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Charging infrastructure latency optimization

Sreten Davidov[1] · Miloš Pantoš[1]

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Abstract

In this paper, a new model for charging infrastructure placement with latency optimization is presented. Nodal charging latency coefficients are calculated including the traffic flow over a candidate location and charging time of the charging technology to be installed. Faster charging and lower traffic flow reduce charging latency and vice versa. To exceed optimization problem's complexity, set-cover modeling is applied to model the road network and the electric vehicle driving trajectories comprising the drivers' behavior. As a result, optimal number and layout of charging locations are found for the minimal charging infrastructure latency, subject to the charging reliability constraint. Numeric results illustrate integration of the charging latency as part of optimal charging infrastructure placement modeling. An optimal locations layout is shown for applying the optimization model to a 10 × 10 discrete grid with driving trajectories. A comparison is made with a reference model that is user-centric and quality of service based to oversee advantages of the newly infrastructure-centric planning model by minimizing charging latency. Differences are found in optimal layouts with the change of optimal locations.

Keywords Latency · Charging · Infrastructure · Vehicles · Reliability

1 Introduction

It might take a longer time for an electric vehicle (EV) to reach its destination, since it can get held up in longer charging queue when arriving at a charging station [1]. This is a major shortcoming in facilitating EV adoption and engaging a wider electromobility. To resolve the charging congestion of the charging infrastructure, EVs can take less direct route to avoid charging queue or from the perspective of the charging infrastructure the solution is to select locations with lower traffic flow that can accommodate a faster charging technology. In terms of wireless communications terminology, the perspective of latency is explored in [2] where the dynamics of the contention-based bandwidth request scheme is modeled by a 3-dimensional Markov chain to derive key performance measures such as system efficiency, mean number of pockets in the buffer and mean head-of-line delay. The proposed paper similarly takes in consideration the traffic flow over a point in the road network and considers as weights in latency coefficients to be included in the optimization process. Charging latency is associated to flow congestions and charging queue which are discussed in [3]. By this definition, the charging latency is defined as the ratio between the traffic flow and charging time in relation to the charging technology. In some cases, excessive charging latency of the charging infrastructure can cause EVs to be unusable for transportation. This is the main motivation and the basis of this research paper to further establish a universal planning model to set the path for unlimited mobility of EVs and ease the EV driving convenience.

More specifically, finite queue length as reflection of charging queuing behavior and various sitting constraints are part of the optimization model presented in [4]. The objective function is to minimize the comprehensive total cost of the charging infrastructure placement. Optimization results show the optimal charging locations (CS) layout and the allowable maximum queue length at charging locations. In reference to the optimization model presented in [3], this paper also shows an optimal charging infrastructure placement layout subject to charging reliability that was firstly incorporated in [4]. Nonetheless, the present paper considers the charging queue as a facilitator to charging congestions with a direct relation to charging latency of the charging infrastructure and as such places the charging latency as

✉ Sreten Davidov
sreten.davidov@fe.uni-lj.si

Miloš Pantoš
milos.pantos@fe.uni-lj.si

1 Faculty of Electrical Engineering, University of Ljubljana, Tržaška 25, 1000 Ljubljana, Slovenia

objective function for optimization. By this point of the paper, it must be emphasized that the present paper takes more general approach in charging infrastructure optimal placement and it is an upgrade of our reference model presented in [4]. In [4] we have introduced a charging infrastructure placement model subject to the quality of service (QoS) and charging reliability. It is a set-covering-based discrete model where the objective function is set on selecting minimal number of locations and the constraints involve the overall disposable charging time of the EV drivers to complete planned trips and the charging reliability. Charging reliability is a term that we have also incorporated as an optimization constraint to engage unlimited mobility for EVs, based on the principle of selecting at least one charging location within the driving range of EVs. It is elaborated more profoundly in [5, 6] and even more thoroughly in [7]. A shortcoming of the reference model [4] for which we have progressed to presenting this model is due to the QoS constraint that is difficult to determine for EV drivers. Still, if QoS is determined as expected service level for the charging infrastructure it can also be incorrect and lead to travel inconveniences. Regarding [4], this improved model finds the charging latency valuable for all EV drivers in more general aspect from the point of charging infrastructure placement and our objective function is to minimize charging latency. The present paper is more universal model that derives from the reference model with set-covering modeling presented in [4] and the charging latency as main novelty involved in charging infrastructure placement used as a conventional index in other areas as in telecommunications, as shown in [8] and [9], information-technology communications [10, 11], etc. Nonetheless, latency in those areas is defined as a change of node due to node occupancy which is like the charging infrastructure placement problem by changing more frequently traffic occupied candidate locations with less occupied that can charge with faster charging times. This is the gap that we targeted and exploited in present paper.

As vital part of the charging latency is the charging congestion. In most of the research papers, charging congestion is targeted by control and adaptive algorithms, such as [12–14]. In [12], an adaptive control algorithm for EV charging is proposed without straining the power system. Congestion signals in relation to traffic flow are deployed across the network and managed by the control algorithm. The present paper includes the traffic flow that comes from driving behavior by considering the EVs driving through a candidate location in the road network within the planning period. In comparison to reference [12] traffic flow is included in present paper since a road network is simpler to be derived and modeled as shown in this paper in comparison to a model of the electric power network which is in addition involved by the connection power of the charging station. Nevertheless, the electric power system is included in the present paper indirectly through the charging time at a candidate location, which is determined by the connection power. In [13], once again the charging congestion is observed from the viewpoint of asset congestion during peak hours. The point is to mitigate congestion in electric network and how to avoid congestion issues. The control algorithm boils down to comparing a controlled and uncontrolled EV charging. In comparison to [13], present paper does not involve any control charging strategy regarding EV charging yet takes a general charging infrastructure optimal placement planning viewpoint. It considers reducing charging congestions by placing the charging infrastructure with an optimal objective function to minimize charging latency as a ratio of the traffic flow at a candidate location and charging time. Other types of exploitation strategies to reduce congestion shown in [14] such as management of EV loads and other cost savings optimization are not within the focus of present paper.

