Analytical framework for autonomous charging stations enabling electrification of transportation systems

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***Abstract*—The anticipated widespread deployment of autonomous vehicles will require the development of services infrastructure. This article particularly considers location-specific customizable Autonomous Charging Stations (ACS) for providing charging services to the autonomous electric vehicles. Using a discrete-event simulation approach, we generated traffic scenarios based on three different arrival rates and three tiers of vehicles defined by current charging parameters. Based on a chosen traffic pattern, an ACS is designed by the number of pumps in each charging tier. The performance of this ACS design with different pump-sharing configurations is measured by the number of vehicles rejected and pump utilization for a total of nine traffic patterns. Each performance measure is applied for the overall and pump level of ACS. The obtained results demonstrate how the developed simulation platform can be used to analyze ACS's operational performance, provide recommendations for operational decisions creating a potential value for stakeholders and businesses.**

***Index Terms*—autonomous charging, transportation electrification, discrete-event simulation, analytical framework.**

I. Introduction

Advancements in diverse fields and technologies during the past decade have enhanced vehicles with autonomous features [1-3]. By 2030, it is anticipated that sixteen million autonomous vehicles (AVs) will be on the US roads with further growth of about 600,000 units per year [4, 5], while the majority of future AVs are predicted to be electric [1, 2]. Precisely, it has been estimated that about 1.4 million personal and over 700,000 service AVs will need to be charged every day in the US in 2030 [2]. Such widespread of AVs will be accompanied by the development of corresponding infrastructures to serve self-driving vehicles (for example, charging, parking, carwash, repair and maintenance, etc.) that can be rendered without any human intervention.

While most services can be performed using the existing infrastructure with an adaptation of autonomy, the charging service needs entirely new infrastructure to accommodate the fast-growing demand. This infrastructure can be represented by a network of autonomous charging stations (ACSs) [1, 2]. Using a bottom-up approach, the network of ACSs can be optimized by systematically integrating individual ACSs. For the integration process to be successful, it must be preceded by the analysis of individual ACSs in great detail. This article is concerned with the operational architecture of an ACS and its performance analysis, which involve modeling an online scheduling process for autonomous charging services and a simulation-based analytical framework for performance evaluation.

The system architecture (further denoted as "architecture") of an ACS need to be optimized for a given set of circumstantial parameters such as the location of the ACS, the traffic pattern around the area, the available energy supply chain, etc. [1, 3, 6, 7]. The initial architecture of ACS was proposed recently [1], which is the only model in the literature to the authors' best knowledge. Its physical implementation is based on recent advancements in diverse technologies: intelligent sensors, highly integrated processors, large-scale integrated circuits, and robust communications. Automated charging connectors (further referred to as 'pumps') are regarded as the key technological components of automated charging services [1]. The main functionality of the proposed architecture was modeled using existing queueing and scheduling approaches adapted from various systems.

In the proposed architecture of an ACS [1], a layered approach was used to describe its analytical framework (Fig. 1), where classification and queueing layers were emphasized. The operation of these two layers is based on the information exchange between vehicles and the charging station via the communication network in real-time (e.g., [8]), and can be described as follows. First, an AV initiates the information exchange by connecting to a charging station when charging service is needed. After the initial contact to the charging station, the vehicle sends a reservation request with its energy consumption parameters. These parameters include the amount of energy to be charged, its acceptance rate classified by 'charging tier' (e.g., fast, medium, and slow tiers) which determines the charging time, and the time window of charging service (i.e., the earliest possible time when the vehicle can arrive at the station and the deadline by which the charging is completed). When the charging station receives this request, the classification layer identifies all pumps (i.e., charging connectors) capable of charging the vehicle and their choice priority based on pre-defined selection rules. For this choice priority of charging pumps, the queueing layer processes the corresponding reservation request considering the constraints regarding its timing and energy availability. Specifically, the queueing layer sequentially checks the pumps in order of highest to lowest choice priorities and schedules the vehicle in the queue of the first pump that satisfies timing and energy requirements. Overall, the queueing layer presents a complex model consisting of multi-tier AVs with various power acceptance rates and multi-tier pumps with different power delivery rates.

The present research extends the previously developed in [1] online scheduling model focusing on the following items:

- shows an implementation of the previously developed online scheduling model in a simulation platform;
- demonstrates how this simulation platform can be used to analyze the performance of the charging station's operation and develop recommendations for operational decisions given a scenario of circumstantial parameters;
- relates the developed recommendations to possible data-driven dynamic pump sharing;
- describes the operation of the queueing and classification layers of ACS and estimates its energy consumption, which will be provided as feedback to the smart grid.

