World Electric Vehicle Journal

MDPI

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e-Fuel: An EV-Friendly Urgent Electrical Charge-Sharing Model with Preference-Based Off-Grid Services

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Abstract: Electric-powered vehicles (EVs) allow for an environmentally friendly and economic alternative to fuel-running ones. However, such an alternative is expected to impose further usage hikes and periods of instability on cities' power systems. From their perspective, cities need to scale their infrastructure grids to allow for adequate power resources to feed such new power-hungry consumers. Indeed, for such a green alternative to proceed, our power grids need to be ready to cope with any unexpected hikes in the power consumption rates without compromising the stability of the services provided to our homes and workplaces. Operators' steps in this path are still modest, and the coverage of EV charging stations is still insufficient as they are trying to avoid any further costs for upgrading their infrastructures. The lack of price consideration for the charging services offered at charging stations may result in EV drivers paying higher costs compared to traditional fuel vehicles to charge their EVs' batteries, hindering the economic incentive of owning such sorts of vehicles. Hence, it may take a while for sufficient coverage to exist. Although for drivers the adoption of EVs represents a city-friendly alternative with affordable expenses, it usually comes with range anxiety and battery charging concerns. In this work, we are presenting e-Fuel, a charge-sharing model that allows for preference-based mobile EV charging services. In e-Fuel, we are proposing a stable weight-based vehicle-to-vehicle matching algorithm, through which drivers of EVs will be capable of requesting instant mobile charge-sharing service for their EVs. In addition to being mobile, such charging services are customized, as they are chosen based on the drivers' preferences of price-per-unit, charging speed, and time of delivery. The developed e-Fuel matching algorithm has been tested in various environments and settings. Compared to the benchmark price-based matching algorithm, the resulting matching decisions of e-Fuel come with balanced matching attributes that mostly allow for 6- to 7-fold shorter service delivery times for a minimal increase in service charges that vary between 9% and 65%.

Keywords: electric vehicles; resource-sharing model; stable matching; preference-based service matching

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Citation: Quttoum, A.N.; AlJarrah, M. N.; Khasawneh, F. A.; Bany Taha, M. e-Fuel: An EV-Friendly Urgent Electrical Charge-Sharing Model with Preference-Based Off-Grid Services. *World Electr. Veh. J.* **2024**, *15*, 520. https://doi.org/10.3390/wevj15110520

Academic Editor: Michael Fowler

Received: 24 September 2024
Revised: 29 October 2024
Accepted: 6 November 2024
Published: 12 November 2024

1. Introduction and Problem Statement

The electric theme of transportation allows for a promising level of services that are considered city-friendly services, from the perspectives of both the environment and the economy. However, the spread of electric charging stations to serve such EVs in our cities is still poor and insufficient. In this context, battery level anxiety is a serious problem that hinders the desired adoption of EVs [1]. Indeed, a stranded dead battery EV has no option but to be towed home or to the nearest compatible charging station. EVs vary not only in their battery capacities and millage efficiency but based on the manufacturing country, they also vary in their charger types and their outlet models [2]. Therefore, for EV drivers, such points of compatibility need to be checked out before heading to any charging station to charge their EVs.

1.1. Discussion

In addition to being a new theme of transportation that allows for a green alternative to the traditional fuel-running vehicles, EVs can be thought of as mobile sources of energy [3,4] that, if efficiently utilized, could allow for distributed energy tanks to feed places that lack sufficient grid infrastructure [5,6]. Indeed, using bidirectional charging mechanisms, EVs can have their batteries charged at home or at a charging station, and later discharge such stored energy to another EV (i.e., vehicle-to-vehicle (V2V)) [7] or return it back to the grid (i.e., Vehicle-to-Grid (V2G)) [6], supplying electrical power to any facility or building [8]. Hence, such a V2V mechanism cloud be utilized to partially cope with the lack of sufficient coverage of charging stations in our cities. With such a mechanism of interaction between EVs, an EV with a surplus charge may support another EV that is in need of instant charging. This could also allow for a charge-sharing business model that EV owners may participate in. Different from traditional charging stations, with V2V, these service-providing EVs allow for mobile charging stations that may reach the charge-requesting EVs at any time and wherever they are. This allows for a flexible service scheme that, if well managed, can motivate the theme of EVs as a reliable anxiety-free transportation alternative to traditional fuel-running vehicles [9].

Uber, Lyft, and Bolt are examples of ride-sharing service applications that provide ride services in different ways compared to traditional taxi services [10]. With such applications, the client requests a ride service, and according to their location, the model running in the background directs the request to the most appropriate driver (i.e., the ride service provider). In such examples, choosing an appropriate driver to serve the received ride request is carried out according to the closest driver to the request. In this work, we are proposing a charge-sharing model that enables EV drivers to request a mobile charging service to be available at their real-time locations. We call it e-Fuel, a charge-sharing model that gives EV drivers a set of varying preferences (i.e., the model clients) in order to refine the chosen candidates to serve their charge requests better. Allowing varying preferences requires different mapping methodologies that consider such variance, which might be different for each client or service provider.

In such a framework of energy sharing, there exist multiple aspects to be taken into account in order to keep the potential of such a service model promising. Service price units are one of the main aspects that need to be carefully tackled and optimized [11]. Truly high service price units will hinder such a charge-sharing model and any potential to be adopted by EV drivers.Indeed, towing and emergency road-side assistance services could be available everywhere; however, they are costly. Therefore, if the price units of such V2V charge-sharing services are not competitive enough, such a model would not succeed, as other costly alternatives exist already. Moreover, the V2V interaction is another important aspect that needs to be considered and well engineered. Indeed, such interactions are defined according to the service requester–service provider matching methodology used to connect the model users together. A price-based greedy algorithm may provide for lower service price matchings [12]; however, such matching decisions might not be stable enough to guarantee the appropriate service delivery [13]. To provide better guarantees, the employed matching algorithm in such models needs to find the best possible match that attributes the requesting EV's service preferences. In addition to the price unit, this could include the time for service delivery and the provided charging service speed (i.e., being fast or slow).

In the context of charging strategies, V2V interaction has been studied in may recent research proposals. In [14,15], the authors worked on proposing flexible V2V charging strategies in an attempt to reduce the anticipated load on the power grids. In the same line, but from the perspective of cooperation strategies among system players, the authors of [16] extended the work of [17] by proposing a matching model that constructs its matching decisions in a flexible manner that aims to benefit both parties, i.e., energy consumers and providers. In their proposal, they employed an algorithm that looks for matching decisions to maximize the welfare of both parties according to their defined utilities. This starts with any feasible solution and iteratively continues to find any better match. Cost-wise, this may provide for good matching decisions, but still, such decisions are not necessarily stable. Thus, in some cases, it would be expected that either the power consumer or the provider may not be satisfied with the provided/required service attributes, and therefore deviate from the model's matching decisions. Therefore, we believe that players' service preferences need to be considered by the matching algorithm in order to allow for a level of matching stability and suppress any motivations of possible deviations.

1.2. Contribution

Accordingly, the contribution of this work comes in proposing the e-Fuel charging model, a model that is developed to allow for the following:

- Anxiety-free driving experience for EV drivers, where with e-Fuel, stranded dead battery drivers would be able to request a prompt charing service direct to their location.
- Mobile EV charging services, as compared to the stationary charing stations that the EV drivers need to reach in order to charge their EVs; with e-Fuel, it is the charging service provider who would reach the EV to deliver its charge services.
- Preference-oriented service in the sense that it enables the EV drivers to set their preferred charge service attributes, besides price units; this includes the charging service type (i.e., slow/fast), the time of service delivery (i.e., distance of the service provider), and the amount of required charge to receive.
- Stable matching decisions, which come as a result of the model's methodology in creating the matching decisions, which is built based on the driver's preferences, leaving no motivation for match deviation.
- A tailored framework for both, the clients and the charge providers, where its methodology checks for the anticipated residual battery capacity at the providers' vehicles after providing the intended charge service. This is proposed in a way to ensure that the providers will not end up with a dead battery status right after providing the intended charge service.

