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Strategies to Reduce Ride-Hailing Fuel Consumption Caused by Pick-Up Trips: A Mathematical Model under Uncertainty

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Abstract: Uber, Gojek, and Grab are companies providing new massive job opportunities for driver partners. Ride-hailing provides convenient services because passengers can determine the position of the vehicle picking the, up in real time. Ride-hailing also provides security because passengers can quickly determine the driver's identity. However, the rapid development of ride-hailing has led to increased congestion and emissions. This study proposes pick-up strategies to reduce fuel consumption and emissions, formulated as an assignment model. The assignment problem is abstracted into a linear programming model by considering the uncertainty of the parameters represented by fuzzy numbers. The proposed assignment model can handle the uncertainty of travel delays caused by unpredictable traffic conditions. The assignment aims to minimize fuel consumption, travel delays, and unserviced requests. The assignment model is designed to work for platforms that allow passengers to walk according to their readiness and the maximum walking distance. The numerical simulation results show that allowing passengers to walk to the vehicle can maintain optimality and significantly reduce fuel consumption. The proposed model's implementation is expected to enable sustainable transport and significantly mitigate emissions caused by vehicle mobility in picking up passengers.

Keywords: walking; assignment model; reduced fuel consumption; reduced emissions; fuzzy parameters; linear programming; ride-hailing

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1. Introduction

Transportation is a means that allows people to access what they need to support survival. However, transportation has adverse effects on the environment; hence, the concept of sustainable transport was initiated to reduce this. Sustainable transport requires balancing the current economic, social, and environmental needs with those of the future; thus, these factors need to be considered in transportation planning [1]. In order to achieve environmental protection, the way in which transportation systems evolve and adapt is essential because the transportation sector is a significant contributor to greenhouse gas emissions and climate change. Increasing transportation's energy efficiency and decreasing the associated carbon emissions are needed to reduce climate change effects to achieve ecological integrity [2,3]. In addition, sustainable transport can realize the main objectives of sustainable cities: using less energy, producing less waste and pollution, using fewer cars, preserving open spaces and delicate ecosystems, and creating a livable and community-focused human environment [4].

There are several styles of mobility in urban areas, such as low-mobility car users, car addicts, car-oriented everyday performers, car-averted low-mobility individuals, public transit enthusiasts, multimodal travelers, environmentally oriented multimodal travelers, and travel addicts [5]. The car-averted low-mobility and multimodal travelers already use public transportation or other environmentally friendly modes of transportation (such as walking and cycling). Low-mobility car users drive more frequently and have fewer symbolic-affective motives to do so. Car Addicts and car-oriented everyday performers mainly use a car because of their symbolic-affective solid motive. Due to their reasons for driving and low ecological standards, these three mobility styles have a low ability to adapt to sustainable mobility solutions. Public transportation enthusiasts are already very sustainable in mobility because they mostly use public transportation and have a low share of car use. Environmentally oriented multimodal travelers are environmentally oriented people, but their mobility is not yet sustainable. They have the most significant potential to accept and utilize sustainable transportation options. Travel addicts do not show a high environmental norm in their mobility. However, it is possible to manage them with sustainable transportation methods as an alternative to car ownership, such as electric shared mobility networks. In addition, individual transport performance and activity space are both highly correlated with mode choice.

Technology and changes in people's behavior can reduce the use of fossil fuels and greenhouse gas emissions in the transportation sector, where people's behavior has a more significant influence than technology [6]. The transportation technology known as ride-hailing can substitute traditional taxis, public transport, private cars, and other modes [7]. Vehicles used by ride-hailing will stay in the parking area if there is no ride, in contrast to public transportation, which may continue to drive along the route without passengers. Ride-hailing has the potential to decrease car ownership [7]. Therefore, ride-hailing is a more environmentally friendly mode of transportation.

Ride-hailing platforms such as Uber, Gojek, Grab, and Lyft provide innovation in transportation by combining traditional public transport and internet networks. Ride-hailing has become one of the most active and exciting research topics in the transportation sector [7,8]. Ride-hailing platforms established a technology and market structure that is more effective than traditional taxi services, enabling passengers to request a vehicle on short notice [9–13]. The ability for passengers and drivers to connect via mobile smartphone applications is made possible by many factors, including social networks, real-time information, and mobile technology [14]. The services are provided to the passengers via mobile smartphones, which are incredibly convenient for supporting people's daily life [15–17].

Ride-hailing has a good impact on human survival, especially in urban areas. Ride-hailing is crucial in influencing people to switch from private vehicles to mass public transportation, reducing emissions [18]. However, ride-hailing platforms have lower fuel consumption than traditional taxis [19,20]. This happens because ride-hailing drivers usually park their vehicles after dropping off passengers and then stay until they receive a new request. However, ride-hailing will still contribute to greenhouse gas emissions because the majority of vehicles today rely on fossil fuels.

Greenhouse gas emissions caused by ride-hailing lie in passenger pick-up and drop-off activities. Deploying vehicles to pick up and drop off passengers is a fundamental problem in ride-hailing, called an assignment, also called matching and dispatch [7,21–23]. Request trips are matched with vehicles to reduce generalized costs in the ride-hailing assignment problem [24]. Assignment can work using a simple algorithm called the first dispatch protocol, where every request is immediately served by the nearest available vehicle [7].

Available vehicles in other areas are immediately deployed to pick up far away requests when there are not enough available vehicles for servicing the requests in the area. This results in long pick-up distances, wasted driver time, increased fuel consumption, increased emissions, and reduced income, yielding an inefficient supply state [25,26]. Batching is an approach that collects requests in a group for as long as a predetermined time window (for example, 30 s), which can handle the imbalance [7]. Rejected requests will join the next group and undergo a re-assignment process. Batch assignment is a better strategy because it reduces everyone's wait time [27]. Batch assignment is more efficient than first dispatch protocol because the decision making considers collected requests rather than individual requests [28]. However, collecting requests over a long window can impact longer waiting times [29]. Therefore, choosing the time window must be considered to make the system more efficient [30].