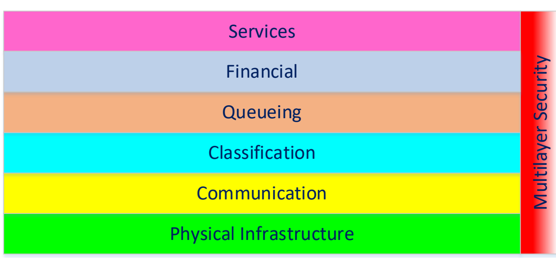

Figure 1 Architectural layers of autonomous charging stations [1].

II. Analytical Framework

This section provides a description of the proposed analytical framework. Upon a service request is electronically received from an AV, necessary information pieces are exchanged to make a decision on the pump assignment and the charging service schedule at the pump. The energy consumption requirement is an important parameter of the charging station's operation, and its power consumption information is key feedback to the smart grid [7, 8].

The analytical framework is developed to support a hierarchical decision-making process that can be implemented from the design phase of an ACS to its operational phase. In the design phase of the ACS, the number of pumps to be installed in each tier need to be decided. It is considered that pumps of each tier have their own power delivery rate, from highest at the first tier to lowest at the last tier. When a vehicle and a pump are in the same tier, the charging performance is maximized. However, when the same tiered pump is unavailable, the vehicle can still be charged by an available pump in a different tier, but the charging performance becomes deteriorated as it results in a slower charging rate (if charged by a low tiered pump) or lower utilization of the pump (if charged by a high tiered pump). Hence, in the operational phase, the number of pumps in each tier that can be used (or 'shared') by vehicles in a different tier can be dynamically optimized to maximize the throughput of the ACS for given circumstantial parameters. These pumps will be denoted as "shareable." Handling charging requests via the online scheduling model results in another operational decision of placing vehicles in queues.

For a given traffic pattern and design of the charging station (i.e., the number of pumps in each tier), the analytical framework via simulation studies is proposed and developed to assess the performance of its operation. In this framework, performance is measured by the number of vehicles rejected from charging service in each tier and the utilization of charging pumps. In addition, it also provides a scheduling and rejection calendar and energy consumption profiles.

One essential circumstantial parameter input to the analytical framework is the current traffic pattern, which is described by the arrival rate of charging requests and the distribution of vehicles among the tiers. It is assumed that the arrival rate of AVs can be described by a Poisson process [1]. The distribution of vehicles among tiers can be ascertained based on the demographic/geographic data of the area. Another important part of the analytical framework is a sequencing model, which was discussed using an approach of pooling various types of AVs and pumps in [1, 9]. The queue discipline is simplified to "first request first schedule." [1]. A realistic and practical placement of vehicles in a queue is performed based on the solution of an online scheduling problem, where the objective function represents the sum of weighted completion times [1]:

$$\sum_{i=1}^{n_k} w_i y_i + w_N y_N$$

$$\begin{aligned}
\text{subject to } & y_i = x_i + c_i && \text{for } i \in N_k \\
& y_N = x_N + c_N \\
& x_i \geq a_i && \text{for } i \in N_k \\
& x_N \geq a_N \\
& y_i \leq d_i && \text{for } i \in N_k \\
& y_N \leq d_N \\
& x_i \geq y_{i-1}(1 - z_i) + y_N z_i && \text{for } i \in N_k \\
& x_N \geq y_{i-1} z_i && \text{for } i \in N_k \\
& x_N \geq y_{n_k} z_{last} \\
& x_i \geq 0, x_N \geq, y_i \geq 0, y_N \geq 0, z_i, z_N \in [0,1].
\end{aligned}$$

The following notation is used in the presented mathematical formulation:

Input Data:

$N_k = \{1,2,\ldots,n_k\}$ – ordered index set of existing vehicles assigned to pump k, where $i < j$ implies that vehicle i is charged before vehicle j;

a_i, d_i, c_i – arrival time, due date, and charging time at the current queue of vehicle $i \in N_k$ respectively ($a_i = 0$ if vehicle i has arrived already);
a_N, d_N, c_N – earliest arrival time, due date, and charging time at the current pump of new vehicle respectively;
w_i, w_N – penalties imposed on the completion times of vehicle $i \in N_k$ and a new vehicle respectively, where $w_i = w_N = 1$ by default for $i \in N_k$.
$y_0 = 0$ defined for the sake of simplicity of formulation.

Decision Variables:
x_i, x_N – start times of charging vehicle $i \in N_k$ and new vehicle respectively;
y_i, y_N – completion times of charging vehicle $i \in N_k$ and new vehicle respectively;
$z_i = 1$ if new vehicle is placed right before vehicle i for $i \in N_k$; 0 otherwise;
$z_L = 1$ if new vehicle is placed after vehicle n_k; 0 otherwise.