A similar idea that comes close to the concept in present paper is reference [15], where a test was made to obtain info whether the efficiency of the traffic system could be enhanced by congestion charges. The test is named "The Stockholm congestion—charging trial 2006," where a different toll rate was set across the cordon of Stockholm to reduce traffic and to motivate vehicle drivers to use alternative routes. Goal was to test if additional charging and increasing toll costs would force vehicle drivers to use less costly tolls. With the overview made in [15] declares that the effects on congestion reduction were larger than anticipated, so that it resulted in favorable benefits for environment, but also in favor to vehicle users. Similar to the idea in [15], present paper uses the input info on candidate locations regarding their traffic flow as starting point in determining their significance in the overall charging latency—if traffic weight is higher, it is more expectable to have congestions and thus the model must be set to select locations to reduce latency while the location is within the driving range of the EVs. Nonetheless, reference [15] is a traffic flow-oriented paper and in present paper traffic flow is part of input data modeling as driving trajectories reflecting EV driving behavior. In other, more recent study, [16], there are substantial findings regarding the outcomes of implementing time-differentiated congestion charging rates—there is higher support for congestion charging with the ultimate purpose of greater delay reduction. Therefore, the aim of the present paper is to further facilitate the transformation of placing charging infrastructure based on more latency reduction-based optimization models.

From a charging infrastructure-centric planning point, there are variety of discrete location models which fall under the categories of coverage, median and dispersion models as noted in [17]. Coverage discrete location models relate to the set-covering theory, i.e., to location set-covering problem (LSCP), [18]. Present paper is a discrete set-covering model, whereas per LSCP definition the optimal objective function is set to find the minimum number of locations to reduce charging latency and to cover the road network with CSs in a way so that they are at least adjacent for a driving range distance. In comparison to [18], distance is used as a coverage criterion used as an optimization constraint defined by the charging reliability which was referenced previously. One of the first discrete set-covering models in relation to finding the location to allocate an ambulance vehicle to cover an area in relation to minimal time of arrival or distance was presented in [19]; however, the improvement of these set-covering models in the framework of charging infrastructure planning must be improved in objective functions and constraints, which is done in present paper by involving the charging latency and the charging reliability as a constraint. In more recent papers, such as [20] a thorough review is made of the formulations and case-studies regarding the optimal placement and locations selection for classical fast and slow charging stations to provide deeper insights. Discrete location problems for example max covering, P-center and P-median models for CI placement are shown comprising the inputs and outputs in the models. Inputs are defined as no. of CS, demand nodes, set-covering inputs, candidate sites and the outputs are locations of CS, max no. of covered nodes, locations of min average driving distance, etc. Objective functions are both cost wise including distribution network expansion, service durations, power quality or other ancillary services costs optimization. Namely, as emphasized in [20], charging stations optimal location selection is an open research topic and in the present paper we have upgraded a classic set-covering optimal charging stations location model with the novelty of integrating latency as a term that merges two vital components including charging time and traffic flow over a potential charging location. Additionality to the classical covering-based charging infrastructure placement models, advanced analytics is applied on travel behaviors of urban residents and thus included in the optimization models. Such example is [21] where the models consist of two parts, i.e., one for short distance commuters which utilize slow charging technology facilities, and the other for long distance travelers which utilize fast recharging technology. Nevertheless, the shortcoming of this paper is that it is strongly depended on the sensitivity analysis of the user behavior, that it has a strong impact on the number and location selection of the CS. On the other hand, the present paper also includes the charging behavior following a trajectory selection and modeling of traffic flow over a charging location with a corresponding charging technology to be placed at a selected location—fast or slow charging technology to find the impact of the charging time to reduce the charging latency. In [22] using discrete modeling of the road network and with additional clustering analysis on user behavior, the electric vehicle charging stations coverage was shown. Similarly, for the purpose to show the patterns of movement of EV users, the trajectories are also part of the set-covering modeling that are further used to set the basis for the charging latency optimization.

Following the literature review above, we have solely focused on the gap where latency from a charging infrastructure planning viewpoint has not been involved in any of the research papers that elaborated on discrete set-covering allocation models in combination with charging reliability. As a well-known and highly utilized index, latency is used in communication networks to reflect the change of a node because of high occupancy which may cause rendering of the applications in-use. Translated to our case, latency served as a main incentive and an idea to define an objective function to select candidate locations (nodes) with lesser charging latency coefficients (occupancy).

Closest references to our paper are [4–7] which all have the charging reliability in-common and derive from the base set-covering models [18, 19]. References [12–14] targeted charging congestion, which is implicitly related to charging latency, however from the electric power system viewpoint that is not in focus of this paper. More closely to the fundamental concept of present paper is elaborated in [15] where the tolls paying ratio (nodes) was adjusted to charge more in areas with higher traffic and the benefits were clear in reducing traffic congestion. Thus, the main scientific contributions and improvements regarding the references specifically elaborated in this paragraph, but also in relation to the literature review are:

- New set-covering charging infrastructure optimization placement model where the objective function is set on minimizing the charging latency subject to the charging reliability;
- Charging latency is the main novelty to be introduced in the research area of CI placement and focus of this paper. It is defined as a ratio of the traffic flow and the charging time of the charging technology to be placed at a candidate location. We consider that these two components in particular impact the most in the optimal charging stations location selection and as such are explored further in this paper;
- Elaboration on the optimization of the charging latency of the charging infrastructure, where given candidate locations with a lower traffic flow and faster charging time technology, the overall charging latency of the charging infrastructure is to be reduced. The constraint on charging reliability was already thoroughly elaborated in [4–7];
- New approach of how to measure the charging congestion of the charging infrastructure as a consequence of optimization of the charging infrastructure latency. The option of calculating the charging congestion can be used to reflect the charging congestion reduction, which is a beneficial information to justify and assess the investments in comparison to other CI placement models. In this paper, the

case study shows the overall charging congestion reduction by comparing the newly involved Latency model over a QoS-based model for CI placement;
- New approach how to assess and oversee the spatial changes in the CI placement model by comparing the Latency and QoS model. The approach shows how to find the difference in selecting and comparing the charging technologies for the optimal locations. This approach can be used to emphasize the significance of the latency coefficients in the optimal selection of charging locations on locations that have fewer traffic loads and can accommodate faster charging stations.

The rest of the paper is organized as follows: the newly proposed optimization procedure is presented in Sect. 2 with Sect. 2.1 on input data preparation and Sect. 2.2 on the charging latency optimization model. Section 3 presents the numerical results. The conclusion drawn from the paper is provided in Sect. 4.