1.3. Paper Organization

The rest of this paper is organized as follows: Section 2 presents the related works, followed by the problem formulation in Section 3. Section 3.2 presents the e-Fuel model, defining its methodology and objectives. Next comes the mathematical modeling and constraints. The benchmark algorithm is introduced in Section 3.2.4. A few samples of the simulation results are presented in Section 4. Finally, Section 5 concludes the paper.

2. Related Work

In the literature, EV-related charging strategies are mostly divided into centralized and decentralized strategies. Using a centralized strategy, one that is managed at the system level, the EV owners are provided with schedules of the appropriate times and locations to recharge the EVs' batteries in a way that helps reduce the load on the power grids and balance such anticipated loads away of the grid's peak hours [18]. On the contrary, with decentralized management strategies, charging schedules are determined individually by the EV drivers. This may allow for a higher level of convenience and flexibility for the drivers; however, load-wise, the grid's stability might be compromised [19].

Those centralized charging schemes direct EV drivers to charge their vehicles according to predefined schedules of times, places, and charging rates. This may allow for shifting such EV consumption loads to low-peak periods and reduce charge service price units; but yet, such schedules are set according to the system's concerns without considering the drivers' real requirements and their stochastic behavior schemes. On the contrary, with the decentralized strategy, EV drivers may choose their charging times and places according to their desired needs. This allows for a convenient and flexible service platform while mitigating the communication requirement [20]. However, from the system's point of view, optimal charging outcomes are not guaranteed with such a scheme. Hence, in terms of network stability and service price units, they would still be inferior to the centralized scheme. In e-Fuel, the matching scheme allows for a kind of mixture between the centralized and the decentralized schemes, it has some characteristics of both. While the matching decision is centralized, it still allows the EV drivers to choose the desired charge service time and place while considering the drivers' service preferences. Load-wise, e-Fuel allows for an off-grid charge-sharing scheme that provides for instant service delivery while indirectly mitigating the grids' power consumption loads.

V2V allows for an interaction mechanism between different EV parties, which, in certain contexts, can be utilized to ease the charge service requests while reducing the consumption loads at the grids' transformers during peak hours. However, most applications of such V2V interactions are centralized, requiring the service requesting EVs to reach a charge-sharing spot (i.e., a charging station) for the energy transmission service. Moreover, this may require connecting both EVs to a common station that handles the energy transmission process, and so, besides the common stations' requirements, users of such sort of service may incur long queuing times for service delivery. Our proposed e-Fuel model utilizes the V2V interaction mechanism to create a kind of direct V2V charging model that provides for a mobile charge-sharing scheme that delivers the charge service to the place of the requesting EV drivers. Not only is it mobile, such a proposed model requires no waiting queues but an instant service model.

Recent research studies worked on proposing models with off-grid charging techniques; as an example, battery swapping may help the EV drivers to mitigate their battery range concerns without imposing any sudden load spikes to the power systems [21]. It allows EV drivers to swap their empty batteries with other charged batteries without being committed to any time schedules or physical locations [22]. However, working on a full-scale optimal solution that considers the varying objectives of the whole entities involved in such a problem can be classified as a non-convex optimization problem. This kind of optimization problems can not be easily solved by conventional mathematical models. Even though, for such sorts of problems, results of several heuristic algorithms found in the literature showed satisfactory results [23]. In this context, a dynamic programming model is developed in [24] to dispatch the EVs into their charging sessions in a way that reduces the system's power losses. With the same goal, the particle swarm optimization (PSO) algorithm is employed in [25] to manage power distribution networks, and in [26] to develop an EV dispatch model while taking into account the EVs' uncertainties. In V2G systems, [27] employed the PSO too in the context of power costs and emission minimizations. A Tabu Search (TS) algorithmic model is proposed by [28] to study how optimal scheduling is influenced by the uncertainties of EVs, and in [29], based on a probabilistic analysis of the EV drivers' charging behavior, a Genetic Algorithm (GA) model is proposed to manage the grid load fluctuations.

Yet, in this work, we are extending the literature by proposing a stable min-weight matching algorithm that allows for an off-grid V2V charging platform. Different from any other work in the literature, besides the other goals attained aforementioned works in the literature, our proposed e-Fuel model provides for stable matching decisions that consider the EV drivers' service preferences as an input to the matching mechanism. Such a mechanism allows for a customized service model while surpassing any motivation for match deviation.

3. Problem Formulation

The development of sufficient coverage of charging stations in our cities is still in its early stages; accordingly, many EV drivers may need to change their daily routes to stay near those limited charging stations, and in some trips, they may need to drive through other directions deviating from their true routes towards their destinations. Not only are they tiring, but such practices may end with increased cost and time requirements of the intended trips. Moreover, with such a limited number of charging stations, cities may create new spots of potential traffic congestions and heavy-loaded grid zones. Indeed, it indirectly forces EV drivers to drive through specific paths to stay close to the charging stations and keep their trips covered and anxiety-free. Therefore, in this work, we are proposing a mobile charge-sharing model for EVs that allows requesting instant off-grid charging services from other EVs in the area.

3.1. Demonstration

As depicted in Figure 1, we are tackling the charge-sharing problem in a city that hosts a set of environmentally friendly EVs. The considered city, like most of our cities, has few charging stations at different locations, but still, their provided coverage is poor. At any time of the day, EVs in a city can be classified into the following three categories: First, EVs that are looking for immediate mobile charging services EV_c. Second, EVs that are employed to provide mobile charge-sharing services EV_p (i.e., an Uber-like service model). Third, those EVs that are not in any of the aforementioned categories EV_d (i.e., do not need immediate charge services at the moment, and are not interested in being a charge-sharing service provider). The city area is represented in Figure 1, and those stranded EVs who are requesting instant mobile charging services are marked with red circles denoted by EV_c, with the charge stations denoted by the red map pins. As Figure 1 shows, those EV_c might be in places that are not close enough to any of those charging stations in the city, and so they need towing to carry them to the closest compatible station.

Figure 1. Problem Demonstration.

Like other service-sharing models—Uber, for example—many of the EV owners may offer to serve as charge service providers (i.e., discharging their EV's batteries to charge other EVs), a service theme that can be described as a charge-sharing service, which we call the e-Fuel service. In our model, EV drivers who need immediate mobile charging service may submit their requests to an intermediate mediator module, denoted by M, which in turn matches the received requests with a set of service providers EV_P that show their willingness to offer their services in the current time slots. The proposed model is developed to simultaneously process multiple charging requests that could be received by the mediator M from different EV drivers EV_C at a time. However, requests vary in their profile attributes and service preferences. Therefore, these received requests are classified according to their different makes and models, locations, and service preference attributes Accordingly, for each charge-sharing request $EV_c \in EV_C$, among its compatible set of candidate charge service providers, e-Fuel finds the best possible match that satisfies its service preferences the best.

The matching mechanism of our e-Fuel model is depicted in Figure 2, which plots the charge-requesting EVs (i.e., vehicles with a red battery icon) at the bottom layer of the figure and those potential service-providers (i.e., vehicles with the plug icon) at the top layer; it maps the charge-requesting with the charge-providing EVs in a way that allows for *social welfare* maximization, through which, for each requesting vehicle EV_c, it finds the provider vehicle EV_p that maximizes its utility defined through the weight function W_{ev_p}. As for the providers, e-Fuel motivates a competing environment that nominates those charge-providing vehicles EV_p whose offered service price unit beside their service-type attributes are competing. Such a mechanism allows for an environment that motivates competitive charge-sharing platforms and rewards those providers who show higher levels of cooperation.