Recent research on the ride-hailing pick-up system considered the uncertainty of future demand [24] using the robust optimization method and integrated the assignment with the rebalancing process. A neighborhood search technique was developed by [31] to find places near a driver. A pick-up system that can be used flexibly for ride-hailing or ride-sharing was developed by [32]. Large pick-up distances in matching systems must be handled, and the authors of [33] proposed a chain method that can reduce the global pick-up distance. The ride-hailing pick-up system has two essential components (assignment and pricing), whereby the authors of [7] developed both of these, particularly for a dynamic pricing regime that considers supply and demand. In order to safeguard both the passengers' and vehicles' location privacy from the ride-hailing server, the authors of [9,15] proposed a privacy-preserving assignment strategy for ride-hailing systems. In order to assess the effects of assignment time intervals and assignment radius, the authors of [12] provided a model that defines the assignment process in ride-sourcing markets. An assignment model with several service alternatives, such as a bundled option, was proposed by [13]. A discrete-time geometric assignment and the effects of spatial pricing were described by [26]. A system built on deep reinforcement learning and decision-time planning for vehicle repositioning on ride-hailing services was described by [34].

The success of assignments, while minimizing denied requests, is affected by drivers, distance, socioeconomic features, and land use [16]. In general, the assignment considers the pick-up travel distance and pick-up travel time [9,12,13,15,24,26,34–36]. Some studies considered minimizing the number of unsatisfied requests [24,32]. Some studies considered maximizing the profit [26,37]. Some studies also established an assignment model to maximize rewards earned [7,38]. Each request must wait a certain time before receiving service; hence, the waiting time must be considered in the assignment model, as proposed by [12,24,26,32]. It can be assumed that the driver and passenger will not cancel a transaction after being assigned [26]. As discussed by [24], the assignment model needs to consider uncertain travel times. However, research on travel time uncertainty and fuel consumption has not been found.

As a novelty, this study proposes a ride-hailing pick-up system that considers the travel time uncertainty and fuel consumption. The pick-up system is designed such that passengers can walk to the vehicle's location; hence, the vehicle does not need to pick up passengers. This model pick-up system can reduce gas emissions because walking is the best zero-carbon and eco-friendly solution [6]. In addition, this research contributes to developing a pick-up system that considers the uncertainty of travel times caused by unpredictable traffic conditions.

The pick-up system problem represented by the assignment problem can be solved using a linear programming approach. Linear programming problems with unknown variables or decision parameters play a significant role in several applications in areas such as transportation management [39]. Fuzzy approaches can handle uncertainties in the parameters of linear programming problems. The fuzzy approach handles the uncertainty as a function of the possibility of the parameter values. We use a fuzzy approach in the hope of achieving an optimal assignment, taking into account an unexpected travel time.

This research aims to determine the impact of allowing walking to reduce fuel consumption and emissions. The model also can reduce congestion because the vehicles can stay in the parking area while passengers walk to their location. Moreover, the model can be extended to systems enabling private mobility on demand, such as ride-hailing with autonomous vehicles.

The main objective of this research was to develop a linear programming model that can form uncertainty parameters in a ride-hailing pick-up system that allows passengers to walk to the vehicle location. To achieve the main objective, we undertook several activities: (i) to formulate mathematical modeling of the ride-hailing pick-up system with a flexible choice of whether or not the passenger desires to walk to the vehicle location; (ii) to reformulate the model using a fuzzy approach to handle the uncertainty parameters; (iii) to compare several conditions on the basis of numerical simulations using real-world request data.

The contributions of this research are as follows: (i) the proposed model has the potential to reduce fuel consumption as the model can flexibly give passengers the choice to walk to the vehicle location before the assignment is made; (ii) the proposed model can handle the delay time's uncertainty using a fuzzy approach, which considers traffic conditions that can vary randomly; (iii) the numerical simulation results demonstrate the reliability of the proposed model.

The paper is organized into several sections: Section 1 presents the introduction and related studies; Section 2 describes the methods used to handle uncertainty parameters; Section 3 describes the mathematical modeling; Section 4 describes the case studies and findings regarding the readiness of passengers to walk so as to reduce fuel consumption according to maximum walking distances. These findings are shown via numerical simulations with real-time requests in the real world; Section 5 discusses the findings; The conclusions obtained in this study are presented in Section 6.

2. Fuzzy Approach for Handling Uncertainty Parameters

Real-world problems often have uncertainty. In mathematical modeling, uncertainty often exists in parameters. The uncertainty parameters can be expressed by fuzzy numbers based on possible values. Generally, the membership function of the fuzzy number $\tilde{a} = (a_1, a_2, a_3, a_4)$ can be written as follows [40]:

$$r = \mu_{\tilde{a}}(x) = \begin{cases} 0 \text{ for } x < a_1, x > a_4, \\ f_{\tilde{a}}(x) \text{ for } a_1 \le x \le a_2, \\ 1 \text{ for } a_2 < x \le a_3, \\ g_{\tilde{a}}(x) \text{ for } a_3 < x \le a_4, \end{cases} \tag{1}$$

where the functions $f_{\tilde{a}}$ and $g_{\tilde{a}}$ are the left and right sides of $\tilde{a}$. Note that $f_{\tilde{a}}$ is an ascending function, and $g_{\tilde{a}}$ is a descending function. The expected interval of a fuzzy number $\tilde{a}$ is given as follows [40]:

$$\begin{aligned} EI(\tilde{a}) &= [E_1^a, E_2^a] \\ &= \left[a_2 - \int_{a_1}^{a_2} f_{\tilde{a}}(x)dx\, , a_3 + \int_{a_3}^{a_4} g_{\tilde{a}}(x)dx\right] \\ &= \left[\int_0^1 f_{\tilde{a}}^{-1}(r)dr\, , \int_0^1 g_{\tilde{a}}^{-1}(r)dr\right]. \end{aligned} \tag{2}$$

The expected value of a fuzzy number $\tilde{a}$ is given as follows [40]:

$$EV(\tilde{a}) = \frac{E_1^a + E_2^a}{2}. \tag{3}$$

Furthermore, if $\tilde{a}, \tilde{b}$ are fuzzy numbers and λ, γ are non-negative real numbers, then the following equations apply [41]:

$$EI(\lambda\tilde{a} + \gamma\tilde{b}) = \lambda EI(\tilde{a}) + \gamma EI(\tilde{b}), \tag{4}$$

$$EV(\lambda\tilde{a} + \gamma\tilde{b}) = \lambda EV(\tilde{a}) + \gamma EV(\tilde{b}). \tag{5}$$

