Original Article

Ride-Hailing Assignment Problem under Waiting Time Uncertainty using Interval-Valued Fuzzy Quadratic

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Abstract: Ride-hailing is a creative idea created by transportation supported by science and technology. Ride-hailing services can help daily community activities. The issue with ride-hailing is that traffic conditions are unpredictable, implying that waiting times are uncertain. The time passengers spend waiting from when they book a ride service until the driver arrives at the pick-up location is called waiting time. This study suggests a quadratic programming technique for minimizing waiting time while accounting for the unpredictability of pick-up travel time. The interval-valued fuzzy quadratic programming method handles the uncertainty and imprecision of the anticipated journey time. When allocating drivers to pick up passengers, interval-valued fuzzy numbers can provide a more realistic representation of waiting time uncertainty. As a result, the interval-valued fuzzy quadratic programming model can handle the uncertainty in waiting time for ride-hailing assignment problems. The model's performance is evaluated using waiting time and the number of people served. The model's performance is demonstrated numerically using the simulation-based case study. This study shows how to utilize a mathematical method to solve real-world problems with uncertainty and improve user welfare.

Keywords: Fuzzy Quadratic Programming; Interval-Valued Fuzzy; Ride-Hailing; Uncertainty.

1. Introduction

Transportation plays a pivotal role in daily life, and the latest innovation in ride-hailing services has become an integral part of modern living. Ride-hailing, a revolutionary transportation solution, has transformed how people move by harnessing technological advancements. Platforms like Grab and Gojek

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have led the charge in providing efficient and rapid access to transportation services through smartphone applications (Azizah & Adawia, 2018; Cramer & Krueger, 2016; Qin et al., 2021; Yang et al., 2020; Yu et al., 2019, 2022). Its convenience significantly aids community activities (Do et al., 2019; Luo et al., 2019; Xu et al., 2022). Notably, Grab and Gojek, Southeast Asia's leading ride-hailing companies, boast massive user bases and driver-partners, revolutionizing transportation dynamics (Chalermpong et al., 2023; Chandler, 2019; Crittenden et al., 2017). Offering real-time driver and fare information, ride-hailing platforms like these streamline reservations and enhance transportation accessibility (Anindhita et al., 2016; Young & Farber, 2019). Ride-hailing has bolstered local economies, particularly in Bandung, Indonesia, due to its affordability and mobility benefits (Nandi, 2019). Furthermore, ride-hailing has become a significant job creator in urban centers worldwide (Wibawa et al., 2018).

The assignment system, crucial to ride-hailing, strategically manages driver-partners to meet passenger demand effectively (Yan et al., 2020). However, this system's efficiency heavily relies on the precise timing of driver pick-ups, influencing its overall quality (Yan et al., 2020). Travel time uncertainty significantly impacts the decision-making within this system (Guo et al., 2021; Megantara et al., 2022). Such uncertainties can render optimized decisions unfeasible if travel times exceed predetermined limits shortly after their determination. To address this, modeling the ride-hailing assignment problem becomes imperative. Within the realm of ride-hailing, the mechanism of matching drivers to passengers plays a crucial role in ensuring overall service efficiency. Various studies have explored different assignment strategies to enhance the effectiveness and efficiency of this matching process (Agatz et al., 2011). Some research has highlighted the importance of considering factors such as distance, waiting time, and driver capacity to ensure optimal assignment (Lyu et al., 2019; Yang et al., 2020). However, there is still an urgent need to address uncertainties in travel time estimations, which remain critical for improving assignment quality. The adaptability of ride-hailing drivers has been linked to increased passenger capacity (Stiglic et al., 2015).

