Comparison of Fast Charging and Battery Switching Technologies for Electric Vehicles

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***Abstract*- In this paper the Electric Vehicle (EV) charging demand on quick charge replenishment (QCR), by Fast Charging and Battery Switching, based on Dutch travel pattern is modeled and compared. A comparison between the QCR methods based on number of visits to these facilities and the time of service is obtained. The extra number of batteries to be introduced into the battery switching network is calculated. Using queuing theory the required number of charging points/ switching lanes per quick charge replenishment station is estimated. Based on this the potential peak power requirements of the two methods are obtained.**

***Keywords*- Electric Mobility, Fast Charging, Battery Switching, Queuing theory**

I. Introduction

Electric vehicles are considered the future of transportation and the deployment of EVs is strongly affected by the infrastructure in place. EVs suffer from range limitation compared to the fossil fuel powered vehicles of today due to expensive and heavy batteries and hence charging infrastructure has to be provided to increase the possible utility of them.

Various studies on electric vehicles based on realistic travel behavior have shown the necessity to have quick charge replenishment systems along with slow chargers [1]. The quick charge replenishment (QCR) systems will help solve range anxiety among the EV owners as well as enable long distance travel by quick transfer of energy.

Obvious technology options is fast charging technology, where the battery is charged with high power in short time (50-100 kW DC output power). The high power has significant effects on grid and also can decrease the lifetime of the battery [2]. Another possible technology for QCR station is battery switching technology (also known as battery swapping), where during the serving process the whole battery is replaced by a similar type full battery [3]. To implement the process, standardized batteries and different ownership model of batteries are required.

However a comparison of the grid impacts of the mentioned QCR technologies as well as the cost aspects for the utility and EV owners have not been investigated thoroughly [4]. For instance a single EV plugging into to a fast charge station demands approximately 54 kW of power from the grid. During peak traffic hours if the infrastructure, i.e. the number of serving units, is not planned properly, the demand on the grid and the waiting time to get served would be unreasonably high [5].

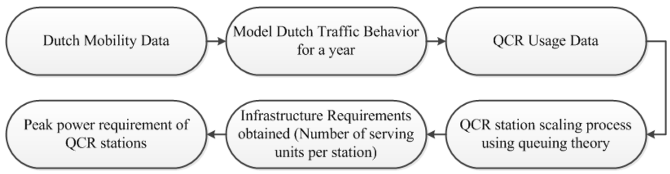

Fig. 1. QCR usage pattern estimation

The aim of this paper is to investigate and compare the QCR technologies. The number of serving units, peak power requirements and in case of battery switching, the extra number of batteries required would be calculated. The methodology described in Fig.1 is used to model the EV behavior and to compare infrastructure requirements and peak power demand of a QCR station

The mobility survey results for Netherlands (MON, 2009) [6] are provided by the Dutch Ministry of Infrastructure and Environment for every year. The data for the year 2009 is used as the reference, since there have been only marginal changes in the mobility of Dutch population since 2003. The results are published as a database with key results for the year and as an online database [7] with data of higher resolution.

The mobility results are used to model the travel patterns of EVs to obtain the demand for QCR. The following information is obtained from the model for QCR – average number of visits to QCR stations per car per year, average time to serve per car, energy share from QCR for mobility and the extra batteries required for battery switching if chosen as the mode of QCR.

QCR stations, like refueling stations of today also would have limited capacity. Queuing theory as a stochastic mathematical method is used to scale QCR stations. Using different charging strategies the minimum number of serving is obtained. This number of serving units is optimized to handle the peak traffic hours. A peak power comparison is made based on this number of serving units between the QCR technologies.

II. Mobility Survey Results

This section describes the mobility patterns analyzed for estimating the grid impacts of Electric Vehicles. The MON, 2009 is the basis for the EV mobility model developed during this work.

The MON survey provides information for researchers and policy makers in the field of transport and mobility of Dutch population. The MON survey analyzes the mobility of the

Dutch population based on responses from a representative set of the population. The major results from MON 2009 are summarized as follows.

TABLE I
MAJOR RESULTS OF MON 2009

Data	Value
Total Dutch Population	16,319,000
Total number of Personal Cars	7,588,000
Total number of households	7,300,000
Average number of Car trips per person per day	0.97
Average distance travelled in car per person per day	16.59 km

The MON results are provided in the form of 'per person per day'. The reason for the same is explained in the database is that the mobility patterns are affected by the level of development of the whole population. For EV simulation we would need the data for each EV. From the above data set the following important parameters can be derived for EVs.

TABLE II
DERIVED RESULTS FOR CARS

Parameter	Value
Persons per Vehicle	2.15
Average number of trips per vehicle per day	2.09
Average distance travelled per vehicle per day	35.67 km
Average Vehicle Trip	17.07 km
Vehicles per Household	1

The parameter persons per vehicle only signify the ratio of number of people in Netherlands to number of personal vehicles in Netherlands. The average number of trips per vehicle and the trip distance per vehicle per day is the most crucial data as unlike any other modeling, the vehicle fleet needs to be modeled using individual vehicles and not as a whole fleet. Without individual vehicle modeling and using the representative trip data for an year the requirement of charging and QCR will follow the average profile we impose on it and will not bring out the many side effects of random trip occurrences.

The trips have been categorized into seven categories by the survey – Commute (Going/Returning from Office), Work Related Trips, Visits/Overnight Stay Trips, Shopping, Education related trips, Recreation Trips and Others. The trip profile for an average data is shown here from the yearly data provided.

