

A MODEL OF CHARGING SERVICE DEMAND FOR THE CZECH REPUBLIC

Jan Pekárek¹

¹Department of Informatics, Faculty of Business and Management, Brno University of Technology, Kolejní 2906/4, 602 00 Brno, Czech Republic

Abstract

PEKÁREK JAN. 2017. A Model of Charging Service Demand for the Czech Republic. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, 65(5): 1741–1750.

The paper introduces a standalone model of electric vehicle charging demand based on large-scale travel survey data of the Czech Republic. This demand model has been intended as a comprehensive input model for following charging infrastructure problem, where a spatial view of charging demand is usually needed. The model uses publicly available data, whose mutual incompatibility and information richness had to be overcome. The necessary data transformations are described and final data representation in the form of a mathematical graph allows the introduction of a point-defined (vertex-defined) charging demand model. Several drawbacks of the model are identified and their effect, as well as an application of whole model, is demonstrated on the large-scale numerical example. Sound demand model is a cornerstone for demand-related problems, such as general large-scale charging infrastructure problem, which is a common issue for countries that stand at the very beginning of the electric vehicle adoption process.

Keywords: electric vehicles, charging service demand, charging stations, graph theory, Czech Republic road network, charging demand model, charging service, charging infrastructure, traffic survey, traffic data

INTRODUCTION

In recent years the electric vehicle (EV) industry has been undergoing rapid development despite many organizational and technological challenges. While many researchers tackle the most urgent technological drawbacks of EV, such as the persisting insufficient battery range or their impact on power networks, others deal with economic challenges of EV adoption and optimal resource allocation. This paper suggests a model of charging service demand to simulate and predict its spatial distribution in order to optimize the deployment of charging stations for EV. One possible version of charging infrastructure model is contained in a previous paper (Pekárek, 2015a). This paper attempts a deeper analysis of charging service demand and designs a model of such demand. The demand model description using graph theory terminology is developed and it is tested on the large-scale example the road network of the Czech Republic.

Literature Review

Several papers dealing with charging service demand have been published in recent years. The focus of these papers is varied: charging infrastructure placement problems (González, 2014; Jamian *et al.*, 2014; Lam *et al.*, 2014; Yi and Bauer, 2016), impact of EV charging on distribution systems (Maheswari *et al.*, 2014), or demand simulation and prediction models (Amini *et al.*, 2016; Bae and Kwasinski, 2012; Fan, 2012; Li and Zhang, 2012). Charging service demand, or simply charging demand, is a crucial part of all of them, because any problem of this kind ultimately depends on the EV owners' charging behaviour and the patterns of use of their vehicles. A well-designed demand model is an entry point to more complex analyses in this field, such as charging infrastructure deployment problems, power load control problems, EV queuing problem at a single charging station etc. Moreover, it is necessary to keep in mind that most of the demand models are strongly data

dependent, which results in high requirements on the data quality.

The assessment of charging infrastructure business models in (Madina *et al.*, 2016) provides a list of different charging alternatives as a list of ordered parameter values of different attributes. These listed attributes correspond to the most significant ones when dealing with the charging infrastructure problem in terms of economic evaluation. The combination of their parameter values then constitutes specific business models.

A model of a charging station location problem is presented in (Zhu *et al.*, 2016), where a city area with the existence of significant parking plots is assumed. The objective function is composed of two weighted sub-objectives. The authors use a standard approach to formulate the optimization problem in the municipal area and get the expected results, however, with certain improvements. Nevertheless, in terms of demand simulation not much work has been done. The authors state that their charging demand is homogenous in terms of vehicles, travellers and charging costs. The assumption of constant charging costs and vehicle types can be considered realistic, but the homogeneity of travellers' behaviour cannot. The main problem here is the spatial and temporal discrepancy in charging needs. When the temporal discrepancy (during workdays) is omitted as it is not considered a research topic, the spatial discrepancy is enough to violate travellers' behaviour homogeneity assumption. This is an example of a situation when a sound model of charging demand should be developed before the optimization process of station placement can begin.

Direct modelling of temporal and spatial charging demand is approached in (Bae and Kwasinski, 2012) using a special highway model. The authors attempt to develop an estimation of charging demand using the fluid traffic theory and the queuing theory in this environment. The focus of the paper is mainly on charging stations located near highway exits, thus mainly highway traffic is considered. The probabilistic power flow (PPF) is used in Li and Zhang (2012) for a similar goal, i.e. charging demand modelling. A methodology based on PPF is provided for developing a single vehicle demand model first and then a more general multiple vehicle demand model. They also consider multiple types of vehicles and show the corresponding overall demand on a numeric example. Their model is quite technical in terms of power generation, power flow and power storage capacity. The queuing theory is also used.

An impressively detailed model of both spatial and temporal charging demand is provided by Cavadas *et al.* (2015), where a mixed integer optimization program is suggested to find optimal places for slow-charging stations within an urban area. The authors suggest an objective function that maximizes vehicle-owners' demand satisfaction in terms of reaching their ultimate destination of travel. This approach is extremely precise and absolutely

correct in theory. But in practice it faces the issue of the necessary data availability. As the authors show in the numerical example, such data can be obtained by a survey; however, 10,000 participants (more than 7% of the municipality population) had to be questioned, while some simplifications (aggregating trip origins and destinations into 129 square sectors) still had to be done. It follows that such a detailed approach is suitable for rather small municipal areas where very detailed travel data are available. Practically, it would be extremely difficult (expensive) to obtain such detailed data from inhabitants of a large city, and almost impossible to obtain such data from citizens of a whole state, such as the Czech Republic. The latter not because of the scale, but because of the fundamental difference between intra-municipality trips and inter-municipality trips. The first are more regular and predictable, trips to work, to school etc.; the second are more ad hoc and unpredictable even for the survey respondent. However, there are countries for which high quality nation-wide travel surveys are available, but such countries usually already have a high standard charging infrastructure (U.S. Department of Transportation, 2009).

