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Evaluating Fast Charging of Electric Vehicles Along Motorways Using Finite Multi-Server Queueing System Simulation

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Abstract Fast DC charging sites are required along motorways to abrogate the car drivers' anxiety of long-distance travels when driving electric vehicles (EVs) with batteries optimised for efficient average reach. This is important to facilitate the mobility transition to EVs. In this study, a queueing model-based approach to simulate and evaluate fast charging sites equipped with many DC charging points is presented. Charging sites are modelled as multi-server queueing systems with finite waiting space, where the servers represent the charging points and the waiting space the parking area available for EVs waiting for service. To evaluate also arrival and service time distributions that are non-Markovian, the queueing system is evaluated using event based simulation. Exemplary results and a comparison with analogous simulation tools complete the presentation of the simulation approach.
On one hand, the simulation reveals the mean potential waiting time per EV before charging can start due to the temporary occupation of all charging points. On the other hand, the tool analyses the aggregated power demand of all charging points. Based on latter, the smart charging mechanism reduces dynamically the individually available charging power if needed to stay below the power grid access limit. This smart charging mechanism causes a small decline in the charging performance at high EV traffic loads when all charging points are maximally occupied. In combination with the state-of-charge depending power demand, the tool provides the user critical insights into realistically expectable waiting times and decreased charging volumes when many EVs charge in parallel. Experimenting with different number of charging points and grid power limitations helps the tool-user, the systems designer, to dimension charging sites along motorways that can efficiently handle future traffic loads.

Keywords: Fast Charging, Smart Charging, Charging Sites, Event-based Simulation, Power Histograms.

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Оцінка швидкої зарядки електромобілів вздовж автомагістралей за допомогою моделювання скінченної багатосерверної системи масового обслуговування

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Анотація. Швидкі зарядні станції постійного струму необхідні вздовж автомагістралей, щоб позбавити занепокоєння водіїв щодо поїздок на великі відстані на електромобілях з батареями, оптимізованими для ефективного середнього запасу ходу. Це важливо для подальшого сприяння переходу на електромобілі. У цьому дослідженні представлено підхід на основі моделі черг для моделювання та оцінки майданчиків швидкої зарядки, обладнаних багатьма зарядними пунктами постійного струму. Зарядні станції моделюються як багатосерверні системи масового обслуговування з обмеженим простором очікування, де сервери представляють пункти зарядки, а простір очікування-паркувальну зону, доступну для електромобілів, які очікують на обслуговування. Щоб оцінити також розподіл часу прибуття та обслуговування, який не є марковським, система масового обслуговування оцінюється за допомогою імітаційного моделювання на основі подій. Прикладні результати та порівняння з аналогічними інструментами моделювання завершують презентацію підходу до моделювання. З одного боку, симуляція демонструє середній потенційний час очікування електромобіля до початку заряджання через тимчасову зайнятість усіх зарядних точок. З іншого боку, інструмент аналізує сукупний попит на електроенергію усіх зарядних станцій. На основі останнього, механізм розумної зарядки динамічно зменшує індивідуально доступну потужність зарядки, щоб вона не перевищувала ліміт доступу до електромережі. Цей інтелектуальний механізм призводить до зниження продуктивності зарядки при високому навантаженні трафіку електромобілів, коли всі зарядні точки зайняті. У поєднанні з потребою в енергії, що залежить від стану заряду, інструмент надає користувачеві критично важливу інформацію про реалістично очікуваний час очікування та зменшення обсягів заряджання, коли багато електромобілів заряджаються паралельно. Експерименти з різною кількістю точок зарядки та обмеженнями потужності мережі допомагають користувачеві інструменту та проектувальнику системи визначити розміри зарядних майданчиків уздовж автомагістралей, які зможуть ефективно впоратися з майбутнім транспортним навантаженням.

Ключові слова: швидка зарядка, розумна зарядка, зарядні станції, моделювання на основі подій, гістограми потужності.

Introduction. To significantly reduce greenhouse gas emissions in the mobility sector and thereby mitigate climate change (Erbach 2024), the transition to electric vehicles (EVs) appears imperative (Tang 2023). EV sales rise steeply and reached 20% or more in many markets, often supported by governmental incentives. Overcoming the range limitations of current EV technology with larger batteries is probably neither efficient nor sustainable because for the majority of distances travelled (Eurostat 2021), the extra weight and cost are not required. Still, for the occasional longer-distance travel, recharging needs to be integrated into the travel planning if recharging opportunities are scarce and recharging occurs comparably slow. To be reliable, a robust, freely accessible, and trusted fast charging infrastructure is required especially along motorways (EUR-Lex 2023) to ensure that travel remains convenient and time-efficient, and to alleviate the common range anxiety among non-EV users.

Recent literature covers mostly the deployment of a distributed AC charging infrastructure in residential areas (Huang 2023, Jansson 2022). Research results on the integration of fast direct current (DC) charging along motorways, where fast charging is most needed, are hardly found and often very complex, as in (Witt 2023). Yet, some companies plan recharging sites with megawatt grid access needs. Are the thereby triggered grid expansions really necessary, or can smart charging considerably reduce the required grid access needs? The answer to this research question depends heavily on the actual EV traffic load expected and the dynamics of fast EV charging (Witt 2023). In addition to the technical and economic challenges of installing and operating such charging sites, also the impact on the electric grid shall be encompassed (Lee 2019).