This data is quite useful in formulating policy for charging infrastructure development. Policymakers will be able to deploy chargers at the points where the EV users would require them the most resulting in better utilization and more insight about the load distribution for the utilities.

The distribution of trips over time of day data shows clearly that there is a lot of trips during day time and the trips are mostly peaking during 7-9 am in the morning and between in 4-6 pm in the evening. This data correlates well with the traffic profile shown by NHTS of USA [8].

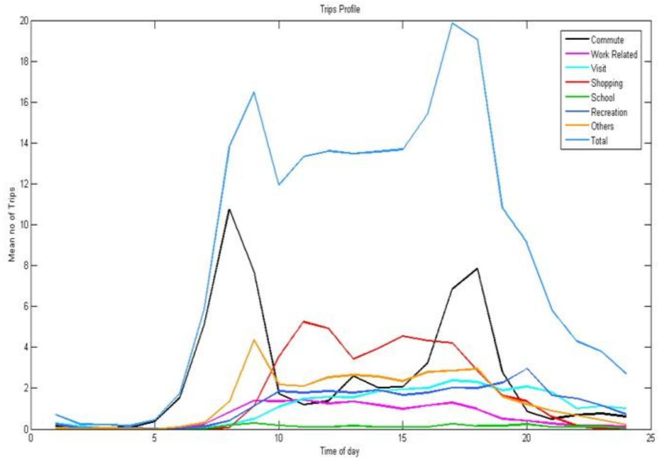

Fig. 2. Average Trip Profile Over a Day by Trip Start Time

The average trip distance for each category can also be estimated from the MON results. The average trip distance for different purposes is estimated using the number of trips and distance covered in each category.

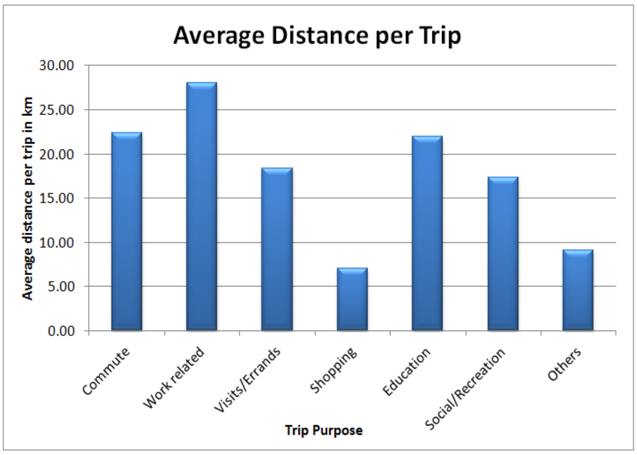

Fig. 3. Average Trip Distance per Purpose.

The MON also shows that 93% of the trips are of duration one hour or less. Since a car performs two trips or one return trip a day, the average parked time of the car is 22 hours every day. This shows the potential to shift the charging time of the EVs to benefit the renewable power integration and for maximizing grid capacity. From the distribution of trip time for a particular trip duration we can estimate the trip speed if the distance is known. This data is used in the model to estimate the travel time of trips.

All the trips are classified according to the trip length and this data provides an insight into the daily usage of vehicles and the corresponding power requirements as well as fast charging needs.

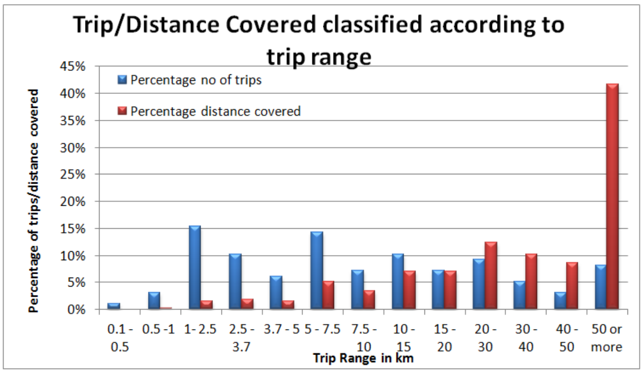

Fig. 4. Percentage of Trips and Total Distance of different ranges.

One of the major data points to be looked at is the distance covered in the '50km or more' category. Even though the number of trips covered is quite small in that category, the distance covered in that category is quite high and consequently the need for fast charging can be quite high with this data set. This data set is corrected using the 2008 MON data analyzed in [9].

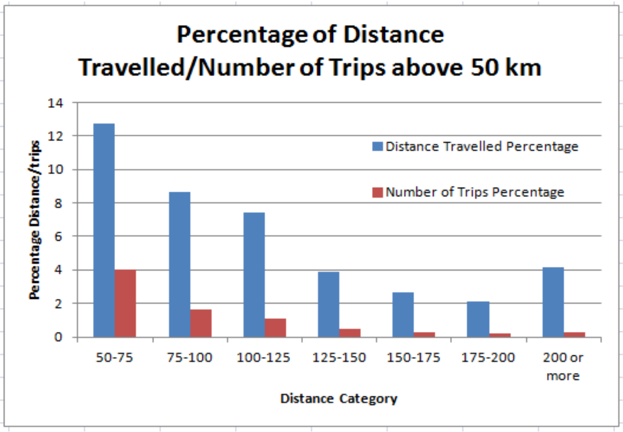

Fig. 5. Percentage of Trips and Total Distance of different ranges.