2 Charging infrastructure latency optimization

The optimization procedure proposed in this paper is complementary to the model presented in [4–7] and is shown in Fig. 1. It consists of three sections, first is the input data preparation followed by the optimization model and results.

The first Subtask Sect. 2.1.1 of the input data preparation is to model the road network in a discrete network represented as a finite set of candidate location points. Next, the goal of the second Subtask Sect. 2.1.2 is to outline the EV drivers' behavior by specifying the road network points as elements of an individual driving trajectory at specific point in time.

In the third Sect. 2.1.3, the main novelty and the main point of this paper are presented—charging latency. It is thoroughly elaborated on this subject on how a charging latency value is found for an individual candidate location. Next that follows is the Subtask Sect. 2.1.4 reserved for charging reliability.

The novel optimization model including the charging latency minimization is presented in Sect. 2.2. The objective function is set on finding the minimal number of locations to minimize charging latency subject to the charging reliability—defined as selecting at least one charging location within the range of the EV.

Numerical results are presented in Heading 3, where the optimal charging infrastructure placement layout is presented for different EV driving ranges and compared with a (reference) QoS-based optimization-based model [4].

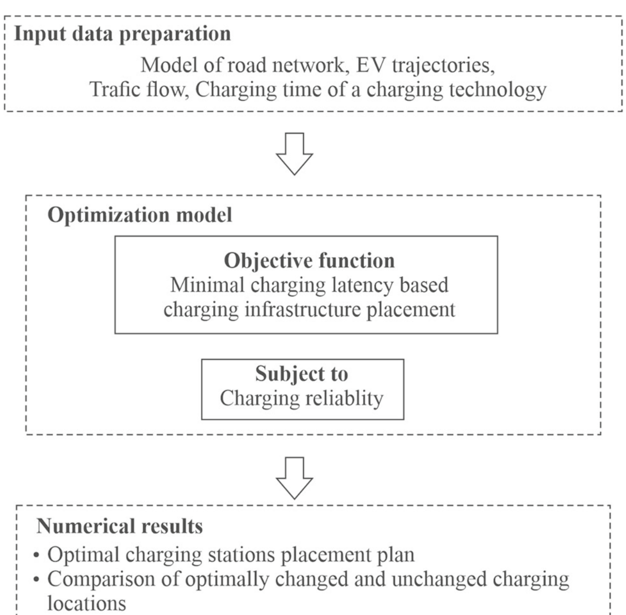

Fig. 1 Optimization procedure

2.1 Input data preparation

Input data preparation consists of several subtasks before the optimization model execution. In these subtasks, data is prepared such as for the modeling of an arbitrary road network as a finite set of discrete points. These points are latter used as candidate locations and as a part of an EV driver trajectory. Charging latency modeling is also presented as the vital part of the optimization procedure. Charging reliability is shown as the concept valuable to engage unlimited mobility for EVs.

2.1.1 Modeling the road network as a final set of discrete points

Complementary to the modeling of the road network shown in our paper [4], the discrete approach is used to form a finite set of discrete elements representing the candidate locations. The discretization is a well-known method that is only applied in this paper as it is and is explained fully in detail in [23]. This is a fundamental first step in reducing the spatial complexity of continuity of the road network and to further prepare the data for the optimization model. The road network is represented by the set M, as follows:

$$M = \{m_1,\ m_2, \ldots, m_i, \ldots, m_I\};\ i = 1, 2, \ldots, I. \qquad (1)$$

M is the finite set of I road network points. The i-th element of the M finite set is m_i that represents the i-th candidate location for placing the charging station.

Figure 2a shows an example road network in continuous domain and Fig. 2b shows the discretized form with 15 discrete points, part of the set M as presented in Eq. (1) with

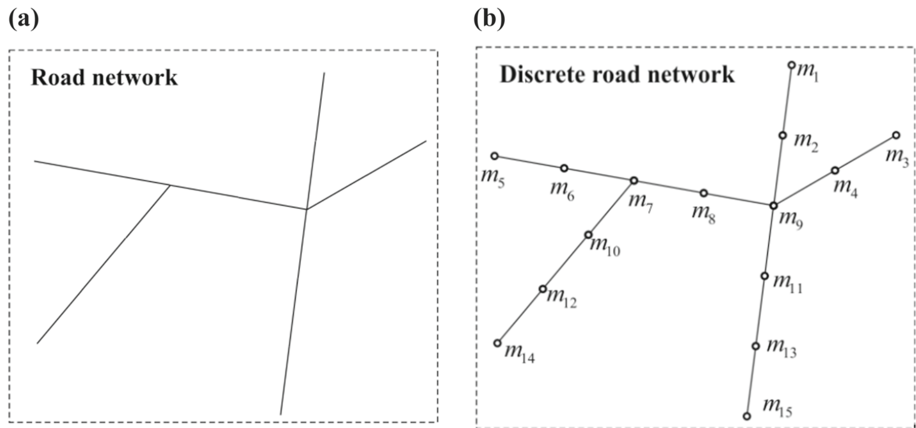

Fig. 2 Example of road network discretization: **a** road network and **b** discretized road network with 15 discrete points

15 elements. The empty markers of the road network are the candidate locations for the optimization model.

2.1.2 Modeling the trajectories as sets of discrete points

EV driving trajectories also comply with the discrete modeling as shown for the candidate locations. For the v-th EV driver, the t-th trajectory is presented as a finite discrete set as in Eq. (2).

$$N_{v,t} = \{n_{v,1,t}, n_{v,2,t}, \ldots, n_{v,j,t}, \ldots, n_{v,J_{v,t},t}\}; \quad j = 1, 2, \ldots, J_{v,t}; \quad \forall v = 1, 2, \ldots, V; \quad \forall t = 1, 2, \ldots, T. \tag{2}$$

$N_{v,t}$ is the t-th finite set of trajectory elements of the v-th EV driver, and $n_{v,j,t}$ is the j-th trajectory element. In a planning period that has T time instances, $J_{v,t}$ stands for the total number of trajectory points of the v-th EV driver at t-th time instance. V is the total number of EV drivers. To give an example of a trajectory, Fig. 3a shows the layout of the trajectories of the v-th EV driver at three different time instances, as explained in Eq. (2). The point $n_{v,1,1}$ $n_{v,1,2}$ and $n_{v,1,3}$ represent the starting trajectory points in three different time instances, and $n_{v,7,1}$ $n_{v,8,2}$ and $n_{v,6,3}$ the finish trajectory points, respectively. In comparison to candidate locations which are empty markers, the trajectory points are noted with black markers.