Another difference between Cavadas's paper (2015) and the issue we are dealing with is that electric vehicle owners tend to charge their vehicles at home if possible (Sears *et al.*, 2014). Therefore, charging stations for inter-municipal trips, e.g. charging stations for long trips, are designed for drivers who cannot use home charging since they are not within the battery range of their home charger.

A difference between the point demand and flow demand models is provided in Tu *et al.* (2016). As the point demand model is usually used in cases of charging demand modelling, the authors argue that the flow model can provide some additional benefits. But similarly to the previous case, quite detailed data are needed for its construction. Origin-destination data for a statistically reliable sample of drivers are naturally the best choice if they exist (Lim and Kuby, 2010). In the case of their absence an alternative approach must be used. Such an approach may be the case when input dataset describes traffic density on road segments (Road and Motorway Directorate, 2016b). The problem of estimation of the traffic flow is briefly discussed by Ge *et al.* (2011). Although the authors consider street network, they point out the non-symmetry of traffic flow on the road section (edge) and conclude that when the traffic flow on the node (vertex) is calculated, it should be counted only from one direction. Sadly, they do not provide a solution of how to achieve this when only aggregated data for both directions are available.

Methods and Background

Let us consider a model for charging infrastructure problem. Such model can be quite specific, or can be defined in an abstract form. Either way, it should deal with the questions: "Where

is the charging wanted/needed?”, and “Where is the charging actually provided?” Asking “where” instead of “when” simply emphasizes that the model considers either mainly, or exclusively the spatial view in contrast with the temporal view. It follows that such model should work with charging demand as a given factor and its goal is to find proper supply (infrastructure positions), which satisfies it.

This paper deals with the first part, the charging demand, as it is considered to be a complex issue, which is necessary to solve before approaching for further problems. The issue of decomposition of complex charging demand variable has been approached earlier (Pekárek, 2015b), where several lower-level variables have been suggested. This paper deals only with spatial and static charging demand, since static traffic data are used. The paper for instance does not deal with another interesting question related to charging demand, which is the growth of charging demand as the adoption of electric vehicles progresses. In fact, it may be the case, that prior existence of charging infrastructure may have a positive catalytic effect on charging demand, because the utility of an electric vehicle is limited when no infrastructure exists and it grows when it is being developed. Therefore, a model of charging demand considering this catalytic effect should also consider the existing charging supply. Such research is not included in this paper, but it is an objective related to the topic of this paper, which can be a part of future research.

The nature of the used datasets is described in the following chapter. At this point it is appropriate to say that the paper focuses mainly on the construction of the mathematical graph structure from the datasets and its use for the charging demand model. The data quality is limited, hence several assumptions are employed. For instance, in the numerical example the results should be understood as ordinal, not cardinal due to the unknown percentage of electric vehicles in the Czech Republic, namely their spatial distribution. The results cannot provide an exact value of demand (regardless of its unit), they can only order the regions according to it. Another assumption is that travel behaviour of electric vehicle owners is the same as the travel behaviour of car owners in general and it has not changed since 2010 when the last nationwide travel survey was conducted. To ease these assumptions, it would be necessary to obtain much more detailed and extensive data than the data available now.

Processing of the Available Data

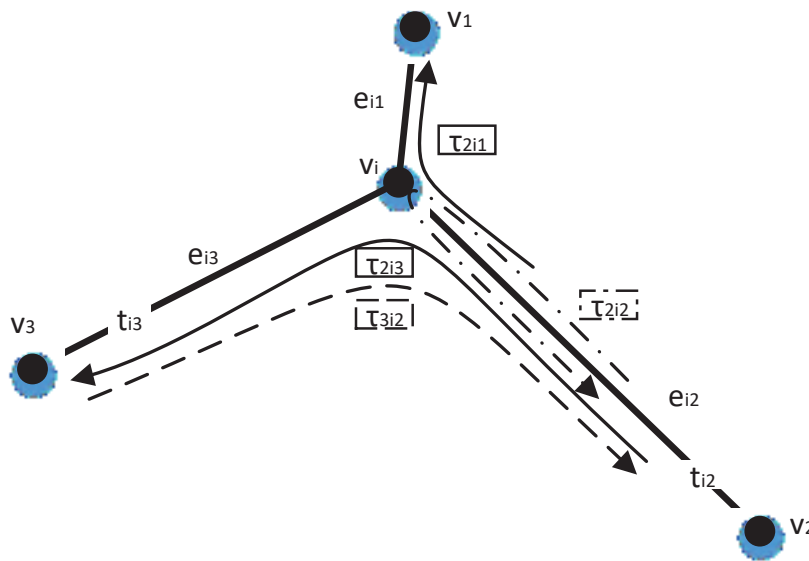
Now let us discuss the key issue in charging demand modelling. There are two kinds of data available in two datasets. The first dataset contains a graph representation of the Czech road network up to class III roads. That means it contains all publicly available highways and speedways as well as three different classes of ordinary roads, graded according to the road importance (Czech Republic, 2016).