This distribution is used to calculate the average trip length in each category. The calculated trip distance in each distance range is given by the probability of number of trips in that category and that distribution is maintained for all the trips in a year. To avoid complicated modeling, the distances are assigned the exact values and tolerance is not introduced. The distance profile maintained is shown here.

It should be noted that the total trip distance of the entire fleet will be equal to that of the total distance covered by vehicles in Netherlands with this distribution. These distances are further scaled with the average trip distance for each of the trip purposes mentioned above to get a distance distribution for each purpose while maintaining the overall distance travelled the same.

The seasonal variations in travel patterns has been modeled implicitly in the model as the model uses the percentage distribution of trips for a whole year as provided by the online database of the MON survey.

III. EV FLEET MODELING

Based on the survey results presented in chapter 2, the potential Dutch EV fleet behavior is modeled. In the model 100 cars are used to keep simulation time down and have the results in percentage. In this case the results of the simulation can be extended easily for any number of cars.

The trip scheduling assigns a distance for the trip and based on the availability of the EV selects one vehicle and deducts the energy required from the vehicle and locks it till the return trip is scheduled. Return trip is scheduled along with the original trip based on the estimated activity duration.

The distance is assigned randomly from the distribution calculated using the mobility survey result for that particular purpose and based on the distance assigned the speed is looked up from the look up table. This approach makes sure that the randomness in the trip pattern is maintained for the fleet. The reason the model does not assign fixed patterns to each vehicle is that such an assignment will only bring out an ideal scenario and user parameters are modeled as fixed throughout the year.

The following efficiency values are assumed in the model [9]. The charging efficiency of the battery is modeled based on the results from [10]. The graph showing the efficiency variation is shown in Fig.6.

TABLE III
EFFICIENCY OF VARIOUS EV BLOCKS

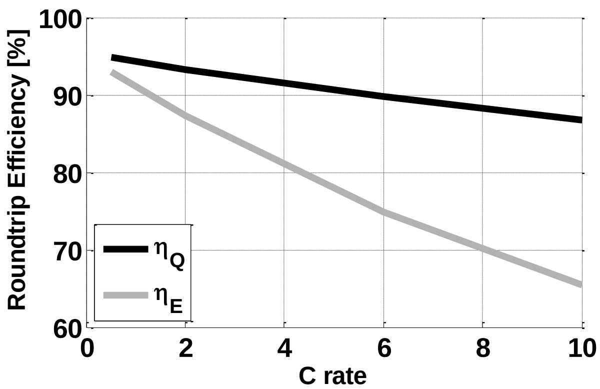

Fig. 6. Energy and Coulombic Efficiency of Li ion Batteries and C rate relation.

Parameter	Value
Energy required to cover one km(at the wheel)	0.15 kWh
Average home charger power consumption	3.6 kW
Average home charger efficiency	95%
Average battery charging efficiency	Based on Fig.6
Drive Train(PE Converters, Motors and Transmission) Efficiency	86.7%
State of charge possible with fast charging	80%
Fast charger power consumption	52.63 kW
Average fast charger efficiency	95%

During the modeling process low voltage charging is enabled at home and work (trips for commute) places. So if the vehicle stops at one of these locations its battery is charged with 3.6 kW. When a vehicle does not have enough energy to cover the next scheduled trip, or if the range is not sufficient to cover the whole journey, QCR is needed to complete the trip. There are two options considered in the model: the fast charging and the battery switching, but only one of them is enabled in a certain simulation. According to the fast charging algorithm if the scheduled destination has a low voltage charging opportunity, only that amount of energy is charged to reach the destination to have cheaper and probably better charging facility for the battery.

There are 19 different scenarios that are defined in the model according to the different range of vehicles. The lowest range is 80 km, while the highest 170 km, and the ranges increasing by 5 km. The important results to be used in queuing theory to estimate the peak power demand and number of serving units are given below.

The average number of visits per vehicle per year is shown for both the QCR methods in the figure below. The average number of visits is always lower for battery switching compared to fast charging since more energy is transferred per switching compared to fast charging.

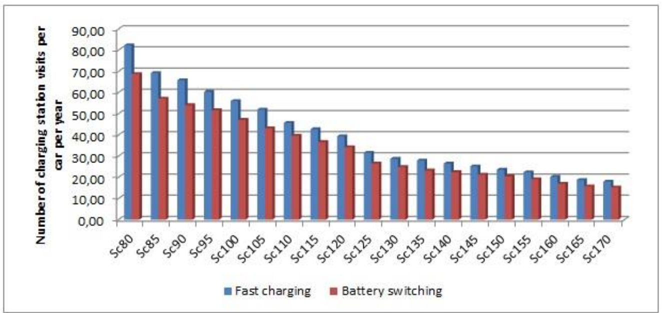

Fig. 7. Number of visits according different QCR technologies and vehicle ranges

The average charging time for fast charging is also obtained and provided later when it is used for estimating the power demand.

Another key result to be considered in the battery switching mode of QCR is the extra number of batteries required for satisfying the travel profile. Each simulation with battery switching was started with 80 percent extra batteries, which equals 80 batteries extra since the simulation includes 100 cars. The following graph shows the amount of batteries that are always full and gives an indication to the extra number of batteries that are never used. At the switch station the batteries are charged at 10.8kW power to obtain the results shown here.