Furthermore, the traffic weight (Fig. 3b) in a planning period T can be derived as shown in next Sect. 2.1.3 in Eq. (4).

2.1.3 Charging latency of the charging infrastructure

The charging latency of the charging infrastructure is focus and novelty in this paper. It combines the traffic flow at a candidate location and the charging time of the charging technology to be installed at that location. Traffic flow is defined by the number of EVs traveling along a candidate location point of the road network within an observed or planning period and the charging time is dictated by the charging power of the charging technology. For the traffic flow, the following definition is involved:

$$W_{i,t} = \begin{cases} 1, & \text{if } m_i \in N_{v,t} \\ 0, & \text{otherwise} \end{cases}; \quad \forall t = 1, 2, \ldots, T; \quad \forall v = 1, 2, \ldots, V; \quad i = 1, 2, \ldots, I \tag{3}$$

where the coefficient $W_{i,t}$ takes the value of 1 if the i-th candidate location point is part of the set of trajectory demand points of the v-th EV driver at t-th time instance, and 0 otherwise. The weight of the i-th candidate location point for placing CS, noted with w_i, is calculated as sum of the coefficients $W_{i,t}$, in the planning period with T time instances, written as:

$$w_i = \sum_{t=1}^{T} W_{i,t}; \quad \forall i = 1, 2, \ldots, I. \tag{4}$$

The weights are shown in Fig. 3b—for the given example of three time instances, the size of the weights shows that along w_7 and w_8, two trajectories overlap and along w_9 three. The size of the marker increases as more overlap over a candidate location. Traffic weight is vital for the charging latency of the charging infrastructure and since takes part of its definition.

Hence, the charging latency of the charging infrastructure that is latter part of the optimization objective function in (9) consists of the individual charging latency coefficients defined for the i-th candidate locations:

$$\mathrm{CL}_i = \frac{w_i}{\mathrm{CT}_k}; \quad \forall i = 1, 2, \ldots, I; \quad \forall k \in K \tag{5}$$

where the CT_k is the charging time of the k-th charging technology to be installed at candidate location and K is a set of charging technologies.

The charging latency coefficient in (5) principally states the following: A charging infrastructure that consists of

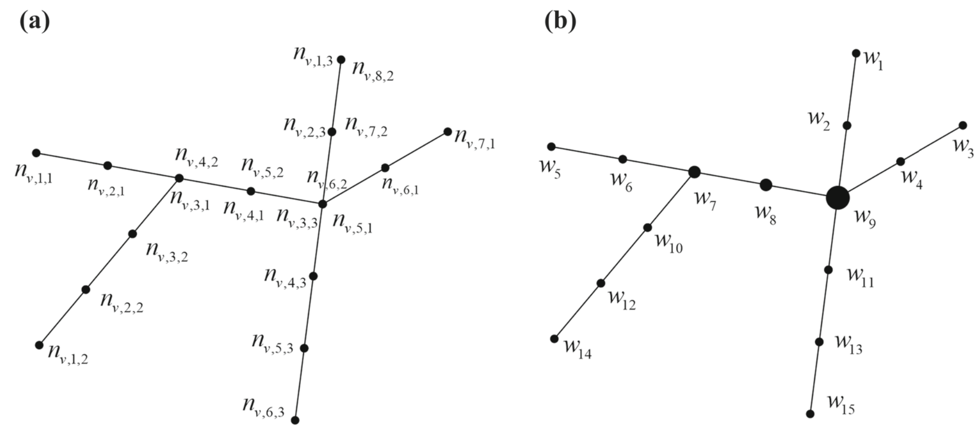

Fig. 3 **a** Representation of the v-th EV driver trajectory at t-th time instance; **b** traffic flow weights

charging locations with high traffic flow and longer charging time, their charging latency is high. Consequently, it will take a longer time for each EV to reach its destination since it will be held up in a longer charging queue.

Optimizing the charging infrastructure placement based on i-th candidate location's charging latency coefficient reflects in selecting the candidate locations that have lower traffic flow and can admit faster charging technology with faster charging times. Our objective is minimizing the charging latency of the charging infrastructure with selecting minimum number of charging locations by also ensuring the charging reliability to engage unlimited mobility, as shown in the optimization model in Sect. 2.2.

2.1.4 Set representation of the charging reliability criterion

The charging reliability criterion is involved in previous research papers [4–7]. In Fig. 4, the charging reliability criterion is shown for the trajectory $n_{v,1,1} - n_{v,7,1}$. It is a criterion involved to exceed the major shortcoming of EVs, i.e., the short range and engage unlimited mobility. In this paper, the charging reliability criterion is not a subject of research, still it is a fundamental constraint to be involved in the optimization constraints in the latter optimization model, presented in Sect. 2.2.

By the set-covering theory, [19, 23], discrete elements of the road network have both dual role—to be elements of the set M and also part of the trajectory finite sets, $N_{v,t}$. Using the Euclidean distance [23], the distance between the candidate location point and the trajectory demand point is defined by the Euclidean distance [24]:

$$\xi_{i,j,v} = \sqrt{(m_i - n_{v,j,t})^2_{\mathrm{dx}} + (m_i - n_{v,j,t})^2_{\mathrm{dy}}};\quad m_i \in M;\ \ n_{v,j,t} \in N_{v,t}. \tag{6}$$

The j-th trajectory point is covered by i-th candidate location, if the criterion of coverage distance noted in (6) is fulfilled.

$$S_{v,i} = \left\{ m_i \in M : \xi_{i,j,v} \le R_v \right\};\quad j = 1, 2, \ldots,\ J_{v,t};\ \forall v = 1, 2, \ldots, V. \tag{7}$$

In Eq. (7), the elements of the finite set $S_{v,i}$ represent all candidate location points m_i, which meet the distance criterion $\xi_{i,j,v} \le R_v$. In other words, $S_{v,i}$ holds the candidate locations which can cover the trajectory points j.

