Driver-Passenger Matching Problem on Online Transportation Using Goal Programming

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Abstract. Currently, online transportation is one of the choices for public transportation. The uniqueness of this online transportation business is that both passengers and drivers can appear anywhere and anytime. This creates difficulties for online transportation service providers in matching drivers and passengers in order to continue to increase service user satisfaction. The service provider must consider factors such as the duration of the pickup, the distance of the pickup, and the rating of the driver. This study aims to include these various factors in the decision-making process to match drivers and passengers using the goal programming method. The test was carried out by comparing the maximum distance limitation of the pick-up duration to 10 and 15 minutes. From the test results, it was found that the number of matches obtained increased by 11.6%, but with the consequence that the average pickup duration increased by 58.8%, and the average pick-up distance increased by 81.8%. Meanwhile, the driver rating obtained decreased by 5%. This needs to be considered because the greater the duration, the longer the passengers wait for pickup. The farther the distance traveled, the greater the costs incurred by the driver in picking him up. This will affect the loyalty of passengers and drivers to the service. It can be concluded that the goal programming method is capable of carrying out the matching process between drivers and passengers by considering various factors.

INTRODUCTION

With the increase in the number of residents in a city, the need for transportation will also increase. In general, transportation options are divided into public transportation (which is generally provided by the government) and private transportation (which is owned or rented). In recent years, alternative transportation has emerged; this transportation business is commonly referred to as "online transportation" [1][2]. This business is similar to transportation rental services, where passengers can rent transportation services to get to their desired destination. The basic difference is that the entire rental process, the assignment where the driver will fulfill the service, and payment are made online (using an application on the cellphone). So, passengers can order services anytime and anywhere. Online transportation service providers will receive orders from passengers and then assign drivers who will fulfill these orders.

Another uniqueness of this business is that the drivers are not employees of the online transportation service provider company. Drivers do not have specific working hours. Drivers can be available or unavailable, depending on the driver. Drivers can also activate available services anytime and anywhere. Of course, these things create supply and demand uncertainties [3][4][5]. On the other hand, online transportation service providers must provide the best service for customers. For example, assigning the best driver, minimizing the waiting time for passengers waiting to be picked up by the driver, and minimizing the pickup mileage because it incurs costs for the driver

The matching assignment between the driver's location and the passenger's location is a very influential factor in this transportation model because it is impossible to meet demand with supply from other areas that are very far away. This will make the duration and distance needed by the driver to reach the pickup location very large. This can increase transportation costs (due to the distance factor) and waiting times (due to the travel time factor) [3]. It can also increase dissatisfaction from both drivers and passengers, which can also lead to the cancellation of orders (from passengers) or the cancellation of appropriate assignments (from drivers) [6][7].

Therefore, online transportation service providers need the right mechanism for assigning drivers to fulfill orders from passengers. This mechanism is expected to consider the distance factor and travel time required by the driver to get to the pickup location. The system must also be able to consider the selection of drivers with high rating factors. This aims to provide the best service for passengers as well as prioritize drivers who have good performance. This aims to provide the best service for passengers and prioritize drivers who have good performance. Because drivers with good performance generally also have good behavior, such as driving safely, being friendly, and providing comfort to passengers. [8][9].

This study aims to combine the factors of pickup distance, pickup duration, and driver rating in the process of appointing drivers to fulfill orders from passengers. This research will simulate online transportation business processes starting from requesting orders from passengers, available drivers, passenger and driver locations, driver ratings, and possible cancellations from passengers and drivers. The simulation will run in real time with a large number of drivers and passengers. The calculation of the pickup distance and duration from the driver to the pickup location will use the Google Maps API [10]. So that the distance and duration data obtained reflect current conditions, considering current traffic.

GOAL PROGRAMMING

Goal programming is a method pioneered by Charnes and Cooper in the early 1960s and further developed by Ijiri, Lee, and Ignizio. Goal programming is used as a method for making decisions by considering various decision criteria [11]. The use of the goal programming method in the matching assignment process has been widely used in various fields, such as determining nursing staff in the surgical process [12], diet programs [13], production planning [14], and allocating students in departments [15].