A fuzzy number $\tilde{a}$ is called trapezoidal if its membership function is expressed by

$$\mu_{\tilde{a}}(x) = \begin{cases} 0 \text{ for } x < a_1, x > a_4, \\ \dfrac{x - a_1}{a_2 - a_1} \text{ for } a_1 \le x \le a_2, \\ 1 \text{ for } a_2 < x \le a_3, \\ \dfrac{a_4 - x}{a_4 - a_3} \text{ for } a_3 < x \le a_4. \end{cases} \tag{6}$$

Trapezoidal fuzzy number (TrFN) $\tilde{a}$ is denoted as quadruplet $\tilde{a} = (a_1, a_2, a_3, a_4)$ and has a trapezoid shape. If $a_2 = a_3$, then we obtain the triangular fuzzy number (TFN) [41]. Note that, for the trapezoidal fuzzy number, we have

$$E_1^a = a_2 - \int_{a_1}^{a_2} \left(\frac{x - a_1}{a_2 - a_1} \right) dx = \frac{a_1 + a_2}{2}, \tag{7}$$

$$E_2^a = a_3 + \int_{a_3}^{a_4} \left(\frac{a_4 - x}{a_4 - a_3} \right) dx = \frac{a_3 + a_4}{2}. \tag{8}$$

Then, the expected interval and expected value for TrFN $\tilde{a}$ are as follows:

$$EI(\tilde{a}) = \left[\frac{a_1 + a_2}{2}, \frac{a_3 + a_4}{2} \right], \tag{9}$$

$$EV(\tilde{a}) = \frac{a_1 + a_2 + a_3 + a_4}{4}. \tag{10}$$

In mathematical modeling, necessary to know which fuzzy number is bigger than another. The degree to which $\tilde{a}$ is bigger than $\tilde{b}$ for any pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$ is given as follows [42]:

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 \text{ if } E_2^a - E_1^b < 0, \\ \dfrac{E_2^a - E_1^b}{(E_2^a - E_1^b) - (E_1^a - E_2^b)} \text{ if } 0 \in [E_1^a - E_2^b, E_2^a - E_1^b], \\ 1 \text{ if } E_1^a - E_2^b > 0, \end{cases} \tag{11}$$

where $[E_1^a, E_2^a]$ and $[E_1^b, E_2^b]$ are the expected intervals of $\tilde{a}$ and $\tilde{b}$. We denote that $\tilde{a}$ is bigger than or equal to $\tilde{b}$ at least in a degree α, i.e., $\mu_M(\tilde{a}, \tilde{b}) \ge \alpha$ as $\tilde{a} \ge_\alpha \tilde{b}$. Before comparing the fuzzy number $\tilde{a}$ and crisp number b, the crisp number b must transform into fuzzy number form as $\tilde{b} = (b_1, b_2, b_3, b_4)$ with $b_1 = b_2 = b_3 = b_4$.

Fuzzy linear programming is a method that can handle uncertain data in a linear programming model, discussed by [43], which was developed using the concept of fuzzy sets introduced by [44]. Fuzzy linear programming can be divided into three categories on the basis of the uncertainty in the model [45] precisely: (i) linear programming with fuzzy variables; (ii) linear programming with fuzzy parameters; (iii) linear programming with fuzzy variables and parameters. Linear programming with fuzzy parameters contains uncertainty parameters on the objectives and the constraints, as expressed below [41].

$$\min_x \{ \tilde{c}^T x : \tilde{A} x \ge \tilde{b}, x \ge 0 \}, \tag{12}$$

where $\tilde{c}$ represents an n-dimensional vector of fuzzy parameters in the objective function, $A = [\tilde{a}_{ij}]_{m \times n}$ represents fuzzy parameters in constraints, $\tilde{b}$ represents an m-dimensional vector of fuzzy parameters in right-hand side constraints, and x is an n-dimensional vector of the crisp decision variable. Fuzzy numbers are used to characterize the distribution of possible values. The approach for solving the linear programming problem with fuzzy parameters was described in [41].

Without loss of generality, we introduce several assumptions for simplicity: (A1) the parameters in objective function are crisp; (A2) the parameters on the right-hand side are crisp. Let us introduce an additional non-negative crisp decision variable, t. Set t as the supremum of objective function which implies that $\tilde{c}^T x \le t$; hence, Equation (12) can be rewritten as follows:

$$\min_{x,t}\{t: \tilde{c}^T x \le t, \tilde{A}x \ge \tilde{b}, x \ge 0, t \ge 0\}. \tag{13}$$

Thus, the assumption (A1) is satisfied. Let us introduce an additional m-dimensional vector of the crisp decision variable, y, with values equal to one; hence, Equation (13) can be rewritten as follows:

$$\begin{aligned} &\min_{x,t,y}\{t: \tilde{c}^T x \le t, \tilde{A}x \ge \tilde{b}y, x \ge 0, t \ge 0, y = 1\} \\ &= \min_{x,t,y}\{t: \tilde{c}^T x - t \le 0, \tilde{A}x - \tilde{b}y \ge 0, x \ge 0, t \ge 0, y = 1\}. \end{aligned} \tag{14}$$

Thus, the assumption (A2) is satisfied.

Crisp linear programming is obtained by reformulation linear programming with fuzzy parameters into parametric linear programming. The decision vector of linear programming with the fuzzy parameters in Equation (3) is feasible in degree α (or α-feasible) if

$$-\tilde{c}^T x + t \ge_\alpha 0, \tag{15}$$

and

$$\tilde{A}_i x - \tilde{b}_i y_i \ge_\alpha 0, \forall i \in I. \tag{16}$$

Keeping in mind Equation (11), Equation (15) is equivalent to

$$\frac{E_2^{-c^T x + t} - E_1^0}{\left(E_2^{-c^T x + t} - E_1^0\right) - \left(E_1^{-c^T x + t} - E_2^0\right)} \ge \alpha. \tag{17}$$

Keeping in mind Equation (5), Equation (17) equivalent to

$$\frac{E_2^{-c} x + E_2^1 t - E_1^0}{(E_2^{-c} x + E_2^1 t - E_1^0) - (E_1^{-c} x + E_1^1 t - E_2^0)} \ge \alpha. \tag{18}$$

Because the −1 and 0 vectors are crisp, Equation (18) is equivalent to

$$\frac{-E_2^c x + t}{-E_2^c x + E_1^c x} \ge \alpha, \tag{19}$$

Which is equivalent to:

$$[(1-\alpha)E_2^c + \alpha E_1^c]^T x - t \le 0, \tag{20}$$

where $1-\alpha$ is a measure of a decision vector's infeasibility likelihood. In the same manner, keeping in mind that $y = 1$, Equation (16) is equivalent to

$$\left[(1-\alpha)E_2^{A_i} + \alpha E_1^{A_i}\right]^T x \ge (1-\alpha)E_2^{b_i} + \alpha E_1^{b_i}, \forall i \in I. \tag{21}$$