The second dataset describes traffic density on some of these roads. It covers highways, speedways and class I roads, but not all lower classes roads are included in the traffic density dataset. For a dataset merge it is necessary to match corresponding vertices and edges of two graphs, which are constructed from the datasets. Let $G_1(V_1, E_1)$ be a weighted undirected graph of road network constructed from the first dataset, where V_1 is a set of vertices, E_1 is a set of edges, i.e. ordered pairs. Let $G_2(V_2, E_2)$ be a weighted undirected graph of traffic densities constructed from the second dataset, where V_2 is a set of vertices, E_2 is a set of edges. Also, let E be an unspecified set of edges, then $L \subseteq E \times \mathbb{R}$ is an injective function $L : E \rightarrow \mathbb{R}$, which assigns a road length to each edge, and $T_e \subseteq E \times \mathbb{R}$ is an injective function $T_e : E \rightarrow \mathbb{R}$, which assigns a traffic density to each edge. L is a part of the first dataset, while T is a part of the second dataset. There is no obvious way to merge the datasets (no common identification number of vertices or edges). Also the cardinalities of vertex sets are different: $|V_1| > |V_2|$. It generally may not be true that $V_2 \subseteq V_1$ and $E_2 \subseteq E_1$, hence G_1 cannot be directly taken as the final graph. Instead, the final graph should be $G_e(V, E, A_e)$, where $V = V_1 \cap V_2$, $E = E_1 \cap E_2$ and A_e is a set of edge-defined attributes, where $A_e = \{L, T_e\}$, L is a road length attribute, T_e is a traffic attribute. By denoting the final graph this way it is possible to add different attributes to the structure ad hoc, e.g. a road type, vehicle speed limitations or road quality. The structure $G_e(V, E, A_e)$ is therefore an undirected “double” edge-weighted graph. This means that each edge has two attributes (weights), instead of one as is common in weighted graphs. The fact that the attributes are edge-defined is important as later in the paper it will be shown that for traffic metric it is more useful to use a vertex-defined format. Hence the lower index e denotes the difference.

The prototypical approach, which has been used originally (Pekárek, 2015a), is based on individual vertex demand values. It is the simplest model and its values are very easily obtainable. It uses edge-defined traffic data and transforms them into vertex-defined traffic data. The structure, that is built up from the data and is used as a cornerstone for further transformations and analyses, is the previously mentioned graph $G_e(V, E, A_e)$. The available data describe the traffic on bidirectional road segments as a sum of traffic in both directions. Besides, vertices are classified according to their degree in a similar manner as in the graph theory, i.e. $\deg(v)$, $v \in V$ marks the degree of vertex v . Since graph G_e is undirected, it equals the total number of edges adjacent to v . There are three main classes of vertices according to their degree.

Classification of Vertices

Class 1 vertices (C1) have $\deg(v) = 1$ and can be described as “dead-end” vertices. It means this vertex literally represents a dead-end road, perhaps



1: Decomposition of aggregated traffic
(Source: Author's own composition)

leading into a small settlement, or the dataset does not contain the traffic data of other edges adjacent to v .

Class 2 vertices (C2) have $\deg(v) = 2$ and in G_e generally work as connection vertices (or partitioning vertices) of the same road. It is necessary here to realize again that G_e is a simplification of the road network. A main road, e. g. a highway, can span tens of kilometres without an intersection. To describe it as an edge it is useful to define it as a series of consecutive edges joined by vertices. Such vertices have their degree equal 2. On the other hand, when the main road is not strictly without intersections, but these intersections are purposely omitted, perhaps because the related roads are too unimportant, it is useful to define these intersections as vertices too in order to capture the potential traffic flow in and out of the main road. In the simplified version this second type of vertices will act as traffic generators, but it is completely normal behaviour, because all other than degree 2 vertices have to act as traffic generators.

Class 3 vertices (C3) have $\deg(v) \geq 3$ and are the most important. They constitute the main body of the road network since they represent all types of important intersections. This type of vertices is the one which is the most difficult to handle. The total traffic t_i upon this type of vertices is calculated as

$$t_i = \frac{1}{2} \sum_{j=1}^{\delta_i} t_{ij} \quad (1)$$

Where δ_i is the degree of vertex v_i and t_{ij} be the traffic on every edge, which is incident to vertex v_i . The calculation of traffic on the C3 vertex is subject to further proof.

Note that the class of a road and the class of a vertex are different terms. While the class of a road describes a specific type of a real-world roads given by the legislation (Czech Republic, 2016), the class of a vertex sorts mathematical objects – vertices are classified according to their degree.

Edge-to-Vertex Traffic Transformation

Let us take the previously explained graph $G_e(V, E, A_e)$ as a structure that holds all the relevant data. Let $v_i \in V$ be a vertex we are computing the traffic demand for. Vertex v_i has a certain degree denoted by $\deg(v_i)$, i.e. a corresponding number of edges $e_{i1}, \dots, e_{i\delta_i}$ incident with v_i , where $\delta_i = \deg(v_i)$. Each edge $e_{ij} \in E$ has defined the amount of daily traffic $t_{ij} = T_e(e_{ij})$, $T_e \in A_e$ which represents the aggregated traffic over both directions. It is possible to decompose this aggregated traffic into its elementary components. These can be marked as τ_{jik} and they represent the amount of traffic (number of cars) going from vertex j through vertex i to vertex k . The direction is important, therefore $\tau_{jik} \neq \tau_{kij}$. So when matrix T is constructed by eq. (2), unlike the original adjacency matrix which represents the whole undirected graph, this one is not symmetric.

$$T = \begin{pmatrix} \tau_{1i1} & \dots & \tau_{1ik} & \dots & \tau_{1i\delta_i} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tau_{ji1} & \dots & \tau_{jik} & \dots & \tau_{ji\delta_i} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tau_{\delta_i i1} & \dots & \tau_{\delta_i ik} & \dots & \tau_{\delta_i i\delta_i} \end{pmatrix} \quad (2)$$

As it can be seen in Fig. 1, traffic τ_{jik} interferes with exactly two traffic aggregates t_{ij} and t_{ik} . Each of the aggregates contains the correspondent partial traffic amounts τ . Equation (3) explains how it works.

