

## Research Article

# Shared Clean Mobility Operations for First-Mile and Last-Mile Public Transit Connections: A Case Study of Doha, Qatar

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With the aid of recent technological advancements, seamless integration of shared mobility services and public transit may offer efficient and affordable connectivity to the transit stations in urban settings, thereby enhancing residents' mobility. A previous research mainly focused on car-sharing services as a self-standing mode of transportation. However, due to rapid urbanization acceleration and regions' extension, commuters often combine the fixed-route/fixed schedules public transportation and car-sharing service in one journey. To this end, we study a one-way, station-based electric car-sharing service interaction with public transportation. We propose an integrated route choice and EV assignment model to address the potential of car-sharing services as a feeder to the public transit network. The integrated model consists of two components, operations of the car-sharing service and the commuter's route choice and the associated mode choice. The service provider decides on the resource levels, allocations, and relocation strategy in the first component. In the second component, the travel options for the commuters are modeled. The two-component model was simulated in an agent-based simulation based on a case study from the state of Qatar. We further extend the integrated model to include the carpooling option, in which multiple passengers sharing the same route can share the same vehicle. Extensive simulation analyses show that the integration can considerably enhance urban mobility and increase public transportation accessibility through enhanced first and last miles linkages. Moreover, the influence of transportation supply and spatial characteristics on the individual mode choice was estimated. Results indicate that public transit ridership can increase up to 17%. Moreover, adding the carpooling option can significantly decrease the number of relocations operations at a minimal impact on the commuters' trip performance.

## 1. Introduction

With the rapid urbanization acceleration, city-regions extend continuously, and the average commute distance of passengers has grown dramatically. Several emerging mobility services have been introduced to encourage public transit ridership, such as autonomous modular vehicles. This innovative transit system relies on a unique transfer operation termed "in-motion transfer" where passengers transfer between coupled modular buses in motion without alighting and transferring between different bus lines. A reader can refer to [1, 2] for information on how this service is designed and operated. Despite the rapid advancement of public

transit services, travel mode choice is no longer restricted to single modes such as private cars, buses, car-sharing, and the metro, and it tends to be multimodal.

Multimodal systems aim to reduce the negative externalities of car travel and increase public transportation accessibility by improving the provisions for first miles-last miles (FMLM) to/from public transportation hubs [3]. Hence, fixed public transportation and flexible transit services can complete each other in an urban area as commuters may use both services to complete their journeys. We briefly describe the multimodal service modes and their role in increasing public transportation connectivity through enhanced FMLM services.

The most flexible form of multimodal services is the on-demand multimodal transit service (ODMT). The ODMT involves moving commuters from their origins/destinations to the main public transportation hubs. Basciftci and Hentenryck [4]; Dalmeijer and Hentenryck [5]; Li and Quadrifoglio [6]; Mahéo, Kilby, and Hentenryck [7]; Narayan et al. [8]; Posada, Andersson, and Häll [9]; Quadrifoglio and Li [10]; and Wang, Liu, and Ma [11] proposed a mathematical programming approach to optimally assign the commuter's travel requests to a fleet of on-demand vehicles. Basciftci and Hentenryck [4] proposed a bi-level optimization model in which the leader model determines the design of the integrated system followed by a model to determine the most cost-efficient and convenient route for riders. Mahéo, Kilby, and Hentenryck [7] proposed a mixed-integer programming (MIP) formulation to design and optimize a hub and shuttle public transit system (HSPTS). Results indicate that the hub and shuttle model can decrease transit time by a factor of two, while not exceeding the existing transit system costs. Dalmeijer and Hentenryck [5] generalized the model proposed by Mahéo, Kilby, and Hentenryck [7] by adding three more practical elements. Different frequencies throughout the network were allowed. Second, additional public transportation modes (e.g., rail and not only bus network) were considered. Third, a limitation on the number of commuter's transfers was added. Yan et al. [12] showed that ODMT might have significant drawbacks insofar as it increases traffic congestion and emission levels.

The on-demand shared automated vehicle (SAV) system is a variant of the ODMT service. It aims to provide FMLM services to older people and people with disabilities, as in the studies by Abe [13]; Dai et al. [14]; Liang, Almeida Correia, and van Arem [15]; and Pinto et al. [16]. Senlei [17] proposed an agent-based model to simulate the on-demand operations of shared automated vehicles SAV in parallel transit service. The authors proposed a time-varying transit service, which can switch service schemes between a door-to-door service and a station-to-station service according to what is best for the service providers and the travelers. Simulation results suggest that SAV systems together with dynamic ridesharing can significantly reduce the average waiting time, the vehicle kilometers traveled, and empty SAV trips, which are the major issues in the SAV service. To reduce the empty SAV trips while increasing public transit accessibility, the authors of [18] proposed a MIP to optimize the SAV fleet size while enabling vehicle relocations to tackle the vehicle imbalance. The authors indicated that railway transit networks and SAV services could be constructed and operated at a lower cost than each service alone. Furthermore, railway accessibility can be governed by a larger fleet size rather than a multilink extension. The authors of reference [19] estimated the public transit usage increase when considering SAV as FMLM solution by formulating an optimum strategy of SAV coupled with PT. Results indicated that the integrated model increased public transit usage by 3% and reduced personal vehicle kilometers traveled by 6%, potentially solving the FMLM connectivity and reducing traffic congestion. However, this increase is governed by SAV's waiting time decrease.

However, SAV has many implementation limitations due to significant concerns regarding users' data privacy [20]. Furthermore, there is a potential increase in traffic congestion due to increased demand as the costs of this service could be lower than the costs of using taxis [21].

Another type of multimodal transit service is the use of microtransit services as a feeder to the public transportation network. Microtransit services involve the movement of commuters between predetermined locations and transit hubs. The services operate either on a fixed schedule and fixed-route manner [22, 23] or by following flexible scheduling and flexible routes [24, 25]. The authors showed that the more flexible system offers cost advantages over regional systems, especially when transit services are frequent, or transit hubs are close together, with little impact on passenger convenience. Liu et al. [26] proposed a hybrid operation in which the bus scheduling frequencies change depending on the demand level. The hybrid model serves as a fixed-route transit service in the morning and a demand-responsive in the evening when the demand is low. Results suggest that transit authorities can minimize passengers' average waiting time and maximize the operator's profits through optimal scheduling of the feeder bus operations. Li and Quadrifoglio [6] found that substantial benefits on urban mobility can be gained from the hybrid operations of microtransit services. However, these benefits depend strongly on the characteristics of the environment: such as the passenger density, the number of stations in the area, and the size of the flex window.

Another form of sharing service is car sharing. Car sharing is a form of car rental that allows users to rent a vehicle for a short time, usually by the hour [27]. It can involve one-way or two-way services. The two-way services limit the user to picking up and returning the vehicle from/to the same station. In contrast, one-way services give more flexibility as users can drop off the vehicle at any shared station. For conceptual reviews of the role of car-sharing services to overcome FMLM issues for the public transportation service, a reader can refer to the work by Huwer [28]; Kodransky and Lewenstein [29]; McCoy et al. [30]; Sachan and Mathew [31]; Shaheen and Chan [32]; and Tabassum et al. [33]. The most common operational supply problem researchers tackle in one-way car sharing is the vehicle relocations as in the works by Boyacı, Zografos, and Geroliminis [34] and Huang et al. [35]. In all the above works, authors assumed an inelastic users' demand. However, to the best of the authors' knowledge, none of the existing work in literature considers both the supply and demand problems simultaneously in a multimodal context. Furthermore, none of these studies modeled and quantified the potential of car sharing on public transportation accessibility increase and urban mobility in general.