Additionally, scholars have highlighted the creation of new employment opportunities spurred by ride-hailing services (Flores & Rayle, 2017). Explorations into multi-objective ride matching (Lyu et al., 2019), centralized assignment optimization, and pricing strategies have also been discussed (Yan et al., 2020). Some studies have tackled specific aspects like optimizing assignment radius to minimize waiting and idle times (Yang et al., 2020) and dealing with waiting time uncertainty using classical fuzzy approaches (Megantara et al., 2022). In response to the challenge of uncertainty, fuzzy quadratic programming has emerged as a significant approach in mathematical modeling. These models allow optimization while considering uncertainties and ambiguities in specific parameters (Huidobro et al., 2022). Moreover, recent advancements in interval-valued fuzzy sets (IVFS) have garnered attention for their ability to handle more complex uncertainties than conventional fuzzy approaches (Huidobro et al., 2022). Through this research, we aim to amalgamate ride-hailing matching with mathematical methods like fuzzy quadratic programming and interval-valued fuzzy concepts. The primary aim of this study is to develop a ride-hailing assignment model that adapts to uncertainties in travel times, thereby optimizing the driver assignment process with higher accuracy and responsiveness to unforeseen road conditions.

2. Materials and Methods

This section discusses methods for solving quadratic programming problems with uncertain objective functions using the interval-valued fuzzy approach referred to by Su (2007).

Definition 1: Signed Distance of an Interval-Valued Fuzzy Number

Let $\tilde{A} = [(a,b,c;\lambda),(p,b,r;\rho)] \in F_{IN}(\lambda,\rho)$ an interval-valued fuzzy number.

For $0 < \lambda < \rho \leq 1$:

$$d(\tilde{A},\tilde{0}) = \frac{1}{\lambda}\int_0^\lambda d^*([A_l^U(\alpha),A_l^L(\alpha)]\cup[A_r^L(\alpha),A_r^U(\alpha)],0)d\alpha + \frac{1}{\rho-\lambda}\int_\lambda^\rho d^*([A_l^U(\alpha),A_r^U(\alpha)],0)d\alpha$$

$$= \frac{1}{8}\left[6b+a+c+4p+4r+3(2b-p-r)\frac{\lambda}{\rho}\right].$$

(1)

For $0 < \lambda = \rho \leq 1$

$$d(\tilde{A}, \tilde{0}) = \frac{1}{8}[4b + a + c + p + r]. \tag{1}$$

Definition 2: Ranking of Interval-Valued Fuzzy Numbers

Given $\tilde{A} = [(a,b,c;\lambda),(p,b,r;\rho)], \tilde{B} = [(d,e,g;\lambda),(u,e,w;\rho)] \in F_{IN}(\lambda,\rho)$:

$$(\tilde{B} \prec \tilde{A}) \text{ if } (d(\tilde{B},\tilde{0}) < d(\tilde{A},\tilde{0})),$$
$$(\tilde{B} \approx \tilde{A}) \text{ if } (d(\tilde{B},\tilde{0}) = d(\tilde{A},\tilde{0})). \tag{3}$$

Definition 3: Property of Interval-Valued Fuzzy Numbers

For a series $\tilde{A}_n, n = 1,2,3,\ldots, \tilde{B} \in F_{IN}(\lambda,\rho)$:

$$\text{If } \tilde{B} \succeq \tilde{A}_n \text{ for all } n = 1,2,\ldots, \text{ then } \tilde{B} = \max_{n \in \{1,2,\ldots\}} \tilde{A}_n. \tag{4}$$

These definitions provide a framework for evaluating, comparing, and establishing relationships between interval-valued fuzzy numbers and within the specified intervals based on their signed distances from the origin.

3. Results

In the ride-hailing context, the Matching Problem addresses the efficient assignment of ride requests to available vehicles while considering objectives to minimize waiting time, reduce abandoned requests, and balance the workload among drivers.

3.1. Matching Model
Parameters:
Set of Ride Requests I**:** This represents the collection of all ride requests made by passengers within a specified timeframe. Each request in the set I requires assignment to an available vehicle, impacting the ride-hailing system's overall efficiency and service quality.

Set of Available Vehicles J**:** Encompasses all vehicles present and ready to undertake ride requests. Vehicles in set J serve as potential matches for the ride requests, influencing the allocation process and determining service coverage.