First, the goal is to transform the edge defined traffic values into vertex-defined traffic values. The traffic on each road can be partitioned from the perspective of the vertex into two groups: 1) the traffic going through the vertex *from* the particular edge and 2) the traffic going through the vertex *to* the particular edge. The first group shall be called outgoing traffic t_{ij}^- (with respect to the particular edge e_{ij}) and the second group is incoming traffic t_{ij}^+ (with the same respect). The outgoing traffic can be further partitioned into individual τ according to its way after it reaches the vertex. Drivers can in fact drive in different directions, their number is δ_i , including the way they came from.

$$\begin{aligned} t_{ij} &= (\tau_{ji1} + \dots + \tau_{jik} + \dots + \tau_{ji\delta_i}) + \\ &\quad + (\tau_{1ik} + \dots + \tau_{jik} + \dots + \tau_{\delta_i ik}) \\ t_{ij} &= \sum_{k=1}^{\delta_i} \tau_{jik} + \sum_{j=1}^{\delta_i} \tau_{jik} \\ t_{ij} &= t_{ij}^- + t_{ij}^+ = t_{ij}^- + t_{ij}^+ \end{aligned} \quad (3)$$

Variables t_{ij}^- , t_{ik}^+ are j-outgoing and k-incoming traffic, respectively. But because the use of different indices j and k does not matter in terms of quantity of the traffic, it can be rewritten to match the indices more clearly using $t_{ik}^+ \sim t_{ij}^-$. Since t_{ij}^- are row sums of matrix T and t_{ij}^+ are column sums of the same matrix, the final sum t_{ij} contains $2\delta_i$ addends while the addend with the same row and column index is there exactly twice. Note that the index order is important and the middle index i is left intentionally as this statement is valid for all vertices.

These partial outgoing and incoming traffic values are mutually dependent via τ_{jik} values. From the previous equation (3) the mutual dependency can be observed, but for the sake of clarity a numerical demonstration shall be provided. Consider the smallest possible C3 vertex v_i , i.e. its $\deg(v_i) = \delta_i = 3$ and the adjacent vertices v_a, v_b, v_c , for simpler indexation denoted as a, b, c . The following system of equations demonstrates their dependency.

$$\begin{aligned} t_{ia}^- &= \tau_{aia} + \tau_{aib} + \tau_{aic} \\ t_{ib}^- &= \tau_{bia} + \tau_{bib} + \tau_{bic} \\ t_{ic}^- &= \tau_{cia} + \tau_{cib} + \tau_{cic} \\ t_{ia}^+ &= \tau_{aia} + \tau_{bia} + \tau_{cia} \\ t_{ib}^+ &= \tau_{aib} + \tau_{bib} + \tau_{cib} \\ t_{ic}^+ &= \tau_{aic} + \tau_{bic} + \tau_{cic} \end{aligned} \quad (4)$$

This system shows how the incoming and outgoing traffic variables are formed and mutually interconnected. It also shows that every variable τ_{jik} is in the system twice. However, the solution of this system is used in eq. (5), where the connection to real traffic values t_{ij} is shown.

$$\begin{aligned} t_{ia} &= t_{ia}^- + t_{ia}^+ \\ t_{ib} &= t_{ib}^- + t_{ib}^+ \\ t_{ic} &= t_{ic}^- + t_{ic}^+ \end{aligned} \quad (5)$$

In this particular example, with respect to substitution via outgoing and incoming traffic values, the traffic on vertex v_i is:

$$\begin{aligned} t_i &= t_{ia} + t_{ib} + t_{ic} \\ t_i &= 2 \left[(\tau_{aia} + \tau_{bib} + \tau_{cic}) + (\tau_{aib} + \tau_{bia}) + \right. \\ &\quad \left. + (\tau_{bic} + \tau_{cib}) + (\tau_{aic} + \tau_{cia}) \right] \end{aligned} \quad (6)$$

Where $T_v \subseteq V \times \mathbb{R}$ is an injective function $T_v : V \rightarrow \mathbb{R}$ which assigns a traffic attribute to each vertex. Lower index v denotes that this traffic metric is vertex-defined. The particular value $t_i \in T_v$ in eqs. (6) and (7) corresponds to vertex v_i and it measures the amount of traffic on this vertex:

$$t_i = \frac{1}{2} \sum_{j=1}^{\delta_i} t_{ij} \quad (7)$$

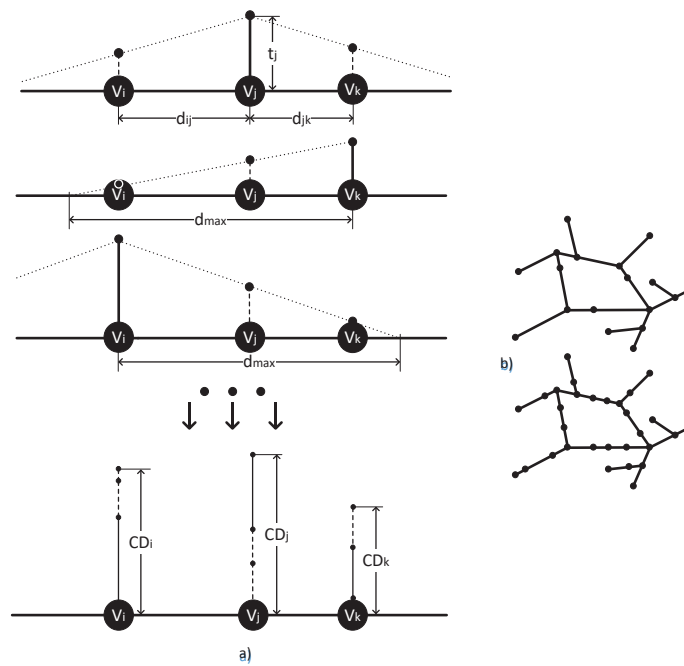
But since the real traffic is represented by values of τ_{jik} , the aggregate t_i shows exactly twice as much traffic, because of the method of calculation and its “double-count” of each partial traffic value τ . Hence the proof of eq. (1) for the amount of traffic on vertex v_i is complete.