To provide a more straightforward notation of candidate locations for the further optimization process, the following Boolean coefficient is involved, i.e., $a_{i,v}$, which is equivalent to the set defined in Eq. (7).

$$a_{i,v} = \begin{cases} 1, & \text{if } \xi_{i,j,v} \le R_v \\ 0, & \text{otherwise} \end{cases}. \tag{8}$$

The $a_{i,v}$ coefficient in Eq. (8) notes whether the distance from the i-th candidate location to the j-th trajectory set element for the v-th driver falls within the scope of the defined distance criterion, $\xi_{i,j,v} \le R_v$. If this criterion is met, the $a_{i,v}$ coefficient takes the value of 1, otherwise its value equals 0.

2.2 Charging latency optimization model for optimal charging infrastructure placement

Our ultimate goal is to set the charging infrastructure to a minimal charging latency, i.e., reduce charging congestion coming from a queue due to the traffic flow going through a candidate location. The objective function is to minimize the charging latency of the charging infrastructure by finding the optimal charging locations layout subject to charging reliability criterion:

$$\mathrm{Min}\left\{ F = \sum_{i=1}^{I} CL_i \cdot x_i \right\} \tag{9}$$

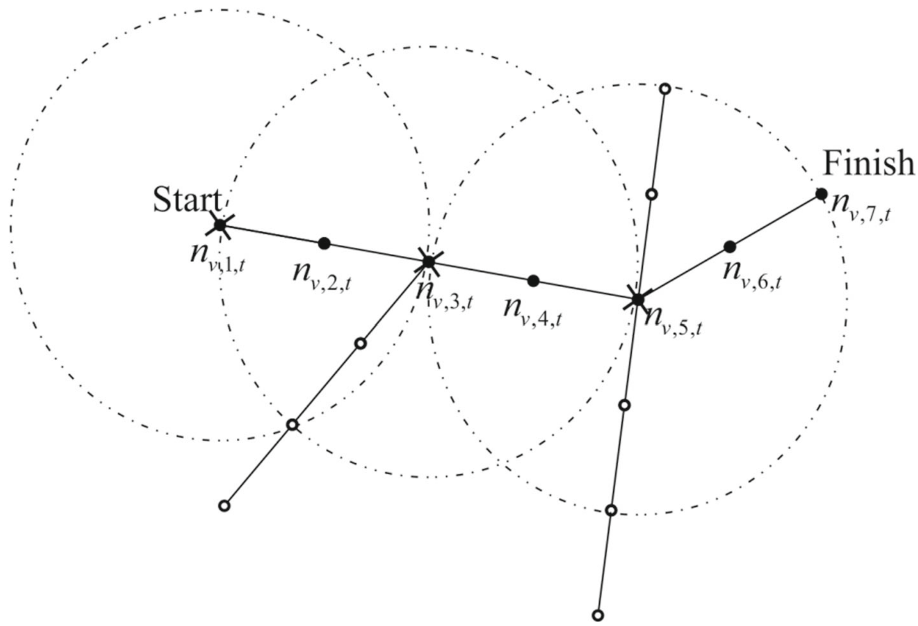

Fig. 4 Charging reliability criterion based on the EV drivers' range [4]

where x_i is the binary decision variable associated with i-th candidate location and CL_i is the charging latency coefficient comprising the traffic flow weight w_i and charging time of k-th charging technology at i-th candidate location as shown in Eq. (5) in Sect. 2.1.3.

The optimization constraints are:

$$\sum_{i=1}^{I} a_{i,v} \cdot x_i \geq 1; \;\; \forall v = 1, 2, \ldots, V \tag{10}$$

$$x_i \in \{0, 1\}; \;\; i = 1, 2, \ldots, I. \tag{11}$$

As elaborated in Sect. 2.1.4, Eq. (10) is included to ensure the charging reliability of the charging infrastructure. The coefficient $a_{i,v}$ of Eq. (10) notes whether the distance from the i-th candidate location to the j-th trajectory set element for the v-th EV falls within the scope of the defined distance criterion, $\xi_{i,j,v} \leq R_v$. If this criterion is met, the $a_{i,,v}$ coefficient takes the value of 1, otherwise its value equals 0. This constraint will impose the optimization to select at least one candidate location within the driving range if the v-th EV.

Constraint (11) states the binary definition of the optimization decision variable for i-th candidate location, i.e., the binary definition of I candidate locations.

2.3 Charging congestion measurement

The charging congestion measurement is determined by using the charging times of the charging technology to be installed at selected optimal locations, $x_{i.}$:

$$\mathrm{CM} = \sum_{i} \mathrm{CT}_k \cdot w_i \cdot x_i; \;\; \forall k \in K. \tag{12}$$

The overall CM gives an outlook of the overall charging time for the selected optimal charging stations locations. Higher values means that the CI placement will result in higher charging congestion and vice versa. This value can be used to justify the investment in an optimal CI placement using the charging latency aspect in comparison to other set-covering model which are based on coverage and do not include other aspects such as charging times or traffic flow.

3 Numerical Results

To show the advantages of the optimization model presented in this paper, an existing test road network is used as shown in Fig. 6 [4] and modeled by Eq. (1). The road network consists with 100 discrete points, equally distributed on a 1 p.u. distance between two adjacent points and 1 p.u. is considered 100 km distance.

According to Eqs. (1) and (2), each point of the network is a both candidate location and part of a driving trajectory. Table 1 lists the driving trajectories for 3 EV drivers at different time instances and their layout is shown in Fig. 5b, modeled as shown in Eq. (2). In this case study, it is assumed that at the beginning of the trajectory the battery, i.e., SoC of the v-th EV driver is fully charged and enables the EV driver to complete a full driving range, R_v. The loss of charge and any other factors having impact on the SoC are not point of research in this paper. EV drivers' mobility behavior can be therefore modeled arbitrary considering any road network point (column 3). The shortest and the longest driving trajectory is driven by 1st EV driver in two different instances.