This research is grounded in the imperative necessity to address climate change through the transition to a sustainable transport sector, in which the strategic shift towards EVs is a critical element (Erbach 2024). As the global automotive market gradually shifts away from fossil-fuelled combustion engines, the establishment of a comprehensive charging infrastructure becomes paramount (EUR-Lex 2023). For an economic deployment, the designers of these infrastructures, the systems engineers, need to anticipate future demands, and cannot cater to the immediate needs of today's EV users only.

This research ventures beyond the common discourse on distributed AC charging solutions at home and at work, which are needed because these cover the vast majority of the recharging events (IEA 2024). The EV adoption is not solely an economic issue, the anxiety concerning the occasional long-distance travel needs to be solved equally for broad acceptance (Sirapa 2022). Delving into the realm of high-capacity, fast-charging sites capable of supporting long-distance EV travel raises other issues, in particular regional grid access limitations (Csanyi 2018). It is therefore critical to assess the potential of smart charging solutions to mitigate the impact on the electrical grid, thereby avoiding or at least postponing extensive and costly grid upgrades (Rahila 2024). The focal point of the presented simulation tool and exemplary study resides in the elaboration of efficient and effective DC charging sites along motorways, pivotal for overcoming the notable barriers to EV adoption, such as range anxiety and long recharging times (Sirapa 2022).

Exploring the interrelation of fast and smart charging technologies, the study adopts a methodology from the telecommunications sector employing event-based simulation and queueing theory (Yang 2018) to efficiently model the dynamics of smart and fast charging sites. This approach offers fresh insights into optimizing charging site performance, managing the actual power demand, and an effective step-by-step expansion path for high-capacity charging sites. In essence, this investigation not only highlights the technical and logistical challenges inherent in the deployment of a high-capacity DC charging infrastructure but also situates these challenges within the larger context of the electricity distribution grid, the complex energy system as a whole, urban planning, and environmental policymaking. By providing a detailed analysis of the requirements and impacts of DC charging sites, the study seeks to inform a wide range of stakeholders, from policymakers to industry leaders, thereby supporting the collective move towards a more sustainable, electrified future.

The purpose that triggered the development of the simulation tool is the need to accurately assess the performance and grid impact of modern DC charging and to use this information for the design of efficient DC charging infrastructures (charging sites) along motorways. The R&D aim is to balance the EV serving capacity and the power demand challenge, ensuring that future EV charging sites, yet planned and soon deployed, deliver efficient, reliable service without overburdening the electrical grid. Through simulation, this study seeks to support the development of smart charging strategies that achieve scalable, sustainable solutions for the mobility transition to a low-carbon mobility future, which requires the rapid integration of a steeply rising number of EVs into the transportation network every day.

The primary research objective is to simulate charging sites with any number of DC charging points considering:

- the dynamic, state-of-charge dependent power demand of DC charging,
- the dynamic charging power limits introduced by smart charging technology,
- visualising the statistical results in publishable quality as scalable vector graphics for increasing traffic loads,
- saving complete scenarios including set parameters in txt and XML format together with all statistical results in CSV and graphical format in a single zip-file for research documentation and open data support.

State-of-the-art and analogous simulation tools. The *Electric Vehicle Queueing Simulation* designed by Ken Lau in 2017 (Lau 2017), is a visualization tool created to model and analyse the traffic intensity at electric vehicle charging stations. It calculates waiting times based on car arrival rates and charging speeds, assuming a Poisson process for the randomised arrivals and negative exponential distributed charging times. The tool users can adjust parameters like mean arrival rate, charging rate, and the number of charging points, to study their effects on key performance indicators such as queue lengths and waiting times. The simulation of this M/M/n queueing system serves as a valuable tool for understanding and optimizing charging station throughput and customer waiting times. However, the electric load and the charging performance are not evaluated, and other than Markovian arrival and service distributions cannot be chosen to better approximate a more realistic charging time distribution.

The C++ simulation of a multi-server queueing system, made public available on GitHub by Zedrex in 2021 (Kabeer 2021), leverages an event-driven approach for efficiently managing customer flows. By simulating customer arrivals, service processes, and departures across multiple servers, it adeptly mimics real-world queuing scenarios. It uses an exponential distribution for generating random inter-arrival and service times, reflecting real-world unpredictability by assuming a memory-less distribution process. Customers are queued and served based on server availability, with the system tracking each customer's journey from arrival to departure. Key methods include event scheduling, handling arrivals/departures, and statistical logging for analysis. This setup allows for detailed insights into queuing dynamics and server efficiency, although it simplifies real-world complexities and relies on an exponential distribution of both, the arrival and the service process.

The *Queueing Simulation* tool implemented in Java and published in open source by Adnan Ansari 2019 (Ansari 2019), aims to model the process of car servicing with two service types: one assumed for Sedans and another for SUVs. It aims to model the process of servicing different EVs (Sedans and SUVs) using a queuing system, where the inter-arrival time and the two service time distributions can be specified by any number of discrete probability densities, which allows it to mimic measured distributions. The main objective is to analyse the performance of the EV service centre (charging site), i.e., average waiting probability and time as well as server utilisation, to assess the efficiency of the configured service resources. The two servers are assumed to have their own queues and are predestined to serve the assigned clients, Sedans or SUVs. However, if the according server is busy and the other server is idle, the over server also serves EVs of the other type. Still, the individual queues are filled with the assigned EV type only. This simulation tool allows to determine key performance indicators of the service and helps to improve service processes, reduce waiting time for customers and optimise the utilisation of resources. On the downside, to evaluate the performance over increasing load (arrival rate over service rate) the distribution definitions need to be accordingly adjusted in the source code. Without prior calculation, the simulated load is difficult to predict and similarly to compose curves over increasing load.