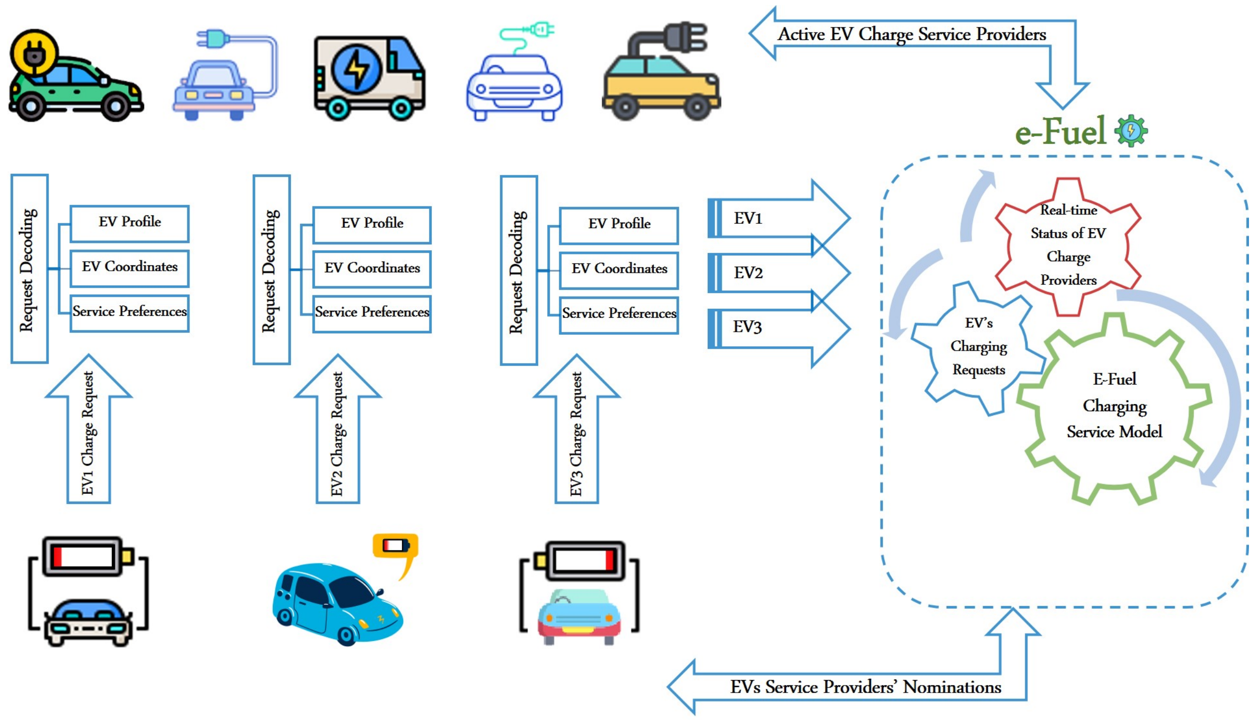

Figure 2. e-Fuel model demonstration.

To elaborate that better, the EV_c-EV_p matching problem is illustrated in Figure 3, in which the bipartite graph shows how a charge-requesting vehicle EV_c is looking for a charge-providing vehicle EV_p that serves its interest better, represented by a weight function for each candidate match. In the graph, the vertices represent the EVs, and the weighted edges represent the utility to be achieved from the corresponding candidate match decision. Consequently, based on the preference values of each charge-requesting vehicle EV_c, the mediator M finds the potential weights (i.e., represented by weighted edges) that the EV_c would expect by getting matched to each of the candidate charge-providers EV_P. Based on these weights, the model chooses the match that best serves the utility of EV_c.

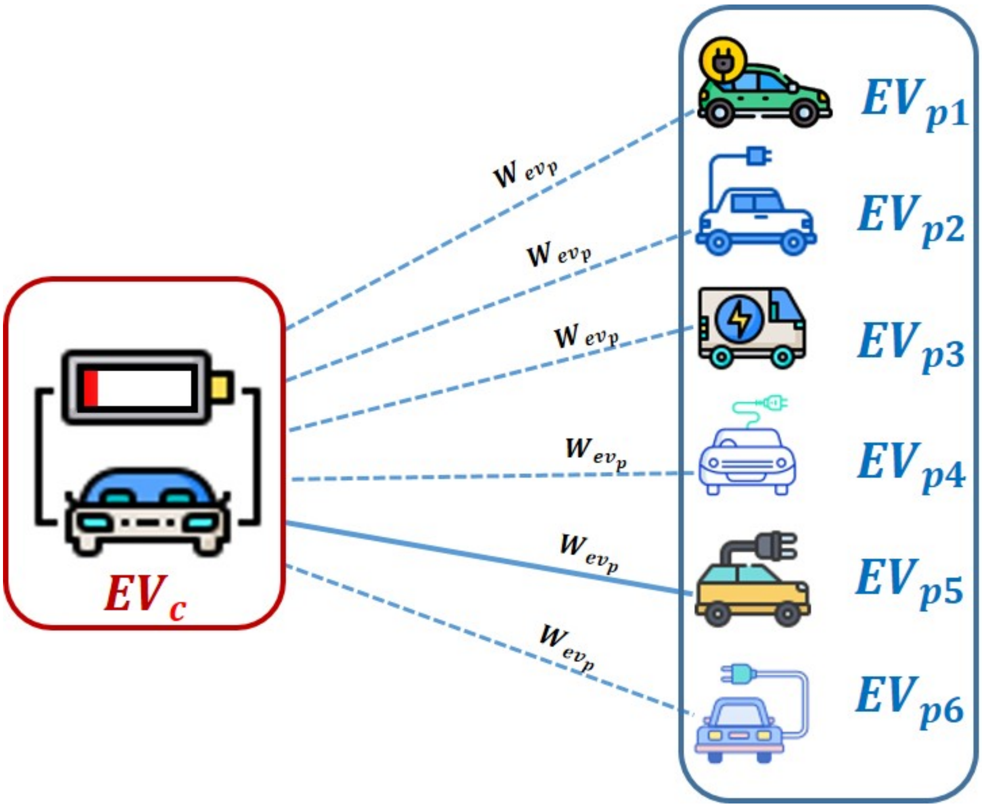

Figure 3. A bipartite graph matching charge requesters to charge providers.

3.2. The e-Fuel Model

Consequently, based on the illustrated relationship at the bipartite graph between the model players (i.e., requesters and providers), this section discusses the mathematical modeling of the proposed e-Fuel matching model which follows a preference-based weight function to formulate its matching decisions. Hence, according to the resulting weight values, it chooses the edge that maximizes the EV_c's utility. In the following, we elaborate on the proposed e-Fuel preference-based vehicle-to-vehicle matching algorithm that allows for utility maximization.

3.2.1. Utility and Weight Functions

For a charge-requesting vehicle $EV_c \in EV_C$, in e-Fuel, we define its utility function U_{ev_c} through a set of weight values that the model finds for each candidate charge service provider $EV_p \in EV_P$ that it recommends for matching. Accordingly, the model maximizes such a utility function U_{EV_c} by choosing the service provider EV_p with the least weight value as will be discussed next. Such weight values are calculated based on (1) the providers' attributes of charging speed, price unit, and time to deliver, besides (2) the requester's service preferences represented in the sub-weight values of $\alpha, \beta, and \gamma$.