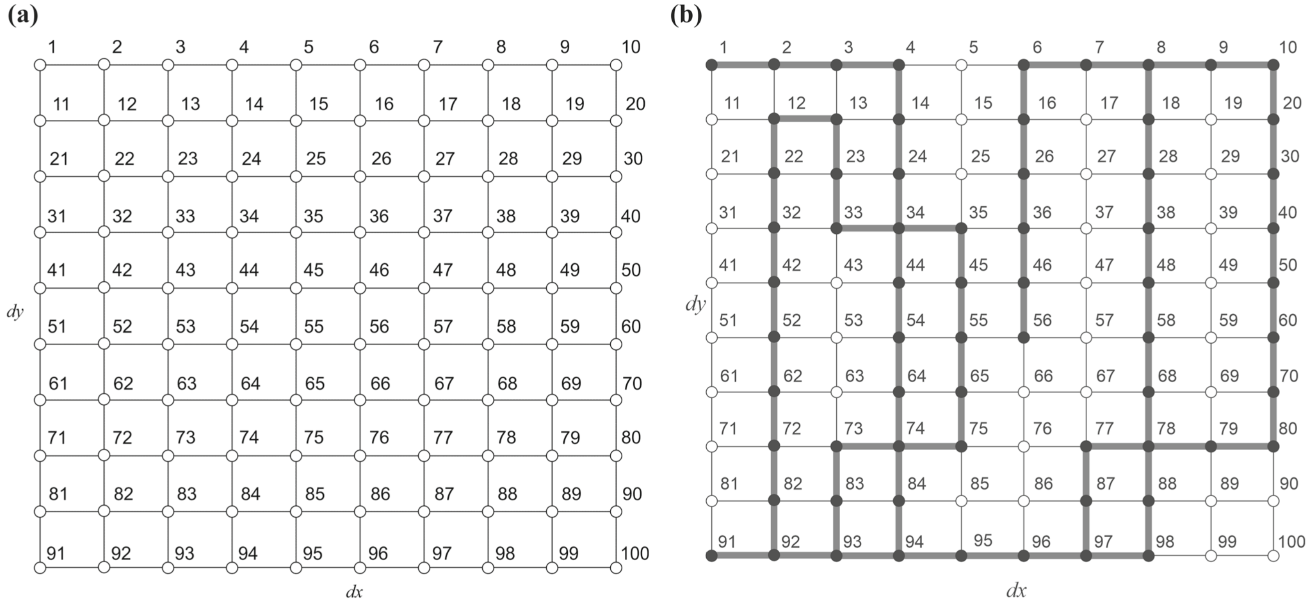

Fig. 5 **a** Fig. 6 in [4], test road network with 100 candidate locations; **b** trajectories of EV drivers

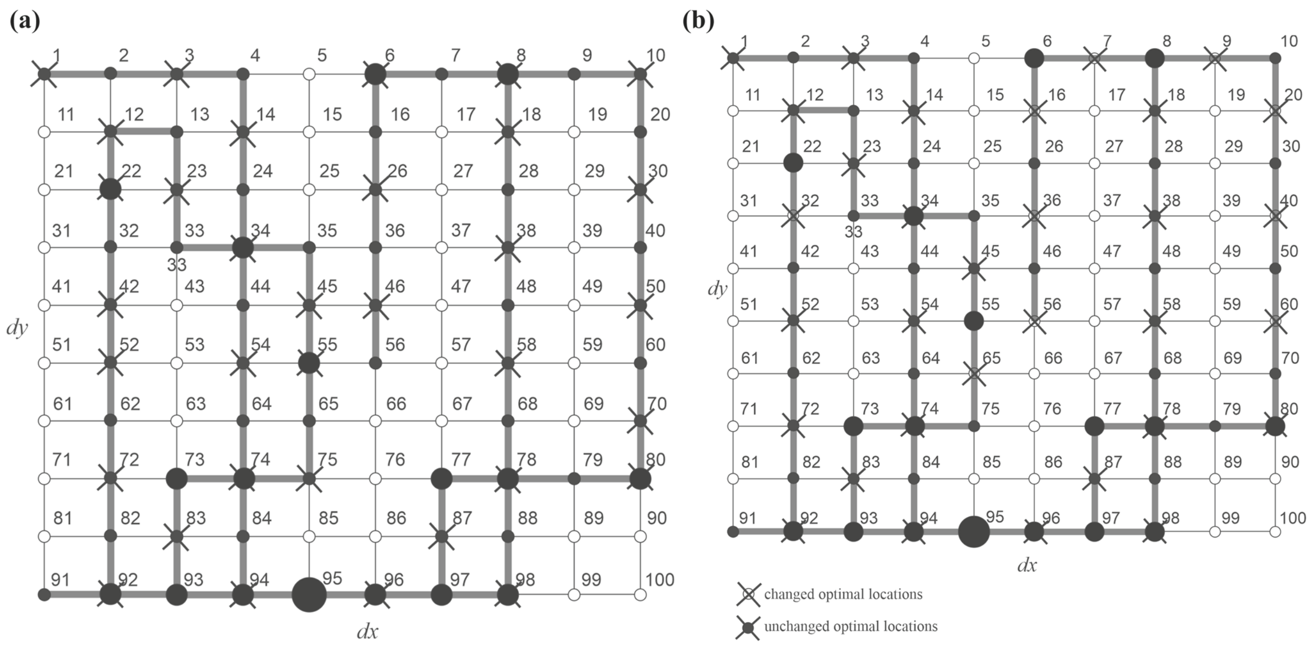

Fig. 6 **a** 3.I optimal solution in Table 4 in [14]; **b** optimal layout based on charging latency optimization

To make this case study clearer and to present the importance of charging latency coefficients, it is assumed that all candidate locations can accommodate a charging technology with charging time of 150 min which is equal to charging a 50 kWh battery with a 20 kW charging power. Table 3, columns 1 and 4 represents the enumerated candidate locations, from 1 to 50 and 51 to 100 and based on Eqs. (3)–(5) the numeric values of candidate location latency coefficients are shown in columns 2 and 7.