From this perspective, this study aims to investigate shared clean mobility and public transport services interactions and how the shared mobility operations affect the commuters' choice. To this end, a route and mode choice module is developed to allow users to combine the shared electric vehicle service (donated by EV service in the following) and fixed public transport service (fixed PT) in a

single trip. The integrated model studies the dynamic supply (the available services) and demand (commuters requests) interactions.

Combining fixed PT and EV service comprises two components: Route and mode choice modeling and one-way fixed EV service operations. The major components of fixed PT (we consider the rail commuting in this study, but the model can easily be extended to include the tram, buses, etc.) involve the rail network structure and the service frequency. On the other hand, the EV service comprises a fleet of EVs managed by a central dispatcher to be rented by users per hourly rate to perform the FMLM trips to fixed PT lines. In the first component, the shared EV service provider decides on the resource levels, allocations, and the relocation strategy. In the second component, the travel options of users are modeled in the route choice model.

This paper fills the gap in the existing literature by quantifying the impact of EV service as an additional mode choice to the commuters to accommodate the FMLM to the fixed PT system. The main contributions of this paper can be summarized as follows:

- (1) We incorporate one-way EV service in the multimodal networks under dynamic supply-demand interactions.
- (2) We propose a multimodal route choice and assignment model that allows commuters to combine fixed public transportation and shared EV service to perform their journey.
- (3) We built an agent-based simulation framework to model the commuter's choice and service operations modules based on real-world instances in the state of Qatar.
- (4) We extend the EV service to include the carpooling option, in which commuters with similar initial locations, departure times timings, and similar transit destinations can share the same vehicle.
- (5) We demonstrate the influence of transportation supply and spatial characteristics on both the individual mode choice and system performance.

The remainder of this paper is structured as follows: Section 2 formally defines the problem and model's components. Section 3 outlines the overall methodology developed. Section 4 details the model settings of the case study along with the simulated scenarios and settings. Section 5 presents detailed simulation result analysis. Summary of the main findings, recommendations for practitioners, and future research directions are presented in Section 6.

## 2. Problem Description

In this study, we aim to analyze the dynamic interaction between the one-way car-sharing service operation and the response of travelers under the multimodal framework. We focus on commuters wanting to commute from residential areas to destinations using the public transportation system, which is rail in this case. Among the considered options, they can use their private vehicles to accommodate the first and

last mile to the rail network, as indicated in Figure 1(a). Alternatively, commuters can use the EV service to accommodate the FMLM to the transit stations. EV service allows commuters to use the EV service from a nearby station to their origin to drive to the metro station and complete their journey via rail, as indicated in Figure 1(b).

The proposed integrated network has the following components:

**Network:** it consists of the rail transit network and its stations along with the road network.

**Demand:** it comprises of commuters' set of origin and destination.

**Supply:** it comprises all available modes of transportation a commuter can use to travel from the origin to destination.

The available modes are as follows:

- (i) Fixed PT: it comprises a metro service that follows a fixed route and fixed schedule.
- (ii) EV service: it comprises a fleet of EVs distributed among EV stations at the start of the planning period. Commuters may rent an EV for a short period and drive it to the metro station stops using the existing road network. A central dispatcher controls the EV fleet to assign the EVs to the incoming travel request by managing a group of relocators to move EVs between stations to achieve system balance.
- (iii) Walk: it involves commuters' movement from the origin to a fixed PT stop/EV station or walking from a fixed PT stop/EV station to their destination.
- (iv) Car: this involves commuters' movement by their private cars from their origin to the fixed PT stop or from their origin to EV station. Or by using a ride-hailing service from a fixed PT stop to their destination or from EV station to their destination if the fixed PT or EV station is not within acceptable walking distance and if the commuter has already used their private car at the first mile leg.

## 3. Methodology

This section details the overall methodology developed. First, for each origin-destination (denoted as  $O - D$  in the following) pair, a path that connects a commuter's origin and destination is generated in the **Route and mode choice** algorithm. Then, based on the **Route and mode choice** algorithm's output, the EV service provider decides to execute the relocation plan in **EV relocation and assignment** if necessary. In the following sections, we will discuss in detail how each module works.

**3.1. Route and Mode Choice.** For each  $O - D$  pair, the *Route and mode choice* module generates all possible paths that connect a commuter's origin and destination (before the quickest path is picked). The result of the route choice algorithm is a sequence of fixed PT stops, services, and the

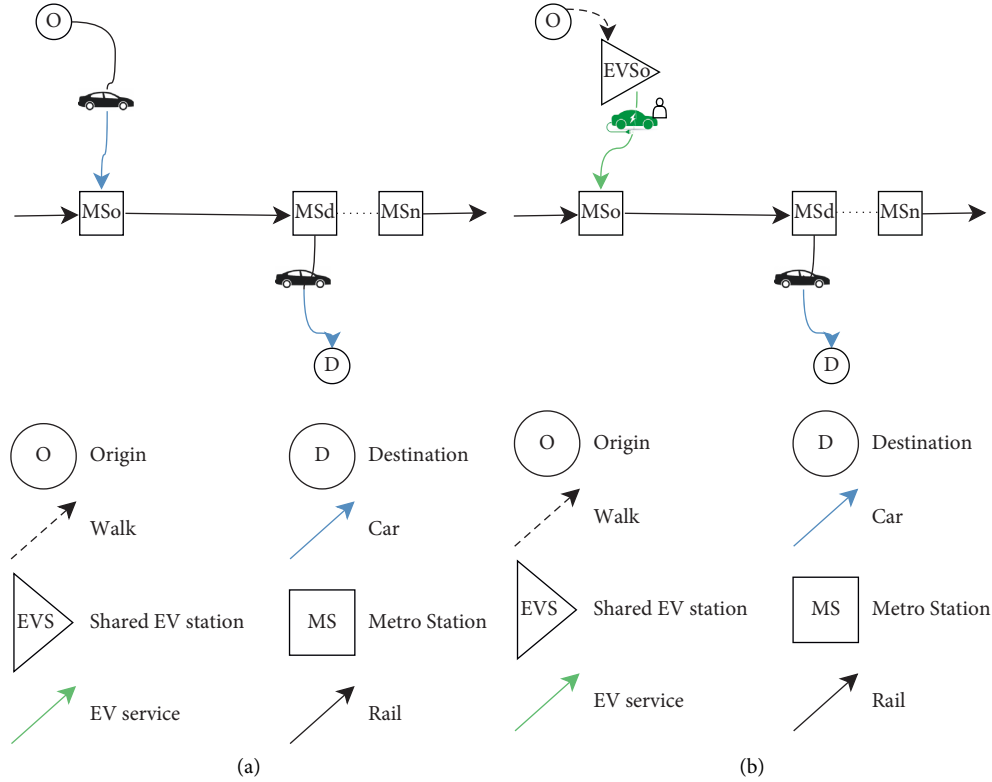


FIGURE 1: (a) Rail commuting vs. (b) integrated (EV service and Fixed PT) transit systems.