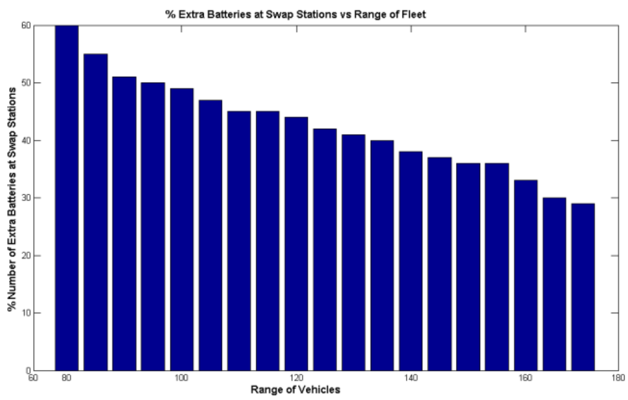

Fig. 8. Extra number of batteries required

In the case of cars of range 160km we can see that only 33 batteries need to be introduces as 47 batteries are always remaining full at the swap stations. With a safety margin of 50% we can recommend to have 50 percent extra batteries for a fleet of range 160 km.

Queuing theory is used to estimate the required number of serving units per QCR station. The results from EV fleet modeling – average number of visits and in case of fast charging average charging time, is used by queuing theory which is described in the following chapter.

IV. QUEUING THEORY

Just as the petrol stations, an electrical charging station has also limited capacity. The charging behavior and load need for a certain vehicle cannot be defined, however taking a large number of vehicles into consideration approximation can be made for the usage of a certain charging station. For the scaling process a stochastic mathematical method, the queuing theory was used [11]. Queuing theory has already been used as a traffic model for the arrival process of telephone calls at a telephone exchange; nowadays it is often used to model generation of internet traffic flows for example [12], [13], [14], or at traffic management [15]. Some papers have already dealt with modeling electric car charging stations with queuing theory ([16], [17], [18], [19], [20], [21], [22]). The paper would like to extend this scope to the investigation of electric car charging station parameters.

[12], [24], [25] and [26] give very good introduction to queuing theory, the most needed parts are cited from them in the following. Among others, a queuing model is characterized by:

1. The arrival process of customers

Usually it can be assumed that the inter-arrival times are independent and have a common distribution. In many practical situations customers arrive according to a Poisson stream [24]. Poisson processes are very important in queuing theory so hereby some of its characteristics are presented briefly. The Poisson process is a continuous-time process, it applies to many cases where a certain event occurs at different points in time. The Poisson process has several important properties, such as [12]:

- Time-homogeneity: every point in time has the same chance of having an occurrence, therefore occurrences are equally likely to happen at all times.
- Inter-arrival times of occurrences are exponentially distributed with parameter λ
- By the memoryless property of the exponential distribution the Poisson process is also memoryless.
- If one would like to model a process as Poisson process they have to determine the scope of this method. Poisson processes can be used if [11]:
- the number of entities is great,
- a single entity has a negligible effect on the system
- entities are independent from each other (time-homogeneity).

The power consumption of one vehicle compared to overall grid consumption is low and the charging of each car is independent from the others, so the charging behavior and the arrival of electric vehicles can be modeled as a Poisson process.

2. The behavior of customers

Are customers willing to wait or leave after a short time? Although this option is not considered here, it is worth mentioning that it is possible with means of queuing theory [24].

3. The service times

It can usually be assumed that the service times are independent and identically distributed and that they are independent from the inter-arrival times [24].

4. The service discipline

There are many possibilities, e.g. first come-first served, random order, last come first served, priorities, etc. [24].

5. The service capacity

The number of serving units is in our case the number of charging points/ switching lanes.

6. The waiting room

There can be limitations with respect to the number of customers in the system [24]. In the case of electric cars this is the number of parking spaces.

After having outlined the characteristics of queuing theory, a simple figure, that would help in understanding the mathematics of the process, is presented. The main characteristics of queuing theory can be summarized using this figure 9.

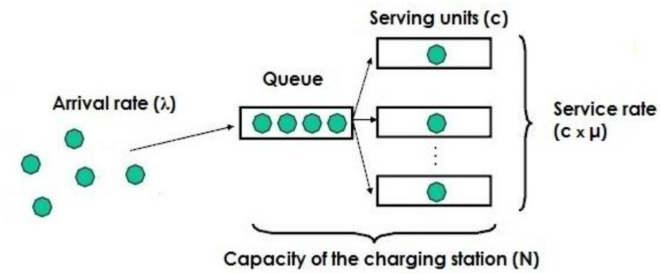

Fig. 9. Main data of queuing theory

The arrival process is usually described by the probabilistic distribution of the intervals between the arriving needs. The reciprocal of the arrival interval is the arrival rate (λ [1/min]), which is usually used in calculations and shows the frequency of arrivals. However, λ can be considered as a function of time: this means that the value of λ can change in every instant, within the certain period it is constant. This can be seen in figure 13. where the daily traffic pattern is presented.

The charging station has a limited capacity (which means that there is a finite number of charging points/switching lanes and even a finite number of parking spaces in a station), so it is more than likely that some customers will have to wait. The aim of paper is to scale a charging station that has an optimal number of charging points/switching lanes and can serve the incoming charging requests. Figure 9. presents that if the number of charging points/switching lanes is not enough, some customers have to wait: they form the queue. Others can have their cars charged. It is obvious that cars are charged in batches, which means that a number of c cars are charged simultaneously, where c denotes the number of charging points/switching lanes (more formally serving units). Just as the arrival rate, the serving of cars also has a rate. The reciprocal of the service time (μ [1/min]) is the service rate, which is usually used in calculations. It shows the number of needs that can be served by the service unit in a certain time.