This paper considers two models: a QoS model (reference model) charging infrastructure optimization placement which is more user-centric and a Latency model (improved model) with charging latency optimization which is more generally infrastructure focused since it uses the well-known latency index that is used for a communications infrastructure or network to be optimized. Reference model is taken from [14], case numbers 3.I–3.III in Table 4 since it is the same road network model, trajectories and a value for a QoS

Table 1 EV divers' trajectories at t-th time instance [4]

EV driver	Time instance	Trajectory
1	$t = 1$	1 2 3 4 14 24 34 44 54 64 74 84 94 95
	$t = 8$	95 96 97 87 77
	$t = 12$	77 78 79 80
	$t = 16$	80 70 60 50 40 30 20 10 9 8 7 6
	$t = 22$	6 16 26 36 46 56
2	$t = 1$	22 32 42 52 62 72 82 92 93 83 73
	$t = 15$	73 74 75 65 55
	$t = 21$	55 45 35 34 33 23 13 12 22
3	$t = 8$	8 18 28 38 48 58 68 78 88 98
	$t = 17$	98 97 96 95 94 93 92 91

where the EV driver has a very long waiting time at disposal for charging, i.e., using slower charging technology. By comparing the reference and improved model, our goal is to examine the impact of optimizing the charging latency on the optimal locations' selection and placement layout, but also to find how the overall charging time of the charging infrastructure is improved. Comparison is made for three different cases of the driving range: 200 km, 400 km and 500 km and it is considered that the driving range is equal for all EV drivers. The planning period is 22 time instances and each time instance represents when a EV trajectory is driven.

Table 2 gives an outlook regarding the optimal locations' solution derived by Latency model in comparison to QoS model (row-wise)—boldly noted locations in QoS model cases are unchanged locations in comparison to improved model. Otherwise, an optimal location is considered unchanged, if it is selected in both optimal location selection solutions. Such locations for 3.I are: 1, 3, 12, 14, 18, 23, 34, 38, 45, 52, 54, 58, 72, 74, 78, 80, 83, 87, 92, 94, 96, 98, for 3.II is only location no. 26 and for 3.III there aren't unchanged locations. It can be concluded that as the driving range increases, the number of unchanged locations drops (column 4) from 22 to 1 to none, for 3.I, 3II and 3.III, respectively. This is due to the new optimization objective function that pushes the optimization model in selecting locations with lower charging latency coefficients as the driving range increases for the charging reliability constraint. In addition, as the range increases, the optimal selection is wider and since the number of changed locations is higher (column 5). Nonetheless, it can be seen in column 3, that the number of selected locations for first case is lower than the reference case by 2 and higher in 3.II by 2 and in 3.III by 1. This occurs since the improved model has found minimum of the objective function at different locations with lower latency coefficients to fulfill the charging reliability constraint.

The models' comparison is further made graphically to compare optimal solutions for the case of a 200 km range. Figure 6a shows the optimal solution layout for the reference case 3.I and Fig. 6b for the improved model, i.e., where are the changed optimal locations in comparison to reference model. Figure 6 shows for both cases the charging latency coefficients with different size noted with black markers in the background. As expected, the improved model shows an optimal solution layout that includes charging latency coefficients with smaller size as listed in Table 3.

To give a deeper significance to charging latency minimization and to make this case study even clearer, we calculated the overall charging time for the charging infrastructure as sum of the charging times for all optimal locations. Overall charging time was derived from Eq. (5) and is only calculated for demonstration purposes as the product of traffic flow and charging time to show how charging latency

Table 2 Selected locations for the reference, QoS model and improved model, charging latency model

Model	Selected locations	No. of selected locations	Unchanged locations	Changed locations
Reference 3.I, Table 4 [14]	**1 3** 6 8 10 **12 14 18** 22 **23** 26 30 **34 38** 42 **45** 46 50 **52 54** 55 **58** 70 **72 74** 75 **78 80 83 87 92 94 96 98**	34	22	
Improved model	1 3 7 9 12 14 16 18 20 23 32 34 36 38 40 45 52 54 56 58 60 65 72 74 78 80 83 87 92 94 96 98	32		10
Reference 3.II, Table 4 [14]	3 8 12 **26** 30 34 38 42 70 74 78 82 93 97	14	1	
Improved model	4 7 20 23 26 28 44 45 52 60 65 68 79 84 92 96	16		15
Reference 3.III, Table 4 [14]	3 8 16 22 34 38 40 42 74 78 92 97	12	0	
Improved model	9 14 26 33 38 50 62 64 75 83 88 91 96	13		13

Table 3 Candidate locations with their charging latency coefficients, charging times for QoS and latency models

i-th node	Latency coefs	200 km		400 km		500 km	
		Ref (min)	Imp (min)	Ref (min)	Imp (min)	Ref (min)	Imp (min)
1	0.0067	150	150	0	0	0	0
2	0.0067	0	0	0	0	0	0
3	0.0067	150	150	150	0	150	0
4	0.0067	0	0	0	150	0	0
5	0	0	0	0	0	0	0
6	0.0133	300	0	0	0	0	0
7	0.0067	0	150	0	150	0	0
8	0.0133	300	0	300	0	300	0
9	0.0067	0	150	0	0	0	150
10	0.0067	150	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0.0067	150	150	150	0	0	0
13	0.0067	0	0	0	0	0	0
14	0.0067	150	150	0	0	0	150
15	0	0	0	0	0	0	0
16	0.0067	0	150	0	0	150	0
17	0	0	0	0	0	0	0
18	0.0067	150	150	0	0	0	0
19	0	0	0	0	0	0	0
20	0.0067	0	150	0	150	0	0
21	0	0	0	0	0	0	0
22	0.0133	300	0	0	0	300	0
23	0.0067	150	150	0	150	0	0
24	0.0067	0	0	0	0	0	0
25	0	0	0	0	0	0	0
26	0.0067	150	0	150	150	0	150
27	0	0	0	0	0	0	0
28	0.0067	0	0	0	150	0	0
29	0	0	0	0	0	0	0
30	0.0067	150	0	150	0	0	0
31	0	0	0	0	0	0	0
32	0.0067	0	150	0	0	0	0
33	0.0067	0	0	0	0	0	150
34	0.0133	300	300	300	0	300	0
35	0.0067	0	0	0	0	0	0
36	0.0067	0	150	0	0	0	0
37	0	0	0	0	0	0	0
38	0.0067	150	150	150	0	150	150
39	0	0	0	0	0	0	0
40	0.0067	0	150	0	0	150	0
41	0	0	0	0	0	0	0
42	0.0067	150	0	150	0	150	0
43	0	0	0	0	0	0	0

