Impact of Stochastic Driving Range on the Optimal Charging Infrastructure Expansion Planning

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Abstract

This paper presents the impact of the stochastic electric-drive vehicles' driving range on the charging reliability of charging infrastructure. For this purpose, it incorporates an additional uncertainty distance in addition to the initial driving range of the electric vehicle to address all probabilistic occurrences that can affect the range, such as the battery charge level, driving style and mobility behaviour, road configuration, air-conditioning, etc. The analysis is performed based on the proposed optimisation model on a test road network applied for different stochastic driving range scenarios, Quality of Service, electric vehicles' trajectories and the types of charging technologies. In general, a dependency is observed where a shorter uncertainty distance increases the number of candidate locations included in the charging reliability criterion resulting in higher overall charging infrastructure placement costs and vice-versa. By becoming familiar with the uncertainty distance impact and its probability of occurrence, charging infrastructure planners could decide in which optimal solution they would invest to both perceive beneficial gains and engage unlimited mobility for electric vehicle users. Above all, planners can use the model as a foundation for future investment incentives in technological development or easier decision making for the adoption of the final charging infrastructure expansion plan.

Keywords
stochastic driving range, uncertainty distance component, electric drive road vehicles, planning of the charging infrastructure, quality of service.

1. Introduction

Transportation mobility of the future is envisioned by the integration of the electric-drive vehicles (EDV). They operate quietly, have high transportation efficiency and are eco-friendly. The share of individuals that actually promote the green revolution in transportation is increasing, Ref. [1], and EDVs are becoming an attractive transportation alternative. However, in order to push the EDVs to the forefront, what needs to be done in terms of technology and infrastructure is to work on reducing the EDVs price, since they remain relatively expensive compared to internal combustion engine vehicles due to the batteries. Furthermore, it is also necessary to provide a reliable charging infrastructure (CI). Electromobility is the key technology for ensuring sustainable transportation mobility, as noted in Ref. [2] and in Ref. [3]. In Ref. [2], the fundamentals, theoretical bases and design methodologies of EDVs are highlighted and their delicate importance to modern transportation due to their contribution to cleaner and healthier environment. Alternatively, Ref. [3] provides an in-depth outlook on the development of battery technology and clarifies the renewed interest in EDVs due to increased concerns with energy security.

Today, refuelling an internal combustion engine vehicle is straightforward; however, electrical charging is anticipated to be equally simple, while providing even greater technical possibilities. One of the main disadvantages of EDVs is recharging, which can be limited in the event of poor CI. It is an everlasting problem for the CI planners to provide a CI for public areas, which would enable EDV drivers to recharge almost anywhere by having electrical charging systems that can be installed quickly at selected locations and provide fast charging for maximum drivers' convenience, as stated in Ref. [4].

In reference [5], a corridor-centric approach to CI planning is proposed. The objective of the model is to select a battery size and charging capacity in terms of both charging power available at each station and the number of stations needed along the corridor to meet a given level of service in such a way that the total social cost is minimised. In this paper, a relaxation is included that involves battery swapping as an alternative to electric charging stations (CS), which deviates from the paper's focus on the planning of electric CSs placement. However, this relaxation is used as an option to oversee the dependency of the level of service and the optimal social welfare in comparison to electric CSs in the CI planning process, which is also beneficial to the CI planning process. In Ref. [6], a novel economic CSs placement planning solution is proposed, which considers the effects of power and transportation systems. The gathered traffic data is utilised to expose the behaviours of the EDVs, while their load templates are used to reflect the uncertain states of distribution networks. The traffic and load capability constraints are integrated into the planning model. The methodology in Ref. [6] mainly deploys the planning of the CSs from the perspective of achieving an economic objective, however, it can be concluded that the paper neglects the charging service level of the CI, which also has an effect on the overall CSs placement costs, as shown in Ref. [7]. Namely, in Ref. [7], it is demonstrated that the Quality of Service (QoS) of the CI has an impact on the overall (installation, maintenance, operation) placement costs, based on having the optimisation option for placing different charging technology types at candidate locations to accommodate the requested charging service level of EDV users. Certainly, faster-charging technology types cost more, but the charging time is shorter. The usefulness of the method is found in the combination of transportation and power systems, which is beneficial for CI planners. In Ref [8], the CI planning of fast charging stations in a competitive market is discussed in detail. Namely, a business-driven CI planning method in a competitive market is studied on the basis of a network-based multi-agent optimisation model. However, the planning method presented in Ref. [8] disregards the market competition with its stochastic nature of occurrence, which could have a valuable effect on CSs investment decisions and the CI cost in a competitive market environment.

EDV driving range is one of the main reasons for EDVs' cruising limitation when going on longer trips. In order to exceed this limitation, optimisation models have been developed to optimally place CSs. So far, the literature has recognised a variety of CI optimisation planning methods. In Ref. [9], a review focuses on the computation and algorithmic aspects of various optimisation techniques of the CSs placement issue. The paper summarises a selected set of publications from a certain time period in one centric table in order to show all beneficial solution methodologies related to CI planning. Ref. [10] elaborates an example of an improved mathematical model for locating CSs in urban environments. The paper considers not only the travellers' parking locations, but also their daily activities in order to link the demand on distinct places, which provides the basis for the so-called demand transference between those locations. Namely, the paper also focuses on the realistic modelling of charging demand, such as dividing the day to multiple time intervals to better reflect the charging demand needs of electric vehicle users. Above all, Ref. [10] is in the focus of this paper, since the discretisation and a multi-period optimisation are introduced, which are also involved in the optimisation procedure presented below. However, since Ref. [10] focuses on multiple intervals with regards to charging demand modelling, it represents an important drawback, as it would be difficult to apply the same approach to the long scale CI planning problems, since its computation complexity increases and the optimisation model becomes more demanding. This can be resolved by pre-processing the charging demand by using heuristics or decomposition approaches. Alternatively, in Ref. [11], a novel model for the CI planning and the optimal CSs location problem is proposed. The objective function minimises the overall CI placement cost by simultaneously handling the problem of where to locate the CSs, which is also in the scope to this paper. Nevertheless, the drawback of the proposed model lies in the EDV behaviour reflected in the traffic flow, which is not included in the optimisation process. For CI planners, the type of charging technology is essential to CS placement. It relates to the charging service level and the overall CSs placement costs, and is thus valuable for the CI expansion plan. With a view to decide on the location and number of public CSs within the CI planning process, Ref. [12] proposes two optimisation models for two different charging types - fast and slow charging, which aim at minimising the total CS placement cost, while satisfying certain spatial coverage goals. Instead of using discrete network points, polygons are employed to represent charging demands. In other words, the employment of the charging technology types in the optimisation procedure is a step forward and a significant improvement, however, the demand representation relaxation, in which the charging demands are aggregated in polygons, is a major drawback, since demand polygons may expose unrealistic charging demands to be covered by the optimisation constraints.