After the cars have fully charged their batteries, they leave the station, and the next waiting customer can start charging.

A. Description of the stochastic process

The M/M/c/N queuing model was chosen for modeling EV charging. M/M/c/N is a shorthand notation introduced by Kendall that characterizes queuing models [23]. The meaning of each letter is the following [11], [17]:

- The first M: arrival time with exponential distribution
- The second M: serving time with exponential distribution
- c: number of serving units
- N: the capacity of the system, the maximum number of vehicle that can stay at a certain charging station (including the charging vehicles)

The rule of service can also be determined. It defines the way the needs will be served, the order in which they are served, and the way in which resources are divided among them. During the calculation the mostly used FIFO principle (first come first served) was used.

It was seen in the introduction of this section that electric car charging can be modeled as follows: car interarrival times can be taken as exponentially distributed, so can the service times be characterized and the charging process can be modeled as a Poisson-process.

A Poisson-process is an example of a continous-time Markov chain, so properties of Markov chains are used in the following in order to conduct numerical computations. Due to the special structure of the continuous-time Markov chain together with a certain property of the Poisson process PASTA (Poisson Arrivals See Time Averages), simulations of continuous-time Markov-chain models can be simplified [12].

B. Setting up equations for numerical computations

The model used is based on the theory of continuous-time Markov chains and so works as follows: each time the process enters state i, it stays at that state for an amount of time which is exponentially distributed before making a transition into a different state. When the process leaves state i, it enters state j with probability denoted Pij. This walk can be graphed in the state space on the so-called flow diagram [24]:

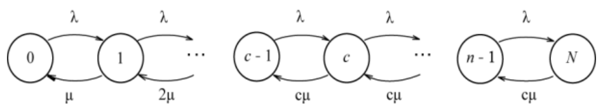

Fig.10. Flow diagram of the M/M/c/N model

The flow diagram shows the transitions from a certain state to another. A fixed inter-arrival time intensity was assumed for a certain time interval, so we write λ on every forward transition, but as more and more cars arrive, they have to be served, so more and more serving units are operated until c (the number of charging points/switching lane) is reached. After this there are no more free serving unit, so the rest of the cars cannot be charged. The serving process is characterized by the backward transitions and it can also be seen that if there are for example (c+2) cars at the station and only one has been served (so we transition to the (c+1)th state), but still only c chargers can be operated, so the charging intensity is still cμ .

From the flow diagram of the model the transition rate matrix A can be constructed (named also as infinitesimal generator of the continuous-time Markov chain [12]). The "From where" states are written in the rows and the "To where" states in the columns, and then the transitioning intensity are written to every corresponding element of the matrix. $\mathbf{A_{ii}} = -\sum_{\mathbf{j \neq i}} \mathbf{A_{ij}}$ must also be satisfied.

$$\underline{\underline{A}} = \begin{bmatrix} -\lambda & \lambda & 0 & 0 & \cdots & & & & & 0 \\ \mu & -(\lambda+\mu) & \lambda & 0 & 0 & \cdots & & & & 0 \\ 0 & 2\mu & -(\lambda+2\mu) & \lambda & 0 & 0 & \cdots & & & 0 \\ 0 & 0 & 3\mu & -(\lambda+3\mu) & \lambda & 0 & 0 & \cdots & & 0 \\ \vdots & & & & & & & & & \\ & & & & \ddots & & & & & \\ & & & & & (c-1)\mu & -(\lambda b_0+(c-1)\mu) & \lambda b_0 & & \\ & & & & & & c\mu & -(\lambda b_1+c\mu) & \lambda b_1 & \\ & & & & & & & c\mu & -(\lambda b_2+c\mu) & \lambda b_2 \\ & & & & & & & & & \ddots \end{bmatrix}$$

Let us illustrate this with an example. From the second state the system can transition forward to the third state with λ intensity, so λ is written in [2,3] (the first number is the row index, the second is the column index of the matrix). The system can also transit backwards to the first state with μ intensity, so μ is written in [2,1]. The sum of the elements in one row of the matrix must equal to 0, so -(λ +μ) has to be written in [2,2]. The matrix can be filled in continuing this method.

In the following few paragraphs the mathematical formalism of calculating the stationary distributions are given [12], [24]. These parameters are needed to determine the indicators of queuing theory. An expressive meaning of the $\boldsymbol{\pi_0}$ stationary distribution can be given though, namely that the system is idle; there is no car that has to be charged. From the transition rate matrix the stationary distributions' row vector π can be obtained by solving the following set of equations:

$$\underline{\underline{A}}^T \cdot \underline{\pi}^T = \underline{0}^T \tag{1}$$

so the nth stationary distribution can be obtained as follows:

$$\pi_n = \pi_0 \frac{\lambda}{n! \cdot \mu^n} \tag{2}$$

and the (n+c)th stationary distribution is

$$\pi_{n+c} = \pi_c \frac{\lambda^n}{c^n \cdot \mu^n} = \frac{\lambda^n}{c^n \cdot \mu^n} \cdot \frac{\left(\frac{\lambda}{\mu}\right)^c}{c!} \tag{3}$$

By considering $\sum_{\mathbf{k=0}}^{\infty} \boldsymbol{\pi_k} = \mathbf{1}$ the stationary distribution $\boldsymbol{\pi_0}$ can be obtained from the above equations [11], [24]:

$$\pi_0 = \frac{1}{\sum_{i=0}^{c} \frac{1}{i!} \cdot \left(\frac{\lambda}{\mu}\right)^i + \sum_{j=c+1}^{N} \frac{1}{c^{j-c}} \cdot \frac{1}{c!} \cdot \left(\frac{\lambda}{\mu}\right)^j} \tag{4}$$

With the stationary distributions the mean queue length, mean waiting times, the number of required charging sockets, etc. can be calculated as depicted in subsection C.).