A different approach is commonly taken when analysing the impact of EV charging on electricity distribution and supply. Most studies rely on real-world data and model all EV charging throughout a whole region, based on modelled, assumed, or empiric driving patterns for rural and urban residents. These studies need to include charging at the owners' premises and at long-term parking spaces, where most charging events occur, and where AC charging suffices because speed is at these locations of minor relevance. These studies, e.g. (Witt 2023), (Grigorev 2021), and (Yang 2021), focus on the impact of electric vehicles (EVs) on the regional electricity supply, with considerations ranging from traffic congestion to the dynamics of the EV charging demand. Grigorev and colleagues explore how EVs could influence traffic congestion and energy consumption through an integrated modelling approach, revealing potential shifts in urban mobility patterns (Grigorev 2021). Witt’s research utilizes real traffic data and discrete event-based simulation to determine the required number of charging stations along a German motorway, providing essential insights for infrastructure planning (Witt 2023). Meanwhile, Yang and co-authors offer a dynamic model for the real-time management of a system of EV fast-charging stations, addressing the challenges of meeting EV charging demand without overburdening the electrical grid (Yang 2021). Each study assumes varying degrees of smart charging control, underscoring the critical role of intelligent charging strategies in harmonizing EV integration with existing electricity networks.

The simulation tool and study closest in its aim to the customised tool developed for the R&D project *eAlloc* (eAlloc 2021), is the tool presented in (Witt 2023). However, the reported results are only mean values, lacking confidence intervals and variance to be convincing. To learn about the system behaviour at different loads the simulation needs to be repeatedly executed and separately visualised with the help of some extra software tool.

Finite multi-server queueing system simulation. The simulation developed in Java models charging sites as finite multi-server queueing systems (Kleinrock 1975) as depicted in Figure 1. A dedicated number of charging points and limited waiting (parking) space determine the site configuration.

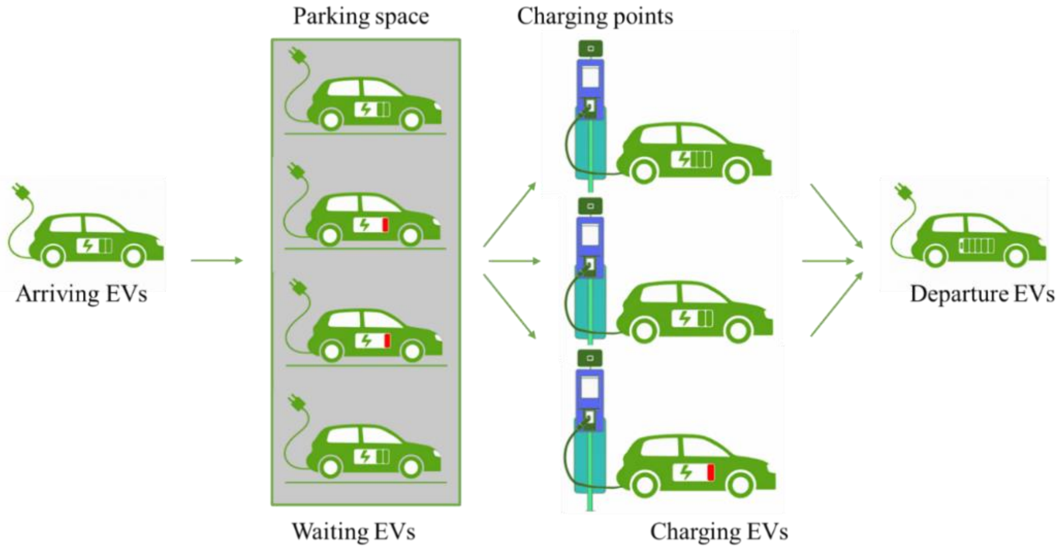


Figure 1. Finite multi-server queueing system modelling a charging site with three charging points and waiting space for four EVs

Markov processes, renowned for their memoryless property, offer a solid foundation for the analysis of queueing systems. This distinctive feature ensures that the future state of a system is determined solely by its current state, rather than the sequence of events leading up to it. When applied to EV charging stations, this principle states that the arrival of vehicles and their respective charging duration are both independent memoryless processes. This simplification aids in the analysis yet effectively captures the core dynamics of people's arrival and queueing behaviour.

Utilizing the theory of Markov processes to model the queuing system for EV charging involves defining the system's states based on the number of EVs either charging or awaiting charge. Transitions between these states are governed by probabilities, i.e., the intensity of EV arrivals and the times spent for charging. Such a methodical approach enables the examination of the queueing system's dynamics, thereby facilitating the identification of an optimal design. This modelling technique simplifies stochastic dynamics into manageable mean values and variances, making it easier to analyse and optimize the operation of for example EV charging sites.