modes used to travel for each leg on the route. Then, the generated routes are evaluated based on the total estimated trip duration. We assume that a commuter is willing to walk to a maximum distance to any fixed PT stop or shared EV station. Based on this maximum acceptable walking distance, the following sets, stops, and notations are defined as follows:

- (1)  $R$ : Set of commuter trips
- (2)  $S(EVS)$ : Set of EV stations
- (3)  $S(MS)$ : Set of metro stations
- (4)  $S(EV)$ : Set of homogeneous EVs
- (5)  $S(o_r, d_r)$ : Set of all origin and destination pairs
- (6)  $evS_{r_o}$ : Closest EV station to the origin of the commuter,  $r \in R, evS_o \in EVS$
- (7)  $evS_{r_d}$ : Closest EV station to the destination of the commuter,  $r \in R, evS_d \in EVS$
- (8)  $MS_{r_o}$ : Closest metro station to the commuter's origin,  $r \in R, MS_o \in MS$
- (9)  $MS_{r_d}$ : Closest metro station to the commuter's destination,  $r \in R, MS_d \in MS$

For each  $O-D$  pair in  $S(o_r, d_r)$ , the algorithm determines the first and last mile paths and the modes used. For the first mile, there are three possible routes:

- (i) If the distance from the commuter's origin to  $MS_{r_o}$  is within the acceptable walking distance, then the path connecting the origin to  $MS_{r_o}$  is assigned to a

walk mode and the path between  $MS_{r_o}$  and  $MS_{r_d}$  is assigned to a fixed PT mode.

- (ii) If the first condition is not met, then the leg connecting the origin to the nearest EV station  $evS_{r_o}$  is assigned to a walk mode if the distance from the commuter's origin to  $evS_{r_o}$  is within the acceptable walking distance. The path connecting  $evS_{r_o}$  to  $MS_{r_o}$  is assigned to an EV service mode, and the path connecting  $MS_{r_o}$  with  $MS_{r_d}$  is assigned to a fixed PT mode.
- (iii) If both conditions are not met, then the path connecting the origin to  $MS_{r_o}$  is assigned to a car mode, and the path connecting  $MS_{r_o}$  with  $MS_{r_d}$  is assigned to a fixed PT mode.

For the last mile, we refer to all the possible paths connecting  $MS_{r_d}$  to the destination  $d_r$ , there are three possible routes to the commuter's destination:

- (i) The path connecting  $MS_{r_d}$  to  $d_r$  is assigned to a walk mode if the distance is within the acceptable walking distance.
- (ii) If first condition is not met, and if the distance from the nearest EV station to the destination,  $evS_{r_d}$  to  $d_r$ , is within the acceptable walking distance, then the path connecting  $MS_{r_d}$  to  $evS_{r_d}$  is assigned to an EV service mode. This path is followed by the path connecting  $evS_{r_d}$  to  $d_r$ , which will be assigned to a walk mode.
- (iii) Otherwise, the path connecting  $MS_{r_d}$  to  $d_r$  is assigned to a car mode.

There are three possible trips types generated from the route and mode choice module:

- (1) A full EV-public transportation trip which is as follows:

Walk + EV service + Fixed PT + EV commute + - Walk: a commuter walks to the nearest EV station, waits for an EV to be available, drives using the EV to the fixed PT stop, waits for a fixed PT service, rail commutes to another fixed PT stop, requests an EV service, waits for EV service, makes EV service trip to EV station, and finally walks to his destination.

- (2) A partial EV-public transportation trip: The first mile or the last mile is not completed using an EV service. This is the case when the commuter walks/drives from the origin to the nearest metro station or when the commuter walks/drives to their final destination from the drop-off nearest metro station. Partial EV-Public transit trip can involve one of the following routes:

Walk + Fixed PT + EV Service + Walk  
Walk + EV Service + Fixed PT + Walk

- (3) Rail commuting(traditional commuting): rail commuting here refers to the commuter's inability to utilize the EV service at any leg of the path connecting the origin to the destination. The possible routes are as follows:

Walk/Car + Fixed PT + Walk/Car

The generated routes are then evaluated based on the total estimated trip duration,  $l_d$ , which is calculated as follows:

$$e_o + \sum_{i \in K} \sum_{j \in K} \hat{t}_{ij} + \sum_{i \in K} \sum_{j \in K} t_{ij} + \sum_{i \in N \cup M} wt_i + \tau + \sum_{i \in K} \sum_{j \in K} \bar{t}_{ij}, \quad (1)$$

where  $N$ : set of all *Fixed PT* stops.  $M$ : set of all *EV service* stations.  $K: S(o_r, d_r) \cup N, M, e_o$ : earliest departure time from the origin of the trips reservation,  $r \in R, \hat{t}_{ij}$ : travel time from location  $i$  to  $j$  on foot,  $i, j \in K, i \neq j, wt_i$ : waiting time at  $i, \tau$ : average time to park Car/EV and start rail commuting.  $t_{ij}$ : travel time from location  $i$  to  $j$  by car/EV service,  $i, j \in K, i \neq j$ , and  $\bar{t}_{ij}$ : shortest travel time between metro stations  $i$  to  $j$  by train,  $i, j \in N, i \neq j$

The total trip duration,  $l_d$  is equal to the travel time for walk, car, EV service, and fixed PT modes, is calculated using actual leg length on the network and the specified speed for each mode. The waiting time of fixed PT is computed from the announced fixed PT schedule and based on the commuter arrival time to the fixed PT stop. Waiting time for an EV service is the time needed for the nearest available staff to move to the nearest available EV to relocate it to the incoming request.

When one or more legs on any path connecting  $O - D$  is assigned to an EV service mode, a *request-based relocation* module is evaluated. Similarly, whenever an EV is dropped at any station (shared EV or metro stations), the *proactive relocation* module is evaluated. The following section details

the *EV relocation and assignment* module. An example of a *route and mode choice* logic's output is shown in Figure 2.

**3.2. EV Relocation and Assignment.** Once a trip path connecting commuter's origin and destination with all possible stops is generated in the *Route and mode choice* module, the next step is to evaluate the *EV relocation and assignment* modules. The relocation modules are evaluated by a central dispatcher unit embedded in the simulation model. This unit manages a fleet of EVs and relocators to ensure that an EV is assigned efficiently to the commuter legs when necessary.

Before explaining how the *EV relocation and assignment* logic works, we need to identify the possible states of EV and the relocators. An EV is considered available if any commuter does not reserve it and it has enough battery charge. To check the EV's current battery level (BL), it should have enough charge to be driven from its current location to the commuter's destination station by considering a realistic consumption rate. The battery level constraint is calculated as follows:

$$BL_t - CoR_{ij} \times Dist_{ij} \geq 30\%BC, \quad (2)$$

where  $BL_t$ : EV current charge level (kWh).  $CoR_{ij}$ : EV consumption rate from  $i$  to  $j$  (kWh/100 km), where  $i$  is the current EV location,  $j$  commuter's destination station.  $Dist_{ij}$ : Travel distance from location  $i$  to location  $j$  (km).  $BC$ : EV battery capacity (kWh).