Recently, ongoing research has been conducted to explore the requested charging reliability of the CI, the charging service level and the associated QoS. For example, in Ref. [13], it is ascertained that the fast CSs are the only ones that can provide high charging level service which will henceforth facilitate the wide market penetration of EDVs. The term QoS is already used in other areas, such as telecommunications, multimedia, communications, etc., and is defined differently in each area. With regards to the CI, EDV drivers would request and expect a QoS of the charging service level that would comfort their charging needs in terms of their disposable charging time when starting a trip. Therefore, in Ref. [7], an optimisation model is presented for the CI expansion planning, where the objective function minimises the overall CS placement cost by satisfying the charging reliability and the QoS expected by EDV users. In fact, by involving the Euclidean distance, the optimisation model ensures the charging reliability of the CI by placing at least one CS within the EDV drivers' driving range using a distance criterion, which is included in optimisation constraints. The charging reliability criterion is fundamental from a CI planner's perspective, since it directly addresses the driving range limitation of EDVs.

Today, the issue of optimal CSs placement revolves mostly on researching the electrification and effect of the transportation sector on the electric power network. What is most significant is the sufficiency and reliability of the power network with a large-scale integration of EDVs. One planning model example of the optimal integration of EDVs by acknowledging the power network limitations is demonstrated in Ref. [14], where a local network is used to analyse the feasibility of using the network potential for charging EDVs during off-peak periods. Nowadays, other papers in the area consider the traffic flow, road network partitioning, parking lots involvement, etc. Still, the charging infrastructure planning area needs additional research to improve the EDV drivers' convenience and to include the mobility and charging behaviours, randomness of battery state-of-charge, trip purposes, passed distances, etc. Alternatively, the improvement of the provided QoS of the CI could remain a primary concern.

The closest paper that discusses the uncertainty related to the service distance of the CSs for the final placement of CI is Ref. [15]. In the CSs placement model, the Trip Success Ratio (TSR) is used to estimate the CS service range, where the uncertainty of trip distances and the remaining range of EDVs are considered. A new model is proposed for optimally allocating CSs with regards to the TSR in order to enhance the CS accessibility for EDV users. Additionally, a diversity of driving behaviours and different trip types are included. In the allocation stage, the model allocates the CSs on a way they cover the road network with certain quantified TSR level. Nevertheless, Ref. [15] does not consider the CSs placement costs in the optimisation objective, but only refers to the covering of the transportation demand concerning the candidate location. In addition, Ref. [16] is also closely related to this paper, since a service range of the CS is defined as an average of the driving ranges of the EDVs which are available on the market at the moment. It must be pointed out that this assumption is vague, since there is a wide scope of EDV driving ranges which can differ enormously and yields a questionable EDV driving range representative. The model in Ref. [16] leads to an optimal placement solution, which considers the CSs placement costs, however, it does not accounts for the inherited uncertainty distance and its probability of occurrence, which are valuable for the initial EDV range and hence, as shown in Ref. [7], for the optimal CSs placement. Other literature review presented in this paper shows that there are no ongoing research studies related to the charging reliability of the CI, nor its related effects on the overall CSs placement costs due to inherited distance uncertainties accounted for in the EDVs driving range.

The main facts that served as incentives for the presented research include:

- Necessity to formulate the uncertainty related to EDV users' driving style, road configuration, air-conditioning and other factors in a significant parameter with a distance unit of measurement.
- Required consideration of stochastic occurrences related to the initial driving range of the EDVs in order to improve the charging reliability of the CI to engage the unlimited mobility of EDVs.
- Planners concerns regarding an inadequate CSs placement and a negative effect on EDV purchasing decision-making for potential customers.
- Necessity to develop a model for CI planners to acknowledge the impact of stochastic EDV driving range on future investments in battery and charging technology development.

The paper presented fills the gap of evaluating the impact of the stochastic driving range on the optimal CI expansion planning. It considers the uncertainty distance related to the initial driving range, which is valuable for the charging reliability of the charging infrastructure and serves to deliver both the EDV users' higher convenience and CI planners' better insight into the CSs placement costs related to the probability of the range affecting occurrences. The main motivation of this paper is to upgrade and improve the charging reliability principle elaborated in Ref. [7]. The main scientific contributions of this paper are:

- Proposal of improved optimisation model for CSs placement based on the model presented earlier in Ref. [7]. A new stochastic module is introduced that presents the stochastic modelling of the driving range. An additional uncertainty distance component is involved with regards to the initial EDV driving range, to show the effect on the creation of the charging reliability criterion. The uncertainty of the driving range and its occurrence probability expose the uncertainty of battery discharge and consequently the related initial 'distance to empty' status due to certain probabilistic factors, such as EDV driver driving style, road configuration, EDV air conditioning, etc. The significance of the stochastic driving range also serves to point out the randomness of the battery state-of-charge levels at the beginning of each trip or the available charge in the battery, which depends on the variety of characteristics related to battery type and capacity. This issue has not been profoundly elaborated in previous research yet, since the charging reliability principle was only conceived in the recently published Ref. [7].

- Improved definition of the sets formation of the charging reliability criterion. The presented formation procedure is useful to demonstrate to CI planners how the uncertainty distance affects the variables while comprising the candidate locations in the charging reliability criterion.
- Optimisation model for CSs placement presented in Ref. [7] upgraded to an option for scenario analysis valuable to CI planners.
- Modelling the dependency of the overall CS placement costs from the stochastic EDV driving range with regards to the charging reliability criterion. The dependency, which also encloses the inherited range probabilities, can help CI planners to oversee which optimal CSs placement solution can bring higher benefits. In addition, the obtained dependency can be used as a foundation for future investment incentives in technological development or easier decision making for the adoption of the final CI expansion plan.