For memoryless (Markovian) arrival processes and independent (also Markovian) charging durations, the state probabilities P*i* of such a queueing system can be calculated analytically. These systems are composed of n charging points and (*N*-*n*) places for EVs to wait, as shown in Figure 2.

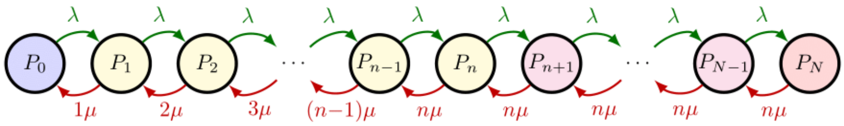


Figure 2. State-transition diagram

In Kendall's notation, this is an M/M/n/N system: the first "M" denotes that the arrivals result from a Poisson process with negative exponential distributed inter-arrival times (memoryless), the second "M" indicates that the service times are also negative exponentially distributed (also memoryless), n represents the number of servers (charging points in this context), and N is the total system capacity, including both charging points and waiting space. Thus, an M/M/5/15 system can accommodate up to 15 EVs at once, with 5 being charged and 10 waiting. If all waiting places are occupied, arriving EVs are deflected (blocked), i.e., are assumed to continue to an alternative charging site.

The theory of queueing systems has become popular with the advent of information and communication technology (ICT) to predict system occupation and client waiting times. However, the theory intensely studied by L. Kleinrock in (Kleinrock 1979, Liu 2021), can be applied to many similar systems where clients arrive, occupy a resource, and after some time leave the system. Based on this theory, the mean number of waiting clients equals the sum of the probabilities that the system is in a waiting state multiplied by the number of clients waiting in each state. *Little's law* E{N} = λ·E{T} yields that the average waiting time T_{wait} equals the mean number of waiting clients divided by the arrival rate λ, as shown in equation (1). Summing over all waiting state probabilities $P_{i>n}$ yields the waiting probability P_{wait}, as shown in equation (2).

$$T_{wait}^{M/M/n/N} = \frac{1}{\lambda}\sum_{i=n+1}^{N}(i-n)\,P_i^{M/M/n/N} \tag{1}$$

$$P_{wait}^{M/M/n/N} = \sum_{i=n+1}^{N} P_i^{M/M/n/N} \tag{2}$$

The individual state probabilities $P_i^{M/M/n/N}$ can be calculated by solving the following equation system:

$$P_i|_{i=1}^{5} = \frac{1}{i!}\frac{\lambda^i}{\mu^i}P_0 = \frac{\rho^i}{i!}P_0 \tag{3}$$

$$P_i|_{i=6}^{15} = \frac{\rho^i}{n!\cdot n^{i-n}}P_0 \tag{4}$$

$$P_0 = 1 - \sum_{i=1}^{15} P_i \tag{5}$$

where the load factor $\rho = \frac{\lambda}{n\mu}$ is introduced, and equation (5) states that the system needs to be in one of the possible states at all times, i.e., $\sum P_i = 1$.

We use equation (1) later on with the presented results to calculate the waiting time of an equivalent M/M/n/N queueing system depicted as narrow black curve. Comparing the simulated waiting time with that calculated for the Markovian system reveals the impact of the actually used distributions compared to the memoryless system that can be analytically solved. Figure 3 proves that the calculated waiting time equals the result of the simulation if we simulate the Markovian system where both, the inter-arrival and the service times are negative exponential distributed.

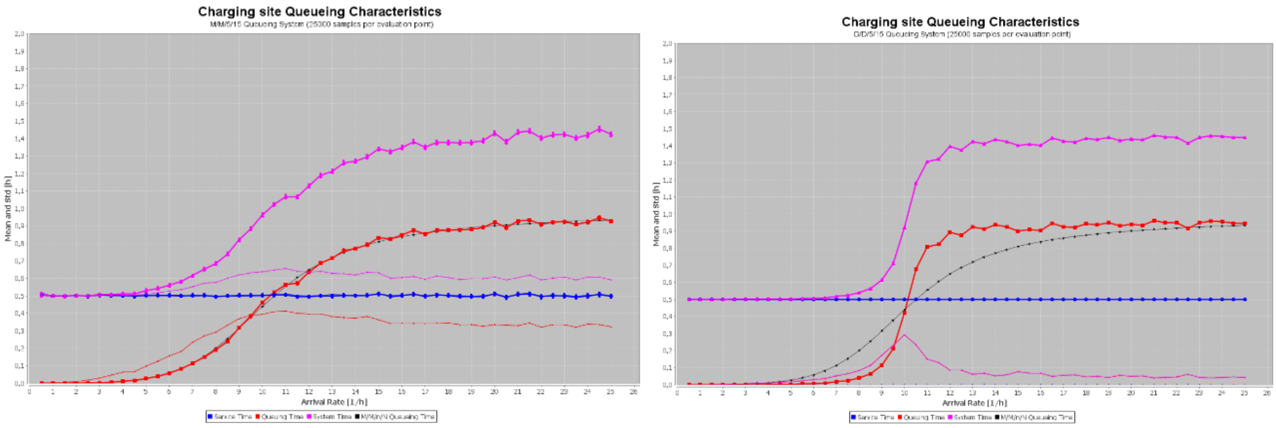


Figure 3. Waiting time over EV arrival rate for M/M/5/15 and U/D/5/15 queueing system

The results for the M/M/5/15 queueing system shown on the left in Figure 3, prove that the statistically derived waiting times (red curve) achieved from simulating the queueing system outlined in the next section equal the waiting times calculated analytically (narrow black curve) using equation (1). The results on the right side in Figure 3 show that for uniformly distributed arrivals (equally probable inter-arrival times between zero and twice the mean) and deterministic service times (all equal), i.e., a U/D/5/15 queueing system, the performance up to the critical load is better, but much worse if the traffic load exceeds the total service capacity (nμ). This example shows that the analytic approach is not always feasible and the simulation of the queueing system is more versatile in the case that the inter-arrival and service time distributions are known and do not fulfil the memoryless property required to be Markovian.