The following are the steps for formulating goal programming:

1) Determine the decision variables.
   Clearly state the unknown decision variables. The more precise the definition, the easier the decision-making process will be.
2) Declare system constraints.
3) Determine the right-hand side values and determine the suitable technology coefficients and decision variables included in the constraints. If deviations are only permitted in one direction, only one deviation variable appropriate to the constraint in question should be used.
4) Determine priorities.
5) Determine the order of priority of existing goals. If the problem has no objective order, this step can be skipped.
6) Determine the weight.
7) Assess the deviation from the existing goals. If the problem has no objective order, this step can be skipped.
8) Declare the objective function.
9) Choose the deviation or deviation variable to be included in the objective function.
10) State non-negative needs. This step is a formal part of the formulation of the goal programming problem.

NORMALIZATION

Normalization is the process of converting different types of values into the same number range. Normalization is very useful in conditions where it is necessary to combine or compare several factors that have different ranges of values and different units of measurement. For example, the duration factor will use hours, minutes, and seconds, while the rating factor will consider centimeters, meters, and kilometers. The duration and distance factors have different number ranges. When these two factors are combined or compared, it will be difficult because they have different units of measurement and different ranges of numbers. The min-max normalization formula is as follows [16]:

$$v' = \frac{v - min}{max - min}(new\_max - new\_min) + new\_min \quad (1)$$

v' is the normalized result of the data, v is the original data value, min is the minimum data from the original dataset, max is the maximum data from the original dataset, new_min is the minimum value limit of the new dataset that has been normalized, and new_max is the maximum of the new dataset that has been normalized.

IMPLEMENTATION

Randomize Driver and Passenger Generator

The simulation will be run using a website application. The simulation will randomize the time of appearance of orders from passengers and their pick-up locations. In addition, the simulation will also randomize the appearance time and location of the available drivers. Then, the application calculates the distance and duration required for each driver to travel from their respective locations to the passenger pick-up location using the Google Map API. The required time and distance have automatically considered the traffic conditions on the route that must be passed during the simulation (in real-time). An example of the results obtained is shown in Table 1.

TABLE 1. Distance and Duration

Passenger ID	Driver ID	
	1	**2**
1	Distance: 1.10 km Duration: 5.42 minutes	Distance: 7.34 km Duration: 20.03 minutes
2	Distance: 0.33 km Duration: 1.07 minutes	Distance: 7.06 km Duration: 21.38 minutes
3	Distance: 5.62 km Duration: 16.00 minutes	Distance: 2.15 km Duration: 7.38 minutes
4	Distance: 6.25 km Duration: 14.40 minutes	Distance: 0.94 km Duration: 4.73 minutes

Data Normalization

The distance and duration are then normalized using a maximum value of one and a minimum value of zero. So, the normalization value is obtained as shown in Table 2.

TABLE 2. Distance and Duration Normalization

Passenger ID	Driver ID	
	1	**2**
1	Distance: 0.109 Duration: 0.214	Distance: 1 Duration: 0.934
2	Distance: 0 Duration: 0	Distance: 0.959 Duration: 1
3	Distance: 0.755 Duration: 0.735	Distance: 0.260 Duration: 0.311
4	Distance: 0.844 Duration: 0.656	Distance: 0.086 Duration: 0.180

The system then retrieves the rating data from the available drivers in the driver data. The system then normalizes in a slightly different way (Equation 2) because the greater the value obtained, the better. This is different from the factor of duration and distance, the bigger it is, the worse it is. The driver data and normalization results can be seen in Table 3.

$$v' = 1 - \frac{v - min}{max - min} \tag{2}$$

TABLE 3. Driver Rating

	Driver ID	
	1	**2**
Rating	3.3	3.9
Normalization	1	0

Goal Programming Set Up

The model of goal programming in this simulation is as follows: The objective function of this simulation is to minimize the pick-up duration (d_1), which minimizes the waiting time for passengers to be picked up, as well as minimizes the pick-up distance (d_2), which minimizes transportation costs for drivers. In addition, the simulation will prioritize assignments for drivers (d_3) with the highest rating.

Each driver will receive an assignment for one order from a passenger, and vice versa. The pickup distance target limit being tested is 3.5 km, or 3500 meters. The target pickup time limit is ten minutes, or 600 seconds, assuming that the duration and time limits are relatively reasonable for both drivers and passengers. Meanwhile, the highest driver rating is five points.