The remaining sections of the paper are organised as follows: the stochastic EDV driving range is explained in detail in Section 2. The location optimisation procedure for the CI placement is presented in Section 3, while Section 4 presents the numerical results. The conclusion drawn from this paper is presented in Section 5.

2. Stochastic Driving Range of Electric-Drive Vehicles

Ref. [7] presents a CI location optimisation model that ensures a complete charging reliability of the CI, which was defined by selecting at least one candidate location to place a CS within the EDVs driving range. In this paper, the complete charging reliability principle discussed in Ref. [7] is addressed in greater detail. By applying the current battery technology, the EDV driving range can be ensured until a certain point, which can be considered as the initial EDV driving range:

$$R_{v,0} = \eta \cdot SoC_v;\ \forall\ v = 1,\ 2, \ldots,\ V \tag{1}$$

where SoC_v is the v-th EDV driver battery state-of-charge (SoC) and η is a parameter targeting the energy conversion efficiency, which is explained in Ref. [19]. However, in this paper, it is discussed that there are uncertainty factors affecting the battery discharge and, consequently, the EDVs' driving range. The most common uncertainty factors alongside battery capacity and temperature at its base, which are considered to have the highest effect on battery discharge, according to Ref. [17] and [18], include the EDV driver's driving style, road terrain configuration (road steepness, road network topology, etc.), status of on-board electric devices (e.g. lights, air conditioning), etc. Other factors include the speed, acceleration, vehicle mass, aerodynamic rolling and grade resistances. Moreover, in comparison with Ref. [7], this paper considers an additional uncertainty distance component due to stochastic occurrences that affect the initial EDV driving range, which is combined and formulated as the stochastic EDV driving range or $R'_{v,s}$:

$$R'_{v,s} = R_{v,0} \pm \Delta d_{v,s};\ \forall\ s = 1,\ 2,\ \ldots,\ S;\ \forall\ v = 1,\ 2,\ \ldots,\ V \tag{2}$$

Where $R_{v,0}$ is the initial v-th EDV driver's EDV driving range that can be ensured by the current battery technology and $\Delta d_{v,s}$ is an uncertainty distance component for the v-th EDV driver, which relates to all uncertainty factors affecting battery discharge to go for a distance equal to the EDV driving range, i.e. $R_{v,0}$, for s-th scenario. This uncertainty distance is modelled in terms of the normal probability density function or RN_v, and expressed as:

$$\Delta d_{v,s} = RN_v\left(\mu_v, \sigma_v\right);\ \forall\ s = 1,\ 2,\ \ldots,\ S;\ \forall\ v = 1,\ 2,\ \ldots,\ V \tag{3}$$

$$RN_v \sim N(\mu_v, \sigma_v) \tag{4}$$

where μ_v and σ_v, represent the mean and standard deviations, respectively. Hence, the stochastic EDV driving range $or\ R'_{v,s}$ includes all distance uncertainties that are valuable to the formation of the CI charging reliability criterion. In order to provide a clear explanation of the impact that uncertainty factors may have on the complete charging reliability of the CI, one should assume that by having an initial driving range $R_{v,0}$, an EDV driver wishes to travel from point **A** to point **B,** as shown in Figure 1(a). In this paper, the notation of the circle centre is introduced as the location of the CS, as presented in Figure 1(a). It is a considered assumption that at point **A**, the battery of the EDV is fully charged to perceive conceptuality and make the presented example clearer. The EDV driver would drive to a distance equal to $R_{v,0}$ and run out of charge; hence, they would not complete their intended trip, since point **B** would not be reached. The other circle represents the EDV driving range distance, if CS 1 is placed at a location that exceeds the endpoint of the trip. Figure 1(b) shows a CS, which is placed at endpoint **B**. Yet again, an EDV driver starting from **A** would not reach **B**, since they can only drive a distance equal to $R_{v,0}$ and would run out of charge before they arrive at endpoint **B**. In this case, the charging reliability is also not ensured, which means that no CS is placed at a location that can be reached within the $R_{v,0}$. Figure 1(c) shows the principle that ensures the complete charging reliability of the CI, where at least one CS is placed within the $R_{v,0}$ distance. Namely, starting from point **A,** the CS 1, is placed within the $R_{v,0}$, so an EDV travelling from point **A** can reach point **B,** thus completing the trip**.** The centres of the overlapping circles represent the location of the CSs and the length of intersection cord in this case equals $R_{v,0}$. The case demonstrated in Figure 1(d) introduces the uncertainty component. The main purpose of the uncertainty distance component, i.e. $\pm \Delta d_{v,s}$, is to comprise the occurrence probability of real-time stochastic occurrences in order to better model the charging reliability criterion for the placement planning of the CSs.

2.1. K-MEANS scenario reduction

By this point, numerous scenarios are generated to include all possible occurrences that can affect the EDV driving range. In subsequent steps, the K-MEANS reduction procedure is applied (explained in detail in Refs. [20], [21], [22]). In Ref. [20], a global K-MEANS clustering algorithm is demonstrated for the minimisation of the clustering error that employs the K-MEANS algorithm as a local search procedure. Alternatively, Ref. [21] provides a profound overview of the K-MEANS clustering, where the problem statement of breaking data up into K groups and the search for the K average concerning the data to derive a cluster is also explained. Above all, in Ref. [22], a procedure is presented for computing the refined starting condition from a given initial point for the K-MEANS clustering which is based on an efficient technique for estimating the modes of distribution.

It must be stressed, that the focus of this paper is not on the reduction procedure, and hence it is taken as a given. This scenario reduction part comes after the stochastic modelling of the driving range to extract a set of the most probable EDV driving range scenarios, which are later executed by using the optimisation model presented in Subsection 3.5. In addition to the K-MEANS reduction procedure, each of the stochastic EDV driving range scenarios has its own probability of occurrence.

3. Location Optimisation of the Charging Infrastructure

Due to its enormous significance and impact, the EDV driving range is one of the main components in the presented location optimisation model. The input data preparation consists of the deterministic module and the stochastic module. In this context, the deterministic module holds all entities that are deterministic, such as the road network, charging technologies, EDV driving trajectories noting the EDV drivers' behaviour, *QoS* and the overall costs of placing a CS at candidate locations in the road network. In turn, the stochastic module holds the stochastic EDV driving range scenario generation accounting for the uncertainty distance component.