Table 3 (continued)

i-th node	Latency coefs	200 km		400 km		500 km	
		Ref (min)	Imp (min)	Ref (min)	Imp (min)	Ref (min)	Imp (min)
44	0.0067	0	0	0	150	0	0
45	0.0067	150	150	0	150	0	0
46	0.0067	150	0	0	0	0	0
47	0	0	0	0	0	0	0
48	0.0067	0	0	0	0	0	0
49	0	0	0	0	0	0	0
50	0.0067	150	0	0	0	0	150
51	0	0	0	0	0	0	0
52	0.0067	150	150	0	150	0	0
53	0	0	0	0	0	0	0
54	0.0067	150	150	0	0	0	0
55	0.0133	300	0	0	0	0	0
56	0.0067	0	150	0	0	0	0
57	0	0	0	0	0	0	0
58	0.0067	150	150	0	0	0	0
59	0	0	0	0	0	0	0
60	0.0067	0	150	0	150	0	0
61	0	0	0	0	0	0	0
62	0.0067	0	0	0	0	0	150
63	0	0	0	0	0	0	0
64	0.0067	0	0	0	0	0	150
65	0.0067	0	150	0	150	0	0
66	0	0	0	0	0	0	0
67	0	0	0	0	0	0	0
68	0.0067	0	0	0	150	0	0
69	0	0	0	0	0	0	0
70	0.0067	150	0	150	0	0	0
71	0	0	0	0	0	0	0
72	0.0067	150	150	0	0	0	0
73	0.0133	0	0	0	0	0	0
74	0.0133	300	300	300	0	300	0
75	0.0067	150	0	0	0	0	150
76	0	0	0	0	0	0	0
77	0.0133	0	0	0	0	0	0
78	0.0133	300	300	300	0	300	0
79	0.0067	0	0	0	150	0	0
80	0.0133	300	300	0	0	0	0
81	0	0	0	0	0	0	0
82	0.0067	0	0	150	0	0	0
83	0.0067	150	150	0	0	0	150
84	0.0067	0	0	0	150	0	0
85	0	0	0	0	0	0	0

Table 3 (continued)

i-th node	Latency coefs	200 km		400 km		500 km	
		Ref (min)	Imp (min)	Ref (min)	Imp (min)	Ref (min)	Imp (min)
86	0	0	0	0	0	0	0
87	0.0067	150	150	0	0	0	0
88	0.0067	0	0	0	0	0	150
89	0	0	0	0	0	0	0
90	0	0	0	0	0	0	0
91	0.0067	0	0	0	0	0	150
92	0.0133	300	300	0	300	300	0
93	0.0133	0	0	300	0	0	0
94	0.0133	300	300	0	0	0	0
95	0.0200	0	0	0	0	0	0
96	0.0133	300	300	0	300	0	300
97	0.0133	0	0	300	0	300	0
98	0.0133	300	300	0	0	0	0
99	0	0	0	0	0	0	0
100	0	0	0	0	0	0	0
Overall sum (min)	6900	**6000**	3000	**2700**	2850	**2100**	

optimization reduces the charging congestion of the charging infrastructure. Table 3 with columns 3, 4, 5 and 8, 9 and 10 (row-wise) acknowledges the difference in the overall charging time of the charging infrastructure for optimally selected locations considering the reference and improved model. As expected, significant contribution in reducing the overall charging time of the charging infrastructure is noted for the improved model as Table 3, columns 3 and 8 lists the results for when the driving range is 200 km, 4 and 9 for 400 km and 5 and 10 for 500 km. Overall charging time is given in row 101 as overall sum of charging times: 6900 min for the reference model and 6000 min for the improved model. In overall, by minimizing the charging latency, the optimal solution given by the improved model reduced the charging time by 900 min. For 400 km and 500 km cases the improved model reduced overall charging infrastructure charging time in comparison to reference model by 300 min and 750 min, respectively.

To examine the overall charging time of the charging infrastructure even more thoroughly we consider charging times in Table 3, columns 3 and 8 (row-wise) and compare changed and unchanged optimal locations in Table 2, rows 2 and 3. We observe that the charging time at reference location 6 is higher in comparison to improved location 7, since the traffic flow is higher. Same for locations 8 10 22 26 30 42 46 50 55 70 75 which were changed by the improved model. The latency coefficients for the changed locations in the improved model in the case of 200 km are lower in comparison to the reference case, 0.0067 (location 7, improved model) in comparison to 0.0133 (location 6, reference model), etc. for the rest of the changed locations; thus, giving head in the optimization objective in the improved model to be selected in the optimal layout solution. By this point, it is clear that the latency coefficients increase their value if the traffic flow is higher or decrease their value for charging technology installed that provides faster charging time. By selecting lower value charging latency coefficients and minimizing the charging latency, the charging infrastructure optimal layout placement is improved (charging congestion time-wise).

4 Conclusions

This paper presents a novelty in optimal charging infrastructure planning called charging latency. Objective function is to minimize charging latency and give an optimal layout of charging locations subject to the charging reliability constraint. In previous papers, charging reliability of the charging infrastructure is defined as selecting at least one charging location within the driving range of the electric vehicle. Charging latency is defined as the ratio of the traffic flow over a candidate location and the charging time of the charging technology that can be installed. Faster charging times and lower traffic flow are points of interest and selecting candidate locations with smaller latency coefficients reduces the overall charging duration. To finding the advantages of the newly proposed model, we have made a comparison with a previously published model that is user-centric based. It involves a quality of service QoS requests by electric vehicle drivers to determine the minimal number of locations and optimal locations layout yet again subject to charging reliability. Since the QoS requests are user specific, present paper gives an infrastructure-centric and universal model where is easier to calculate nodal charging latency coefficients to be included in objective function. Numeric results show the advantages and the improvements made by the Latency model in relation to QoS model. Comparison is made to see which optimal locations were changed because of the newly defined charging latency coefficients. To give an outlook in reducing the charging latency, overall charging time of the charging infrastructure is calculated for both models. Latency model gives clear improvement in reducing the overall charging time in comparison to QoS model. A shortcoming of this paper is that considers the charging infrastructure planning from an infrastructure point of view and does not consider the electric power system. Still, electric power system is included indirectly given the determination of the charging technology that can be installed at a candidate location given the allowable connection power. Further research will comprise the electric power system in this model.

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