Waiting Time t_{ij}**:** Represents the estimated waiting time incurred when assigning request i to vehicle j. The waiting time t_{ij} influences decision-making in assigning requests to optimize passenger wait times and overall service efficiency.

Driver Performance d_j**:** the most recent performance or rating of driver/vehicle j. Incorporates the driver's latest performance, influencing the workload capacity or maximum tasks a driver can handle daily.

These parameters together play crucial roles in modeling the ride-hailing system, encompassing various aspects such as waiting times, assignment decisions, abandonment rates, workload distribution, and driver performance to optimize service quality and efficiency.

Decision Variables:

Ride Request Assignment Variable x_{ij}**:** Indicates whether ride request i is matched with vehicle j (binary value 0 or 1). This variable serves as a binary decision indicator. If $x_{ij} = 1$, it signifies that ride request i is assigned to vehicle j, facilitating the efficient allocation of requests to available vehicles. If $x_{ij} = 0$, it indicates that this specific ride request is not assigned to vehicle j at that instance.

Abandoned Request Variable y_i**:** Indicates whether ride request i is abandoned (binary value 0 or 1). This binary variable captures whether a specific ride request i is marked as abandoned $y_i = 1$ or not $y_i = 0$. If $y_i = 1$, it implies that the corresponding ride request has been abandoned or unfulfilled. On the contrary, if $y_i = 0$, the ride request is either successfully matched with a vehicle or is in the process of being matched.

Driver Workload Variable z_j**:** Represents the current performance or workload of driver j. This variable quantifies the workload or performance of each driver j. It's a numerical value that reflects the cumulative workload or the number of assigned ride requests that driver j is currently handling. It is updated based on the assignment of ride requests to drivers and contributes to measuring the variance in workload among drivers.

These decision variables play pivotal roles in the optimization model, determining the assignment of ride requests to vehicles, tracking abandoned requests, and measuring the workload or performance of individual drivers in the ride-hailing system. They enable the model to make informed decisions regarding request allocation, abandonment status, and workload distribution among drivers.

Objectives:

Minimizing Total Waiting Time: The first objective focuses on minimizing the cumulative waiting time experienced by passengers. By efficiently assigning ride requests to available drivers, this objective aims to reduce overall waiting times, enhancing customer satisfaction and service efficiency.

$$\min \sum_{i \in I} \sum_{j \in J} t_{ij} x_{ij}. \tag{2}$$

Reducing Abandoned Requests: The second objective aims to minimize the number of abandoned ride requests. Unfulfilled requests impact customer satisfaction and pose challenges in maintaining service reliability. Minimizing abandoned requests contributes to a more seamless and reliable service experience.

$$\min \sum_{i \in I} y_i. \tag{3}$$

Balancing Driver Workload: The third objective introduces fairness by minimizing the variance in driver performance or workload. It ensures a more equitable distribution of tasks among drivers, preventing situations where some drivers are overburdened while others are underutilized. Balancing workload enhances driver satisfaction and system efficiency.

$$\min \frac{1}{|J|} \sum_{j \in J} (z_j - \overline{z})^2, \tag{4}$$

where

$$\overline{z} = \frac{1}{|J|} \sum_{j \in J} z_j. \tag{5}$$

is the average performance among drivers.

Constraints:

Vehicle Capacity Constraint (Each vehicle handles at most one request):

$$\sum_{i \in I} x_{ij} \leq 1, \forall j \in J. \tag{6}$$

This constraint ensures that each vehicle can handle at most one ride request at a given time. It limits the assignment of multiple requests to a single vehicle concurrently, ensuring that vehicles can efficiently cater to passengers without exceeding their capacity.

