcel amount.

Now consumers share location information by mentioning the destination as per the given format to the server:

$$\text{Location}_{\text{Consumer}}(C_{\text{ID}}; C_{\text{Type}}; \text{Mode}; L_{\text{Size}}; L_{\text{No}}; \text{Src}_{\text{Lat}}; \text{Src}_{\text{Lon}}; \text{Dest}_{\text{Lat}}; \text{Dest}_{\text{Lon}}),$$

where C_{ID}: consumer identification, C_{Type}: consumer type, (passenger, food packet, parcel), mode: shared, non-shared, L_{Size}: luggage size is categorized as small (below 10 sq cm), medium (below 15 sq cm) and large (equal or above 15 sq cm), L_{No}: luggage number refers to the number of small/medium/large luggage, Src_{Lat}: source latitude, Src_{Lon}: source longitude, Dest_{Lat}: destination latitude, Dest_{Lon}: destination longitude.

It is assumed that consumers will travel/move within the same city/town. In case the consumer wishes to travel outside the city, a special category of services such as Intercity-Vehicle service can be availed, which is excluded here.

Once the Server has information about both the driver and consumer, it matches the nearest pair of driver and consumer, without exceeding the coverage area (or radius) mentioned by the driver or its company. Once a successful pair of drivers and the consumer gets selected, the trip request is sent to the driver. After that trip request needs to be accepted by the driver, the server exchanges selective information between them. It implies sharing driver information with consumers and consumer information to drivers along with initial fare and pick-up time. Now both respective drivers and consumers will be in a session till the end of the trip. If the driver rejects the trip request, again server initiates searching for the nearest pair of drivers and consumers excluding the driver who rejected the request.

A consumer can book a vehicle either in shared or non-shared mode. In non-shared mode, the consumer needs to pay for all the seats and spaces, despite a few vacant seats and spaces. In this mode, the driver cannot accept other requests from consumers till the end of the trip. The initial fare is calculated based on the base fare, surcharge and waiting time. Base fare is dependent on the distance between the source and destination. The surcharge is dependent on the timing of the journey and the venue of the journey. In case of peak time or in case of any popular event, a surcharge will be higher such as a multiple of 1.5, 2, 2.5, 3 etc. of Base Fare. The final fare will be calculated based on the initial fare, average waiting time and surcharge amount. The unit of fare is Indian Rupee. Pick-up time is dependent on the distance between the driver and consumer and also on the presence of an intermediate passenger.

$$\text{Basefare} = 50(\text{INR}).$$

$$\begin{aligned}\text{Initialfare (non-shared)} \\ = \text{base fare} + \text{surcharge} \times \text{price high} \\ \times \text{distance} \quad \text{between-source-and-destination}\end{aligned}$$

$$\begin{aligned}\text{Initialfare (shared)} &= \text{base fare} + \text{surcharge} \times \text{price low} \\ &\times \text{distance between-source-and-destination}\end{aligned}$$

$$\text{Finalfare} = \text{initial fare} + 3 \times \text{waiting}_{\text{time}}\text{average}$$

$$\begin{aligned}\text{Distance}_{\text{between}}(\text{driver and rider}) \\ = \text{pickup time}/\text{average speed of the vehicle}\end{aligned}$$

$\text{Price}_{\text{high}}$ is generally a high price applicable for the consumer in non-shared mode. On the other hand, $\text{Price}_{\text{low}}$ is a comparatively low price applicable for the shared consumer.

Base fare depends on company policy. Here base fare is assumed as INR 50 which may differ in other cases.

The surcharge amount is 1 in a normal case. But that value goes to a higher fraction value (more than 1) such as 1.1, 1.2, 1.3, 1.4 etc. in case demand gets higher.

INR 3.00/km is charged for waiting time other than the average trip time.

In Table 10, for the same source and destination, three alternative routes are considered with different route IDs. The optimal route is selected based on the least consumption of time and distance. Nodes under the optimal route are considered intermediate stations for further computation. Distance under optimal route is used for computing fare. The efficiency of the program depends on time and memory space consumption.

But in shared mode, the driver may get another consumer to join during the trip. Attempts are made to fill up empty seats with consumers as early as possible. Matching of another consumer (second consumer onwards) with the current trip takes place in the following way.