The following weight function W_{ev_p} presented in Equation (1) shows how such weight values are calculated according to the service attributes of each provider while taking into account the requester's service preferences. Hence, having the weight value W_{ev_p} minimized means getting matched with a charge service provider that best matches the EV_c deriver's preferences to maximize its utility as presented in (2). Charging speed Sev_p, charge price unit Pev_p, and the service delivery time Dev_p are parameters that describe the service preferences of the EV_c's driver.

$$W_{ev_p} = \alpha \frac{1}{S_{ev_p}} + \beta P_{ev_p} + \gamma D_{ev_p} \tag{1}$$

$$U_{ev_c} = min(W_{ev_p}), \forall ev_p \in ev_P \tag{2}$$

The weight values defined by (α, β, γ) are used to describe the EV derivers' varying preferences in terms of charging speed (i.e., being slow or fast), and its other attributes like service price unit and the service delivery time. Accordingly, each service client, EV_c, may set such weights based on the way it values the aforementioned three attributes.

Accordingly, when required, each charge-requesting vehicle EV_c needs to submit its charge-sharing request to the mediator module, M, which, in turn, finds the EV_c's real-time location and the corresponding service preferences defined by the weight values. Next, the model sets the search area boundaries to find a provider match. In this context, the e-Fuel model is developed to allow for both: zone-oriented and zoneless settings. In the zone-oriented option, based on the EV_c's location defined by the (x, y) coordinate points, the model limits the search space to a predefined area with reference to these points of (x, y), which can help to limit the service delivery time D. Moreover, such a zone option allows for less number of candidate service providers EV_P, this could also help to reduce the model's running time. However, it may limit the number of available EV_P which means fewer options in an environment that we may describe as less competitive. On the contrary, the zoneless option allows for more candidate service providers EV_P to choose from, and therefore, the matching process may deliver lower service costs and/or faster charging speeds. Yet, such an option may impose further delays in service delivery time for the model's chosen matches.

3.2.2. Model Constraints

To shape the model's behavior and refine its outcomes, the aforementioned weight function, W_{ev_p}, is bounded with the following constraints to satisfy:

EV-Compatible Providers:

For each charging request EV_c received to the mediator M, among the set of charge providers EV_P, the model chooses to consider only those service provider vehicles EV_{P^c}, $EV_{P^c} \subseteq EV_P$, which are compatible with the requesting vehicle make and model.

$$EV_{P^c} = \begin{cases} 1 & \text{if provider } EV_p\text{'s make and model are compatible with vehicle } EV_c \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Providers' Availability:

Among the set of compatible charge providers EV_{P^c}, only those providers with active status $EV_{p'^c}$, $EV_{p'^c} \subseteq EV_{P^c}$, are contacted; others are not. Hence, only those providers who show their willingness to work at the current time slot are considered true candidates.

$$EV_{p'^c} = \begin{cases} 1 & \text{if provider } EV_{p^c} \text{ has active status to provide charge-sharing services} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Sufficient Capacity:

For each candidate provider in the set of active-compatible providers $EV_{P'^c}$, the mediator M needs to verify if the provider's real-time battery State of Charge (SoH) is sufficient enough to cover the required charge units of EV_c or not. Such readings of the battery SoC, location coordinates, and service availability status are assumed to be dynamically available at the mediator M and updated on a real-time basis. Accordingly, only those providers with sufficient charges stay in $EV^b_{P'^c}$.

$$EV^b_{P'^c} = \begin{cases} 1 & \text{if provider } EV_{p'^c},\, EV_{p'^c} \in EV_{P'^c}\text{, has sufficient capacity to charge } EV_c \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Residual Capacity:

$EV^{b}_{p'c}$ lists the candidate providers whose vehicles have battery SoC that is sufficient enough to cover the required charge units. Yet, those chosen service providers still need to have sufficient residual charges to resume their trips toward home or the next charging station. Consequently, our model is developed to check for the expected residual battery charges at the service providers' vehicles $EV^{b}_{p'c}$, $EV^{b}_{p'c} \in EV^{b}_{P'c}$, right after the potential charge services they might be assigned to provide. Those providers who pass the residual capacity constraint are listed in the list $EV^{rb}_{P'c}$.

$$EV^{rb}_{P'c} = \begin{cases} 1 & \text{if } EV^{b}_{p'c}\text{, would have sufficient residual charge after serving } EV_c \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

One-to-One Matching Only:

For each EV_c request received to the mediator M, there must be only one service provider $EV^{rb}_{p'c}$ being matched to satisfy the service request. Multiple matching is not allowed.

$$\sum_{\forall EV_c \in EV_C} EV^{rb}_{p'c} \leq 1 \qquad ; EV^{rb}_{p'c} \in \{0,1\} \tag{7}$$

Having the model constraints defined, the weight function of (1) is rewritten in (8). Now, for any charge-requesting EV_c, the set of candidate service providers to match is being filtered by the aforementioned set of constraints defined in (3) to (7), and according to the set of preference attributes (α, β, γ), the weight value of each candidate provider $EV^{rb}_{p'c}$, $EV^{rb}_{p'c} \in EV^{rb}_{P'c}$ is calculated as presented in (8). The weight values are then sorted in ascending order, and the provider with the minimum weight value as shown in the updated utility function U_{ev_c} in (9) is nominated as the match for the given request EV_c.

$$W_{EV^{rb}_{p'c}} = \alpha \frac{1}{S_{EV^{rb}_{p'c}}} + \beta P_{EV^{rb}_{p'c}} + \gamma D_{EV^{rb}_{p'c}} \tag{8}$$

$$U_{ev_c} = min(W_{EV^{rb}_{p'c}}), \forall EV^{rb}_{p'c} \in EV^{rb}_{P'c} \tag{9}$$

3.2.3. e-Fuel Matching Algorithm

The model's methodology is abstracted in Algorithm 1. As described, the mediator M first receives the charge requests from the EV drivers, where each request carries the requesting EV location coordinates, its make and model, the required charge units, and the required service preferences set by the driver. Based on that, the mediator M forwards the charge requests to the candidate service providers among EV_P, and then filters them by the set of constraints defined in (3) to (7) to find the most appropriate match to assign. In the case of no appropriate service match found for an EV charge-sharing request, as stated in line 21 of the e-Fuel Algorithm, the model expands the lookup space to a wider area in a way to find an appropriate charge service candidate for the assigned request.

Algorithm 1: The e-Fuel price-based requester-to-provider matching algorithm

The e-Fuel Price-based Matching Algorithm
1: ***input:*** At time, t, the mediator M reads the received set of charge-sharing requests, EV_C; for each, it obtains the following:
2: (1) the EV's current location coordinates (x, y),
3: (2) the EV driver's weight of the charging speed α,
4: (3) the EV driver's weight of the service price unit β,
5: (4) the EV driver's weight of the time for service delivery γ,
6: (5) the EV's make, model, battery SoC and State of Health SoH, and the requested charge units,
7: **for** each charge-sharing request EV_c, $EV_c \in EV_C$:
8: **find** all service provider candidates, EV_P, that are:
9: (1) compatible with the requesting EV_c's make and model: EV_{p^c},
10: (2) available for charge-sharing service provision at time t: $EV_{p'^c}$,
11: (3) with sufficient battery capacity to satisfy the EV_c's charge requirement: $EV^{b}_{p'^c}$;
12: (4) expected to have enough residual capacity after the anticipated service provision: $EV^{rb}_{p'^c}$;
13: **run** the **e-Fuel** matching model, list all candidate service providers $EV^{rb}_{P'^c}$ in L, and **then**
14: **while** the list L is not empty, and there is at least an $EV^{rb}_{p'^c}$ in it, then **do**;
15: **retrieve** the driver's preference weight values: α, β, γ;
16: $\forall$ candidates $EV^{rb}_{p'^c} \in L$, **solve** the weight function $W_{EV^{rb}_{p'^c}}$ for each, and accordingly:
17: based on the $W_{EV^{rb}_{p'^c}}$ values, **sort** the list L in an ascending order, **update** L,
18: select provider $EV^{rb}_{p'^c}$ with the least weight value $W_{EV^{rb}_{p'^c}}$, and print it as a match decision,
19: **else;**
20: inform EV_c: "No Appropriate Match is Found For Your Request At This Time",
21: choose a wider lookup space for an EV_p to the request EV_c, find a new list L,
22: **get back to** line 5 again,
23: ***output:*** the stable preference-based matching decisions for every $EV_c \in EV_C$;