Matching or Abandonment Constraint (Matching or abandonment of requests):

$$\sum_{j \in J} x_{ij} = 1 - y_i, \forall i \in I. \tag{7}$$

This constraint governs the relationship between the assignment of a ride request i to vehicles x_{ij} and its abandonment y_i. This constraint dictates that each ride request must be assigned to at most one vehicle or marked as abandoned. It prevents the scenario where a single request is simultaneously assigned to multiple vehicles, maintaining the integrity of the assignment process. It ensures that if a request is assigned to a vehicle $x_{ij} = 1$, it is not marked as abandoned $y_i = 0$, and vice versa. It guarantees that each request is either assigned or marked as abandoned, but not both.

Driver Workload Update Constraint (Updating drivers' current performance):

$$z_j = d_j + \sum_{i \in I} x_{ij}, \forall j \in J. \tag{8}$$

This constraint updates the current performance (workload) of each driver j based on the requests assigned to their respective vehicles x_{ij}. It considers the initial driver workload d_j and adds the assigned requests, reflecting the cumulative workload each driver handles due to the assigned requests.

Variable Domains:

$$x_{ij}, y_i \in \{0,1\}, z_j \geq 0, \forall i \in I, \forall j \in J. \tag{9}$$

This model seeks to optimize ride request assignments by minimizing waiting time, reducing abandoned requests, and balancing driver workload for improved efficiency and customer satisfaction in the ride-hailing system.

3.2. Interval-Valued Fuzzy Matching Model

Interval-valued fuzzy quadratic programming is used to deal with the uncertain problem. In this study, we assume that waiting times are uncertain parameters since drivers have different speeds when they drive, also due to unpredictable traffic conditions. The model becomes:

$$\min \sum_{i \in I} \sum_{j \in J} \tilde{t}_{ij} x_{ij},$$

$$\min \sum_{i \in I} y_i,$$

$$\min \frac{1}{|J|} \sum_{j \in J} (z_j - \bar{z})^2,$$

$$s.t. \tag{10}$$

$$\bar{z} = \frac{1}{|J|} \sum_{j \in J} z_j,$$

$$\sum_{i \in I} x_{ij} \leq 1, \forall j \in J,$$

$$\sum_{j \in J} x_{ij} = 1 - y_i, \forall i \in I,$$

$$z_j = d_j + \sum_{i \in I} x_{ij}, \forall j \in J.$$

$$x_{ij}, y_i \in \{0,1\}, z_j \geq 0, \forall i \in I, \forall j \in J.$$

corresponding to (13), by definition 1, 2, 3 we get quadratic programming in the fuzzy sense as following:

$$\min Z = \frac{1}{2} d\left(\tilde{Z}, \tilde{0}\right) = \sum_{i \in I} \sum_{j \in J} t_{ij} x_{ij} + \frac{1}{16} \sum_{i \in I} \sum_{j \in J} \left[\delta_{ij3} - \delta_{ij2} + \left(4 - 3\rho\right)\left(\delta_{ij4} - \delta_{ij1}\right) \right] x_{ij},$$

$$\min \sum_{i \in I} y_i,$$

$$\min \frac{1}{|J|} \sum_{j \in J} (z_j - \overline{z})^2,$$

$s.t.$

$$\overline{z} = \frac{1}{|J|} \sum_{j \in J} z_j, \tag{11}$$

$$\sum_{i \in I} x_{ij} \le 1, \forall j \in J,$$

$$\sum_{j \in J} x_{ij} = 1 - y_i, \forall i \in I,$$

$$z_j = d_j + \sum_{i \in I} x_{ij}, \forall j \in J.$$

$$x_{ij}, y_i \in \{0,1\}, z_j \ge 0, \forall i \in I, \forall j \in J.$$

3.3. Case Study

Ride-hailing services have transformed modern transportation, necessitating efficient algorithms to swiftly pair riders with available drivers. This case study delves into optimizing ride-hailing matching algorithms using simulated data to minimize waiting times and enhance service quality. The study utilizes simulated data emulating ride-hailing scenarios consisting of 25, 50 riders and 25, 50 drivers across 10 historical periods. Simulated waiting times between rider-driver pairs and driver performances form the core parameters analyzed in this study. Employing a heuristic-based weighted sum algorithm, the study focuses on efficiently matching riders with drivers. Factors such as waiting times, abandoned requests, and driver performance variance are considered to optimize pairings and reduce waiting times. The algorithm iteratively runs simulations to identify optimal rider-driver matches. Each iteration aims to reduce waiting times for riders, manage abandoned requests, and allocate drivers effectively, culminating in enhanced matching strategies.