In addition, the EDV driving range stochastic scenarios are reduced to a specified set of scenarios by using the K-MEANS reduction procedure. The stochastic EDV driving range in the reduced scenario holds an EDV range value and an occurrence probability.

For the stochastic value of the EDV driving range, the charging reliability criterion sets are formed. In accordance with a distance criterion based on the Euclidean point-to-point distance measurement principle and the value of the stochastic EDV driving range, candidate locations in the road network are determined, which are subsequently included in the optimisation model for the CSs placement.

Hence, optimal solutions for the CS placement are derived for the reduced set of stochastic EDV driving scenarios. Each of the optimal CS placement solutions holds its occurrence probability, which is inherited by the value of the stochastic EDV driving range scenario.

3.1. Finite sets formation of the charging reliability criterion

The charging reliability of the CI is now dependent on the stochastic EDV driving range or $R'_{v,s}$. In this paper, we use the Euclidean distance as a measurement for determining which EDV trajectory points are to be included in the optimisation model. In addition, the Euclidean distance measurement is formulated as follows:

$$\xi = \sqrt{(m_i - n_{v,j,t})^2_{dx} + (m_i - n_{v,j,t})^2_{dy}};\ m_i \in M;\ n_{v,j,t} \in N_{v,t} \tag{5}$$

where ξ is the Euclidean distance between the i-th candidate location point or m_i and the v-th driver, j-th trajectory demand point at t-th time instance or $n_{v,j,t}$. The dx and dy values represent the coordinate directions. The candidate location point or m_i is an element of the finite set of candidate locations in the road network, which is defined as:

$$M = \{m_1, m_2, m_3, \ldots,\ m_i, \ldots,\ m_I\};\ i = 1,2,3,\ldots,\ I \tag{6}$$

while $n_{v,j,t}$ is part of the finite EDV driver trajectory set:

$$N_{v,t} = \left\{n_{v,1,t},\ n_{v,2,t}, \ldots,\ n_{v,j,t}, \ldots,\ n_{v,J_{v,t},t}\right\};\ \forall\ j = 1,\ 2, \ldots,\ J_{v,t};\ \forall\ v = 1,\ 2, \ldots,\ V;\ \forall\ t = 1,\ 2, \ldots,\ T \tag{7}$$

where M is the finite set of I elements, i.e. discrete points, of the road network, and m_i represents the i-th candidate location for placing the CS. $N_{v,t}$ is the finite set presenting the v-th EDV driver trajectory within the modelled road network at t-th time instance, and $n_{v,j,t}$ is the j-th element of the finite set of the EV driver's trajectory. The overall number of observed time instances is noted with T time instances. $J_{v,t}$ stands for v-th EDV driver and the overall number of elements of the trajectory at t-th time instance, while V is the total number of EDV drivers involved.

The finite sets computed in terms of the Euclidean distance between the trajectory discrete demand point $n_{v,j,t}$ and the candidate location m_i are noted with $S_{v,j,t,s}$, which is defined as follows:

$$S_{v,j,t,s} = \left\{m_i \in M : \xi \le R'_{v,s}\right\};\ j = 1,\ 2, \ldots,\ J_{v,t};\ \forall\ v = 1,\ 2, \ldots,\ V;\ \forall\ t = 1,\ 2, \ldots,\ T;\ \forall\ s = 1,\ 2, \ldots,\ S; \tag{8}$$

In equation (8), the elements of the finite set $S_{v,j,t,s}$ represent all candidate location points m_i, which meet the distance criterion $\xi \le R'_{v,s}$ for the v-th EDV driver in the s-th scenario. In order to obtain a positive value of the uncertainty distance component, i.e. $+\Delta d_{v,s}$, equation (8) should comprise an additional number of candidate locations to be included, while negative value, i.e. $-\Delta d_{v,s}$, may be achieved by reducing the number of candidate locations included in the optimisation. At this point, we expect that the objective function in the optimisation model will consequently be affected. Therefore, the optimal solution for the CS placement will be different for the stochastic EDV driving range values. Ta provide a more straightforward notation of candidate locations, the following Boolean coefficient is involved, i.e. $a_{i,v,j,t,s}$, which is equivalent to the set defined in equation (8).

$$a_{i,v,j,t,s} = \begin{cases} 1, \text{ if } \xi \le R'_{v,s} \\ 0, \text{ otherwise} \end{cases} \tag{9}$$

The $a_{i,v,j,t,s}$ coefficient in equation (9) notes whether the distance from the i-th candidate location to the j-th discrete point of the v-th EV driver at t-th time instance for the s-th EDV driving range scenario falls within the scope of the defined distance criterion. If this criterion is met, the $a_{i,v,j,t,s}$ coefficient takes the value of 1, otherwise its value equals 0.

3.2. Traffic load weights of candidate locations

Another input parameter, which is known *a-priori*, is the individual weight of the i-th candidate location point. The weights are identified with respect to the traffic flow, defined by the number of EDV users travelling along a candidate location point of the road network, thus reflecting its importance. To calculate the weights, the following coefficient must first be defined:

$$W_{i,t} = \begin{cases} 1, \text{ if } m_i \in N_{v,t} \\ 0, \text{ otherwise} \end{cases};\ \forall\ t = 1,2,\ldots,T;\ \forall\ v = 1,2,\ldots,V;\ i = 1,2,\ldots,I \tag{10}$$

where the $W_{i,t}$ coefficient 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 EDV driver at t-th time instance, otherwise it equals 0. The weight of the i-th candidate location point for placing a CS, expressed by w_i, is calculated as the sum of $W_{i,t}$ coefficients in the observed optimisation period with T time instances, noted as:

$$w_i = \sum_{t=1}^{T} W_{i,t};\ \forall\ i = 1,2,\ldots,I \tag{11}$$

3.3. Candidate charging technology types

The candidate charging technology types, which are crucial for deciding the placement of CSs at selected candidate locations, play a vital role for the temporal duration of the battery charging process. Therefore, the following equation notes the charging time duration accounting for the type of charging technology required to travel a distance equal to the initial EDV driving range:

$$L_{k,v} = CT_k / R_{v,0}\,;\ \forall\ v = 1,2,...,\ V;\ \forall\ k = 1,2,...,\ K \tag{12}$$

where CT_k is the charging time using the k-th candidate charging type technology to reach distance equal to the initial EDV driving range, i.e. $R_{v,0}$.Candidate charging technology types are related to their overall costs, which are expressed by $c_{i,k}$ for the purpose of placing the k-th candidate charging type technology at the i-th candidate location. The overall costs of individual charging technology type candidates include investment, maintenance and operation costs related to candidate locations and are henceforth taken in consideration in the objective function in the optimisation model presented in Subsection 3.5.