Charging site analysis based on simulation. EVs are assumed to arrive with negative-exponentially distributed inter-arrival times, which models the independent arrivals of vehicles to a charging site. Considering the typical similarity of charging times (service time), which results from the commonly faster charging possibility of larger batteries, we assume the service time to be Erlang-2 distributed. The charging demand is assumed to be Beta distributed between 0% and 100% of the battery capacity, assuming a mean state of charge (SoC) when EVs arrive at the charging site between 10% and 30% SoC. Figure 4 depicts the analytically calculated characteristic probability density function (pdf) of these distribution functions as red lines and the histograms of the generated random samples via blue bars.

The EV charging time is in general not negative exponential distributed but peaks at some rather short duration between 15 minutes and one hour, as shown in the presentation in (Lau 2017). This can be approximated with an embedded Markov chain and solved analytically, but easier and applicable for any distribution is the simulation of the queueing system using the event-based simulation technique. This enables the analysis of general G/G/n/N queueing systems (for any inter-arrival and service time distribution that can be generated) and in addition, to directly evaluate also the dynamic interactions among decreasing charging power demand (the SoC dependence) and smart charging (dynamic power limit adjustments) at the charging site. This involves considering the fast-charging curve of EVs, which is not constant, in particular not when the SoC rises above 80% (Witt 2023). Key metrics of the individual charging and the aggregated electricity grid load are recorded, analysed and visualised to reveal the charging site's performance as exemplarily shown in the results presented next.

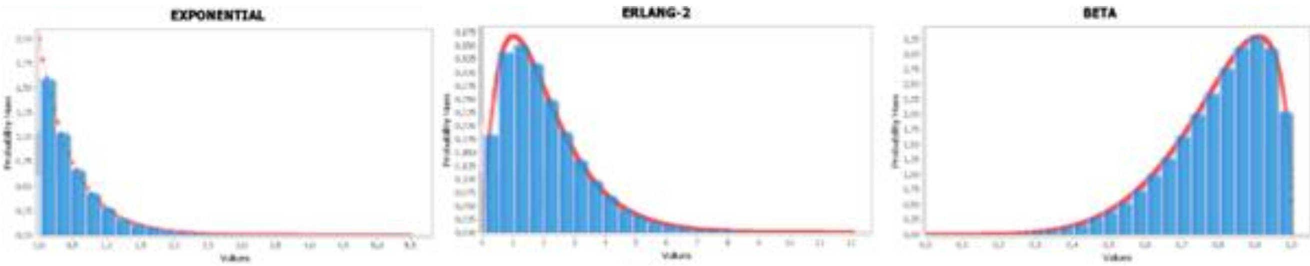
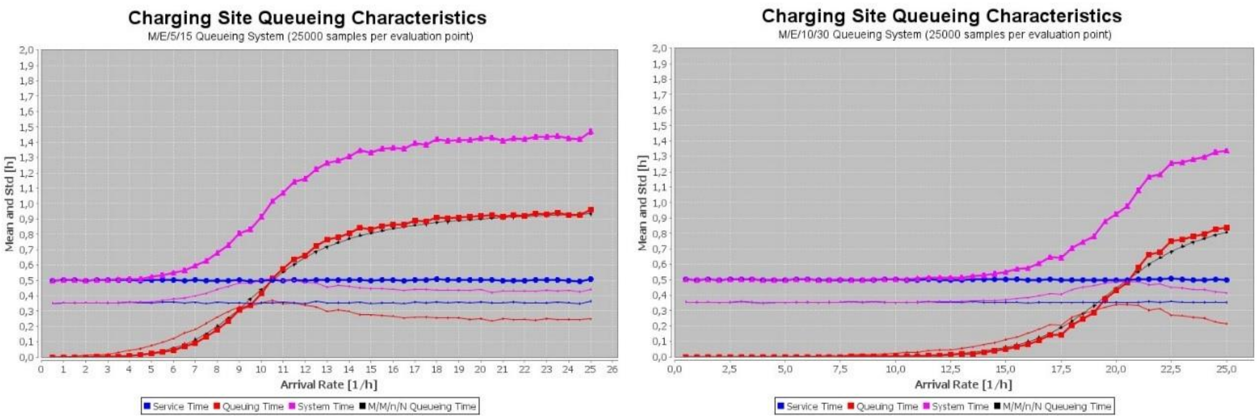


Figure 4. Random distributions characterising negative exponential distributed EV arrivals (left), Erlang-2 distributed charging times (middle) and Beta distributed charging demands (right)

Exemplary simulation results. Using the above outlined simulation of a finite multi-server queueing system, we can analyse EV charging sites as they soon may become deployed along motorways. According to the expected increase of EVs on the road, also the traffic load served by these charging sites will accordingly rise.