Alternatively, minimizing the makespan can be employed as the objective function, intending to shorten the total charging time of all vehicles in the queue.

Due to its scalability for systems with high complexity [1, 10], a discrete-event simulation-based platform is used for the implementation of the analytical framework. The simulation platform of the analytical framework was developed in Matlab™, where the Gurobi™ optimization solver is called to solve a mixed-integer linear program, which is a mathematical optimization problem representing the online scheduling model [1]. However, it is worth noting that this implementation can be extended to an open-source platform built in any programming language.

The flowchart describing the simulation-based platform is illustrated in Fig. 2. This implementation consists of three main phases: *vehicle data generation*, *pump data generation*, and *scheduling*. The vehicle data generation phase 1) reads vehicle parameters including the arrival rate (λ), number of tiers (N), distribution of tiers ($R_1, R_2, \dots, R_N$), probability of request type: walk-in or reservation (R_W or R_R), and the number of vehicles to be simulated (Veh_{max}); 2) generates exponential random variates to simulate inter-arrival (IA) times (i.e., time intervals between consequent arrivals); and 3) generates arrival times of charging requests (arr_t), the type and tier of charging requests, the charging time of each vehicle (charg_t), the earliest possible arrival time to the charging station (e_arr_t), and the charging deadline (deadl_t).

The pump data generation phase 1) reads pump parameters including the number of tiers (N), the total number of pumps ($Pump_{tot}$), the total number of pumps in each tier ($Pump_1, Pump_2, \dots, Pump_N$), and the number of shareable pumps in each tier ($PS_1, PS_2, \dots, PS_N$); 2) defines the pump selection rules as a static order of pumps, which will be used for selecting a pump when a charging request is considered for scheduling; and 3) retrieves vehicle data including arrival time, due date, and energy demand, which is further used to define vehicle charging time (as described in section III), generated in the vehicle data generation phase (Fig. 2).

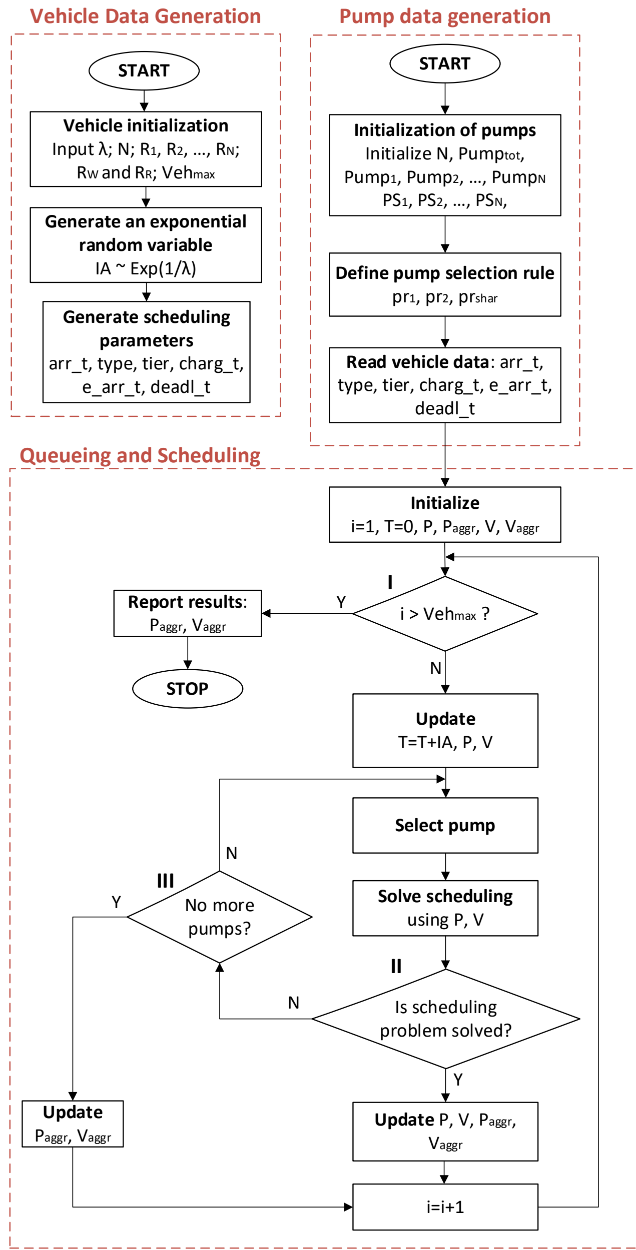

Figure 2 Flow chart of a simulation implementation of the online scheduling procedure.