C. *Indicators of the queuing theory*

The efficiency and performance of a queuing system can be measured by the following indicators [25], [26] (we have already introduced some of them in subsection A):

1) *Utilization efficiency [Ue]:* Utilization efficiency, also known as traffic intensity, describes whether the service units are able to handle the arrival needs or not. The utilization efficiency can be defined as following:

$$U_e = \lambda / (c * \mu) \tag{5}$$

If Ue >1, the incoming needs are arriving faster than the service process could serve them. The aim is to determine utilization efficiency to calculate the minimum number of service units which is capable to serve the certain arrival rate. In the case when the number of serving units (c) is contained in the following formulas, the utilization efficiency is going to be denoted as 'a' and used in the calculations as follows

$$a = \lambda / \mu \tag{6}$$

2) *Average queue length [N(s)]*: The average queue length defines the average number of needs waiting in the queue:

$$N(s) = \frac{\pi_0 \times a^{c+1}}{c! \times c} \times \left[\frac{1}{\left(1 - \frac{a}{c}\right)^2} \right] \tag{7}$$

, where $\boldsymbol{\pi_0}$ is the probability that there is no need in the system, which was described in (4).

In the following figure the average queue length can be seen as a function of serving unit number for 125km range scenario in aim to illustrate the c dependence of this indicator. There are 3 different cases within the scenario according to the charging technology and strategy, which are going to be defined in Section V.

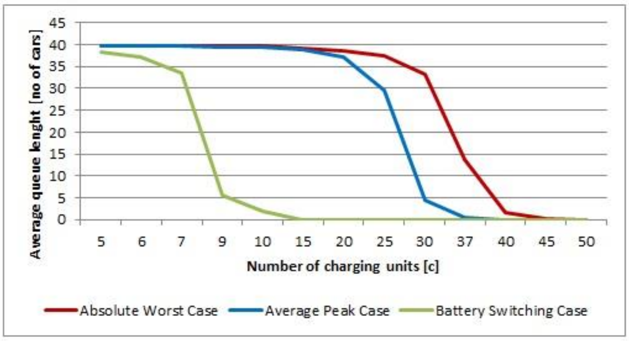

Fig. 11. Average queue length as a function of serving unit number

It is clear from the figure that after a certain point there is no reason to further increase the number serving units, because it has no beneficial effect on the queue length. Queue length 40 is the supremum of the average queue lenght because the capacity of the charging station is set to 40.

3) *Average number of vehicles in the system [N(r)]:* The average number of vehicles in the system metric defines the sum of charging and waiting needs in the system.

$$N(r) = a + N(s) \tag{9}$$

4) *Average time spent in the system [T(v)]:* The sum of serving time and waiting time.

$$T(v) = N(r) / \lambda \tag{10}$$

5) *Average waiting time in the queue [T(vs)]:* The average time waited to start charging for those needs that has already arrived in the system but cannot be served immediately.

$$T(vs) = T(v) - (1 / \mu) \tag{11}$$

In the following figure the Average waiting time can be seen as a function of serving unit number also for 125km range. During the calculation the goal was to decrease the average waiting below than 10 minutes.

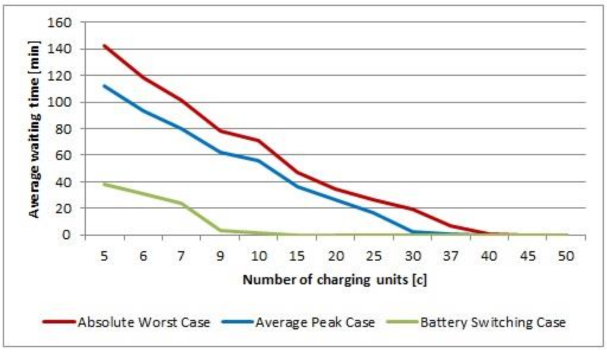

Fig. 12. Average waiting time as a function of serving unit number

V. Initial Data of the Scaling Process

A. Used number of EVs and QCR stations

In 2009, the Dutch government announced its ambition for the Netherlands to become a guiding country and international learning environment for electric mobility. A prognosis and action plan was drawn up by transport minister, who expects 1,000,000 electric cars on the Dutch roads until 2025 [27].

In 2012, estimation was made by a Dutch company (The New Motion) that the Netherlands can be covered by 100 fast charging points to aim to extend the range of electric vehicles. The key idea is to have fast charging replenishment in every 50 km radius next to highways [28].

These EV and QCR station numbers are used during the calculation.

TABLE IV
Used number of EVs and QCR stations

The estimated number of BEVs in the Netherlands until 2025	1,000,000
Number of QCR station	100

Using the results of the mobility analysis (the number of QCR station visits per car per year and the average fast charging time data) the two main indicators of queuing theory were estimated as follows.

B. Arrival rate

The arrival rate estimation is based on the number of QCR station results per car per year as shown in Fig: 7.

Vehicles with higher range can cover more distance with a single charge and need less number of visits by a charging station. It can be seen from the figure that the number of visits belongs to fast charging technology remains higher during the whole pattern. This is because lower energy (until SOC 85%) can be charged by a single visit by fast charging technology and these vehicles need to go more often to recharge during a trip.