Crisp linear programming that handles the fuzzy parameters is given by

$$\begin{gathered} \min_{x,t} t \\ \text{subject to } [(1-\alpha)E_2^c + \alpha E_1^c]^T x - t \le 0 \\ \left[(1-\alpha)E_2^{A_i} + \alpha E_1^{A_i}\right]^T x \ge (1-\alpha)E_2^{b_i} + \alpha E_1^{b_i}, \forall i \in I \\ x \ge 0, t \ge 0. \end{gathered} \tag{22}$$

Assuming that fuzzy parameters can represent by a fuzzy trapezoidal number and keeping in mind Equation (10), Equation (22) becomes

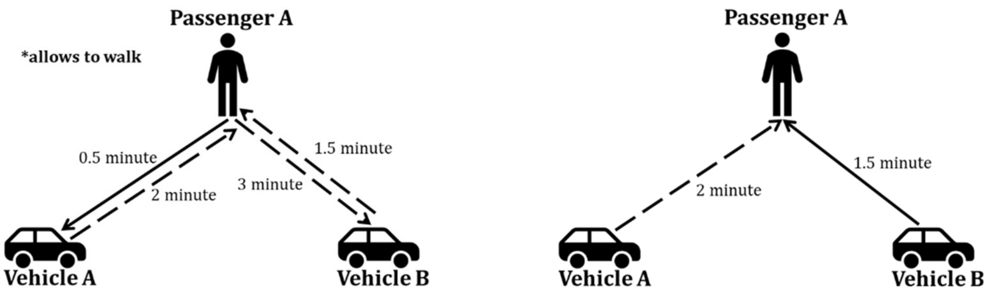
$$\begin{gathered} \min_{x,t} t \\ \text{subject to } \left[(1-\alpha)\frac{c_3 + c_4}{2} + \alpha\frac{c_1 + c_2}{2}\right]^T x - t \le 0 \\ \left[(1-\alpha)\frac{A_{i_3} + A_{i_4}}{2} + \alpha\frac{A_{i_1} + A_{i_2}}{2}\right]^T x \ge (1-\alpha)\frac{b_{i_3} + b_{i_4}}{2} + \alpha\frac{b_{i_1} + b_{i_2}}{2}, \forall i \in I \\ x \ge 0, t \ge 0. \end{gathered} \tag{23}$$

3. Mathematical Modeling

3.1. Assignment Model

The decision taken by the ride-hailing system to send available vehicles to pick-up requests or waiting for the passengers to walk to each vehicle's location is determined by the optimum assignment of each possible assignment. Travel delay is the difference between pick-up time and request time, which refers to the waiting time taken by a request before sitting in a vehicle.

The main components used in the assignment model are decision variables, constraints, and objective functions. The assignment has travel delays which are uncertain due to unpredictable traffic conditions. Figure 1a illustrates the condition of the ride-hailing system that allows passengers to walk to the vehicle location. The ride-hailing system can guide passengers to walk to the vehicle location. Before that, passengers must inform the ride-hailing system about their walking readiness. This condition is intended to minimize vehicles turning on a road when the traffic is one-way, allowing passengers to cross the road to reach the vehicle by walking quickly. The vehicle does not need to take a detour to pick up the passenger on the other side of the road, instead waiting for the passenger to arrive at the vehicle location by walking. This assignment model can also reduce fuel consumption, gas emissions, and traffic congestion because the vehicles only stay until passengers arrive at the vehicle location.



(**a**) (**b**)

Figure 1. Illustration assignment strategy: (**a**) allowing passengers to walk; (**b**) not allowing passengers to walk. The dotted line represents an alternative decision, while a straight line represents the optimal decision. Symbol "*" to indicate that the part after the symbol is a description.

Figure 1b illustrates the condition of the ride-hailing assignment that does not allow passengers to walk to the vehicle location. Each passenger must wait to be picked up by the assigned vehicle. This condition is intended to minimize passengers' movement so that passengers do not need to spend extra energy by walking to the vehicle location.

3.1.1. Parameters

The set used in this model is I, which represents requests, and J, which represents the available vehicles. The parameters used in this study are t_{ij}, which represents the travel delay (seconds) when request i walks to vehicle j location, τ_{ij}, which represents the travel delay (seconds) when request i waits to be picked up by vehicle j in request location, d_{ij}, which represents the distance (kilometers) when all passengers in request i walk to vehicle j, t_{max}, which represents the allowed longest travel delay, d_{max}, which represents the allowed longest distance (kilometers) for passengers in requests to walk to the vehicle, r_i, which represents the readiness of all passengers in request i to walk, and M, which represents the penalty given for rejecting a request.

3.1.2. Variables

The decision variables used in this study are x_{ij}, which decides that all passengers in request i will walk to vehicle j, which is 1 if the request i got a ride from vehicle j and must walk to the vehicle location, and 0 otherwise, χ_{ij}, which decides that the request i will pick-up by vehicle j, which is 1 if the vehicle is j assigned to pick up all passengers in request i, and 0 otherwise, and y_i, which decides on providing service to request i, which is 1 if request i does not get a vehicle ride, and 0 otherwise. The decision variables are given by Equation (24).

$$x_{ij}, \chi_{ij}, y_i \in \{0,1\}, \forall i \in I, \forall j \in J. \tag{24}$$

3.1.3. Objectives

The main objective of the proposed model is to minimize reduce fuel consumption and gas emission. To achieve this objective, maximizing the number of walking passengers is an option because walking does not consume fuel or emit carbon. The objective function, which maximizes the number of walking passengers, is given by Equation (25).

$$\max \sum_{i \in I} \sum_{j \in J} x_{ij}\,. \tag{25}$$

The objective in Equation (25) only considers the fuel consumption, but not the passenger satisfaction. To maximize passenger satisfaction, the model should minimize the total travel delay. If a request is rejected, a large constant is added to the objective as a penalty for rejecting the request. The penalty is given to minimize the number of rejected requests. The objective function, which minimizes the total travel time and the total rejected requests, is given by Equation (26).