With the vertex-defined traffic data T_v obtained, it is possible to formally express a set of vertex-defined attributes $A_v = \{T_v\}$. The final structure is an undirected graph $G(V, E, A_e, A_v)$ with a set of edge-defined attributes $A_e = \{L\}$ and a set of vertex-defined attributes $A_v = \{T_v\}$. This notation allows more vertex-defined attributes to be added in the future, i.e. various vertex properties such as GPS coordinates, land value, power supply etc.

Charging Service Demand Model

This basic type of a charging demand model was briefly mentioned in the previous paper (Pekárek, 2015a). The model assumes that charging demand is derived from the traffic and it is defined exclusively by separate points – vertices of $G(V, E, A_e, A_v)$. Following model then assumes its distribution through edges and calculates the overall demand level in the area (but still existing only in separate points). The previously proposed method cannot interpret the vertex-defined charging demand properly and uses topology coefficient m to simulate charging demand propagation through the network, which ensures the rationality of the drivers' behaviour (the reach of drivers' charging demand is not exclusively spatially located on their current position, it also spreads to entire local area, i.e. to the vertices within a certain distance from the current position). This coefficient assumes a gradual decrease in the charging demand level as the distance rises. In this basic version it assumes a linear decrease but generally there is no reason why the shape of the decrease function could not have been different, sigmoidal or quadratic, for example. The originally published coefficient m is replaced with distance diminishing function g for clearer explanation.

Fig. 2a shows how the linear version of the demand model works. Assume a set of ordered pairs $S \subseteq v_i \times V$, $v_i \in V : d((v_i, v_j)) \leq d_{max}$, $v_j \in V$, where $\forall (v_i, v_j) \in S : (v_i, v_j)$ vertices $v_i, v_j, v_k \in V$ of graph G which follow the condition, where distance $d_{ab}(v_a, v_b)$



2: a) Composition of charging demand / b) Difference in density of class 2 vertices
(Source: Author's own composition)

is the length of the shortest path between vertices v_a and v_b in the connected graph. d_{max} is the maximal feasible distance derived from the maximal feasible radius of the service area (Pekárek, 2015a). Each of these vertices has a correspondent value of vertex-defined traffic $\{t_i, t_j, t_k\}$ calculated using eq. (1). Charging demand CD_i on a particular vertex v_i can be calculated as a sum of all traffic values on all nearby vertices diminished by the distance of these vertices from vertex v_i . The total charging demand on the vertices follows the condition of the maximal distance and it goes as follows:

$$\forall \{v_a, v_b\} \subseteq \{v_i, v_j, v_k\} : d_{ab}(v_a, v_b) \leq d_{max} \quad (8)$$

$$CD_i = \sum_{j=1}^{n_i} g_{ij} t_j \quad (9)$$

$$S_i \subseteq v_i \times V, \quad \forall (x, y) \in S_i : d(x, y) \leq d_{max} \quad (10)$$

$$n_i = |S_i| \quad (11)$$

Where g_{ij} is the distance diminishing function (in basic case linear), t_j is traffic on vertex v_j and n_i is the total number of vertices which follow the condition of maximal distance between the given vertex v_i and vertex v_j which satisfies the condition (10). Note that this condition always restricts only pairs of vertices with respect to the particular vertex v_i . It causes the number of these pairs to be different for each vertex v_i , where $i = 1, 2, \dots, |V|$, therefore an indexation in the number of vertices n_i has to be used.

Distance Diminishing Function

The previously mentioned distance diminishing function $g_{ij}((v_i, v_j), d_{max})$ should be explained here

in detail. The key idea behind it presumes that the demand for charging services has a continuous spatial distribution within the road network or in the graph as its model representation. The demand can be quantified in all points of the road network; it is derived from amount of traffic in these points and it is “propagated” through the road network. This means that the demand in a particular point does not rely upon the amount of traffic only in that point, but takes into account the nearby area as well (adjacent vertices and edges), which is collectively called a service area. The exact definition of a service area can be found in the original paper (Pekárek, 2015a). Function $g_{ij}((v_i, v_j), d_{max})$ calculates the distance-based diminishing factor, which is used to decrease the effect of distant traffic values. This function can have multiple variants, in the paper a linear variant is used (12), but other variants of shapes are also possible (13).

$$g_{ij}((v_i, v_j), d_{max}) = \frac{d_{max} - d((v_i, v_j))}{d_{max}} \quad (12)$$

$$g_{ij}((v_i, v_j), d_{max}) = \frac{1}{2} + \frac{1}{2} \sin \left[\pi \left(\frac{1}{2} + \frac{d((v_i, v_j))}{d_{max}} \right) \right] \quad (13)$$

An image of function $g_{ij}((v_i, v_j), d_{max})$ is an interval $[0, 1]$, so it has that desired diminishing effect on the total product of CD_{ij} , i.e. a contribution to charging demand in vertex v_i gained from vertex v_j . The ordered pairs of vertices $(v_i, v_j) \in S_i$ follow the condition from eq. (10) and d_{max} is again the maximal feasible distance.