Intermediate stations/locations in the current trip:

$$I_{\text{L}} = \{L_1, L_2, ..., L_n\}.$$

Surrounding locations from the source position is calculated with radius (coverage area) r_1 and centre $S_{\text{C}-i}$ (source location of consumer $- i$):

$$S_{\text{S}} = \{S_1, S_2, ..., S_n\}.$$

Surrounding locations are again calculated with radius (coverage area) r_2 and centre $S_{\text{D}-i}$ (destination location of consumer $-i$):

$$\text{SD} = \{D1, D2, ..., Dn\}$$

Now there will be an intersection between I_{L} and S_{S} and I_{L} and S_{D}. $A = I_{\text{L}} \cap S_{\text{S}}$.

$$B = I_{\text{L}} \cap S_{\text{D}}.$$

In either case, if the set value is empty; the consumer cannot avail of the shared trip by driver-j. Otherwise, when both sets A and B are non-empty, then the request of consumer-i will be accepted by driver-j under the condition that

Table 10 Alternative routes based on statistical data

Route ID	Source	Destination	Distance	Nodes	Time consumption	Memory consumption
$R1$	X	Y	$Z1$	a, b, c	$T1$	$S1$
$R2$	X	Y	$Z2$	b, a, c, d	$T2$	$S2$
$R3$	X	Y	$Z3$	a, c, d	$T3$	$S3$

seats and required spaces (space for passenger luggage) are available.

After that server calculates the nearest point from the set S_S from the driver's current location to pick up the consumer. Now the driver will choose a consumer for whom the trip will be completed first. Once a trip for a particular consumer is completed, the driver chooses another consumer to deliver the trip. Every time a new consumer is chosen by a driver, trip updating takes place based on the selected consumer destination.

Fare calculation for the non-shared consumer will take place based on the travelling distance and travelling time of the trip. The price charged in shared mode (Price low) is comparatively low compared to non-shared mode (Price high). But the base price in both cases is kept the same and is applicable to each consumer. Initially based on estimated distance and estimated travelling time, fare gets calculated. But in case of an increase in travelling distance or travelling time, the fare is increased. As the shortest travelling distance and minimum travelling are estimated, there is less chance of decrease in the values.

For the shared consumer, the fare is shared among multiple consumers. Fare distribution is not equal among the shared consumers. By considering risk factors (possibility of cancellation of the trip), the first shared consumer is charged comparatively more than the other shared consumer so that in case another consumer does not avail of the trip, the fare can be managed. Except for the first consumer, other consumers are charged 30–40% less.

For any complaint, a refund takes place against a driver or consumer based on the validity of the complaint.

During the trip, a session is maintained, and key information is updated on the server and the server holds this information on a temporary basis till the end of the trip, mentioned in Table 2 (shown in Fig. 1). Once the trip is over, irrelevant data are removed and necessary information is kept stored permanently in the server for the purpose of future use.

Cancellation of a trip intentionally or unintentionally either from the driver or consumer end may happen which is considered with utmost care. In case of cancellation by a consumer, based on the distance travelled by a driver or the waiting time of a driver, the amount is charged. This charged amount is paid to the driver. On the other hand, when a driver cancels a trip, based on waiting time amount is charged and paid to the consumer.

$$\mathrm{Cancellation}_{\mathrm{Charge}}(\mathrm{For}-\mathrm{consumer}) = \mathrm{Max}(\mathrm{Price}_{\mathrm{Per}}\mathrm{km} \times \mathrm{Distance}_{\mathrm{Travelled}}, \mathrm{PricePerSec} \times \ \mathrm{WaitingTime})$$

$$\mathrm{Cancellation}_{\mathrm{Charge}}\mathrm{For}-\mathrm{driver} = \mathrm{Max}\left(\mathrm{Price}_{\mathrm{Per}}\mathrm{Sec} \times \mathrm{Waiting}_{\mathrm{Time}}\right)$$

For food packet delivery service, few seats are held in reserve. Two food packets are carried per seat. The reserved number of seats for food packets is based on the size of the car. Except for two-wheeler, other vehicles provide parallel service both for carrying a passenger as well as carrying food packets. In a two-wheeler, either passenger will be carried, or a food packet will be carried. Considering the security, cleanliness and hygiene process, food packets are not placed in the luggage area. Food packets are kept inside the container and containers are kept on reserved seats.

In many cases it was found, vehicles running full of consumers, but luggage spaces were unfilled. To further utilized these spaces, parcel requests are accepted which are carried out in the luggage area. Therefore, the parcel can move in the same vehicle and also at the same time by which passenger and food packets are moving. Such kind of strategy drastically reduces charges for the services and thereby service cost becomes very cheap.