$$\min \left\{ \sum_{i \in I} \sum_{j \in J} \left(t_{ij} x_{ij} + \tau_{ij} \chi_{ij} \right) + \sum_{i \in I} M y_i \right\}. \tag{26}$$

3.1.4. Constraints

The constraint, which ensures that each vehicle can only receive at most one request, is given by Equation (27).

$$\sum_{i \in I} \left(x_{ij} + \chi_{ij} \right) \le 1, \forall j \in J. \tag{27}$$

The constraint, which ensures that each passenger cannot walk to the vehicle location and wait to be picked up by a vehicle at the same time, is given by Equation (28).

$$\sum_{j \in J} \left(x_{ij} + \chi_{ij} \right) \le 1, \forall i \in I. \tag{28}$$

The constraint, which ensures that each request can only be served by one vehicle and not by all vehicles, is given by Equation (29).

$$y_i + \sum_{j \in J} \left(x_{ij} + \chi_{ij} \right) = 1, \forall i \in I. \tag{29}$$

The constraint, which ensures the travel delay does not exceed the limit, is given by Equation (30).

$$\sum_{j \in J} \left(t_{ij} x_{ij} + \tau_{ij} \chi_{ij} \right) \le t_{max}, \forall i \in I. \tag{30}$$

The constraint, which ensures that each passenger walking to the vehicle location will not exceed the limit, is given by Equation (31).

$$\sum_{j\in J} d_{ij}x_{ij} \le d_{max}, \forall i \in I. \tag{31}$$

The constraint, which indicates whether the passenger is ready to walk or not, is given by Equation (32).

$$\sum_{j\in J} x_{ij} \le r_i, \forall i \in I. \tag{32}$$

The assignment model with fuzzy parameters is given by decision variables in Equation (24), constraints in Equations (27)–(32), and objectives in Equations (25) and (26).

3.2. Assignment Model with Fuzzy Travel Delay

The fuzzy linear programming technique allows us to more naturally and directly consider tolerances with respect to the value of the decision model parameters [46]. Fuzzy linear programming is essential in situations where it is necessary to consider tolerances for parameter values due to the impossibility of determining them precisely. Moreover, it is used when the decision maker consciously assumes some tolerance with respect to a parameter.

This study assumes that the travel delay parameter $\tilde{\tau}_{ij}$ is fuzzy. The fuzziness of the travel delay is caused by the pick-up travel time depending on unpredictable traffic conditions. Linear programming with fuzzy parameters is handled by reformulating the model into crisp parametric linear programming, as discussed in Section 2. The fuzzy parameters in the assignment model with fuzzy travel delay are described in Equations (26) and (30). By substituting $\tilde{\tau}_{ij}$ into the objective function in Equation (26), we obtain a new objective function,

$$\min\left\{\sum_{i\in I}\sum_{j\in J}\left(t_{ij}x_{ij} + \tilde{\tau}_{ij}\chi_{ij}\right) + \sum_{i\in I} My_i\right\}, \tag{33}$$

and by substituting $\tilde{\tau}_{ij}$ into the constraint in Equation (30), we obtain a new constraint,

$$\sum_{j\in J}\left(t_{ij}x_{ij} + \tilde{\tau}_{ij}\chi_{ij}\right) \le t_{max}, \forall i \in I. \tag{34}$$

The objective function in Equation (26) is replaced with Equation (33), and the constraint in Equation (30) is replaced with Equation (34); hence, we have an assignment model with a fuzzy travel delay parameter. The assignment model with a fuzzy travel delay parameter has no fuzzy parameters on the right-hand side (the right-hand side is crisp); therefore, the assumption (A2) is satisfied. The objective function in Equation (33) can be rewritten as Equation (35).

$$\min\left\{\sum_{i\in I}\sum_{j\in J} t_{ij}x_{ij} + \sum_{i\in I}\sum_{j\in J}\tilde{\tau}_{ij}\chi_{ij} + \sum_{i\in I} My_i\right\}. \tag{35}$$

The fuzzy parameter in the objective function in Equation (35) can be removed by focus reformulation on its fuzzy part as follows:

$$\sum_{i\in I}\sum_{j\in J}\tilde{\tau}_{ij}\chi_{ij}\,. \tag{36}$$

Let u be an additional non-negative decision variable, where u is the supremum of Equation (36), which can be written as follows:

$$\sum_{i\in I}\sum_{j\in J}\tilde{\tau}_{ij}\chi_{ij} - u \le 0, \tag{37}$$

$$u \geq 0. \tag{38}$$

Furthermore, the objective function in Equation (35) can be rewritten as

$$\min\left\{\sum_{i\in I}\sum_{j\in J} t_{ij}x_{ij} + u + \sum_{i\in I} My_i\right\}, \tag{39}$$

thus satisfying Equations (37) and (38). The objective function in Equation (33) is replaced with Equation (38), and the expression in Equation (37) is an additional constraint; therefore, assumptions (A1) and (A2) are satisfied. The assignment model with fuzzy parameters is given by the decision variables in Equations (24) and (38), constraints in Equations (27)–(29), (31), (32), (34), and (37), and objective in Equation (39).

The crisp assignment model is obtained by reformulating the assignment model with fuzzy parameters into parametric linear programming. Note that the model has fuzzy parameters in the constraints in Equation (34) and (37); thus, the decision vector is feasible in degree α if

$$\sum_{j\in J}\left(t_{ij}x_{ij} + \tilde{\tau}_{ij}\chi_{ij}\right) \leq_\alpha t_{max}, \forall i \in I, \tag{40}$$

and

$$\sum_{i\in I}\sum_{j\in J} \tilde{\tau}_{ij}\chi_{ij} - u \leq_\alpha 0. \tag{41}$$

By repeating the same steps of Equations (15)–(21), Equation (40) is equivalent to

$$\sum_{j\in J}\left(t_{ij}x_{ij} + \left[(1-\alpha)E_2^{\tau_{ij}} + \alpha E_1^{\tau_{ij}}\right]\chi_{ij}\right) \leq t_{max}, \forall i \in I, \tag{42}$$

and Equation (41) is equivalent to

$$\sum_{i\in I}\sum_{j\in J}\left[(1-\alpha)E_2^{\tau_{ij}} + \alpha E_1^{\tau_{ij}}\right]\chi_{ij} - u \leq 0. \tag{43}$$