The distribution of these visits is determined by the charging behavior of car owners during the day, which cannot be considered as steady. This distribution of the arrivals, according to the daily traffic pattern, for a certain charging station (e.g.: next to the highway) can be modeled as follows:

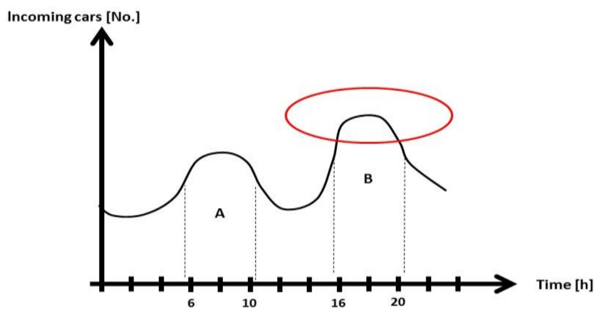

Fig. 13. Daily charging pattern of a certain QCR station based on daily traffic pattern

It can be seen from the figure that the usage of a charging station is concentrated on two certain interval (shown as A and B). 80 % of the visits are realized in these two intervals, in a share of 1/3 and 2/3 respectively. By the scaling process of a QCR station, the number of serving points is usually scaled to be able the handle maximum number of incoming cars. According to this in the model the arrival rate is determined from the evening peak (B).

The investigation of the localization of the charging station is not part of this paper, so the distribution of the vehicles is steady, which means every QCR station needs to serve 10,000 cars.

C. Service rate

There were three different charging strategy cases defined during the investigation depending on the technology itself and used charging strategy as follows:

1) Fast charging-Absolute Worst Case: the aim is to model the maximum usage and energy need, which could ever occur in a fast charging station by charging full energy for each incoming car in the evening peak. It means that the maximum energy (using the highest amount of charging time) is charged from the minimum driving reserved range (10 km) SOC to SOC 80%.

2) Fast charging-Average Peak Case: the aim is to model the average energy consumption for a certain fast charging station in the evening peak. The average charging times are based on the mobility analysis. In the following figure the charging time difference between the two Fast Charging cases can be seen.

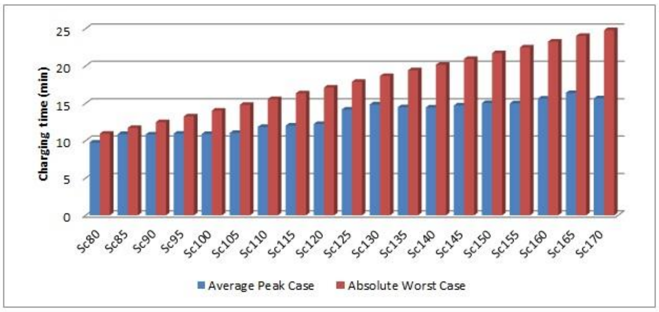

Fig. 14. Charging time according the different fast charging strategies and vehicle ranges

3) Battery Switching Case: the serving time is steady, which only depends on the technological process of changing the battery (5 min). The changed battery is always full.

The time spent for recharging (charging time or service time) is significantly different for each case, and has fundamental effects on the queuing theory. The service rate, which indicates how many cars can be served in a certain time, is reciprocal of the charging time and this indicator is used in the queuing theory.

VI. Determining the Required Number of Serving Units per Station

The serving unit can be defined as plug-in point at fast charging technology, and battery switching unit for battery switching technology. The minimum number of charging points is calculated by iteration, determining the utilization efficiency, so the minimum c is required to solve the following inequality.

$$U_e = \lambda / (c \times \mu) < 1 \quad (12)$$

Considering the consumers behavior optimization process was needed to optimize the permeability of these charging stations. 10 minutes was considered as an acceptable average waiting in a queue. This is the time that the driver is probably willing to wait before charging. During this optimization process the goal is to decrease the average waiting time by increasing the number of serving units per station.

Although decreasing process can be seen for all three cases, the way of reducing is significantly different by charging technologies and strategies. Vehicles with higher range need less number of visits per year and it decreases the incoming car density per station (arrival rate), so lower number of serving units can handle the fast charging needs by higher vehicle ranges.

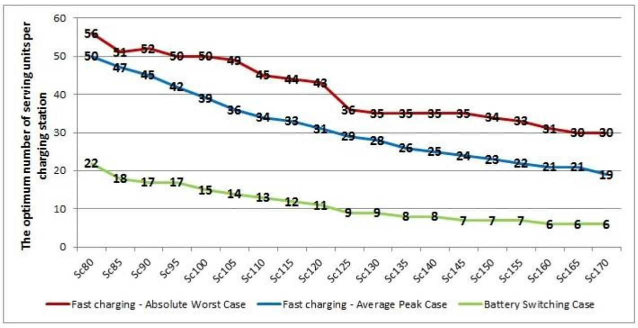

Fig. 15. The optimum number of serving units for all cases

In Absolute Worst Case the battery is charged fully during every visit in the peak hours, which means the serving units, are used for longer time per one car and the incoming car density is high. To handle this situation the highest number of serving units is required in Absolute Worst Case. As the number of visits pattern fell at Sc125, the same drop can be recognized at the number of serving units trend too.