Notations:
i = 1, 2, 3, …m (id drivers)
j = 1, 2, 3, …n (passenger id)
n = number of drivers
m = number of passengers
d = negative/positive deviation
w = Priority weight of each goal
Xij = the required duration from driver i to passenger j
Jij = distance required from driver i to passenger j
Ri = rating of driver i

Objective Function:

$$Min\ Z = w_1 d_1 + w_2 d_2 + w_3 d_3 \tag{3}$$

Minimize pick-up duration

$$d_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} Xij * Yij \tag{4}$$

Minimize pick-up distance

$$d_2 = \sum_{i=1}^{n} \sum_{j=1}^{m} Jij * Yij \tag{5}$$

Maximize *driver rating*

$$d_3 = \sum_{i=1}^{n} \sum_{j=1}^{m} Ri * Yij \tag{6}$$

Constraint

Constraint to ensure there is only 1 driver assigned to 1 passenger

$$\sum_{i=1}^{n} \sum_{j=1}^{m} Yij = 1 \tag{7}$$

Constraint to ensure there is only 1 passenger assigned to 1 drive

$$\sum_{i=1}^{n} \sum_{j=1}^{m} Yji = 1 \tag{8}$$

Constraint to limit pick-up duration to a maximum of 10 minutes/600 seconds

$$\sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{Xij} <= 600 \tag{9}$$

Constraints to limit the pick-up distance to a maximum of 3.5 km/3500 meters

$$\sum_{\mathrm{i}=1}^{n} \sum_{\mathrm{j}=1}^{m} Jij <= 3500 \tag{10}$$

Constraints to ensure that the pick-up duration is the minimum

$$\sum_{i=1}^{n}\sum_{j=1}^{m} Xij * Yij - d_1^{+} = 0 \quad (11)$$

Constraints to ensure that the pick-up distance is the minimum

$$\sum_{i=1}^{n}\sum_{j=1}^{m} Jij * Yij - d_2^{+} = 0 \quad (12)$$

Constraints to ensure that the most driver rating is maximum

$$\sum_{i=1}^{n}\sum_{j=1}^{m} Ri * Yij + d_3^{-} = 5 \quad (13)$$

Driver-Passenger Matching Testing

In this test, the simulation was run for 60 batches with a duration of 60 seconds for each batch (as seen in Table 4). Passenger or driver orders that fail to get matched in a certain batch will be entered into the next batch with a cancellation percentage of 25% (canceled orders or drivers are no longer available). The testing attempts to compare the differences in waiting time limits for ten and fifteen minute passengers. This aims to determine the difference in the results obtained after changing the limit on the goal programming that has been made.

TABLE 4. Testing Result

	Testing 1 - 10 Minutes Limit	**Testing 2 - 15 Minutes Limit**
Batch Number	60	60
Assignment Success	172	192
Driver and Passenger not Assigned	56	40
Min Passenger Waiting Time	0.600 minutes	0.365 minutes
Max Passenger Waiting Time	10.697 minutes	17.067 minutes
Avg Passenger Waiting Time	4.784 minutes	7.343 minutes
Total Passenger Waiting Time	822.275 minutes	1351.493 minutes
Min Pick-up Duration	0.600 minutes	0.365 minutes
Max Pick-up Duration	9.954 minutes	16.950 minutes
Avg Pick-up Duration	4.215 minutes	6.695 minutes
Total Pick-up Duration	724.217 minutes	1264.267 minutes
Min Pick-up Distance	0.302 km	0.152 km
Max Pick-up Distance	4.085 km	6.863 km
Avg Pick-up Distance	2.451 km	4.457 km
Total Pick-up Distance	240.957 km	433.395 km
Average Driver Rating	3.63	3.45

From the test results, it was found that the goal programming that had been made was able to run as expected by minimizing the pickup distance and duration and maximizing drivers who had high ratings. This is proven by the acquisition of the maximum duration that is close to the predetermined limit, which is 9.954 minutes, and the maximum pickup distance that is close to the limit, which is 4.085 kilometers.

Testing using a pick-up duration limit of 15 minutes resulted in a higher number of successful assignments (192 assignments). However, the average pickup duration is quite high, at 6.695 minutes, and the average pickup distance is 4.457 kilometers. This resulted in a greater average passenger waiting time of 7.343 minutes (compared to the 10 minute pickup time limit of 4.784 minutes).