Otherwise, the EV will be in an unavailable status. Similarly, relocators are in an available state if they are not assigned to a relocation task.

Two following relocation modules are proposed: request-based relocation and proactive relocation. Request-based relocation is evaluated at commuter's trip announcement at the origin. The proactive relocation module is evaluated when a commuter drops off an EV at any station (shared EV station or a metro station). This section will detail both relocation modules based on the generated route from the route choice module.

**3.2.1. Request-Based Relocation Algorithm.** To clearly explain how relocation decisions are made, let us take an example of the route choice algorithm output Figure 2 shows an example of commuters journey from origin to a destination that contains a sequence of stops and the modes traveled on each arc.

When a commuter announces a trip reservation at time  $t_0$ , the commuter is estimated to arrive to the nearest shared EV station at time  $t_0 + \delta$  (based on the mode's speed and the actual path length extracted from Google Maps). The central dispatcher checks the availability of EV at  $evS_o$ . If there is an available EV at that station, no relocation request is issued, and the dispatcher reserves that EV and changes its status to be unavailable. However, if there is no EV available and no incoming EV to that station within a  $(t_0 + \delta) - t_0$  interval, a request for an EV is initiated. The dispatcher assigns an available relocator to relocate an available EV to the shared station. It is noteworthy to mention that the relocation

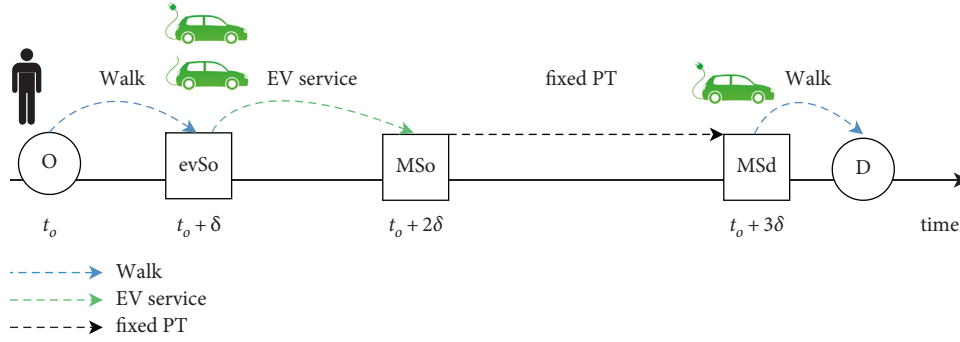


FIGURE 2: Example of route and mode choice module's output.

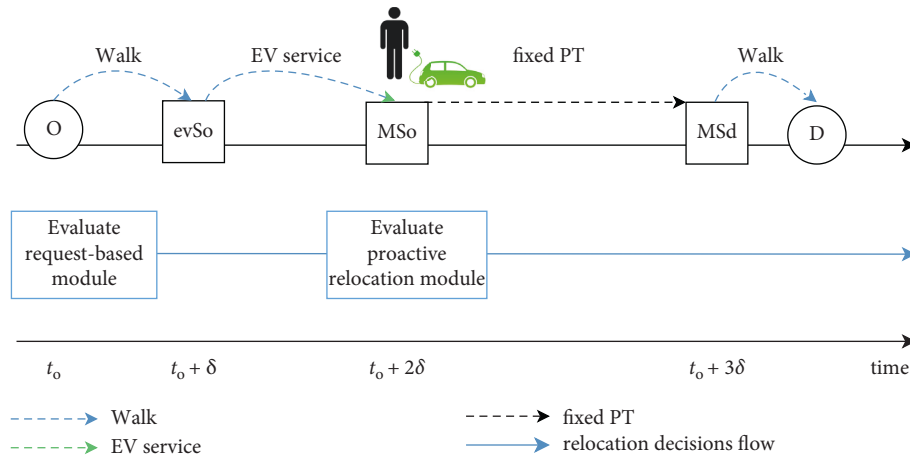


FIGURE 3: Example of an route and mode choice module's output and the associated relocation decisions.

operation starts at time  $t_0$ , before the commuter's arrival to  $evS_0$ .

Moreover, the request-based algorithm ensures that the total relocation distance is minimized. The relocation distance consists of two-leg components: *movement*, which is the distance from an available staff to an available EV, and *relocation*, which is the distance from the available EV to the commuter (who is at  $evS_0$ ). The next section describes the proactive relocation module.

**3.2.2. Proactive Relocation Module.** As indicated earlier, the proactive relocation module is evaluated whenever a commuter drops an EV at any station. Before illustrating how the proactive relocation module operates, we need first to define supplier stations,  $S(EVS)_s$ , and demander stations,  $S(EVS)_d$ , as follows:

- (1)  $S(EVS)_s$ : set of stations that have an excess of EVs at time interval  $[t_0, T]$ .
- (2)  $S(EVS)_d$ : set of stations that have a shortage in the number of EVs at time interval  $[t_0, T]$ . Each EV in  $S(EVS)_d$  has a priority score based on the total number of EVs needed at time interval  $[t_0, T]$ .

where the time interval length ranges from one to three hours based on the historical demand load.

To illustrate how the proactive relocation module works, we will continue on the route example from the earlier section. When a commuter drops off an EV at  $MS_0$  at time  $t_0 + 2\delta$  (Figure 3), the *proactive relocation* module is evaluated. This module starts by evaluating the current state of the EV station at that time, whether it is a supplier or a demander station. If it is a demander station or a supplier station with no EVs, then the EV will remain on that station. However, if the station is a supplier station and has a minimum number of EVs, the dropped EV will be relocated to a demander station with the highest *weighted score*. The score depends on two parameters: the *priority* of the demander station during that time and the *closeness* of the demander station to the supplier station. The *proactive relocation* logic is summarized in Figure 4. Figure 3 summarizes the interaction between the route choice output and the EV assignment and relocation modules.

**3.3. Integrated Model Implementation.** Shared EV service operations for the FMLM connection with fixed PT were simulated using AnyLogic 8.7.4 University Researcher software and coded using the Java programming language. AnyLogic is an open-access simulation software that integrates GIS technologies with the built-in Road Traffic and Rail libraries. Road Traffic Library can simulate detailed