Significantly lower required number of serving units can be seen in Average Peak Case. Arrival rates for this case are the same as for Absolute Worst Case, but the time spent with recharging is considerably lower. It means that one serving unit can serve more cars in a certain time, and the whole station can handle the same traffic behavior with lower number of serving units. The difference between the two fast charging cases could be more than 10 serving units. In contrast the previous trend there is no drop of fall, the pattern decreases steadily. This caused by the average charging time trend has a big step at the same scenario (Sc125) as where the arrival rate pattern has a drop. It balances the number of serving units trend. The trend follows the expected behavior.

Almost third of the number of serving units is needed in Battery Switching Case. The incoming car density is slightly the same as for fast charging technology, but the serving time is significantly lower (5 min), which can result that same traffic behavior can be handled with less number of serving units.

During optimization process maximum 3 extra serving units were added for the charging station to keep the queuing time less than 10 minutes.

VII. ESTIMATING THE POWER REQUIREMENTS

These numbers are presenting the power requirements per fast charging station at the same time in evening peak for both charging strategies (see the figure below), and power requirement for battery switching station if the changed batteries are needed as soon as possible and starting be recharged immediately (uncontrolled and high power charging) to be ready deployed in the next hour. The power numbers are from the grid side, including the charger efficiency of 52.63kW (50 kW output) fast chargers for each case, calculating with the optimum number of serving units.

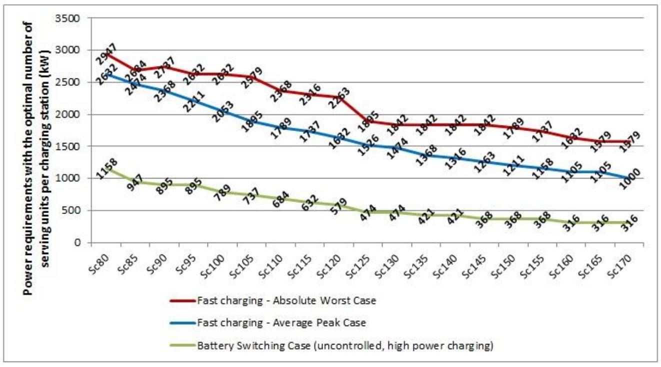

Fig. 16. Power requirements with the optimal number of serving units per charging station

While the power requirement of a certain charging station only depends on the number of serving units used at the same time, the power requirement trends follows the previously presented Number of serving units trends.

As it can be seen the maximum power of Absolute Worst Case by fast charging technology can exceed the 2.9 MW per a single station at lowest vehicle range, and still remains over 1.5MW. The power requirements are lower in the Average Peak Case, but are still between 1-2.6 MW range. The peak power demand for Fast Charging stations requires a connection to the medium voltage grid instead of low voltage grid.

The result of Battery Switching Case shows the worst case scenario, which can ever happen at a battery switching station. All batteries need to be recharged as soon as possible so full power (50kW DC output fast charger) charging strategy is used. Even if the absolute worst scenario is used by the battery switching technology the all power results are third of the average power number of fast charging technology.

It should be noted that the big advantage of the battery switching station is that the charging processes can be shifted in time and can be controlled, even more overnight or green (charging when more energy is available and it is needed) charging strategies or just simply storing more battery at the station, can significantly optimize the power requirement of a battery switching station.

In the future the charging power at fast charging stations is poised to increase. In the following figure we can see the number of serving units as a function of charging power. While the charging power increases the time spent for charging and the number of serving units significantly decreases, the peak power requirements of the charging station only slightly increases. Hence if the batteries can be charged at higher powers the cost of Fast charging stations will reduce without having any additional impact on the grid. It has to be noted that with higher power charging process the battery charging efficiency slightly decreases.

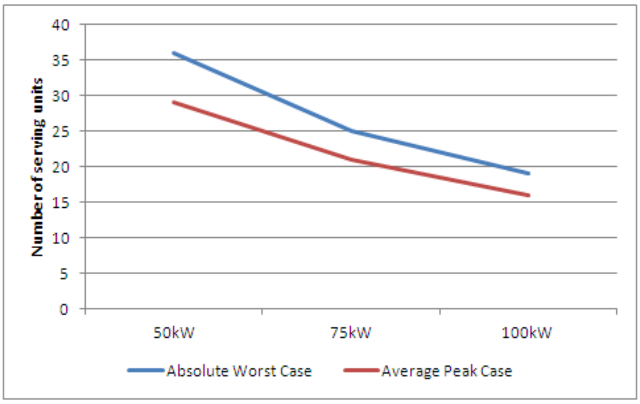

Fig. 17. Number of serving units as a function of charging power for Sc125

VIII. CONCLUSIONS

The Quick Charge Replenishment Infrastructure requirements and grid impacts are the main focus of the study.

Depending on the range of the EV fleet, the required number of charging points/ switching lanes can be significantly different. The power requirements of these public charging stations hardly depend on the required number of serving units and the used charging strategy, as it was described. DC fast charging technology can represent huge charging loads in rush hours, but with suitable grid installation conditions they could be handled. If the EV batteries of the future can handle higher charging powers, the number of serving units and time of charging can decrease while not causing additional stress on the grid.

Battery switching technology, with the possibility to change the charging strategy (time of charging, rate of charging), means it is more beneficial to the grid. The battery switching method requires lesser number of serving units and does not put as much stress on the grid as fast charging. Another benefit of using battery switching is that the capacity of concentrated EV batteries could be used for grid regulation. The extra number of batteries required is directly dependent on the range of the fleet and for a fleet of range 160 km we only need to introduce 50 percent extra batteries into the system.

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