Discussion and Numerical Example

Limitations of the Model

The main drawback of the model from eqs. (8) to (11) comes from the various values of n_i . Fig. 2b shows the case of a situation where this model exhibits significant errors. This situation represents the case where a different density of C2 vertices influences the results of the model. It may occur when insignificant roads are omitted, therefore they are not represented by their own vertices, yet they influence the amount of traffic on the main road (as was pointed out in the definition of the C2 vertex). In this case the charging demand CD_i on the particular vertex v_i is influenced by the density of nearby vertices. However, this effect is not realistic, simply because the arbitrarily defined points on the road do not change the traffic on that road, therefore these points cannot change the charging demand derived from traffic. To prove this statement, just consider one segment of the road (one edge) with defined traffic t_{12} and its two different endpoints (two vertices) v_1 and v_2 , which satisfy condition (8). Then calculate CD_1 for v_1 according to eq. (9). Then arbitrarily split the segment into two parts and mark the split point as v_3 . Calculate vertex traffic for v_3 according to eq. (1) and calculate charging demand CD'_1 for this new case. Since $n_1 = 2$ changes to $n'_1 = 3$ by adding the additional vertex v_3 and since $t_3 > 0, g_{13} > 0$, then CD'_1 must be different (greater) from CD_1 . But this result fails to reflect the reality properly, therefore this suggested form of the demand model is not sufficient yet.

Relative Strength of Demand Contribution

In order to fix the drawback mentioned above, it is possible to change equation (9) by adding the total number of vertices. The sum will then have a form of average traffic (or demand) per vertex (14), so adding more C2 vertices will not affect the results in an unrealistic way. It will make the results more realistic, if traffic on the new C2 vertex is determined properly. A drawback of this measure is lowering of differences in the total value of charging demand, which may cause worse readability of regions with extreme demand values.

The case of adding another C2 vertex into the graph also opens the problem of mutual relation of C2 and C3 vertices in terms of vertex-defined traffic data. Equation (1) is applicable to all vertices of a positive non-zero degree (the proof for C3 vertices is applicable to C1 and C2 vertices as well).

$$CD_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \frac{2}{\delta_j} g_{ij} t_j \quad (14)$$

$$CD_i = \frac{1}{n_i} \sum_{j=1}^{n_i} g_{ij} t_j \quad (15)$$

Both of these possible fixes were tested on the numerical example, where they unfortunately did not bring any significant improvement in

the terms of drawbacks. They both diminish the impact of the drawbacks, so they are not so visually striking, but they do not remove them. From a certain point of view these fixes are even harmful, since they hide the drawbacks of the calculation method and make it difficult for a user to identify them.

The best improvement has been achieved when only class 3 vertices were used as carriers of a charging demand value. It prevented class 2 vertices from influencing the value of charging demand and their arbitrary density does not matter anymore. However, the density of the road network itself, i.e. the number of mutual interconnections, still remains an issue, as shown in the numerical example.

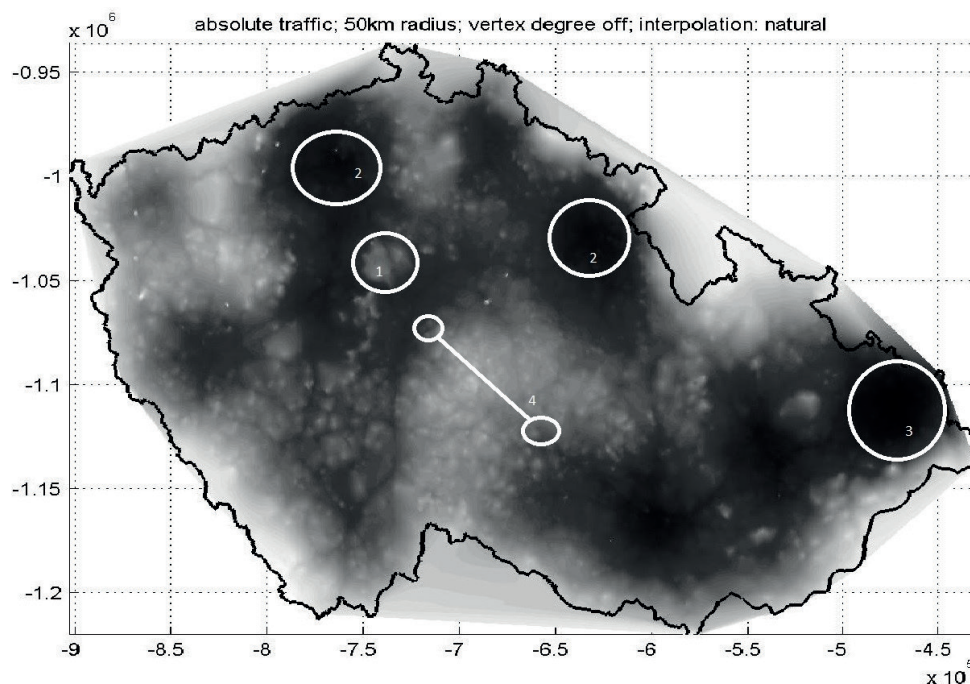
Numerical Example

The proposed demand model is intended to be used for a large modelling of charging station placement. Hence large-scale data of the whole Czech Republic are used for the numerical example. Two datasets were obtained from the Road and Motorway Directorate (RMD), which describe both the road network of four different types of roads (RMD, 2016a) as well as the results of the countrywide traffic survey from 2010 (RMD, 2016b). The first dataset (RMD, 2016a) is vector description of 30,952 road segments of the Czech road network. According to their class, the roads are divided into 4 categories: highways, 1st, 2nd and 3rd class roads (Czech Republic, 2016). The second dataset (RMD, 2016b) contains 8,317 road segments, on which the 2010 traffic density survey was held.