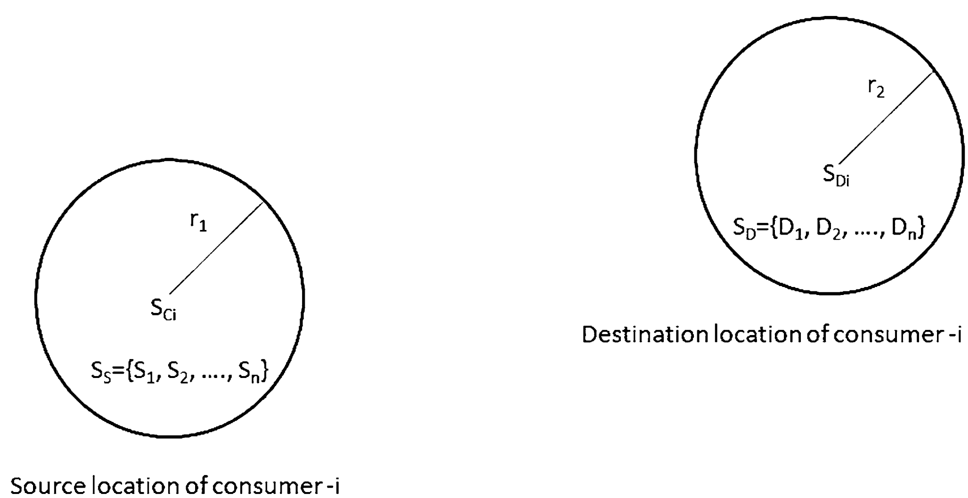

Fig. 1 Matching process with one consumer request

Verification of the Proposed Strategy

Quick matching of the nearest pair of the driver, and consumer and at the same time maximization profit is one of the important jobs. Though maximizing profit is one of the prime wishes, still there are many constraints which need to be satisfied. Optimizing function with various constraints is discussed below.

The objective function for profit Z is

$$\mathrm{Max}Z = \sum \left(\sum v_\alpha \times F_{\mathrm{pas}_i} + v_\alpha \times F_{\mathrm{par}_j} + v_\alpha \times F_{\mathrm{fp}_k} + v_\alpha \times F_{\mathrm{med}_l} - v_\alpha \times \mathrm{cost} \right),$$

where v_α refers to vehicle identification with ID α, F_{pas_i} is the fare charged to passenger pas_i, F_{par_j} is the fare charged to the parcel par_j, F_{fp_k} is the fare charged to the food packet fp_k, F_{med_l} is the fare charged to the medicine box med_l.

Cost refers to fuel cost, driver cost and other maintenance costs related to the vehicle total number of trips by vehicle (v_α) in a day is

$$T_t = \mathrm{pas}_i + \mathrm{par}_j + fp_k + \mathrm{med}_l.$$

Each service will get an equal preference. There is no additional preference for passengers. The driver will not declare any route initially.

The nearest driver will be allotted to the consumer.

The maximum amount of time a driver can serve in a day is: $\mathrm{Max}_{\mathrm{time}}\mathrm{Driver}$.

The maximum distance driver can travel in a day is: $\mathrm{Max}_{\mathrm{dist}}\mathrm{Driver}$.

$$\mathrm{time}(\mathrm{source}, \mathrm{destination}) \leq \left(\mathrm{Max}_{\mathrm{time}}\mathrm{Driver} - \mathrm{time\text{-}Already\text{-}Spent} \right)$$

$$\mathrm{dist}(\mathrm{source}, \mathrm{destination}) \leq \left(\mathrm{Max}_{\mathrm{dist}}\mathrm{Driver} - \mathrm{dist\text{-}Already\text{-}Covered} \right)$$

The time of travel of the consumer must lie between the working hour of the driver. start-Time-Driver ≤ travelling-Time-Consumer ≤ end-Time-Driver

The maximum coverage area of a vehicle will be decided by the company itself. By default, the maximum coverage area is $\mathrm{cov}_{\mathrm{area}}$ (= 3 km).

$$\mathrm{dist}(\mathrm{Consumer}, \mathrm{Driver}) \leq \mathrm{cov}_{\mathrm{area}}$$

$$\mathrm{SizeOf\ Luggage/Parcel/FoodPacket} \leq \mathrm{UnallottedSpaceOfLuggageArea}$$

Insertion of consumers takes place by Greedy Algorithm, in the case of the shared ride. But it must satisfy earlier conditions which are applicable to the first consumer. Additional travel distance is applicable if the second/third/fourth consumer request is/are accepted, under the following condition.

$$\mathrm{additional}_{\mathrm{dist}} \leq \delta_{\mathrm{dist}},$$

where δ_{dist} is the difference between distance through a new route and distance through an earlier or initial route, which is 10% of the original or initial route distance.

Additional travel time is also allowed under the following condition

$$\mathrm{additional}_{\mathrm{time}} \leq \delta_{\mathrm{time}}.$$

where δ_{time} is the difference between time through a new route and distance through an earlier or initial route, which is 10% of the original or initial route time.

Algorithm

Step-1: the driver initiates the process by sharing his/her id, vehicle id and location information with the server. The driver also mentions the coverage area from his/her current location.