The recorded performance samples are statistically analysed and visualized to determine the efficiency and effectiveness of different charging site configurations. For the EV drivers, the waiting times and the amount charged in the intended charging time are of prime relevance. For the charging site operator and the adjacent distribution grid operator, the aggregated load and the efficiency of the peak power limitation provided by the dynamic load limiting implemented by smart charging are of prime concern. In Figure 5 the waiting time performance for two differently configured charging sites is compared.



sFigure 5. Waiting time over increasing EV arrival rate for two exemplary charging site configurations

The charging site shown on the left side provides five charging points and ten waiting places, the site on the right has ten charging points and twenty waiting spaces, i.e., twice the size. In consequence, the site shown on the left becomes overloaded at an arrival rate of ten EVs per hour, whereas the site on the right remains uncritical for up to twenty EV arrivals per hour. Practically, waiting times up to few minutes are commonly accepted by the EV drivers, thus five charging points yield in average acceptable waiting times up to six EV/h and ten charging points for up to 15 EV/h, which shows the efficiency of size effect that here twice the number of charging points can more than twice the traffic load with the same performance.

Figure 6 shows the change of the site power demand for increasing EV arrival rates.

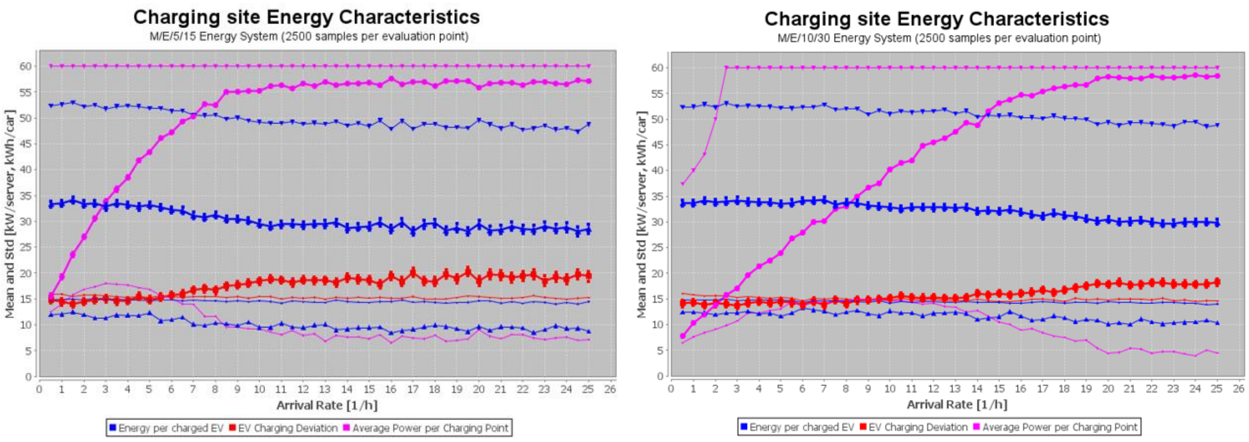


Figure 6. Waiting time over increasing EV arrival rate for two exemplary charging site configurations

The bold blue line in Figure 6 (Energy per charged EV) shows the average amount of energy charged. This amount drops slightly with increasing traffic load (EV/h) due to the dynamic site power limitation. The narrow blue lines with triangle markers above and below show the 90% and 10% percentiles of the samples. The bold red line shows the average battery capacity not charged when the EV leaves the charging site after completing the randomly determined charging time. This curve shows the opposite behaviour compare to the blue line because the sum of the two needs to equal the mean battery capacity of the charged EVs. We see that in average the battery is loaded to nearly 80%, which indicates that the simulated mean charging time is in average sufficient.

The bold magenta line in Figure 6 (Average power per charging point) shows the average power consumed by each charging point. It is calculated as $\bar{P} = \frac{\sum P_i}{n}$ and increases as the frequency of vehicle arrivals increases causing parallel charging events. Because the total site power is limited, which is shown by the narrow magenta line on the top, the dynamic power limiting (smart charging) causes that it levels off slightly below the maximum possible. For the smaller dimensioned charging site on the left side in Figure 6 this line rises rapidly as arrival rates (the frequency of cars arriving for charging) increase. Doubling the capacity shifts the rise to higher arrival rates, which is shown on the right side.

The narrow lines without markers show the standard deviation in respect to the equally coloured results. A higher deviation indicates higher variability and accordingly less stable charging performance. To better visualise the variance of the site power, Figure 7 shows the histograms of the site power for increasing arrival rates.