3.4. Quality of Service of the charging infrastructure

As already explained and discussed in Ref. [7], the QoS_v for the v-th EDV driver is defined as:

$$QoS_v = DCT_v / D_v\,;\ \forall\ v = 1,2,...,V \tag{13}$$

where DCT_v is the overall disposable charging time of the v-th EDV driver to reach the overall travel distance D_v.

3.5. Optimisation model for charging stations placement

At this stage, it must be emphasised that the effects of the s-th stochastic EDV driving range scenario in an optimal CSs placement solution are deliberated. The objective function in equation (14) minimises the overall CSs placement cost based on the input data applied to the deterministic (road network, charging technology types and QoS) and stochastic (EDV driving range) modules.

$$Min\left\{ F_s = \sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{k=1}^{K}\frac{1}{w_i}c_{i,k}\cdot x_{i,t,k} \right\} \tag{14}$$

In equation (14), $x_{i,t,k}$ is a Boolean decision variable, which takes the value of 1, if the k-th candidate charging technology for i-th candidate location at the t-th time instance is selected, otherwise, it equals 0, in an optimisation period with T time instances. K is the overall number of candidate charging technology types to be placed at a selected location, I is the overall number of candidate locations in the road network, while $c_{i,k}$ represents the overall costs related to the candidate charging technology type for the CS to be installed at a candidate location.

The objective function is expressed as follows:

$$\sum_{i=1}^{I} a_{i,v,j,t,s}\cdot x_{i,t,k} \geq 1;\ j = 1,2,...,\ J_{v,t};\ t = 1,\ldots,\ T;\ v = 1,2,...,\ V;\ k = 1,2,...,\ K;\ \forall\ s = 1,2,...,\ S \tag{15}$$

$$\sum_{i=1}^{I}\sum_{k=1}^{K} L_{k,v}\cdot x_{i,t,k} \leq QoS_v;\ t = 1,\ldots,T;\ v = 1,2,...,V;\ k = 1,2,...,\ K \tag{16}$$

$$x_{i,t+1,k} = x_{i,t,k};\ t = 1,\ldots,T-1;\ i = 1,2,...,I;\ k = 1,2,...,K \tag{17}$$

$$x_{i,t,k} \in \{0,1\};\ t = 1,2,\ldots,T;\ i = 1,2,...,I;\ k = 1,2,...,K \tag{18}$$

The first constraint is vital for the purpose of this paper, since is comprises the stochastic EDV driving range in the formation of sets for the charging reliability of the CI. By using the $a_{i,v,j,t,s}$ coefficient, the candidate locations, which fulfil the given distance criterion, are selected to be included in the optimisation. In addition, the principle of charging reliability is applied as follows: if the value of the uncertainty distance is negative, i.e. $-\Delta d_{v,s}$, the initial value of the $R_{v,0}$ range is shortened, and hence, a lower number of candidate locations are included in the constraint, which consequently has an decreasing effect on the objective function and optimal CS solution plan. On the other hand, if the uncertainty distance is positive, i.e. $+\Delta d_{v,s}$, the initial value of the $R_{v,0}$ range is augmented, which means that a higher number of candidate locations are included and an increasing effect on the objective function may be expected. The left-hand side of the constraint (16) ensures the placement of the k-th candidate charging technology at the i-th candidate location with the k-th technology charging time CT_k to reach a distance equal to $R'_{v,s}$ in order to achieve the EDV driver's requested quality of service level QoS_v, as defined in equation (13). The equality constraint (17) is introduced to obtain the continuity of the k-th charging technology to be placed at the i-th candidate location decision variable during the optimisation period of T time instances. Therefore, the equation (17) must be read as follows: if the k-th charging technology is placed at the i-th candidate location and is selected at the t-th time instance, the selection decision must be committed to the following $t+1$ time instance for the observed time period with T instances. The constraint expressed in equation (18) states the binary definition of the k-th charging technology at the i-th candidate location decision variable at the t-th time instance, i.e. the binary definition of K charging technologies, I candidate location points in an optimisation period of T time instances.

4. Numerical Results

Numerical results capture the essence of the importance of the EDV driving range in the proposed location optimisation methodology for the CSs placement. This is the initial first block called the "Input Data Preparation" of the principle scheme shown in Figure 2 of Section 3. Table 1 presents the initial data for the deterministic and stochastic modules. The deterministic module includes the road network, charging technology types, EDV driving trajectories, *QoS* and overall costs. The EDV driving trajectories are illustrated in Figure 3. The stochastic module includes the initial value of the EDV driving range, the values of the mean (μ) and standard deviations (σ) and the number of stochastic scenarios (S). It is assumed that all EDV drivers have an equal EDV driving range.

It must be emphasised that the entities of the deterministic module (EDV trajectories, requested *QoS* and overall costs) are considered in combination with individual stochastic EDV driving range scenarios for the optimisation procedure execution.

In addition, it must also be noted that the starting point for the EDV driver may be anywhere within the discretised road network grid. EDV drivers coming from beyond the modelled grid are also eligible to be included, nevertheless, an input point on the grid and the state-of-charge at that point must be identified in order to determine candidate locations to be included in the location optimisation procedure in accordance with the process explained in Subsection 3.1.

On the basis of Equations (2) - (4), stochastic scenarios (S = 10 000) are created to establish the uncertainty distance and, consequently, the EDV driving range. Creating stochastic scenarios of the EDV driving range also includes the uncertainty related to the randomness of the battery SoC which is important when going on longer trips. Certainly, the battery SoC is also a function of the battery capacity. The uncertainty related to the initial driving range of EDVs is valuable for CI planners, since it cannot be assumed that in reality all EDV users will have a fully charged vehicle at the start of each run. Henceforth, the number of scenarios was reduced to a set of 10 most probable scenarios by using the K-MEANS reduction procedure (Subsection 2.1). The number of scenarios for the reduced set was pre-defined, since the optimisation procedure is executed on a methodological test network and a set of 3 EDVs. It must be noted that as the number of scenarios increases, the probability of scenario occurrence will drop and vice-versa. Hence, the different stochastic range scenarios can have different effects on the decision making of the CI planners. The block called "Scenario Generation" in the principle scheme shown in Figure 2 covers both the reduced set of range scenarios and its probability of occurrence. The stochastic scenarios are presented in Table 2. Column 2 of Table 2 presents the scenario occurrence probability, while the value of the stochastic EDV range, which is applied to form the charging reliability criterion for the CSs placement, is shown in Colum 3.