3.2.4. Benchmark Model and Algorithm

To validate the proposed e-Fuel model and evaluate its efficiency, from the literature, we chose the traditional algorithm of such sort of service-sharing models as a benchmark one. In which, the EV charging algorithm tries to find the match that satisfies the price objective being the least [12]. Hence, with such a benchmark algorithm, the requester–provider matching mechanism will target the service price as the utility function that it tends to satisfy. Therefore, with the aforementioned constraints in Equations (3)–(7), the requester's utility function U_{ev_c} that the model tries to satisfy is formulated as the cost of the charge-sharing service that the model needs to minimize as shown in (10). To clarify that better, the benchmark matching criteria are presented in Algorithm 2.

$$U_{ev_c} = min(P_{EV^{rb}_{p'^c}}), \qquad \forall EV^{rb}_{p'^c} \in EV^{rb}_{P'^c} \tag{10}$$

Algorithm 2: The benchmark price-based requester-to-provider matching algorithm

The Benchmark Price-based Matching Algorithm
1: ***input:*** At time, t, the mediator M reads the received charge-sharing requests, EV_C; for each, it obtains the following:
2: the EV's current location coordinates (x, y),
3: the EV's make, model, battery SoC and State of Health SoH, and the requested charge units,
4: **for** each charge-sharing request EV_c, find all candidate service providers EV_P that:
6: are compatible with the EV_c's make and model: EV_{p^c},
7: are available for charge-sharing service provision at time t: $EV_{p'^c}$,
8: have sufficient battery capacity to satisfy the EV_c's requirement: $EV^{b}_{p'^c}$;
9: would have sufficient residual capacity after service provision: $EV^{rb}_{p'^c}$;
10: **run** the price-based matching model, list all candidate service providers $EV^{rb}_{P'^c}$ in L, and **then**
11: **while** the list L is not empty, **and** there is at least an $EV^{rb}_{p'^c}$ in it, then **do**;
12: $\forall\, EV^{rb}_{p'^c} \in L$, find the service price $P_{EV^{rb}_{p'^c}}$ to charge EV_c, and accordingly:
13: sort the list L in an ascending order, update L,
14: select provider $EV^{rb}_{p'^c}$ with the least value $P_{EV^{rb}_{p'^c}}$, and print it a recommended match decision,
15: **else;**
16: inform EV_c: "No Appropriate Match is Found For Your Request At This Time",
17: choose a wider lookup space for an EV_p to the request EV_c, find a new list L,
18: **get back to** line 5 again,
19: ***output:*** the least-priced service provider EV_p for every $EV_c \in EV_C$;;

4. Simulation and Discussion

To assess the efficiency of the proposed e-Fuel charge-sharing model and evaluate its chosen requesters-to-providers matching decisions, in this section, we compare its performance results with those of the benchmark model that employs the least-price charging protocol to choose its matching pairs.

As a testbed environment, we consider having a 50 km × 50 km city area represented in an xy-plane as depicted in Figure 4. In this city area, we assume having a set of 10,000 EVs divided into three categories (the number of EVs in Figure 4 is for demonstration only): one is considered as the charge service requesters category EV_c, another as the service providers category EV_p and the last category consists of those who do not belong to any of the aforementioned two categories EV_d. Those EVs are randomly distributed in the city area, and each has a profile that defines the following: (1) its xy-based location coordinates, (2) its category and related service attributes, and (3) its make, model, and battery readings of SoC and SoH. In this context, it is worth highlighting that, for simulation, the distances in the city areas are calculated as direct lines regardless of the city road zones and their traffic status.

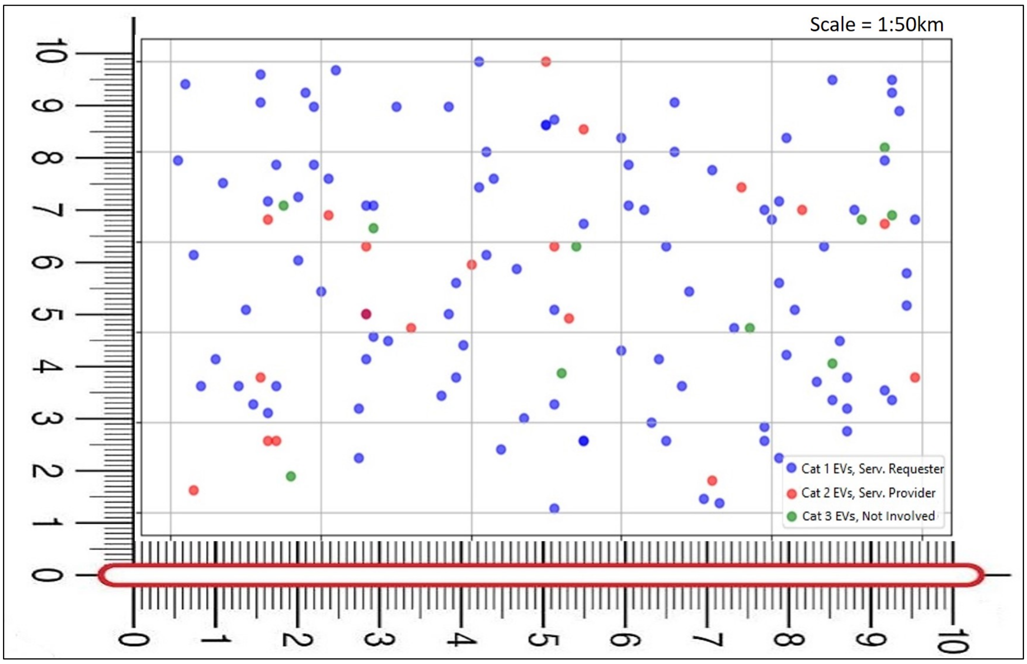

Figure 4. Testbed city area.

As an input to the simulated models, in the dataset we created, those charge-requesting EVs are chosen from 10 different makes, where each make comes in three to five different models as shown in Table 1. As an example, the make BYD comes in the following five models: Tang, Seagull, Seal, Dolphin, and Han. The charge-providing EVs follow the same distribution scheme; however, to preserve the constraint of compatibility for each make, all those providers who belong to any of the considered makes are named by one of the make models and assumed compatible with the rest. In the aforementioned example, the BYD service-providing EVs are all named BYD Tang and assumed charge compatible with the rest models of Seagull, Seal, Dolphin, and Han.

The simulation platform is developed using Python, and the libraries of NumPy, Matplotlib, and Seaborn. To simulate the real-life scenario, we consider reading the received charge-sharing requests on a real-time basis, which correspond to the dynamic state of the system. Therefore, at every moment, t, the system reads (1) the incoming requests EV_C and (2) the real-time status of the available charge service providers EV_P.

Table 1. EV makes and models *.