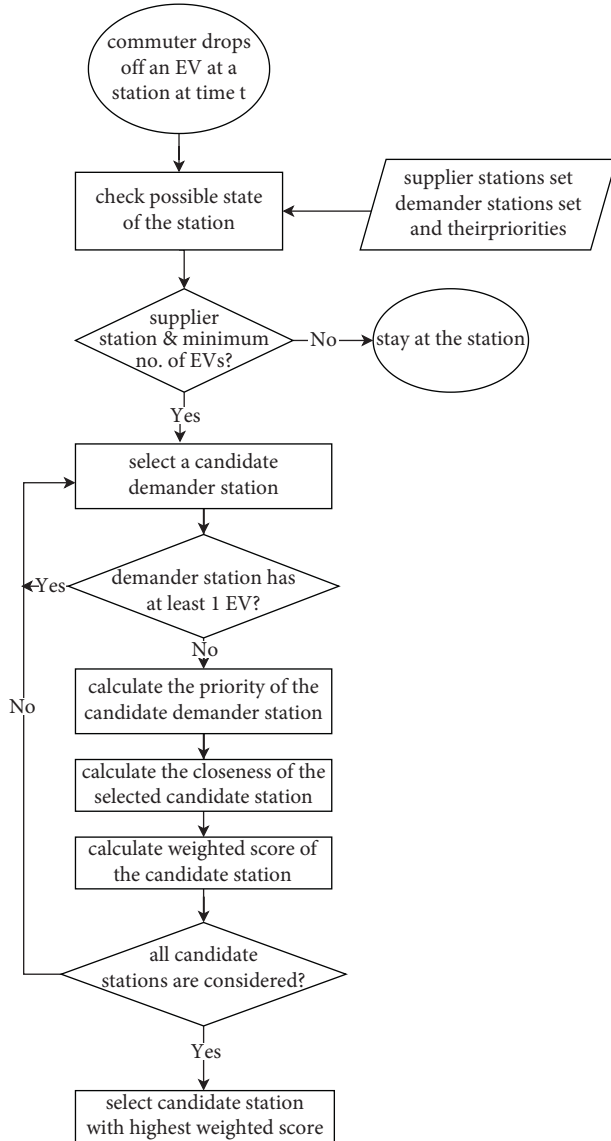


FIGURE 4: Proactive relocation flowchart.

traffic movements because the built-in predefined algorithms account for typical driving regulations like speed control or collision avoidance.

Travel options of the commuters are modeled in the *Route and mode choice* module based on the lowest trip duration. Based on the generated routes and mode choices, the central dispatcher manages the relocations operations in *EV relocation and assignment* module to assign the users demand over the choice alternatives. Then, the commuters trips with different modes are loaded to the real road and fixed PT networks inhibited in simulation framework. The overall modeling framework is depicted in Figure 5.

## 4. Case Study

**4.1. Network Settings.** We study the shared EV service operations as a FMLM connection to fixed PT network in Doha, the capital of Qatar (Figure 6). The main aim is to gain

insights into the implications of the integrated systems on commuters' mode choices, trips quality, and the relocations operations in Doha.

Fixed PT network consists of three metro lines (red, gold, and green) having 32 metro stations and two transfer hubs. Transfers between lines are only possible through the transit hubs located in downtown Doha. It is noteworthy that all the metro stations are located to serve Doha and all suburbs within an easy and convenient reach. For this study, we assume that all metro stations have park and ride facilities, i.e., parking lots for the EVs, but they are not equipped with electrical charging infrastructure. The speed of the trains,  $\bar{t}_{i,j}$ , is assumed to be 80 km/hr for urban trains. Moreover, we assume that there are 30 shared EV stations distributed within major locations of the network.

At the start of each planning day, the relocation staff and EV fleet are distributed among the stations according to one of the two possible configurations: centralized (C) or decentralized (D). A centralized configuration refers to a setting where all the resources at the start of the planning period are placed at the city's center transit hub. A decentralized configuration, however, refers to the settings where the resources are distributed among the network demander and supplier stations. The network consists of 61,045 nodes and 170,415 links. The commuters' demand profiles are generated based on historical trip transactions obtained from the Ministry of Transportation and Communication (MOTC) in Qatar. The demand comprises activity-based travel demand data, with each agent performing a series of activities for a 24-hour simulation day. It consists of 10,194 agents making 33,742 trips.

The data provided for each commuter include the origin location,  $o_r$ , destination location,  $d_r$ , and earliest departure time at origin,  $e_o$ . Driving times on roads,  $t_{ij}$  and the estimated walking times,  $\hat{t}_{ij}$ , between stations in the system were calculated using actual road distances from Google Maps. During the peak times, the link vehicle's speed was adjusted.

### 4.2. Model Settings

**4.2.1. Model Attributes.** Commuters are assumed to announce their trip at the origin location. Moreover, it is assumed that commuters are already aware of the fixed PT schedule. Also, we assume that the average time a commuter takes to park a car/EV and start rail commuting,  $\tau$ , to be about 5 minutes. These parameter values are similar to those used in [36] work. Further, we assume that the commuter is willing to accept a trip with a maximum of three stops. Moreover, we assume that the maximum distance a commuter is willing to walk to the EV station/metro station,  $aw$ , is about 1.5 kilometers at a walking speed of 5 km/hr.

**4.2.2. Dynamic Relocation and EV Dispatching.** During the day, some stations may have an excess of EVs, while other stations may have a shortage of EVs. Hence, dynamic relocation and EV dispatching are necessary to achieve a system balance. The relocation operation is managed by a central dispatcher unit that manages, in real-time settings, a

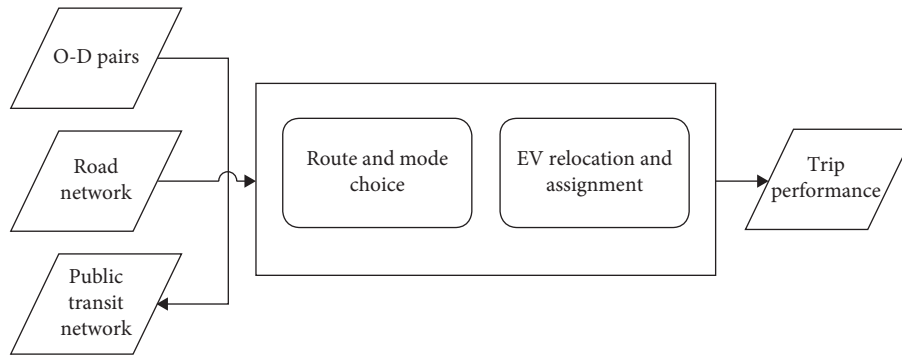


FIGURE 5: Methodology framework.



FIGURE 6: Road and railway network of Doha.

group of personnel to move vehicles between stations as explained in the *relocation operations* section. The simulated EV fleet has a battery capacity,  $BC$  of 27.3 kWh covering a range of 150 km, with average electrical consumption,  $CoR$ , of 18.2 kWh/100 km. Empty to full charging time is within 4–5 hours by using fast charging speeds of 7 kW. However, as mentioned earlier, the EV is considered unavailable when the battery level is 30%.

**4.2.3. Single or Shared EV Ridership.** We considered two EV riding preferences; single rider or multiple riders sharing the same EV. The concept of carpooling in literature is defined as a group of commuters with similar departure locations, timings, and heading to the same (shared station or metro station) willing to share the same vehicle. Commuters can share the same EV from a shared EV station to a metro station or from the metro station to a shared EV station. Figure 7 presents the two EV riding preferences.

**4.3. Simulated Scenarios.** We have simulated three scenarios considered as summarized in Table 1. In the base case (first) scenario, the modes available for commuters are walk, car, and fixed PT service. In the second scenario, however, commuters may also use the shared EV service in addition to the modes available in the first scenario to complete their trip from the origin to the destination.