The highest value of the uncertainty distance is 23.12 km (positive) and lowest is -23.15 km (negative). The average negative uncertainty distance equals to -11.02 km, while the positive distance equals to 11.77 km. These values indicate that on average, the randomness of the state-of-charge at the beginning of the trip or the driving behaviour while the EDV is on-route, shorten or extend the initial range of 200 km by nearly 11-12 km. It can be ascertained that the stochastic modelling of the uncertainty distance in the formation of the charging reliability criterion becomes a necessity in order to better include the realistic occurrences, which would meet both the EDV users' and CI planners' needs. Scenario no. 2 holds the maximum occurrence probability, while Scenario no. 3 has the lowest probability. Namely, this probability for the uncertainty distance can, in reality, relate to the possibility of having an EDV user frequently unplugging the vehicle at certain charged level before the battery is fully charged and continuing along with their drive. Another example would be when an EDV user charges the battery fully each time, but various factors, such as the driver's sudden acceleration, speed, breaking, air-conditioning and other external factors, i.e. road steepness, road resistance, wind, etc., drain the battery while travelling.

The following step refers to the execution of the optimisation model presented in equations (14) - (18) for the 10 stochastic scenarios in combination with entities of the deterministic module. For the formation of the charging reliability criterion, the value of the stochastic EDV driving range is considered equal for all EDVs in each particular scenario. The execution of the optimisation model corresponds to the block entitled "Optimisation model for CS placement", which can be seen in the principle scheme shown in Figure 2. Thus, 10 different optimal solutions for the CS placement were reflected, along with the occurrence probability for the stochastic range scenario. The results of the objective function value for the s-th scenario (F_s), the no. of CSs and the unary percentage increase/decrease from F_{ref} and dF_s are shown in Table 3.

The dependency of the optimisation objective function value F_s for different values of the stochastic EDV driving range is shown in Figure 4. From this figure, CI planners can easily determine which stochastic range scenario will bring about higher benefits along with the occurrence probability of that scenario.
At this point, it can be concluded that for scenarios 1, 2, 4, 7 and 8, the F_s value is higher than F_{ref}, which is the consequence of the lower value of the individual stochastic scenario for the EDV driving range (< 200 km), as may be observed in Figure 4 and Table 3, Column 4. In this case, a higher number of CSs is selected in the final optimal solution, as seen in Table 3, Column 3, which will definitely have an effect on increasing the EDV users' convenience. This fact is unfavourable for CI planners, since they would need to place a higher number of CSs. For scenarios 3, 5, 6, 9 and 10, the F_s value is lower than F_{ref}, which is the consequence of higher stochastic EDV ranges (> 200 km). This happens in case of range scenarios for which the number of CSs is lower than the reference case, which indicates that the EDV users' convenience will be disrupted because a lower number of CSs will be placed; however, CI planners would obtain higher benefits. This can also affect the mass adoption of EDVs.

It can be concluded that a negative value of the uncertainty distance component will contribute to higher CI placement costs, since an increased number of candidate locations in comparison with the reference case, where no uncertainty component is considered, is included in the optimisation procedure, thus increasing the CI placement costs. In the event of a positive dF_s (unary percentage increase from F_{ref}), it can be concluded that it represents an additional cost for the CI planners, however, all possible stochastic occurrences having a profound effect on battery discharge are comprised in these scenarios IDs. In the event of a positive uncertainty distance component, the overall CI placement costs are reduced in comparison to the reference case. Hence, the positive value of the uncertainty distance components generates positive gains for the CI planners, i.e. reduced CI placement costs and higher savings, which may be used for additional investments for improving the battery charging technology, increasing the battery stamina, capacity, etc. As a consequence, the possibility to invest generated savings increases the initial EDV driving range.

This paper shows that CI planners can assess the impact of the stochastic EDV driving range on the overall optimal CSs placement costs. The stochastic driving range, as shown in Table 3, makes an effective change in the formation of the charging reliability criterion which is significant to exceed the major EDVs drawback, such as their limited mobility. Moreover, the related probabilities of occurrence for the uncertainty distance of the initial driving range, as shown in Table 2, can be associated with the CI placement costs and can thus be used by the CI planners as a foundation for future CI expansion plans. So far, no paper has been published that would address the effect of the uncertainty distance for the initial EDV driving range and its probability of occurrence on the optimal CSs placement solution. Although the presented method is only tested on a methodological road network, a lower number of EDVs and trajectories, and fewer charging technologies, this model is general and can be applied to real cases. The findings can also be used in the area of research, as researchers may extract useful information from this paper.

5. Conclusions

The model presented in this paper is an improved version on an earlier optimal charging stations placement model. An additional uncertainty distance component concerning the initial driving range is introduced to bring the model closer to real-life occurrences, such as an incompletely charged battery at the beginning of a longer trip, the drivers' driving behaviour (sudden acceleration, over-speeding, breaking, etc.) or other external factors (road steepness and grade resistance, wind, temperature, etc.). Thus, the paper presents an improved definition of the charging reliability criterion formation, which is involved in the optimisation placement model. Namely, the uncertainty distance has an effect on the number of candidate locations for placing a charging station to be comprised in the charging reliability criterion. Previously, the charging reliability was introduced to exceed the electric vehicles' mobility limitation and selecting at least one candidate location within the initial driving range, which, in this paper, is only upgraded to expand the accuracy of station placements valuable for both electric vehicle users and the charging infrastructure planners. A more accurate placing of charging stations increases the drivers' convenience and can lower the overall placement costs. The impact of the stochastic driving range and the effectiveness of the proposed location optimisation procedure is demonstrated on a test road network together with electric vehicle trajectories representing the drivers' behaviour. After executing the optimisation algorithm, the results show that the involvement of the uncertainty distance component accounting for the driving range and the charging infrastructure charging reliability formation criterion have a significant effect on the optimal charging stations location selection and overall charging infrastructure placement costs. The presented model also provides an option of scenario analysis, an opportunity to derive the optimal station placement solution for different scenarios and conduct a more detailed comparison. This paper represents the basis for future work that will consider the employment of new probabilistic approaches in the modelling of uncertainty distance for the electric vehicle driving range with a view to better comprise the stochastic occurrences in real-time to enhance electromobility by surpassing the electric vehicle range limitation and better meeting the electric vehicle charging needs.