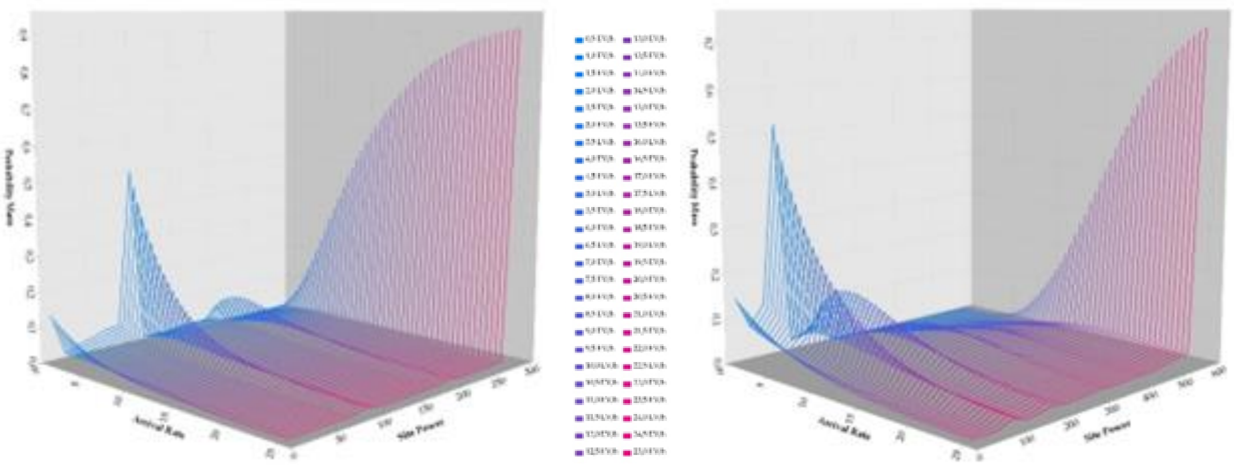


Figure 7 – Site power demand histograms over arrival rate for the two exemplary charging site configurations

Notably, we see ripples caused by the maximum power the charging points offer, here 100 kW each, which are in particular visible at low arrival rates. The EVs per se, could charge with higher power. Still, the maximum site power, which for five charging points is limited to 300 kW (left side) and to 600 kW for ten charging points (right side), is in both cases dominant at high arrival rates indicating a reduced charging performance per EV.

If we configure a charging site with five charging points that provide 150 kW each and 500 kW maximum site power, and consider a more diverse mix of EV types including 30% hybrid EVs that cannot use fast charging, i.e., are limited to 22 kW maximum charging power, we see in Figure 8 that the site power limit is not so often reached even though five times 150 kW would be beyond the site power limit. This example represents a good charging site configuration, where performance and effort are better balanced.

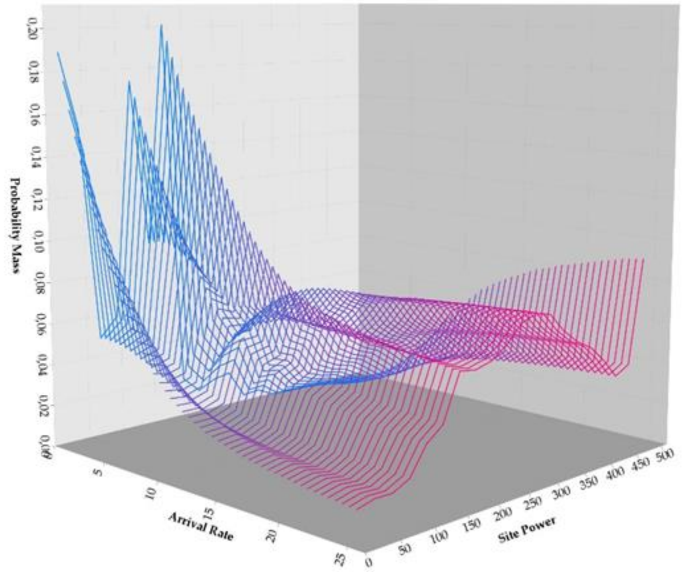


Figure 8 – Site power histogram over increasing EV arrival rate for a well-configured charging site

By analysing the different performances of different charging site configurations, potential bottlenecks and areas for improvement in the EV charging infrastructure can be identified. Visualization of key statistical measures such as mean, standard deviation, and confidence intervals are utilized to provide a comprehensive view of the system's performance for increasing traffic loads.

Comparison with analogous simulation options. The customised tool fulfils the criteria required to directly generate publishable R&D results, as requested. Tables 1 to 3 show that analogous simulation tools provide different features but not the precise set required by the client, the *eAlloc* project team, for whom the software tool is developed exclusively. The tools compared serve quite different purposes, including a PhD thesis on the topic (Jansson 2022), simple visualisation and on-line calculators for multi-server queueing systems (Lau 2017, Kabeer 2021, Ansari 2019) and complex real-world simulation tools (Witt 2022, Lee 2019, Liu 2021) interlinked with other simulation tools.

Table 1 reveals that no other tool supports selecting a distribution function to model the arrival and charging time distribution. KTH and EVCsim import pdfs and patterns respectively, which is very versatile. Witt and ACN rely exclusively on gathered field data, which focuses the studies on real scenarios of today. Smart Charging in respect to the grid access limitation P_{max}^{site} was no where found. Most studies considering the energy demand focus primarily on energy costs but consider no electricity grid access power limitation or peak power costs to be paid by the site owner.