In the third scenario, commuters use the same modes used in the second scenario; however, they have the carpooling option when using the EV service as described in the previous section. The shared vehicle is assumed to accommodate a maximum of four passengers. Also, the maximum waiting time varies from 5, 10, or 15 minutes for passengers to complete the vehicle's capacity or for the vehicle departs with one passenger if the waiting time passes without a second passenger showing up (within the maximum waiting time) to share the ride. Moreover, we assumed that 50% of commuters are willing to accept the carpooling option.

For planning purposes, it is vital to investigate the impact of the staff size, fleet size, and initial resources (staff and vehicles) distribution on the overall system performance. Sensitivity analysis with respect to the staff and fleet sizes for the second scenario was performed. The staff sizes are equivalent to 2, 4, and 6 percent (%) of the simulated population. However, the fleet sizes are equivalent to 4, 6, and 8 percent (%) of the simulated population. Fleet sizes were based on lower and upper bound identified in [37]. Finally, the resources are distributed at one of the following settings: centralized (C) or decentralized (D). We observe the simulation parameters that yield the best performance for the second scenario and feed it to the third scenario.

The integrated route choice and EV assignment module is implemented in AnyLogic 8.7.4 University Researcher software. The simulation runs were made using an Intel(R) Core(TM) i7-8550 U CPU @1.80 GHz 1.99 GHz. The time until convergence for the first iteration was approximately 15 hours for running the first replicate for the first scenario. Each simulation model setting was replicated 10 times to minimize the stochasticity in the results. Then, the key performance indicators were averaged and reported.

## 5. Simulation Results

We organize the simulation results as follows: first, we discuss the impact of the integrated shared EV service and fixed PT on the commuters' trip and the EV service operator activities in Section 5.1. Next, based on the parameters that result in the highest overall performance from Section 5.1, we discuss how the carpooling option affects the commuter's trip and the operators' activities in Section 5.2.



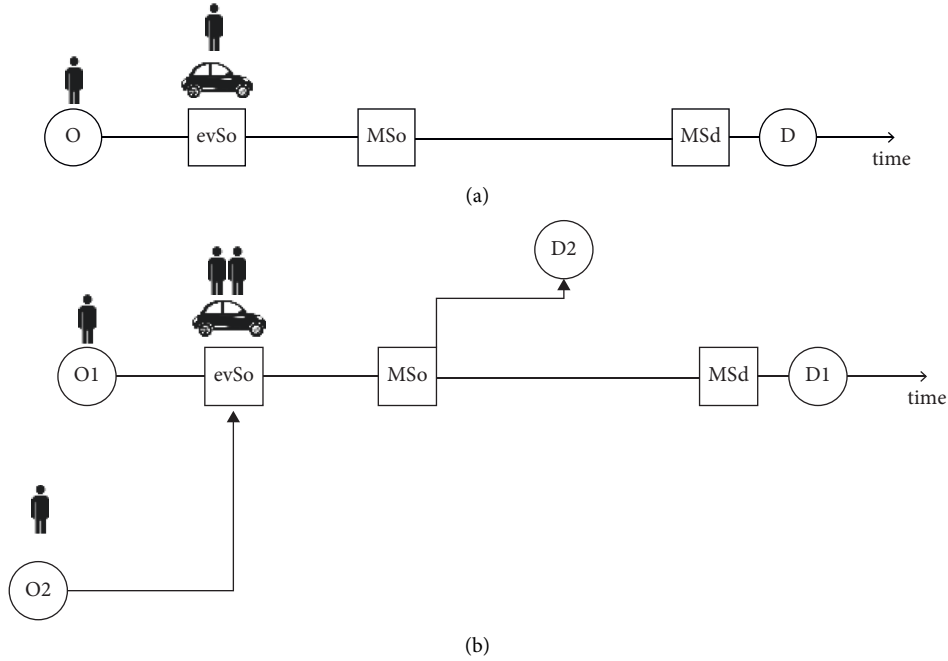


FIGURE 7: Riding preferences. (a) single rider and (b) multiple riders.

TABLE 1: Simulated scenarios. S:Single rider and M:Multiple riders.

Scenario	S/M riders	Walk	Car	EV service	Fixed PT
First scenario	—	Y	Y	N	Y
Second scenario	S	Y	Y	Y	Y
Third scenario	M	Y	Y	Y	Y

**5.1. First and Second Scenarios: Single Rider.** This section discusses the performance of the first and the second scenarios. We first analyze the percentage of trips performed by each travel mode in *modal usage* and how the waiting times, resulted from the EV service provider activities, have a significant impact on the mode choice. Then, waiting time analysis is presented in the *service level evaluation*. Finally, we discuss the implication of the EV service and fixed PT integration on the relocation staff activities in *EV service staff activities*.

**5.1.1. Modal Usage.** When assessing the EV service and Fixed PT ridership compared to the car ridership, we notice an increase in the integrated service ridership and a decrease in car ridership (Table 2). Figure 8 details the the EV service and fixed PT ridership Figure 9 and the car ridership versus the various resource levels and their initial distribution, respectively.

To explain this trend, we look at the average waiting times plot at various resource levels and initial distributions as shown in Figure 10. From Figure 10, it becomes clear that average waiting times decrease sharply as the staff size increase from 2% to 4%, irrespective of the fleet size and the initial resource distribution. As the waiting times decrease in Figure 10, the EV service and fixed PT ridership increase in Figure 8 while the car ridership decrease as in Figure 9. A

similar pattern was observed when the resources (EV fleet and the staff) were distributed according to the (*D*) settings. The highest waiting times (Figure 10) and the highest car ridership (Figure 9) were observed when the resources were distributed according to (*C*) settings, irrespective of the resources levels.

Therefore, from Figures 8–10, it becomes evident that EV service and Fixed PT ridership increase is governed by waiting times reductions.

**5.1.2. Service Level Evaluation.** Since the commuter's mode choice depends on the service level provided (waiting times reductions); in this section, we perform a sensitivity analysis with respect to the impact of *resource level* and *initial resource distribution* on the waiting times. When assessing the impact of the various *resource levels*, we consider the resources to be distributed according to (*D*) setting. Similarly, when assessing the impact of the *initial resource distribution*, we fix the fleet size and staff levels to 4% of the simulated population.

To assess the impact of the *resource level*, we analyze the percentages of commuters who wait for less than 10 minutes, between 10 and 20 minutes, and more than 20 minutes under various resource configurations in Table 3. From Table 3, the fraction of trips with shorter waiting times (<10) minutes increase as the staff size and fleet size increase. However, increasing the staff size beyond 4% and fleet size beyond 6% does not decrease the fraction of trips with longer waiting times (<20) minutes. Therefore, service quality improvement does not always come from having more resources but rather from a more efficient system configuration.

To evaluate the impact of *initial resource distribution* on the waiting times, passengers' waiting time throughout the

TABLE 2: Modal share per mode percentages.