The crisp assignment model that handles the fuzzy travel delay is given by the decision variables in Equations (24) and (38), constraints in Equations (27)–(29), (31), (32), (42), and (43), and objective in Equation (39). Assuming that that fuzzy travel delay can be represented by a fuzzy trapezoidal number and keeping in mind Equation (10), Equation (42) becomes

$$\sum_{j\in J}\left(t_{ij}x_{ij} + \left[(1-\alpha)\frac{\tau_{ij_3} + \tau_{ij_4}}{2} + \alpha\frac{\tau_{ij_1} + \tau_{ij_2}}{2}\right]\chi_{ij}\right) \leq t_{max}, \forall i \in I, \tag{44}$$

and Equation (43) becomes

$$\sum_{i\in I}\sum_{j\in J}\left[(1-\alpha)\frac{\tau_{ij_3} + \tau_{ij_4}}{2} + \alpha\frac{\tau_{ij_1} + \tau_{ij_2}}{2}\right]\chi_{ij} - u \leq 0. \tag{45}$$

The assignment model with a fuzzy travel delay represented by a trapezoidal membership function is given by the decision variables in Equations (24) and (38), constraints in Equations (27)–(29), (31), (32), (44), and (45), and objective in Equation (39). The assignment model for each uncertainty is presented in Table 1. The assignment model in Table 1 is characterized by uncertainty and the representation of the uncertainty parameter.

Table 1. Assignment model based on uncertainty parameter assumption.

Descriptions	Crisp Parameter	General Fuzzy Parameter	Trapezoidal Fuzzy Parameter
Objectives	(25), (26)	(25), (39)	(25), (39)
Constraints	(27), (28), (29), (30), (31), (32)	(27), (28), (29), (31), (32), (34), (37)	(27), (28), (29), (31), (32), (44), (45)
Decision Variables	(24)	(24), (38)	(24), (38)

The assignment models have a multi-objective linear programming form that can be handled using a lexicographic approach; hence, the model can be easily solved using a solver in python.

4. Numerical Simulation

4.1. Case Study

The case study used Manhattan New York City taxi trip data in 2013, which are commonly used to simulate taxi demand [47]. These data are usually used in research on ride-hailing and ride-sharing to show the model's performance. These taxi trip data contain the exact location of origin and destination of taxis, along with the pick-up and drop-off times. The taxi travel criteria used are as follows: (i) the origin and destination of the taxi are within the Manhattan area; (ii) the vehicle has a minimum capacity of zero and a maximum capacity of four. Vehicle capacity reflects the number of passengers in the taxi plus the driver.

We simulated the proposed model using real-world data from Manhattan taxi trip data on 1 January 2013 from 12:00 p.m. to 12:59 p.m., as shown in Figure 2, with 13,425 requests. On the basis of historical sample data, we deployed 2000 vehicles at 11:59 p.m. We assumed no further vehicle additions or deletions during the simulation. Vehicles continuously pick up and drop off passengers based on real-world request data. Requests are collected in 30 s time windows and assigned with available vehicles in batch. We assume that requests only tolerated a maximum delay time of 5 min. We set the maximum walking distances to 100, 200, and 300 m. All requests not serviced within the maximum delay times were removed from the queue.

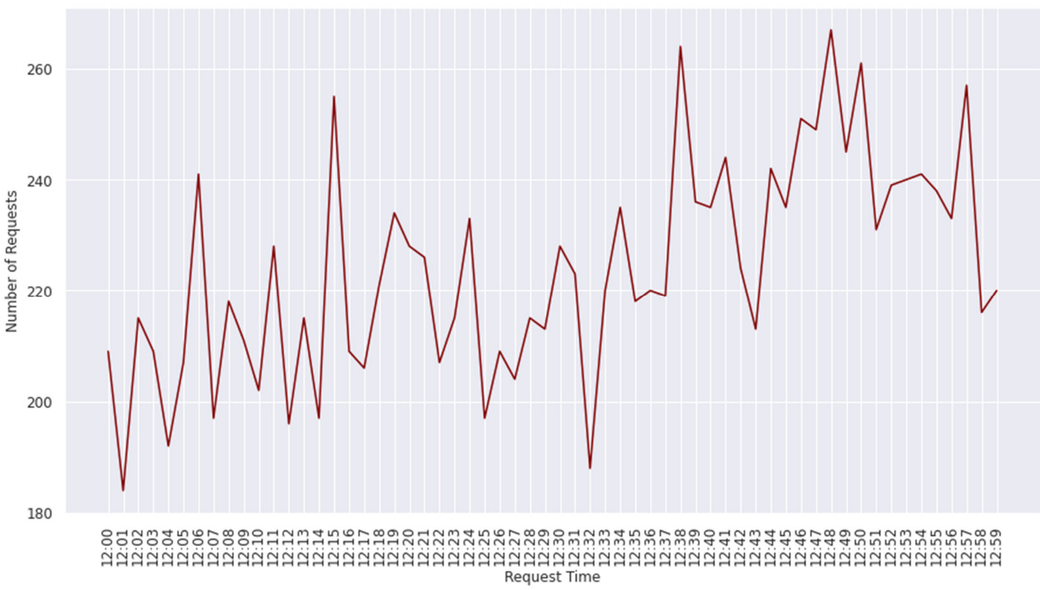


Figure 2. Manhattan taxi trip requests on 1 January 2013.

The shortest path for each location was pre-computed using OSMnx and stored as pivot data. OSMnx is a Python package for downloading OpenStreetMap geospatial data and modeling, projecting, visualizing, and analyzing real-world road networks [48].

OSMnx is capable of providing complex road network mapping specifically for the Manhattan, New York City location. Origin and destination coordinates are needed to find the shortest path, as well as the corresponding travel time and distance.

Moreover, the shortest path can be calculated using a weight, such as the travel time and distance. We can obtain the shortest travel time and the shortest distance between each location from the shortest path along with the travel time weight and distance weight. Travel times obtained from the shortest path with travel time weight depend on the built-in speed of OSMnx. Furthermore, travel times are calculated on the basis of walking and driving. Walking times are calculated according to the shortest distance path with a constant walk speed of 5 km/h. Even though the passengers can walk faster, we assume that they are walking at a constant speed because the driver it is unaffected.

Driving times are calculated as a function of the shortest time path and shortest distance path (with constant speeds of 20, 30, and 40 km/h). The shortest time path is calculated on the basis offree-flow travel. Keeping in mind that the congestion cannot be predicted and can impact the travel time, we generated travel by multiplying free-flow travel time with some level of flow travel (50%, 60%, 70%, 80%, and 90%). Driving times also feature many possible values; thus, they are uncertain.