Upon completion of simulations, crucial metrics are generated for evaluation. These include abandoned rider counts, percentage of served riders, total waiting time, average waiting time per rider, percentage of deployed drivers, average driver performance, and variance in driver performance. This case study provides insights into the efficacy of heuristic-based ride-hailing matching algorithms utilizing simulated data. The study highlights the algorithms' potential to minimize waiting times, manage abandoned requests, and optimize driver deployment strategies for improved service quality. In the fuzzy approach for modeling waiting times in a ride-hailing system, we employ a methodology that captures the uncertainty and variability present in historical waiting time data. This approach utilizes four distinct delta values, each computed based on the historical waiting times of rider-driver pairs. To start, we consider the historical waiting times dataset, which contains waiting time information for various rider-driver pairs across multiple historical periods. This dataset allows us to derive insightful measures to quantify the deviation and spread within these waiting times. Delta Calculations:

- δ_1: Variance from Minimum represents the difference between the mean and minimum waiting times observed across historical periods. It captures the deviation from each rider-driver pair's lowest recorded waiting time.

- δ_2: Deviation from Midpoint (Lower Bound), signifies the difference between the mean waiting time and the midpoint between the mean and minimum waiting times. It measures the deviation from the average of the lowest and mean waiting times.

- δ_3: Deviation from Midpoint (Upper Bound), quantifies the difference between the midpoint of the mean and maximum waiting times and the mean waiting time. It reflects the deviation from the average of the highest and mean waiting times.

- δ_4: Variance from Maximum represents the difference between the maximum and mean waiting times. It captures the variance from each rider-driver pair's highest recorded waiting time.

These delta values, computed from historical waiting time data, are pivotal indicators of the variability and dispersion in waiting times.
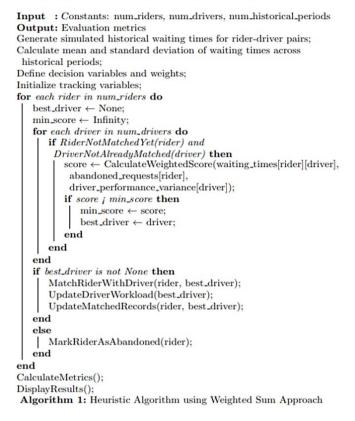
```
Input  : Constants: num_riders, num_drivers, num_historical_periods
Output: Evaluation metrics
Generate simulated historical waiting times for rider-driver pairs;
Calculate mean and standard deviation of waiting times across
  historical periods;
Define decision variables and weights;
Initialize tracking variables;
for each rider in num_riders do
    best_driver ← None;
    min_score ← Infinity;
    for each driver in num_drivers do
        if RiderNotMatchedYet(rider) and
           DriverNotAlreadyMatched(driver) then
            score ← CalculateWeightedScore(waiting_times[rider][driver],
               abandoned_requests[rider],
               driver_performance_variance[driver]);
            if score ¡ min_score then
                min_score ← score;
                best_driver ← driver;
            end
        end
    end
    if best_driver is not None then
        MatchRiderWithDriver(rider, best_driver);
        UpdateDriverWorkload(best_driver);
        UpdateMatchedRecords(rider, best_driver);
    end
    else
        MarkRiderAsAbandoned(rider);
    end
end
CalculateMetrics();
DisplayResults();
 Algorithm 1: Heuristic Algorithm using Weighted Sum Approach
```

Figure 1. Pseudocode for simulation-based case study

In the context of a fuzzy logic-based ride-hailing system, they aid in adjusting and accommodating uncertainty to optimize decision-making processes related to matching riders with drivers based on waiting time considerations.