Simulation Visualization

The results of the assignment process are then displayed on a Google Map (Fig. 1). Available drivers are visualized using a blue marker icon, while passenger booking locations use a red marker icon, and destination locations use a green marker icon. The red route is used to visualize the pickup route from the driver's starting point to the passenger's pick-up point.

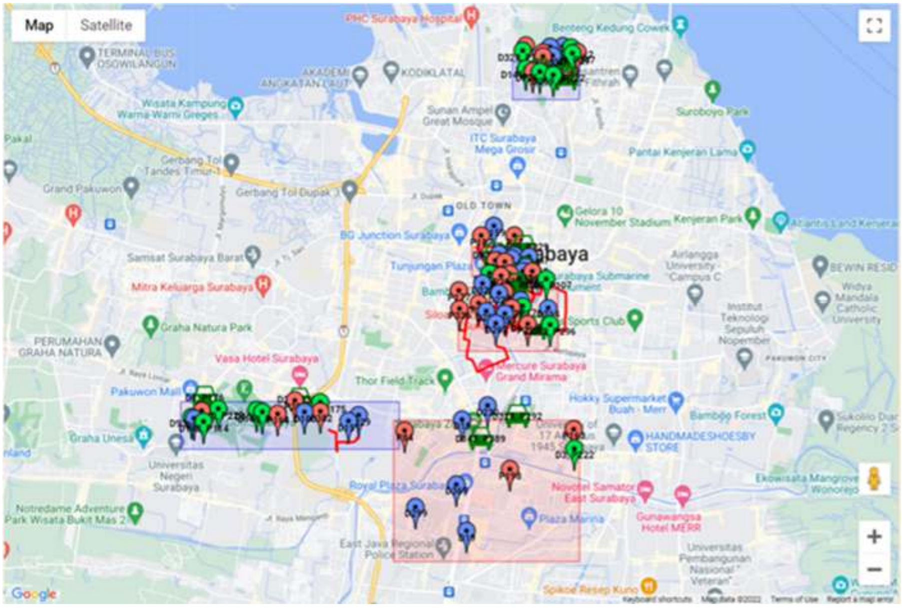

FIGURE 1. Mapping results on Google Map

CONCLUSION

With the increasing needs of the community in terms of transportation, the online transportation business is growing rapidly and has become a choice of transportation for the wider community. In this business, both passengers and drivers can appear anywhere and anytime. This creates a high factor of uncertainty in supply and demand. Online transportation service providers must consider various factors when assigning drivers who will fulfill orders from passengers, such as duration of pickup, pickup distance, and driver rating. This study simulates matching between drivers and passengers by considering these factors using goal programming. The matching is carried out with a one passenger one driver model with a maximum pickup duration limit of ten minutes, and a maximum pickup distance limit of 3.5 kilometers, maximizing the rating of the assigned driver. The process is simulated using duration and distance data in real-time at the time of testing using the Google Maps API so that the data takes traffic factors into account.

The test results show that goal programming performs the expected matching process between drivers and passengers. The maximum duration obtained is close enough to the predetermined limit, which is 9.954 minutes, and the maximum pickup distance is 4.085 km. Testing was also carried out by changing the pickup duration limit to 15 minutes. From this comparison, it is known that the number of matches obtained increased by 11.6% (192 assignments), but with the consequence that the average pickup duration increased by 58.8% (6.695 minutes) and the average pickup distance increased by 81.8% (4.457 kilometers). This needs to be considered because the greater the duration, the longer the passengers wait for pickup. whereas the farther the distance, the greater the costs incurred by the driver in picking it up. This will affect the loyalty of passengers and drivers to the service. The driver rating obtained also decreased by 5% (3.45). Therefore, further research can include other factors, such as rush hour or night hours, as a consideration for limiting pickup duration and pickup distance in order to obtain flexibility in determining matching. Future research can also compare the results obtained with other problem assignment methods, such as branch and bound, Hungarian, and others, in order to obtain better results.

ACKNOWLEDGMENT

We thank our colleagues Lienny Ferlinda, Viona Angelica, Tanti Octavia for their valuable input, discussion and feedback.

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