Scenario	EV fleet size	Personnel level	Distribution	Walk	Car	EV service	Fixed PT	EV service and fixed PT
Base case	NA	NA	NA	43	49	NA	8	NA
EV service and fixed PT	4	2	C	43	34	14	9	23
			D	48	18	19	15	34
		4	C	47	22	18	13	31
			D	50	13	21	16	37
		6	C	47	21	18	14	32
			D	50	13	21	16	37
	6	2	C	44	30	15	10	25
			D	49	15	20	16	36
		4	C	47	21	18	13	31
			D	50	12	21	16	37
		6	C	49	15	20	15	35
			D	50	12	21	16	37
	8	2	C	45	27	16	12	28
			D	50	14	20	16	36
		4	C	47	21	18	14	32
			D	50	13	21	16	37
6	C	49	16	20	15	35		
	D	50	12	21	17	38		

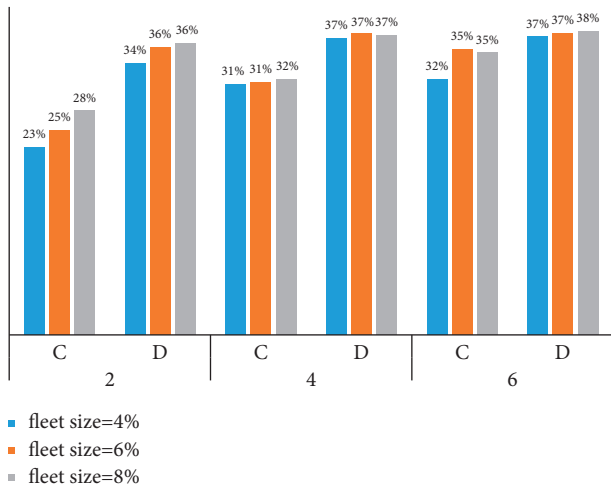


FIGURE 8: EV service and fixed PT ridership (%) versus various resource levels and initial distribution.

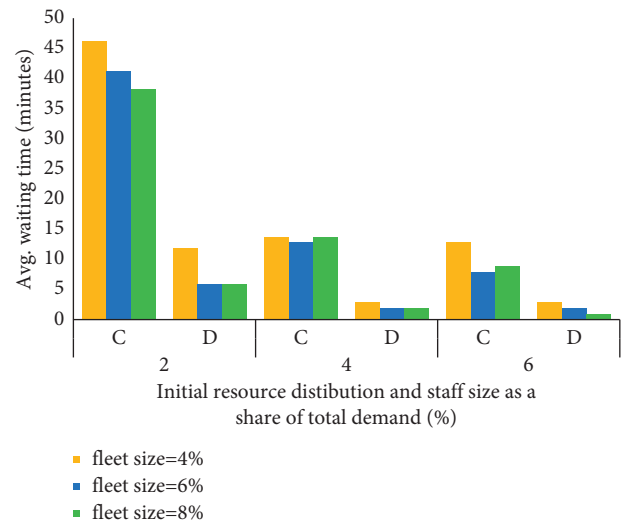


FIGURE 10: Average waiting times at corresponding resource levels and initial distribution.

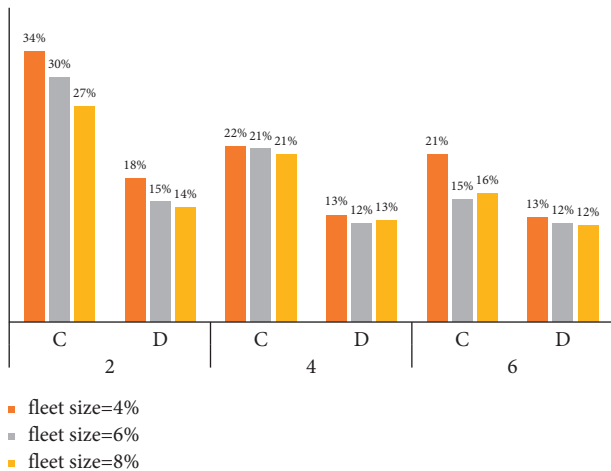


FIGURE 9: Car ridership (%) versus various resource levels and initial distribution.

day by fixing the resource levels, i.e., utilizing 4% EVs and 4% staff size is analyzed. Figure 11 shows the impact of initial resource distribution on commuters' waiting times throughout the three predefined peak periods morning- 06:00-08:30 (a), mid-day-1200-1400 (b), and evening-17:00-18:30 (c). More than 95% of commuters wait for less than 10 minutes in the morning peak time. However, as the day goes on, as shown in Figure 11(c), this percentage drops to 21% and 83% for C and D, respectively.

Therefore, initially distributing the resources among the demander/supplier stations (D) leads to an increased percentage of commuters waiting for less than 10 minutes in the corresponding periods. Although distributing the resources according to the (D) settings would lead to the least waiting times, the impact of the initial resource distribution becomes less critical with a higher resource level.

TABLE 3: Waiting time analysis: % of commuters waiting for <10 (min), 10–20 (min) and >20 (min).

Fleet size (%)	Staff (%)	Distribution	Waiting times (min)		
			<10	10–20	>20
4	2	C	22	11	67
		D	75	6	19
	4	C	47	21	31
		D	90	5	5
	6	C	50	23	28
		D	90	6	4
6	2	C	27	15	57
		D	87	4	10
	4	C	50	20	30
		D	93	4	2
	6	C	66	24	11
		D	92	6	2
8	2	C	30	24	46
		D	89	3	8
	4	C	52	20	28
		D	93	4	3
	6	C	62	24	13
		D	95	4	1