Greedy Algorithm Performance displayed robust performance across diverse scenarios, showcasing its effectiveness in handling ride-hailing demands:

Case 1: 25 Riders, 25 Drivers.

In this scenario, the Greedy Algorithm ensured optimal utilization of available resources, achieving a 100.0% service rate without any riders being abandoned. The total waiting time was recorded at 384.99 units, with an average waiting time of 15.40. All available drivers were effectively deployed, maintaining a high average driver performance 49.2. However, there was a moderate variance in driver performance, reaching 503.2, indicating slight inconsistencies among drivers.

Case 2: 25 Riders, 50 Drivers.

With an increased pool of drivers, the algorithm efficiently served all riders but at a reduced deployment rate of 50.0%. Despite this reduction, no riders were abandoned, and the total waiting time slightly decreased to 379.78 units, resulting in an average waiting time of 15.19 units. The average driver performance reduced to 43.92, possibly due to the expanded driver base, while the variance in driver performance increased notably to 740.63, reflecting increased performance fluctuations among drivers.

Case 3: 50 Riders, 25 Drivers

In this scenario, with an imbalanced ratio of riders to drivers, 25 riders were unfortunately abandoned, resulting in a 50.0% service rate, and the total waiting time decreased to 338.30 units, correlating to an average waiting time of 13.53 units. However, despite the reduced rider abandonment, the average driver performance stood at 42.4, and the variance in driver performance persisted at 617.12, indicating challenges in handling an imbalanced demand-supply ratio.

Case 4: 50 Riders, 50 Drivers.

The algorithm efficiently served all riders, recording a 100.0% service rate. Despite this, the total waiting time increased to 773.62 units, resulting in an average waiting time of 15.47 units. The deployment rate of drivers remained optimal at 100.0%, maintaining an average driver performance of 48.7. However, the variance in driver performance spiked to 876.65, signifying increased disparities in driver ratings despite optimal service coverage.

Tabu Search Algorithm demonstrated comparable performance to the Greedy Algorithm across various scenarios:

Case 1: 25 Riders, 25 Drivers.

Similar to the Greedy Algorithm, Tabu Search achieved a 100.0% service rate without abandoned riders. The total waiting time was reduced to 281.47 units, resulting in an average waiting time of 11.26. Additionally, the algorithm deployed all available drivers effectively, maintaining an average driver performance of 49.2. However, like the Greedy Algorithm, the variance in driver performance stood at 503.2, highlighting similar inconsistencies among drivers.

Case 2: 25 Riders, 50 Drivers.

In this scenario, Tabu Search served all riders efficiently while deploying only half of the available drivers. The total waiting time it was further decreased to 246.08 units, resulting in an average waiting time of 9.84 units. However, similar to the Greedy Algorithm, the variance in driver performance increased notably to 740.63, indicating the impact of increased driver numbers on performance inconsistencies.

Case 3: 50 Riders, 25 Drivers.

Tabu Search achieved a 100.0% service rate without abandoning any riders, resulting in a total waiting time of 246.80 units and an average waiting time of 4.94 units. Despite the imbalance in demand and supply, the algorithm effectively utilized available drivers, maintaining an average driver performance of 42.4. However, similar to previous scenarios, the variance in driver performance remained at 617.12, reflecting consistent challenges in handling imbalanced rider-driver ratios.

Case 4: 50 Riders, 50 Drivers.

With an increased pool of drivers, Tabu Search managed to serve all riders without abandonment, recording a total waiting time of 536.84 units and an average waiting time of 10.74 units. All available drivers were effectively deployed, maintaining an average driver performance of 48.7. Yet again, the variance in driver performance persisted at 876.65, reflecting the impact of driver pool size on performance disparities.