EV Make	Models
Toyota	Bz4X AWD, Bz4X FWD, Bz3
BYD	Tang, Seagull, Seal, Dolphin, Han
Nissan	Townstar, Ariya 63, Ariya 87, Leaf, Leaf e+
Volkswagen	ID6, ID4, ID3, ID7 Tourer Pro, ID Buzz SWB Pro
Kia	e-Soul 64, Niro EV, EV6 GT, EV3, EV3 Long Range
BMW	i4 eDrive40, i5 eDrive40, iX eDrive, i7 xDrive60, i4 M50
Mercedes-Benz	EQA 250, EQB 250+, EQS SUV 500 4Matic, G 580, EQS 450+
Hunday	Ionic 5 2WD, Inster, Kona Electric 65, Ionic 5 N, Ionic 5 84 RD
MG	ZS Long Range, MG4 Electric 64 XPower, Cyberster GT, ZS EV, Marvel R
Tesla	Model X Plaid, Model 3, Model Y, Model S Plaid, Model Y L.R. Dual Motor

* The names of these makes and models are used for the sake of simulation only and do not necessarily reflect the true names in real life.

Result Samples

In this section, we are presenting part of the simulation results for the two models we tested, our proposed e-Fuel model and the least-price benchmark model. In the city area shown in Figure 4, at time t, a set of EV requests is assumed to be received by the mediator M, which in turn, needs to match it with the available set of service-providing EVs. The matching results of the two tested models reflect the different matching methodologies between our e-Fuel model and the benchmark one are shown in Figures 5 and 6, respectively. With e-Fuel, the system is developed to allow the EV driver to shape its utility by setting its service preferences in terms of charging speed, price unit, along with distance and time for service delivery. On the contrary, the benchmark model looks for those matching decisions that only satisfy the price objective regardless of any other service attributes.

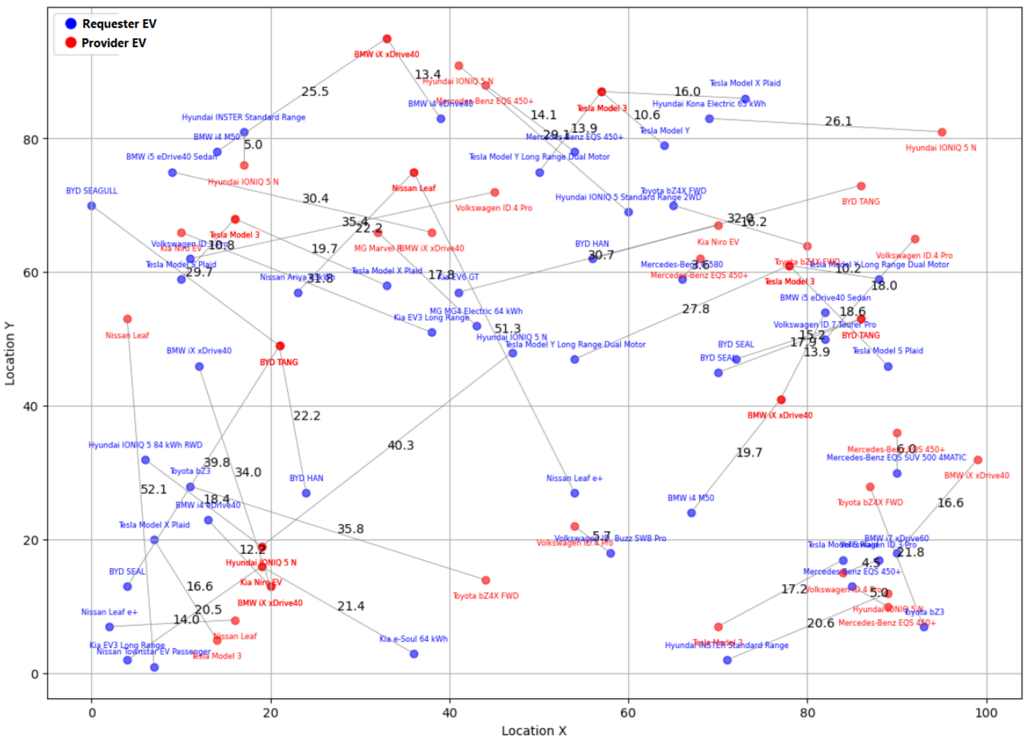

Figure 5. Matching map of the proposed e-Fuel model.

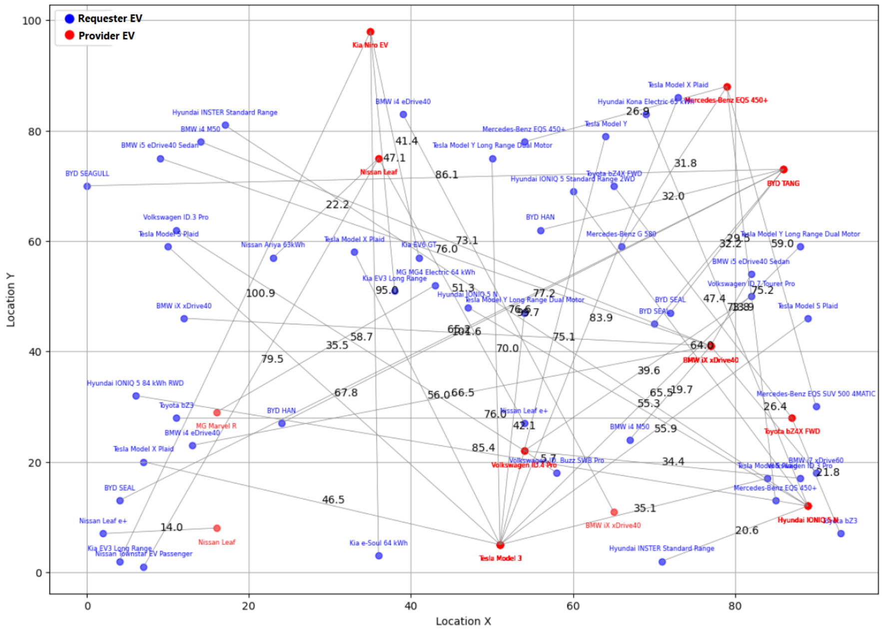

Figure 6. Matching map of the price-based benchmark model.

Figures 7 and 8 show the matching decisions of five different EV charge-sharing requests received by the mediator M looking for service-providing matches. Based on the e-Fuel matching methodology, the matching decisions for the five requesting EVs are presented in Table 2. Those of the benchmark model are presented in Table 3. Reading the matching decisions in Tables 2 and 3, for each service requesting EV, we can clearly note that the nominated matchings are restricted by the charger type. Indeed, to preserve charger–type compatibility, matchings are restricted to the same EV make, which blocks other potential matches that may allow for better service attributes. Hence, in real-life implementations, as in the smartphone industry, which now all come with type C chargers, companies might need to start thinking of a standardized universal type of charge for all EV makes and models.

Table 2. e-Fuel matching decisions: charge-requesting to service-provider EVs.

Charge-Requesting EV	Matched Charge Service Provider EV
MG Cyberstar GT (ID: 125)	MG Marvel R **(ID: 190)**
MG4 EV 64 (ID: 161)	MG Marvel R **(ID: 224)**
Mercedes EQS 500 (ID: 989)	Mercedes EQS 450+ **(ID: 25)**
Toyota bZ4X FWD (ID: 14)	Toyota bZ4x FWD **(ID: 92)**
BMW iX xDrive 40 (ID: 995)	BMW iX xDrive 40 **(ID: 179)**

Table 3. Benchmark matching decisions: charge-requesting to service provider EVs.