Table 1. Features of exemplary EV charging simulation tools

features --- tool	traffic load and charging time modelling					charging technology		
	mean	pdf	data	pattern	function	AC	DC	P_{max}^{site}
eAlloc	+	-	-	-	+	+	+	+
KTH	-	+	-	-	-	+	-	-
Witt	-	-	+	-	-	+	+	-
ACN	-	-	+	-	-	+	-	-
EVQS	+	-	-	-	-	+	-	-
MSQS	+	-	-	-	-	+	-	-
Qsim	+	-	-	-	-	+	-	-
EVCsim	-	-	-	+	-	+	-	-

Table 2 reveals that the waiting time T_{wait} is evaluated by most tools, only MSQS focuses on the charging time T_{ch}. Some tools also provide the waiting probability p_{wait} and EVQS the mean queue length L_{queue}. Naturally, the plain queueing system tools EVQS, MSQS, and Qsim do not yield information on the charging performance and the power demand. Those that model also the charging itself, focus on the charged energy E_{ch}, the SoC or ΔE_{ch} at departure. The total power demand $\sum P_{\text{ch}}$ is also a topic in most of the studies, even though no grid access limit is commonly considered.

Table 2. Simulation aims of exemplary EV charging simulation tools

aims --- tool	queueing performance					charging performance		
	T_{wait}	P_{wait}	L_{queue}	T_{ch}	T_{in-out}	E_{ch}	SoC	$\sum P_{ch}$
eAlloc	+	-	-	+	+	+	+	+
KTH	+	+	-	+	-	+	+	-
Witt	+	-	-	-	-	+	-	+
ACN	+	-	-	-	-	-	+	+
EVQS	+	-	+	-	-	-	-	-
MSQS	-	-	-	+	+	-	-	-
Qsim	+	+	-	+	-	-	-	-
EVCsim	+	+	-	+	-	+	-	-

Table 3 shows that all except one lack the scientific rigour to include information on the stochastic quality of the derived statistical results: Non includes confidence intervals (ci) or standard deviation (std), only EVCsim (Liu 2021) states at least mean and maximum, as well as the median. Lacking access to the source code of some tools, some properties could not be determined and needed to be derived from the provided results. ACN-Sim does not bother to perform a statistical evaluation and delivers simply the gathered traces, delegating the data processing to the user.

The plain queueing system tools without charging performance and power demand considerations assume negative exponential inter-arrival and service time distributions, i.e., a Markovian system, for which the mean values can be analytically calculated (Kleinrock 1975). K. Lau mentions in the presentation in the EVQS (Lau 2017) documentation on GitHub that in practice the service time appears not to be negative exponential distributed and suggests to use a Gamma distribution instead. Actually, the empirically achieved histogram presented shows similarity with an Erlang-7 distribution, which is more smooth than the Erlang-2 distribution assumed for the above presented results.

Table 3. Outputs of exemplary EV charging simulation tools

outputs --- tool	data quality					means and formats		
	mean	ci	std	traces	peaks	GUI	CSV	SVG
eAlloc	+	+	+	-	+	+	+	+
KTH	+	-	-	-	-	+	-	-
Witt	+	-	-	-	-	-	-	-
ACN	-	-	-	+	-	+	-	-
EVQS	+	-	-	-	-	+	-	-
MSQS	+	-	-	-	-	+	+	-
Qsim	+	-	-	-	-	+	-	-
EVCsim	+	-	-	-	+	+	+	-

Conclusions. The customised charging site simulation tool developed, attempts to fill the existing research gap by enabling the user to predict the demand for, and performance of, fast charging along motorways. It focuses on key parameters such as the aggregated power demand and expected charging performance, and the expected waiting time and need for parallel recharging facilities (charging points). Calculated expectable waiting times are for example used for the multi-objective EV assignment optimizer, developed as part of the R&D project *eAlloc* (eAlloc 2021), to consider the EV driver's common wish not to wait for the recharging. The presented study seeks to enhance the current understanding of fast EV charging infrastructure requirements and to facilitate more efficient and user-friendly charging solutions and related services that support widespread EV adoption. The project objectives are:

- to consider the dynamic power demand of fast charging,
- to simulate charging sites offering many charging points in parallel,
- to conveniently visualize the statistical results,

such that both, the characteristics of different charging site configurations and the electricity grid access demands, become understandable and apparent. The results show the demand for the number of charging points at charging sites along motorways and the expected power demand for any future EV traffic load. Thereby, the strategic planning for electric vehicle infrastructure development is supported and stakeholders can make informed decisions regarding the deployment of charging infrastructure extensions to meet future needs.

The developed tool enables future research that provides valuable insights into the dynamics and requirements of smart DC charging as it will probably be required along motorways in the near future when mobility is primarily based on electric vehicles. The presented approach shows a comprehensive tool to better understand the properties and performance issues of EV charging sites along motorways. The findings highlight the importance of adequate planning and investment in charging infrastructures to conveniently accommodate the anticipated electrification of the mobility sector. High-quality visualization of the analysed site's performance using vector graphics provides the quality necessary for high-quality publications in scientific media.

The event-based simulation of the finite multi-server queueing system that models a charging site enables thorough statistical analysis, including not only mean values but also confidence intervals (ci) and higher moments, e.g., the standard deviation. Approximating possible future traffic loads by generated random traffic using different distribution functions that can be chosen to mimic the statistical properties (mean and histogram) of recorded traffic data enables upscaling by simply increasing the mean value. Each implemented distribution can be checked by generating a histogram from a generated sample and comparing that with the analytically calculated pdf as shown in Figure 4. The event-based simulation itself can be checked by simulating a Markovian queueing system and comparing the statistically gained waiting time curve with the analytically calculated as shown in Figure 3.

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