Fuzzy Approach Comparison - Integrating fuzzy logic into the Greedy Algorithm and Tabu Search models provided valuable insights into handling uncertainty within the ride-hailing system. These approaches demonstrated distinctive outcomes across different scenarios by operating with varying degrees of uncertainty ($\rho=0.75$).

Fuzzy - Greedy Algorithm Results - Applying the fuzzy approach to the Greedy Algorithm revealed intriguing observations:

Case 1: 25 Riders, 25 Drivers.

Despite serving all riders, the waiting times exhibited substantial variability. The total waiting time of 384.99 units had a notably optimistic waiting time of 84.19 units and a pessimistic waiting time of 683.84 units, with an average waiting time of 15.40 units.

Case 2: 25 riders, 50 Drivers.

While managing to serve all riders, the waiting times displayed significant variation. The total waiting time amounted to 379.78 units, with an optimistic waiting time of 85.64 units and a pessimistic waiting time of 685.11 units, averaging at 15.19 units.

Case 3: 50 Riders, 25 Drivers.

An imbalance was encountered, leading to the abandonment of 25 riders. The total waiting time stood at 338.30 units, showing optimistic waiting times of 68.64 units and pessimistic waiting times of 662.91 units, with an average waiting time of 13.53 units.

Case 4: 50 Riders, 50 Drivers.

All riders were served without abandonment. The total waiting time was 773.62 units, with an optimistic waiting time of 200.40 units and a pessimistic waiting time of 1358.77 units, averaging 15.47 units.

Fuzzy - Tabu Search Results - Tabu Search, integrated with inteval-valued fuzzy, presented similar outcomes:

Case 1: 25 Riders, 25 Drivers.

All riders were served with varying waiting times due to uncertainty. The total waiting time was 292.89 units, with an optimistic waiting time of 57.54 units and a pessimistic waiting time of 595.44 units, averaging 11.72 units.

Case 2: 25 Riders, 50 Drivers.

Demonstrated successful service to all riders, exhibiting total waiting times of 280.06 units, with an optimistic waiting time of 57.40 units and a pessimistic waiting time of 608.98 units, averaging 11.20 units.

Case 3: 50 Riders, 25 Drivers.

Despite an imbalance resulting in abandonment, the Tabu Search managed a total waiting time of 247.60 units, with an optimistic waiting time of 50.73 units and a pessimistic waiting time of 571.83 units, averaging 4.95 units.

Case 4: 50 Riders, 50 Drivers.

Displayed no abandonment, providing a total waiting time of 542.92 units, an optimistic waiting time of 97.45 units, and a pessimistic waiting time of 1130.20 units, averaging 10.86 units.

These observations illustrate how the inclusion of fuzzy logic affected service quality and efficiency metrics within the ride-hailing system under varying degrees of uncertainty, showcasing the adaptability of these algorithms in managing such uncertainties. Complete results can see in Table 1.

Table 1. Simulation results

Algorithm	Case	No. of Abandoned Riders	% of Served Riders	Total Waiting Time	Average Waiting Time	% of Deployed Drivers	Average Performance	Variance in Driver Performance
Greedy	1	0	100	384.99	15.4	100	49.2	503.2
Greedy	2	0	100	379.78	15.19	50	43.92	740.63
Greedy	3	25	50	338.29	13.53	100	42.4	617.12
Greedy	4	0	100	773.62	15.47	100	48.7	876.65
Tabu	1	0	100	281.47	11.26	100	49.2	503.2
Tabu	2	0	100	246.08	9.84	50	43.92	740.63
Tabu	3	0	100	246.8	4.94	100	42.4	617.12
Tabu	4	0	100	536.84	10.74	100	48.7	876.65
Fuzzy-Greedy	1	0	100	384.99	15.4	100	49.2	503.2
Fuzzy-Greedy	2	0	100	379.78	15.19	50	43.92	740.63
Fuzzy-Greedy	3	25	50	338.29	13.53	100	42.4	617.12
Fuzzy-Greedy	4	0	100	773.62	15.47	100	48.7	876.65
Fuzzy-Tabu	1	0	100	292.89	11.72	100	49.2	503.2
Fuzzy-Tabu	2	0	100	280.06	11.2	50	43.92	740.63