The readiness to walk is measured when a passenger wishes to request a ride-hailing service via a smartphone. Passengers are given two choices on smartphones: walking to the vehicle or waiting for the vehicle to pick up. When the passengers walk to the vehicle, the required fuel is reduced since the vehicle does not need to pick up passengers. As a reward, ride-hailing fares are decreased for passengers willing to walk. This reward is aimed at increasing the willingness for passengers to walk.

4.2. Numerical Simulation Results

This subsection shows the numerical simulation results for the assignment model with fuzzy travel delay with 0.5 degrees of feasibility. As mentioned earlier, walking times are certain; therefore, the travel delay when the passengers walk to the vehicle's location is also certain. On the other hand, pick-up travel times are uncertain; thus, the travel delay when the passengers wait to be picked up by any vehicle also uncertain. The uncertainty is represented by the trapezoidal fuzzy number, which is represented by the minimum, average of the minimum and mean, average of the maximum and mean, and maximum, respectively. We compared the impact of allowing passengers to walk using two cases. In the first case, we assume that the ride-hailing platform allows passengers to walk and that all passengers are willing to walk to the vehicle location ($r_i = 1, \forall i$). In the second case, we assume that the ride-hailing provider does not allow passengers to walk to the vehicle location ($r_i = 0, \forall i$). The algorithm for the numerical simulation can be seen in Figure 3.

```
Data: user, vehicles, pickup travel times and distances, walking travel
      times and distances
Result: optimal assignment
Initialization:
assignment model;
current server time = 12.00 PM;
end simulation time = 13.00 PM;
time windows = 30 seconds;
while current server time + time windows <= end simulation time do
    get unserviced requests;
    get available vehicles;
    if either requests or available vehicles is zero then
        no assignment result;
    else
        calculate assignment result;
        update serviced requests info;
        update not available vehicles info;
    end
    current server time + = time windows;
end
show the final result;
```

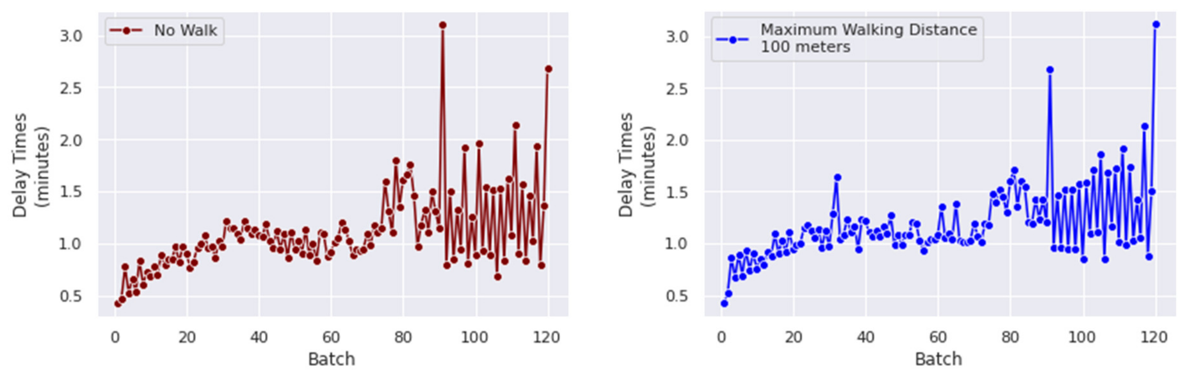
Figure 3. Numerical simulation algorithm.

The optimal results for assignment with fuzzy travel delay based on the readiness of all passengers to walk are presented in Table 2. In general, the readiness of passengers to walk maintained the quality of the assignment results. However, supposing that passengers are willing to walk, the walking strategy also had an optimum result nearly equal to the no-walk strategy regarding service requests and travel delays. The travel delays were not even close to the maximum set limit.

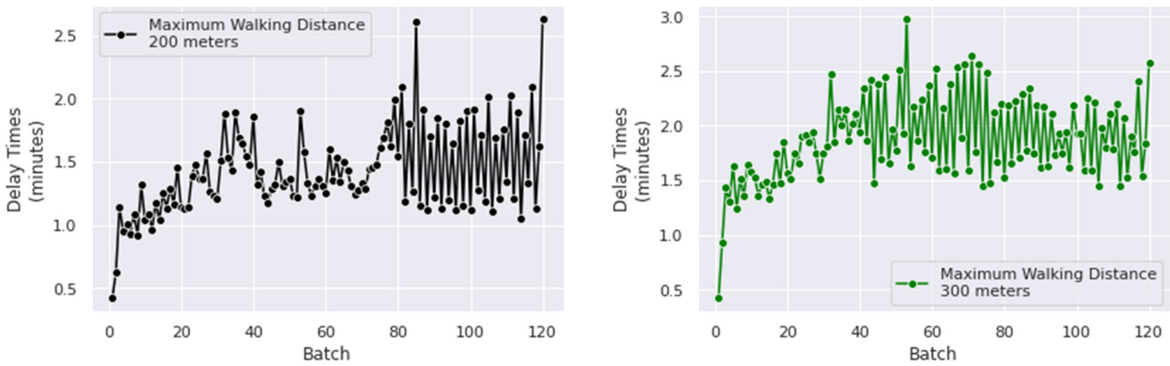
Table 2. Optimal results based on passengers' walk readiness.

Walk Readiness	Serviced Requests (%)	Average of The Pessimistic Travel Delay (min)	Average of The Most Possible Travel Delay (min)	Average of The Optimistic Travel Delay (min)
Not at all	94.36%	1.723712	1.101740	0.564525
100 m	94.46%	1.751536	1.165116	0.658548
200 m	93.86%	1.973035	1.394026	0.893963
300 m	92.04%	2.397733	1.838633	1.355686

Travel delays for each maximum distance can be seen in Figure 4. As can be seen, the travel delays were within 3 min. It can be seen that, for a time window of 30 s, the batching process did not have a travel delay, which was always within the threshold of 5 min. The proposed model could meet customer satisfaction for all maximum walking distances.



(**a**) (**b**)



(**c**) (**d**)

Figure 4. Travel delays for each maximum walking distance: (**a**) 0 m, i.e., no users willing to walk; (**b**) 100 m; (**c**) 200 m; (**d**) 300 m.