Charge-Requesting EV	Matched Charge Service Provider EV
MG Cyberstar GT (ID: 125)	MG Marvel R **(ID: 116)**
MG4 EV 64 (ID: 161)	MG Marvel R **(ID: 203)**
Mercedes EQS 500 (ID: 989)	Mercedes EQS 450+ **(ID: 146)**
Toyota bZ4X FWD (ID: 14)	Toyota bZ4x FWD **(ID: 216)**
BMW iX xDrive 40 (ID: 995)	BMW iX xDrive 40 **(ID: 284)**

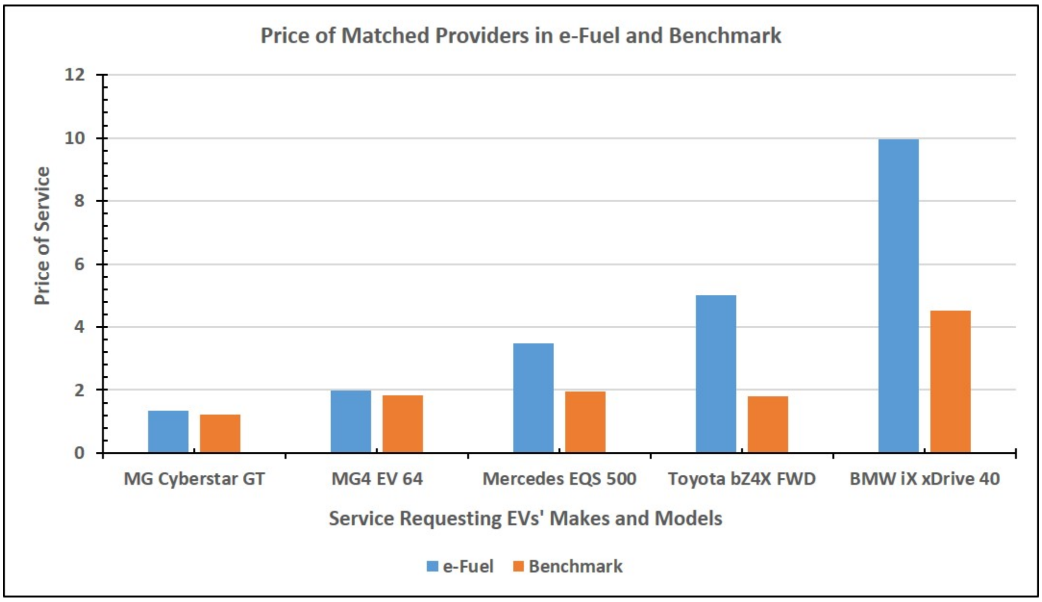

Figure 7. Charge service prices.

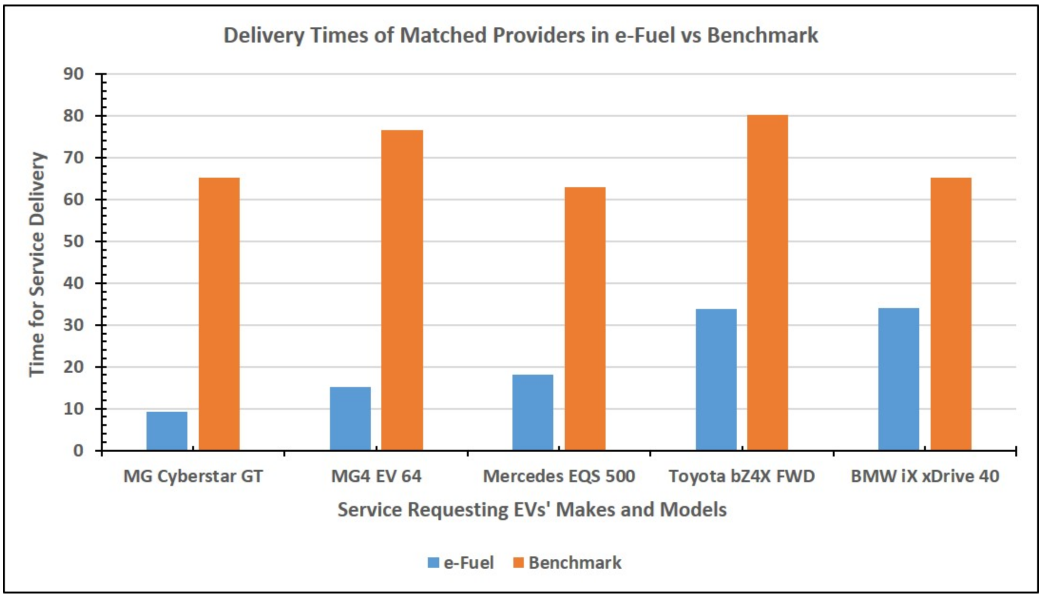

Figure 8. Time for service delivery.

The matching decisions shown in the aforementioned tables reflect the different methodologies of the two models, the e-Fuel and the benchmark. Consequently, for each request, we would expect two matching options, each with a different service price, a different distance or time for service delivery, and perhaps different charging speeds too. Figure 7 shows the difference in service prices for the matching decisions resulting from the two models, and in the same way, Figure 8 shows the corresponding times needed by the chosen service providers for service delivery to the matched requesting EVs. By reading the results presented in Figures 7 and 8, we could say that although the benchmark model recommends lower-price matches within the range of (9% to 65%), the waiting times are still expected to receive the required services exceed the value of price reduction. Indeed, back to the chosen matches shown in Figure 8, we can notice the scale of increase in the time for service delivery; as an example, for a 54% reduction in the service price, the benchmark recommended match requires an increase of 191% in service delivery time for the match of the BMW iX xDrive EV compared to that of the e-Fuel. It is almost 7-fold higher than the delivery time for the MG Cyberstar GT EV matched provider, which comes with only

9% savings in the service price compared to that match of the e-Fuel. It is worth highlighting that longer times of service delivery may lead to traffic jams and congestions that result from those stranded EVs waiting for the charger service delivery.

Figure 9 compares the matching results of another set of charge-requesting Evs and shows the fraction of increase or decrease in the results of the tested matching models concerning price and time of service delivery, respectively. As the results reveal, the e-Fuel matching model may recommend candidate matches with prices that are 0.4- to 1.75-fold higher, but when it comes to the service delivery, it reduces the time requirement in a way that could reach 80-fold less compared to those of the benchmark matchings.