6. References

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NOMENCLATURE

Indices:

i Subscript index of candidate locations for charging station placement
t Subscript index for time instance
v Subscript index for electric vehicle driver
s Subscript index for scenario
j Subscript index for trajectory demand discrete point
dx Subscript index for noting the x axis
dy Subscript index for noting the y axis
k Subscript index for candidate charging technology

Variables and functions:

$RN_{(\cdot)}$ Normal probability density function
$F_{(\cdot)}$ Optimisation objective function (cost minimisation)
F_{ref} Optimisation objective function for the initial driving range of electric vehicles
$dF_{(\cdot)}$ Unary percentage increase/decrease from $\mathrm{F}_{\mathrm{ref}}$
$x_{(\cdot),(\cdot),(\cdot)}$ Binary decision variable associated with the placement of candidate charging technology to be placed at a candidate location at a specific time instance

Sets:

M Finite set of candidate locations for charging station placement
$N_{(\cdot),(\cdot)}$ Finite set of trajectory points
$S_{(\cdot),(\cdot),(\cdot),(\cdot)}$ Finite set of the charging reliability criterion formation

Parameters, Constants and Coefficients:

I Number of road network points
$m_{(\cdot)}$ Candidate location for charging station placements
$n_{(\cdot),(\cdot),(\cdot)}$ Trajectory demand point
T Overall number of time instances
$J_{(\cdot),(\cdot)}$ Total number of trajectory points of an EV driver in specific time instance
ξ Euclidean distance
$R_{(\cdot),0}$ Initial driving range of an electric vehicle
$R'_{(\cdot),(\cdot)}$ Stochastic driving range of an electric vehicle
η Energy conversion efficiency
$SoC_{(\cdot)}$ Battery state-of-charge level
$\Delta d_{(\cdot),(\cdot)}$ Uncertainty distance component
$\mu_{(\cdot)}$ Mean deviation
$\sigma_{(\cdot)}$ Standard deviation
$\alpha_{(\cdot),(\cdot),(\cdot),(\cdot),(\cdot)}$ Coefficient to relax the formation of sets related to the charging reliability criterion
$W_{(\cdot),(\cdot)}$ Coefficient related to the traffic load
$w_{(\cdot)}$ Traffic load weight of a candidate location
K Number of candidate charging technologies to be placed at candidate locations
$L_{(\cdot),(\cdot)}$ Ratio considering the charging duration time of a candidate charging technology to reach a distance equal to the driving range of an electric vehicle with a fully charged battery
$CT_{(\cdot)}$ Charging duration time using a candidate charging technology
$c_{(\cdot),(\cdot)}$ Investment cost for placing a candidate charging technology at a candidate location
$QoS_{(\cdot)}$ Quality of service for an electric vehicle driver
$DCV_{(\cdot)}$ Overall disposable charging duration time of an electric vehicle driver to reach the overall travel distance
$D_{(\cdot)}$ Overall travel distance of an electric vehicle driver
V Number of electric vehicle drivers

S Number of scenarios
$p_{(\cdot)}$ Scenario probability

Abbreviations:
EDV Electric-drive vehicle
CI Charging infrastructure
CS Charging stations
TSR Trip success ratio

FIGURE CAPTIONS

Figure 1: Charging reliability principle and uncertainty distance with regards to the EDV driving range
Figure 2: Principle scheme
Figure 3: EDV driving trajectories in the discretised road network
Figure 4: F_s dependency of the stochastic $R_{v,s}$

TABLE CAPTIONS

Table 1: Initial data for the deterministic and stochastic module
Table 2: Stochastic scenarios for the uncertainty distance and EDV driving range
Table 3: Objective function value, the no. of CSs for the reduced set of stochastic scenarios of the EDV driving range and the unary percentage increase/decrease from F_{ref}

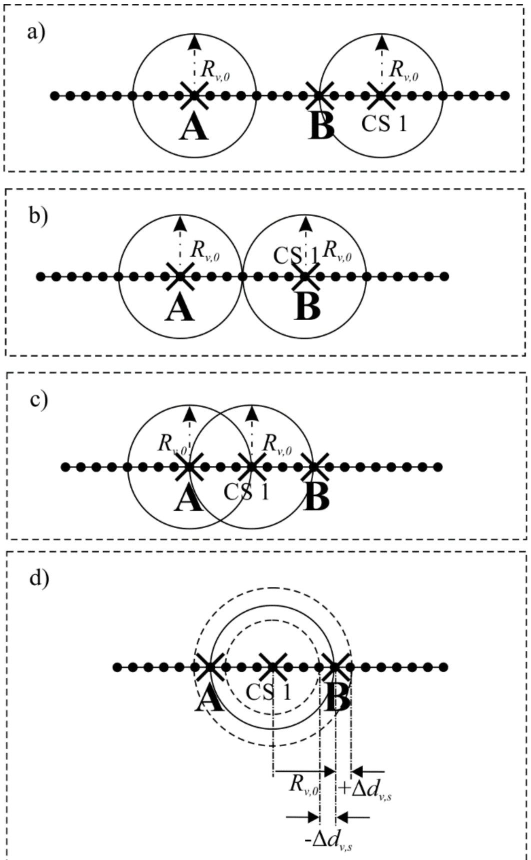

Figure 1: Charging reliability principle and uncertainty distance with regards to the EDV driving range