Data processing had to be carried out first to merge both these datasets. Not all existing road segments were included into the traffic survey and also within the traffic dataset there were empty segments or segments of zero length. Then the proposed transformation from an edge-defined to a vertex-defined graph took place and traffic densities on particular points of the road network of the Czech Republic were obtained. To represent this graph in a legible manner, the set of vertices shall have another attribute – position, represented as GPS coordinates. Formally, the position $P \subseteq V \times R^2$ is an injective function $P: V \rightarrow R^2$ which assigns an ordered pair of GPS coordinates to each vertex from V . P is vertex-defined, which makes it a vertex-defined attribute, therefore $P \in A_v$.

With all three attributes – vertex traffic, vertex position and edge length, a model of charging demand can be formed and vertex-defined charging demand can be calculated using eq. (9). This basic result can be understood as a cornerstone of more complex charging demand models.

The results can be represented as a roadmap using 3D scattered natural interpolation. Note that the linear method of interpolation returns very similar results. The data are not spaced equidistantly; to display the graph as a country roadmap it is necessary to attach the data points to a mesh and use



3: Results of the Czech Republic charging demand model.
(Source: author's own computation)

grayscale for different values of charging demand. One of the resulting figures is presented in Fig. 3.

The Fig. 3 discovers some drawbacks of the proposed model. There are two. The first is related to the content of the datasets and the second is related to the method of calculation. The datasets only include information about roads, not streets. This causes the situation that in area 1, where the capital city of Prague should generate the highest amount of charging demand, there is nothing to see, because the data are missing. Luckily, this drawback is known a priori, but the proposed model cannot avoid it at the current state. The reason for that is mainly missing data about municipal traffic, which prevents the calculation of charging demand in municipal areas.

The second drawback is the fact that the calculated charging demand is overrated in certain areas with a high density road network. Namely areas 2 exhibit a large amount of charging demand, but this is due to the fact that there is a road with high traffic within the area with a high density road network. This causes the method of calculation (namely for high values of d_{max}) to return this false impression

of a high charging demand region. A similar situation can be observed in area 3, but there is in fact quite high traffic as well, therefore the result can be understood as slightly less overrated than in the case of the two areas 2. Area 4 marks another representation problem related to the method of calculation, which is visual absence of a high traffic highway in the picture. This highway connects three largest cities of the country (Praha, Brno, Ostrava); it exhibits high traffic, but in the marked area it almost completely disappears. This paradox can be explained again by the way charging demand is calculated. The highway has relatively few exits in the area, therefore the road density is quite small. In fact it is so small that in the picture, in comparison to other regions, charging demand is marginal in this area. This last problem does not hold for all highways. The charging demand on most highways is calculated correctly, namely the regions of South and East Bohemia (south and east of area 1) reflect the real traffic situation very well. Similarly, Moravia (the right half of the picture) is calculated nicely, apart from area 3 mentioned above.

CONCLUSION

The proposed charging demand model for the Czech Republic uses available data that are not as rich as the data available for other countries. Furthermore, the obtained datasets are not directly compatible or errorless, some adjustments for both must be done to merge them. A mathematical graph structure can be formed from the obtained dataset with sets of vertex-defined and edge-defined attributes. This allows further measurement, such as lengths in the graph (using shortest path algorithm) or position of the vertices (using their GPS coordinates).

The proposed charging demand can be calculated in different ways. The most convenient way is to determine a charging demand value for a point of the road network, which is represented as vertex in

the graph. The reason for that comes from the ultimate use of the model – its use as a part of the charging infrastructure model. And because the infrastructure is represented by charging stations/terminals, which are seated in particular locations, the amount of charging demand should be determined for precise locations as well (as opposed to the vague locations in the case of its determination for roads, i.e. graph edges). Also, the charging demand value on the vertex can be adjusted by the vertex degree, or the number of vertices in the area. Both measures, however, do not bring significant improvement in terms of the discussed drawbacks.

Vertex-defined traffic must be calculated first using the provided equation (1) in order to get vertex-defined charging demand. The amount of charging demand then relies on this vertex traffic and the traffic from “nearby” vertices diminished by the increasing distance. The “nearby” vertices are vertices within the service area of the vertex, for which the charging demand is being calculated. The service area is the shortest paths tree (Wu *et al.*, 2004) with its root in the current vertex and the condition that the maximum depth of the tree is lower or equal than the maximal value d_{max} . The specific value of d_{max} is a task for further research. There are different views on this in the literature; it may be understood as a reach of an electric vehicle with the lowest reach in the market, or it can be understood as the willingness of drivers to detour to charge their vehicles.

The proposed charging demand model works quite well in the numeric example in most regions, although it has some identified issues. Some of them can be marked as external, since they rely upon the content of data and cannot be easily repaired by the adjustments in the model. Other are internal and may cause distortion of the results. At the moment, these have been identified and their likely causes have been proposed. As the author cannot provide a fix for these drawbacks at the moment, this issue is postponed for future research.

Acknowledgements

This research was supported by project no. FP-J17-4174 – Use of Artificial Intelligence in Entrepreneurship – at the Department of Informatics at the Faculty of Business and Management of Brno University of Technology.