Step-2: the passenger, food packet or parcel is treated as a Consumer. A consumer mentions his/her type of service looking for, pick-up and drop-off location. Based on service type, luggage details are also mentioned. Mode of travel whether in non-shared mode or shared mode is also mentioned. All this Consumer information is uploaded to the server.

Step-3: once the server receives the Consumer request, it starts calculation to find out the nearest pair of Driver and Consumer by satisfying various constraints.

Step-4: server sends matched Consumer information with location information to the matched Driver. Then Driver needs to accept that request. After accepting the request, the shortest route is calculated between them and the Driver approaches following that direction.

Step-5: after receiving the Consumer, the Driver starts the trip. While the trip is started, the best possible route is calculated with respect to the current location considering various constraints, which is followed by the Driver.

Step-6: under non-shared mode, only a single request is accepted. So a single party is allowed to avail of the service.

Step-7: under shared mode, other requests may be accepted based on seat and space availability and also based on other constraints such as pick-up and drop-off location. So multiple parties may avail of the service under the same vehicle. In this mode, the Server finds out a similar type of Consumer such as a Consumer with the same route or intersecting route or route with little deviation or the nearest drop-off location or nearest pick-up location.

Step-8: under non-shared mode, a party is dropped as mentioned in the destination location. After that Drive can go for another trip.

Step-9: under shared mode, the party which is close to the path of the journey is dropped first. Following the same pattern, other parties are dropped. While completing the trip of one party, other trip requests can be accepted. This process continues until the Driver stops accepting the request or else the Driver exceeds the daily time limit of his service.

Step-10: both are non-shared and shared modes, final fare is calculated based on the mode of journey, surcharge rate, distance between pick-up and drop-off location, and average waiting time. The final fare is paid to the Driver either in online or offline payment mode.

Case Studies

Condition 1:

At first passenger request comes then a food request comes

If ($\mathrm{fd}_{\mathrm{time}} \leq D_{\mathrm{p}}$) accepts the order and delivers the food along with the passenger in the cab

Condition 2:

At first passenger request comes then a food request comes

If ($\mathrm{fd}_{\mathrm{time}} > D_{\mathrm{p}}$) accepts the order and collects the food along with the passenger in the cab and delivers later after dropping the passenger.

Condition 3:

At first food request comes then a passenger request comes

If ($\mathrm{fd}_{\mathrm{time}} \leq D_{\mathrm{p}}$) accept the passenger request and drop the passenger along with food in cab.

Condition 4:

At first food request comes then a passenger request comes

If ($\mathrm{fd}_{\mathrm{time}} \geq D_{\mathrm{p}}$) accept the passenger request and drop the passenger along with food in the cab.

Condition 5:

(Rejecting request)

If (any of the above conditions is not satisfied, then a new request won't be accepted) In this condition driver will be going with one of the services at a time.

Accuracy of the Proposed System

The accuracy of our proposed system is evaluated through various essential performance indicators, including on-time performance, matching efficiency, and service reliability. Upon assessing the on-time performance, we observed that both pickup and drop-off times were consistently achieved within an average range of 1–6 microseconds. In terms of matching efficiency, the process of pairing riders with available drivers was completed within 3–10 microseconds. Furthermore, when measuring service reliability, we found that the system consistently fulfilled ride requests with a high availability rate of close to 100%. These metrics collectively demonstrate the accuracy and reliability of our proposed system.

Complexity Analysis

In our proposed model, five goals are considered and the priority orders of the goals are arranged as per their importance to the decision-maker. Priorities as per order are: Maximize the Net Income per month, Maximize the Incentive amount, Maximize the probability of getting Tips, Maximize the Rating, and Minimize the Delivery Delay as much as possible. Both our analytical and strategic solutions have considered these five goals to get the optimal solution. To achieve these five goals we have optimized four variables: the number of riders, number of parcels, number of food packets, and number of medicine boxes. Complexity analysis can be estimated in terms of time and space, but in our case, we have evaluated it in terms of time only. Through various permutations and combinations and considering various test cases, we found our model complexity lies between $O(\log_n)$ and $O(n \times \log_n)$.

Conclusion

The model is illustrated through an example which is solved manually using the modified simplex method and then later validated using LINGO Software. This study focuses on optimizing the monthly targets or goals of a delivery partner. Since it is difficult and time-consuming, it is solved manually with a large GP problem containing many variables. The proposed model is flexible for modifications suiting the requirements of the delivery executive based on certain characteristics.

In the future, the model can be improved by considering other constraints such as order cancellation rate, income per order, traffic collision rate in regions and many other criteria to name. Several other methods can be applied to solve this kind of optimization problem.

Acknowledgements The authors are thankful to Amity University, Kolkata, North-Eastern Hill University and Management Development Institute Murshidabad for the necessary support.

Declarations

Conflict of interest The authors do not have any conflict of interest regarding this publication. The authors do not have any financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

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