Fuzzy-Tabu	3	0	100	247.6	4.95	100	42.4	617.12
Fuzzy-Tabu	4	0	100	542.92	10.86	100	48.7	876.65

4. Discussion

The application of interval-valued fuzzy quadratic programming in the context of the ride-hailing matching problem provides a robust method for handling uncertain parameters such as waiting times. The algorithm can deal with imprecise or vague information inherent in real-world ride-hailing scenarios by accommodating uncertainty through interval-valued fuzzy sets. Interval-valued fuzzy quadratic programming allows for the simultaneous optimization of multiple objectives in a ride-hailing system, like minimizing waiting times, reducing abandoned requests, and balancing driver workloads. This multi-objective approach, within an uncertain environment, aids in achieving robust and balanced solutions that cater to the various stakeholders' needs. Using interval-valued fuzzy quadratic programming for the ride-hailing matching problem differs from conventional crisp optimization methods. This advancement aligns with the evolving trend in operations research and optimization, acknowledging and addressing uncertainties in real-world decision-making processes.

The significance of interval-valued fuzzy quadratic programming in managing uncertainties parallels prior studies advocating for adaptable and resilient optimization frameworks in dynamic systems. This adaptability is crucial in ride-hailing services due to the ever-changing demand, driver availability, and traffic conditions. The successful application of interval-valued fuzzy quadratic programming in the ride-hailing context demonstrates its practical potential in real-world deployment. The algorithm's ability to handle uncertainties can significantly enhance decision-making and operational efficiency in ride-hailing platforms. Future research may explore fine-tuning the interval-valued fuzzy quadratic programming model by incorporating additional fuzzy logic mechanisms or integrating real-time data streams to improve further the robustness and accuracy of decision-making in ride-hailing systems. Moreover, investigating the impact of different uncertainty levels on the system's performance could offer insights into optimal strategies for handling varying degrees of imprecision.

5. Conclusions

The Ride-Hailing Matching Problem poses a complex optimization challenge in the dynamic landscape of urban transportation systems. This study addressed this problem by leveraging Interval-Valued Fuzzy Quadratic Programming (IVFQP), a robust framework capable of handling uncertainties inherent in ride-hailing operations. Our research made significant strides in addressing the uncertainties prevalent in ride-hailing services. By formulating the problem within the IVFQP framework, we successfully managed imprecise parameters such as waiting times, driver performance, and workload. We used interval-valued fuzzy sets, which allowed for a comprehensive representation of uncertain and vague information, enabling more realistic modeling of real-world scenarios. Through extensive experimentation and analysis, our findings demonstrated the effectiveness of IVFQP in optimizing multiple objectives concurrently. The algorithm efficiently minimized waiting times, reduced the rate of abandoned requests, and balanced driver workloads, showcasing its ability to cater to the diverse needs of passengers and drivers. The implications of this research extend beyond the realm of ride-hailing services. The successful application of IVFQP in optimizing multi-objective goals within an uncertain environment opens doors for its implementation in other complex decision-making systems across various domains.

As we look to the future, exciting opportunities remain for further advancements. Fine-tuning the IVFQP model, integrating real-time data streams, and exploring different levels of uncertainty would enhance the robustness and adaptability of the algorithm. Additionally, investigating the scalability of the model and its practical deployment in large-scale ride-hailing platforms would be pivotal for its real-world applicability. In conclusion, this research presents IVFQP as a promising tool for addressing the challenges posed by the Ride-Hailing Matching Problem. IVFQP showcases its potential to revolutionize decision-making processes in dynamic and uncertain environments by embracing uncertainty and employing a multi-objective optimization approach. The advancements made in this study lay the groundwork for future innovations aimed at improving the efficiency, reliability, and adaptability of ride-hailing services and similar complex systems.

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