REFERENCES

- AMINI, M. H., KARGARIAN, A. and KARABASOGLU, O. 2016. ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation. *Electric Power Systems Research*, 140: 378–390.
- BAE, S. and KWASINSKI, A. 2012. Spatial and Temporal Model of Electric Vehicle Charging Demand, *IEEE Transactions on Smart Grid*, 3(1): 394–403.
- CAVADAS, J., DE ALMEIDA CORREIA, G. H. and GOUVEIA, J. 2015. A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. *Transportation Research Part E: Logistics and Transportation Review*, 75: 188–201.
- CZECH REPUBLIC. 1997. Zákon 13/1997 Sb. zed ne 23. ledna 1997 o pozemních komunikacích. In: *Sbírka zákonů České republiky*. Částka 3/1997. Available at: <https://portal.gov.cz/app/zakony/zakonPar.jsp?idBiblio=44836&fulltext=13~2F1997&rpp=15#local-content> [Accessed: 24. 8. 2016].
- FAN, Z. 2012. A Distributed Demand Response Algorithm and Its Application to PHEV Charging in Smart Grids. *IEEE Transactions on Smart Grid*, 3(3): 1280–1290.
- GE, S., FENG, L. and LIU, H. 2011. The planning of electric vehicle charging station based on Grid partition method. In: *2011 International Conference on Electrical and Control Engineering*. 16–18 Sept. 2011, Yichang, China.
- GONZÁLEZ, J., ALVARO, R., GAMALLO, C., FUENTES, M., FRAILE-ARDANUY, J., KNAPEN, L. and JANSSENS, D. 2014. Determining Electric Vehicle Charging Point Locations Considering Drivers' Daily Activities. *Procedia Computer Science*, 32: 647–654.
- JAMIAN, J. J., MUSTAFA, M. W., MOKHLIS, H. and BAHARUDIN, M. A. 2014. Simulation study on optimal placement and sizing of Battery Switching Station units using Artificial Bee Colony algorithm. *International Journal of Electrical Power & Energy Systems*, 55: 592–601.
- LAM, A. Y. S., LEUNG, Y. and CHU, Y. 2014. Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions. *IEEE Transactions on Smart Grid*, 5(6): 2846–2856.
- LI, G. and ZHANG, X. 2012. Modelling of Plug-in Hybrid Electric Vehicle Charging Demand in Probabilistic Power Flow Calculations. *IEEE Transactions on Smart Grid*, 3(1): 492–499.
- LIM, S. and KUBY, M. 2010. Heuristic algorithms for siting alternative-fuel stations using the Flow-Refueling Location Model. *European Journal of Operational Research*, 204(1): 51–61.
- MADINA, C., ZAMORA, I. and ZABALA, E. 2016. Methodology for assessing electric vehicle charging infrastructure business models. *Energy Policy*, 89: 284–293.

- MAHESHWARI, P., TAMBAWALA, Y., NUNNA, H. S. V. S. K. and DOOLLA, S. 2014. A Review on Plug-in Electric Vehicles Charging: Standards and Impact on Distribution System. In: *IEEE International Conference on Power Electronics Drives and Energy Systems 2014*, 16–19 Dec. 2014 Mumbai, India.
- PEKÁREK, J. 2015a. A Dynamical Model of the Charging Station Placement Problem. In: *Innovation Vision 2020: From Regional Development Sustainability to Global Economic Growth 25*. Amsterdam, Netherlands: International Business Information Management Association (IBIMA), pp. 2292–2302.
- PEKÁREK, J. 2015b. Determination of Electric Vehicle Charging Demand. In: *Innovation Management and Sustainable Economic Competitive Advantage: From Regional Development to Global Growth 26*. Madrid, Spain: International Business Information Management Association (IBIMA), pp. 1211–1220.
- ROAD AND MOTORWAY DIRECTORATE. 2016a. *Vector data of Czech Republic road network*. Road Database and NDIC Department, Road and Motorway Directorate, Praha, Czech Republic. [Obtained: 10. 12. 2014].
- ROAD AND MOTORWAY DIRECTORATE. 2016b. *National Traffic Survey 2010*. Road and Motorway Directorate in cooperation with the Transport Research Centre, Prague, Czech Republic [Obtained: 10. 7. 2015].
- SEARS, J., GLITMAN, K. and ROBERTS, D. 2014. Forecasting demand of public electric vehicle charging infrastructure. In: *2014 IEEE Conference on Technologies for Sustainability (SusTech)*, Portland, USA, 2014-07-24, pp. 250–254.
- TU, W., LI, Q., FANG, Z., SHAW, S. and ZHOU, B. 2016. Optimizing the locations of electric taxi charging stations: A spatial-temporal demand coverage approach. *Transportation Research Part C: Emerging Technologies*, 65: 172–189.
- U.S. DEPARTMENT OF TRANSPORTATION, FEDERAL HIGHWAY ADMINISTRATION. 2009. *National Household Travel Survey* [Online]. Available at: <http://nhts.ornl.gov> [Accessed: 17. 9. 2016].
- WU, B. Y. and CHAO, K. M. 2004. *Spanning trees and optimization problems*. Boca Raton, FL: Chapman & Hall/CRC.
- YI, Z. and BAUER, P. H. 2016. Optimization models for placement of an energy-aware electric vehicle charging infrastructure, *Transportation Research Part E: Logistics and Transportation Review*, 91: 227–244.
- ZHU, Z., GAO, Z., ZHENG, J. and DU, M. 2016. Charging station location problem of plug-in electric vehicles. *Journal of Transport Geography*, 52: 11–22.