The relationship of maximum walking distances with the percentage of fuel consumption savings can be seen in Figure 5. It can be seen that greater maximum walking distances result in greater fuel consumption savings. This case study obtained fuel consumption savings for maximum distances of 100, 200, and 300 m, saving the fuel needed to travel 363.881, 483.632, and 800.362 km.

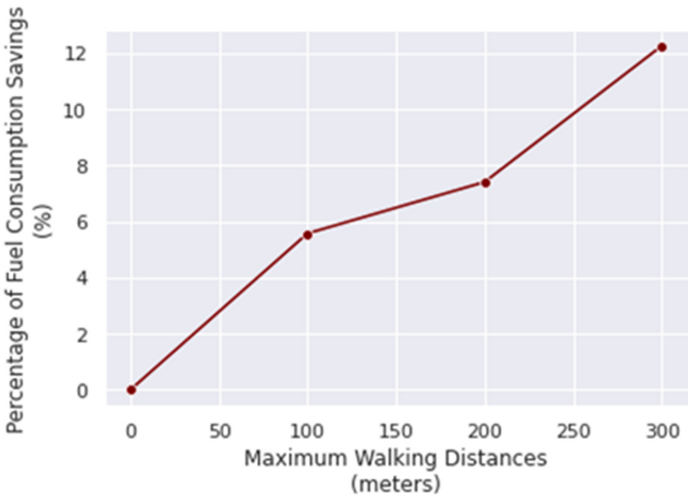


Figure 5. Percentage fuel consumption savings for each maximum walking distance.

The percentage of ride-hailing passengers walking to the vehicle location is as high as 20%, as can be seen in Figure 6. The proportion of ride-hailing passengers who walk and do not walk is sensitive to the maximum walking distance. A small value of walking distance can give significant results with respect to the number of passengers walking near to the vehicle. This shows that, in practice, vehicles may be assigned to pick up passengers who are very close, allowing them to effortlessly reach the location within a few minutes of walking.

Figure 6. Proportion of ride-hailing passengers.

5. Discussion

The assignment model that allows passengers to walk significantly reduces fuel consumption. It can reduce the fuel consumption needed to pick up passengers. In addition, allowing vehicles to stay until passengers arrive at the vehicle's location can reduce the possibility of traffic congestion. Maximum travel distance also has a significant impact on reducing fuel consumption. Furthermore, this strategy must be applied to ride-hailing platforms to realize sustainable transport. However, this strategy requires the passengers' approval because not everyone is in a condition that allows them to walk (e.g., when sick). Cost reductions for passengers who walk to the vehicle location must be given as a reward since they have reduced fuel use. The cost reductions also can increase the willingness of passengers to choose walking.

From a technological point of view, it is possible to rebalance the number of vehicles from areas with low demand to move to areas with high demand. Rebalancing can also work by dividing an area into several smaller areas, which are called subregions. The vehicle rebalancing problem is an assignment problem whose role is to assign empty vehicles to other areas on the basis of estimated future demand [24]. The vehicle rebalancing may consume fuel; therefore, strategies should consider the fuel consumption. However, rebalancing can work better when information about future demand density is known. The ride-hailing assignment system models assignment and vehicle rebalancing separately [49]. Integrating assignment and vehicle rebalancing strategies into a single model can increase the ride-hailing assignment system's performance [50]. The optimization model that integrates assignment and vehicle rebalancing has not been widely researched [24].

Our findings show that allowing passengers to walk to the vehicle does not reduce ride-hailing performance, which can be used to substitute pick-up systems. This study builds on several innovations proposed by many researchers in international papers, particularly [32]. We also show that considering the uncertainty of delay time is reliable for use in ride-hailing pick-up systems, which was not considered by other studies. Although the authors of [24] considered and handled the demand uncertainty using the robust optimization method, they did not consider the uncertainty of the delay time caused by uncertain travel times.

6. Conclusions

This study proposed a pick-up system that considers the fuel consumption and uncertainty of travel time. The model is reactive to real-time requests while assigning these requests to available vehicles in two ways: walking and waiting to be picked up. Our proposed model also considers the uncertainty of travel delays caused by uncertain travel times when the vehicle picks up the passenger. The pick-up time may be uncertain depending on traffic conditions. We performed numerical simulations to demonstrate the impact of considering passengers' willingness to walk on assignment quality in terms of waiting time and serviced requests.

We showed that up to 92% of requests can be served for several maximum walking distances when passengers walk or not. Our analysis showed that allowing passengers to walk to vehicle locations based on passenger ability could significantly reduce fuel consumption significantly. We presented that the sensitivity of the maximum walking distance parameter could affect fuel consumption but not the percentage of serviced requests. Our model is flexible for passengers to choose to walk to the vehicle location or wait to be picked up, thus not forcing passengers to walk in uncomfortable conditions (e.g., in bad weather or when sick). Furthermore, our model can reduce the mobility of vehicles and minimize the possibility of traffic congestion.

The proposed assignment model can be applied as a pick-up system on a ride-hailing platform. This pick-up system can be used when the ride-hailing platform wants to give passengers the freedom to walk to the vehicle to reduce fares. In addition, the assignment model with fuzzy parameters can be used as a pick-up system that can handle the uncertainty of the delay time. The delay time may vary depending on the traffic conditions. If the delay time uncertainty is not considered, the delay time may be greater than expected. As a result, the vehicle is used by passengers longer (vehicle supply is inefficient), and the passenger will eventually reach their destination.

There are several limitations to this study. Firstly, the model used has more than one objective function; hence, it has a computational cost that is more expensive compared to a model with a single objective function. In future research, formulating the model using single-objective and non-constrained optimization can reduce computational costs. Secondly, the proposed model does not consider future demand. In future research, forecasting the future demand can be achieved using spatiotemporal methods. The uncertainty demand can also be solved using a fuzzy approach. Lastly, the proposed model does not efficiently utilize the vehicle supply. In further research, the supply of vehicles can be utilized more efficiently by considering the time required for vehicles to serve passengers.

Future research may look into ways to use rebalancing to reduce the supply–demand imbalance. Rebalancing can be an alternative technology to reduce the supply and demand imbalance and the percentage of rejected requests. Rebalancing can be achieved by dividing the region into several sub-regions. Forecasting supply and demand per region is needed for a better rebalancing technology, especially when using spatiotemporal methods. The forecast results are not 100% accurate, causing the supply and demand forecast to be uncertain; hence, rebalancing needs to be modeled using a method that can handle parameter uncertainty.

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