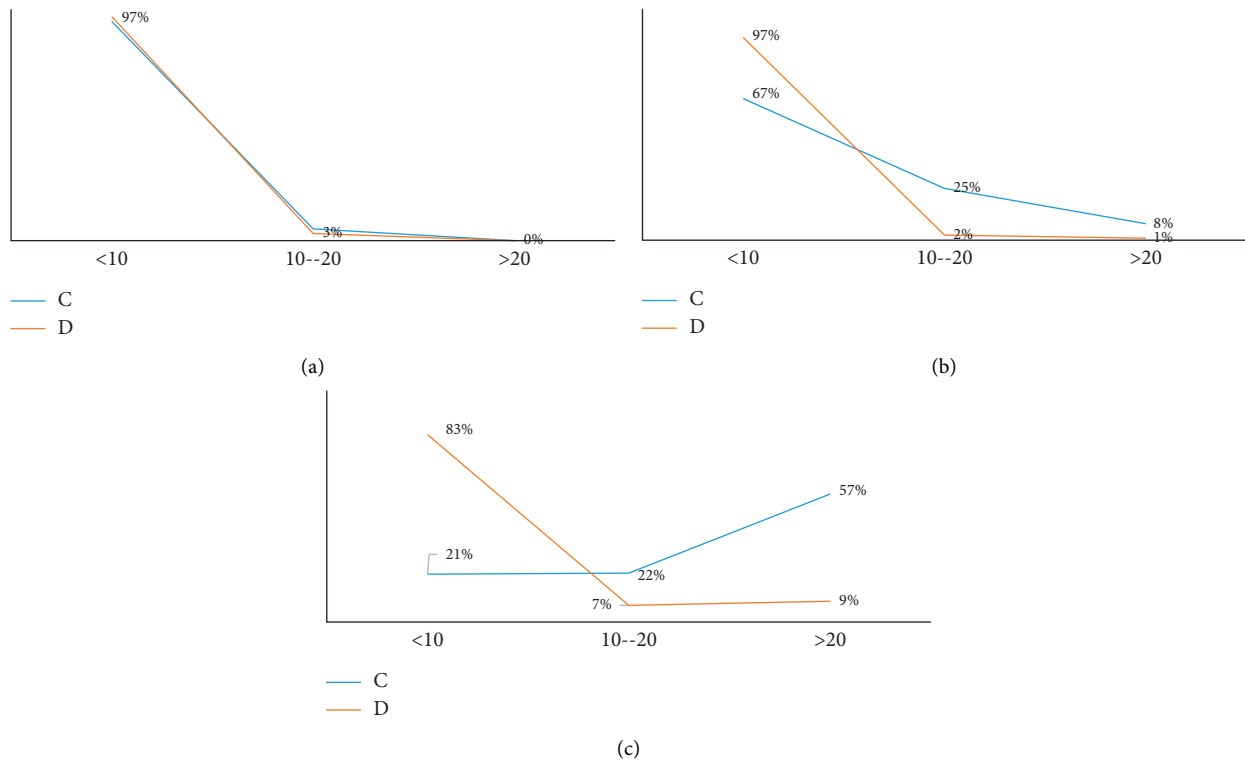


FIGURE 11: Percentage of commuter’s waiting for an EV service during the (a) morning peak time, (b) mid-day, and (c) evening peak time at a fleet size of 4% and staff size of 4%.

5.1.3. *Service Provider Operations.* This section discusses EV service provider’s activities, namely, the percentage of moving, relocating, and idle times as summarized in Table 4.

Table 4 indicates that relocators’ activities are directly proportional to the initial system settings and the resource levels. From Table 4, we can conclude the following: first, it becomes evident that there is no need to utilize more than

6% of EVs or hire more than a staff size more than 4% of the simulated population. Second, the relocation operations decreased significantly when the resources were distributed to the demander/supplier stations, (D) settings.

Therefore, efficient initial resource distribution leads to lower resource levels need. Also, fewer moving and relocating times are achieved, and hence, less congestion.

TABLE 4: Relocator activity at various system configurations.

Fleet size (%)	Staff (%)	Distribution	Relocator activity		
			Moving	Relocating	Idle
4	2	C	68	61	Overtime needed
		D	29	26	45
	4	C	24	30	46
		D	10	10	80
		6	C	14	20
D	5		6	89	
6	2	C	68	59	Overtime needed
		D	26	22	52
	4	C	28	28	44
		D	11	11	78
		6	C	16	18
D	7		7	86	
8	2	C	71	56	Overtime needed
		D	26	22	52
	4	C	31	28	41
		D	11	10	80
		6	C	17	19
D	5		5	90	

5.2. *Third Scenario: Multiple Riders.* This section discusses the third simulated scenario, where commuters can choose to share the ride with other commuters heading to the same station. We assumed that 50% of commuters are willing to share the same vehicle from a shared EV station to the nearest metro station or from a metro station to the nearest EV station as described in 4.3. To present the results, we show the system performance under the best performance settings from the previous sections. Namely, we will report in Table 5 the carpooling percentage matching rate, the average time to depart, and the average fill rate under the (*D*) settings, and by utilizing a staff and EV fleet size equivalent to 4% of the simulated population.

From Table 5, the percentage matching rate increases significantly as the maximum waiting time to reach total vehicle capacity, i.e., to fill the car (maximum four passengers per ride), is increased from 5 minutes to 10 minutes. The matching rate can increase up to 82% if the commuters are willing to wait for more than 5 minutes but less than 10 minutes. However, this percentage stabilizes as we increase the waiting time to 15 minutes. Hence, raising the waiting time to the 15 minutes parameter did not have a systematic effect on the percentage of the matched riders as the average time the vehicle takes to reach its capacity (average batch time) ranges between 7 and 10 minutes.

To compare the system's performance when the carpooling option is added, we compare the overall trip duration increase and the total reduction in relocation decrease compared with the second scenario in Table 6. The results indicate that for the same system configurations (*D* settings and resources at 4% of the simulated population), the trip duration increase is more when commuters are willing to wait for 5 minutes compared to the trip duration increase when commuters are willing to wait for 10 minutes. This unpredicted observation is justified as commuters may wait for additional 5 minutes while no other passenger shows up.

TABLE 5: Carpooling matching parameters at various waiting times.

Waiting time (min)	Matched (%)	Avg. Batch time (min)	Avg. Batch size
5	74	3.60	2.79
10	82	6.14	2.99
15	83	8.40	3.20

TABLE 6: Trip performance and service provider's activities at various waiting times.

Waiting time (min)	$\Delta$ Trip duration (%)	$\Delta$ Number of relocations (%)
5	44	-33
10	39	-43
15	56	-26

Regarding the overall decrease in the relocation operations, the relocation operations can decrease up to 44% when the waiting time window is between 5 and 10 minutes. This reduction in the relocations can be translated to a reduction in the congestion levels and also a reduction in the number of resources needed (both the EVs and the staff).

## 6. Conclusion

This study sheds light on the potential benefits of the integrated EV service and fixed PT on urban mobility. We proposed an integrated route choice and assignment model that allows commuters to combine EV service with the fixed PT service in one journey. The proposed model is implemented in agent-based simulation software based on the network in the city of Doha, the capital of Qatar.

Extensive simulation analyses were performed to test the influence of the transport supply on the individual's mode choice and the service providers' operations. Sensitivity results show no significant performance gain by increasing

the fleet size by more than 4% and the staff size beyond 4%. Furthermore, it shows that the initial resource distribution among the stations is vital in increasing public transit share, but its impact is less significant at a higher resource level.

Results suggested that EV service covers less than 25% of the commuter trip length, indicating that it was mainly used to access the fixed PT. However, EV service can increase fixed PT accessibility up to 9% to 17%, depending on the resource size and their initial distribution.

Moreover, we extended the simulation model to include the carpooling option. We evaluated the impact of this option addition on both the service provided and the relocations operations. Results indicated that there is an insignificant impact on the commuters' trip duration when choosing to ride with other passengers. However, a substantial reduction in the number of relocations performed. Relocation operations can decrease up to 44% when about 50% of commuters choose the carpooling option.

We demonstrate that fixed PT and EV service mode usage increase is governed by waiting time reductions. Results indicated a direct correlation between waiting times and the supply characteristics of initial resource distribution, resource levels, and relocations strategies. From this perspective, the limitations of the assignment model used in this study can be addressed in future research by employing a proactive EV relocation based on an hourly prediction of commuters' demand. Moreover, this work can be extended to propose a mathematical programming model to optimize the tactical and operational decisions of the car sharing operators to maximize the commuters' utility. It is important to note that mobility transformation can also be done by adopting policies and procedures. Hence, governments should encourage public and private partnerships. Private car sharing operators' partnership with public transportation would bridge the gaps in the transportation networks by developing clean, reliable, and connected transportation networks.

## Data Availability

The data that support the findings of this study are available on request from the corresponding author, A. Eliyan. The data are not publicly available and can be published with the permission of the Ministry of Transportation and Communication in Qatar.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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