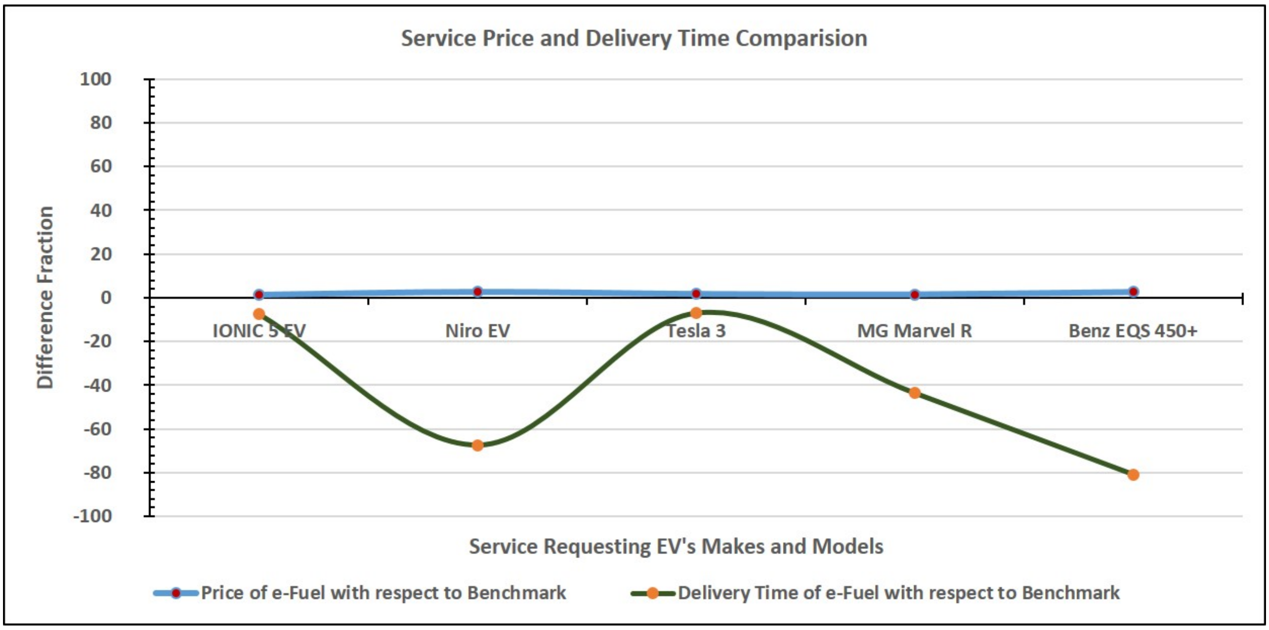

Figure 9. Price to time increase and decrease fractions.

Consequently, the benchmark model may indeed recommend matches with lower service prices; yet, such matches may impose further waiting times for the service delivery which contradicts the goals of the proposed model that aim to encourage the EVs' diffusion in our cities and reduce any reasons of EV navigation anxiety. What is more, such models exist to allow for instant mobile charge-sharing services that, besides the aforementioned goals, aim to avoid any possible congestion caused by any stranded EV with a dead battery in the middle of the road waiting for late charge-sharing providers.

Moreover, even when we consider an Uber-like methodology that chooses the closest (i.e., distance-wise) driver to collect the ride-sharing requesters, simulation results show that e-Fuel matching allows for a balanced theme of service that considers the main attributes of price, time, and distance. Intending to find the fastest delivery matchings, Figure 10 shows the behavior of the benchmark model being reconfigured to find the fastest delivery times compared to those nominations of the e-Fuel model. Considering the EV charge request from those EVs with the following IDs: 340, 681, and 691. The matching results presented in Figure 10 show how e-Fuel allows for balanced matching decisions that consider the whole attributes of the provided service. For the benchmark model, the nominated matchings reveal a kind of greedy decisions that consider only the distance attribute regardless of the service price.

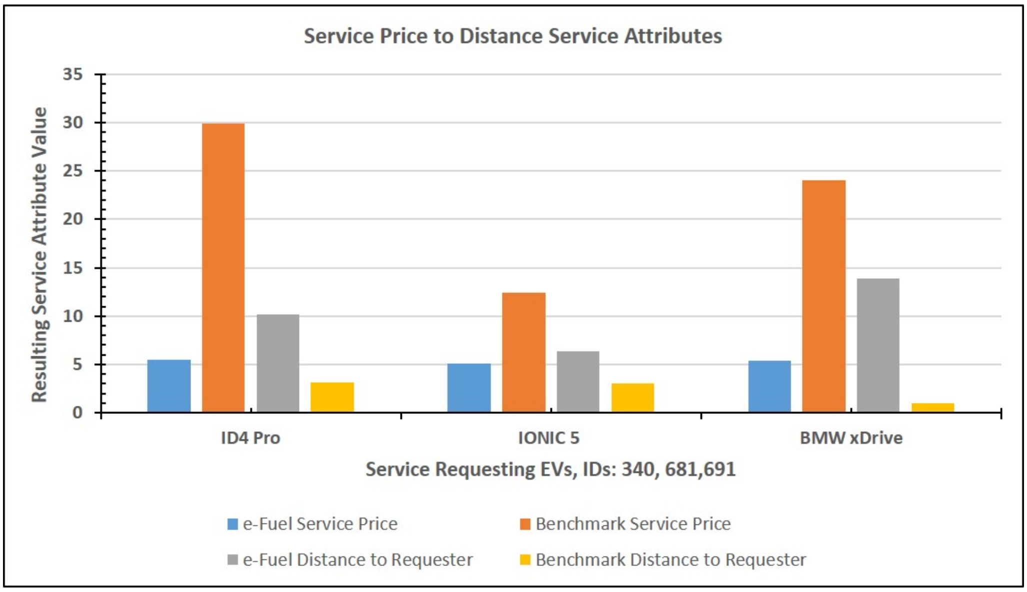

Figure 10. Balanced distance and price service attributes.

5. Conclusions

In this work, we tackled the problem of electrical power charge-sharing between different EVs throughout a managed platform that provides a sort of preference-based theme of services. Besides EV drivers, this work also considered easing the EV charge-sharing problem in a way that allows for fewer loads on the city's power grid systems. Through this, the model seeks a service provision framework that is off-gird without imposing any further loads that may affect other power-dependent sectors at homes or workplaces. Our proposed charge-sharing model, e-Fuel, enables EV drivers to request mobile instant charging services. To do so, besides their live location coordinates and their EVs' profiles, drivers can set their service preferences as input to the requester-to-provider matching methodology. With such preference attributes, the provider charge-sharing services can be customized for each driver according to its dynamic needs and desired requirements. Compared to the traditional price-based models, the simulation results proved that e-Fuel is capable of narrowing the matching decisions in a way that nominates balanced service price units that are relatively close to those of the least-price models while avoiding their lengthy service delivery times. Indeed, the results show a few cases with multiple folds (reaching 10s of folds) of service delivery time for only 10% or less of price savings. Waiting for longer service delivery times for relatively minor savings in cost represents matchings that might be worthless and misleading. Not only are they misleading, but such matching nominations may increase the possibility of traffic jams and congestions as a result of long waiting times for those EVs who are stranded in the middle of the city roads waiting for such a late charge provider to arrive. It is worth highlighting that for such a model to succeed and proceed forward, in real-world implementation, charge service providers would need to be incentivized to keep their willingness for participation motivated. Indeed, such behavior of battery charging and discharging may negatively affect their batteries leading to deteriorated lifetimes. Such motivations could come through a new price model or a kind of feedback record. Moreover, solving the charger compatibility issue would allow for greater space of competition among the service providers which allows for enhancing the matching outcomes with competing service price units and shorter times for service delivery. However, even with the current configurations, a matching methodology like that of the e-Fuel proposal is expected to motivate the adoption of such EVs, leading to an environmentally-friendly and truly economic transportation alternative.

Author Contributions: Conceptualization, A.N.Q.; methodology, A.N.Q., M.N.A., F.A.K. and M.B.T.; software, A.N.Q. and M.N.A.; validation, A.N.Q., M.N.A., F.A.K. and M.B.T.; formal analysis, A.N.Q., M.N.A., F.A.K. and M.B.T.; investigation, A.N.Q., M.N.A., F.A.K. and M.B.T.; resources, A.N.Q., M.N.A., F.A.K. and M.B.T.; data curation, A.N.Q., M.N.A., F.A.K. and M.B.T.; writing original draft preparation, A.N.Q.; review and editing, A.N.Q., M.N.A., F.A.K. and M.B.T.; visualization, A.N.Q., M.N.A., F.A.K. and M.B.T.; supervision, A.N.Q.; project administration, A.N.Q.; funding acquisition, A.N.Q. All authors have read and agreed to the published version of the manuscript.

Funding: This work is partially funded by the Deanship of Scientific Research at the Hashemite University.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest, and the funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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