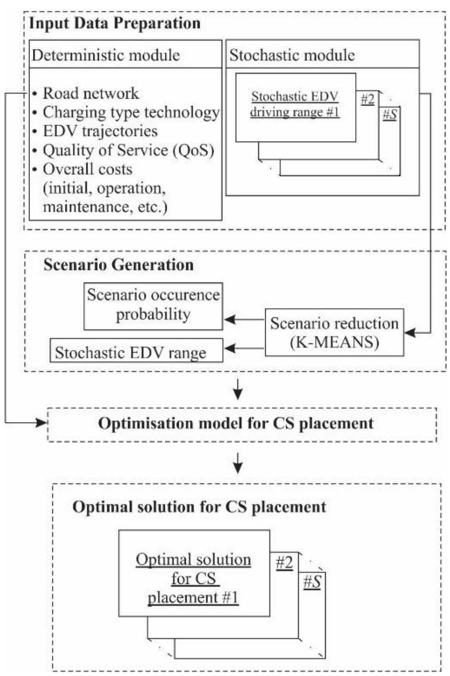

Figure 2: Principle scheme

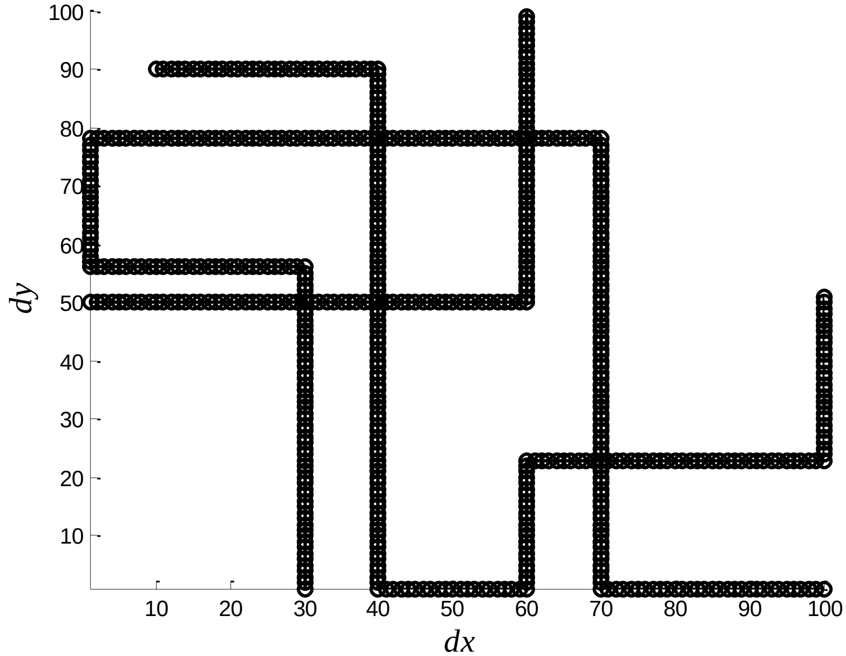

Figure 3: EDV driving trajectories in the discretised road network

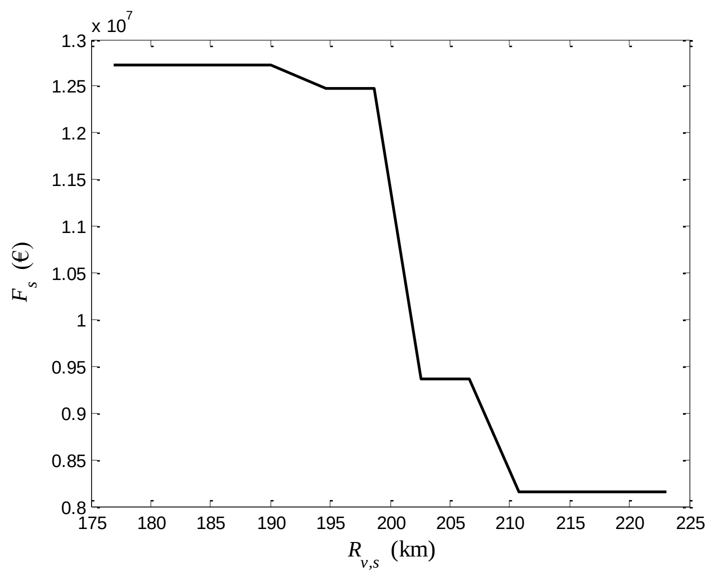

Figure 4: F_s dependency of the stochastic $R_{v,s}$

Table 1: Initial data for the deterministic and stochastic module

Deterministic module		*Stochastic module*	
No. of discrete points in the network (I)	10 000	*Initial driving range ($R_{v,0}$)* (km)	200
No. of charging technologies (K)	2	*Mean value (μ)*	0
$L_{1,v}$ (min/1000 km)	1200	*Standard deviation (σ)*	0.1
$L_{2,v}$ (min/1000 km)	100	*Stochastic scenarios (S)*	10 000
$c_{i,1}$ (€)	20 000		
$c_{i,2}$ (€)	100 000		
No. of EDV drivers (V)	3		
Optimization period (T)	24		
EDV trajectory 1 (endpoints)	1010 - 5000		
EDV trajectory 2 (endpoints)	5001 - 100		
EDV trajectory 3 (endpoints)	9930 - 10 000		
QoS_1 (min/1000 km)	1256		
QoS_2 (min/1000 km)	1840		
QoS_3 (min/1000 km)	915		
Distance between two consecutive points in the road network (km)	10		

Table 2: Stochastic scenarios for the uncertainty distance and EDV driving range

Scenario ID	p_s (%)	$R'_{v,s}$ (km)	$\Delta d_{v,s}$ (km)
1	2.58	176.85	-23.15
2	15.48	198.71	-1.29
3	2.31	223.12	23.12
4	11.68	189.99	-10.01
5	10.3	210.72	10.72
6	15.13	202.63	2.63
7	15.39	194.63	-5.37
8	7.74	184.69	-15.31
9	12.91	206.57	6.57
10	6.48	215.84	15.84

Table 3: Objective function value, the no. of CSs for the reduced set of stochastic scenarios of the EDV driving range and the unary percentage increase/decrease from F_{ref}

Scenario ID	F_s (€)	No. of CSs	dF_s (%)
Reference	11,760,000.00	27	0
1	12,720,000.00	29	+8.16
2	12,480,000.00	28	+6.12
3	8,160,000.00	17	-30.61
4	12,720,000.00	29	+8.16
5	8,160,000.00	17	-30.61
6	9,360,000.00	20	-20.41
7	12,480,000.00	28	+6.12
8	12,720,000.00	29	+8.16
9	9,360,000.00	20	-20.41
10	8,160,000.00	17	-30.61