The queueing and scheduling phase implements a discrete-event simulation run and updates/collects output data such as the current clock time at each iteration; vehicle that is being currently scheduled; charging station's power consumption; current and historical (further named as "aggregated" and denoted as "aggr") pump status matrices (P and P_{aggr}, respectively) as well as current and historical vehicle status matrices (V and V_{aggr}, respectively). P and P_{aggr} matrices keep a record of each pump's tier, type (shared or non-shared), and vehicles scheduled to each pump. Similarly, V and V_{aggr} matrices keep a record of each vehicle's type, tier, and scheduling parameters for each vehicle (Fig. 2). Besides, this phase includes the solution of this problem for each vehicle. The final results of scheduling are reported at the end of this phase (Fig. 2). Specifically, a vehicle will be scheduled for its charging service at the considered ACS if a solution of the described online scheduling problem is found and rejected otherwise.

III. Simulation Scenarios

The utilization of the analytical platform is demonstrated via a simulation study. Vehicle traffic scenarios are generated by assigning arrival parameters in the vehicle initialization step (Fig. 2). Considering traffic patterns to the existing gas stations in urban areas [11], the aggregate arrival rate (λ) of 10 veh/hour, 12 veh/hour, and 14 veh/hour were tested for this simulation study. The arrival rate of 12 veh/hour is used as a baseline scenario representing the current traffic pattern. Whereas, 10 veh/hour and 14 veh/hour arrival rates are also tested to reflect possible traffic scenarios for future reduction or growth in vehicle population in the area. The number of vehicles simulated (Veh_max) is set as 1000. In this case, the duration of the simulation for the baseline scenario was about 100 hours. Using the information about the most popular types of commercial electric vehicles available in the US, three tiers of vehicles (N=3) were considered [1]. The corresponding charging parameters of vehicles in each tier are provided in Table 1. Based on the average annual sales and driving patterns of these vehicles [12], the ratios of arriving vehicles with respect to tiers 1, 2, and 3 were approximated as 0.2, 0.3, and 0.5, respectively. This gives arrival rates of 2.4 veh/hour, 3.6 veh/hour, and 6 veh/hour for respective tiers.

Another vehicle-related parameter is the amount of energy to be provided per visit by the charging station. The platform randomly generates scenarios for energy demand per visit from the range between 70-90% of the battery capacity with an average of 80%. The indicated range of energy demand is based on the recommended spare battery capacity [13] and can be updated following state of the art technologies.

Table 1 - Charging parameters of each tier

Tier	Battery size, kWh	Power acceptance rate, kW
1	81	120
2	20	6.6
3	14	3.3

It is assumed that a charging rate of each pump in a tier is equal to the power acceptance rate of the vehicles in the same tier (Table 1). As mentioned above, the average energy demand per visit is assumed to be 80% of the battery capacity. Using this information, the average charging time is calculated as in Table 2. In turn, the information about charging service rates of three tiers is displayed in the same table. This information, along with the aggregate arrival rate of vehicles, defines the total number of charging pumps in the station as 32. This number corresponds to the aggregate service rate overprovisioned by 20% with respect to the aggregate arrival rate to ensure the system is stable (i.e., the aggregate utilization is theoretically 0.83 [14]). Then, these 32 pumps are partitioned into 2, 9, and 21 for tiers 1, 2, and 3, respectively, so that the service rate per tier can be defined from Table 2. This service rate exceeds its arrival rate defined by a certain traffic pattern (e.g., 10 veh/hour) and a considered arrival distribution scenario from Table 3 (e.g., balanced arrival ratio (BAR)). After this partitioning, when no pumps are shareable, theoretical utilizations become approximately 0.65, 0.97, and 0.97 for tiers 1, 2, and 3, respectively, with this set of charging pumps [14].

Table 2 – Parameters of each tier of charging pumps

Tier	Average charging time per vehicle, hours	Average service rate per pump, veh/hour	Number of pumps	Pump ID
1	0.54	1.85	2	1, 2
2	2.42	0.413	9	3, 4, …, 11
3	3.39	0.295	21	12, 13, …, 32

Table 3 – Considered arrival distribution scenarios

Tier	BAR	LFT	HFT
1	0.2	0.1	0.3
2	0.3	0.4	0.2
3	0.5	0.5	0.5

We also consider different ratios of arrival rates among three tiers, which will result in rather unbalanced utilization of pumps when pumps are not shared. We particularly experimented with increasing and decreasing the tier 1 arrival rate with the opposite change in the arrival rate of tier 2 accordingly, while keeping the same arrival rate for tier 3. This results in three different settings for vehicle ratios in tiers 1, 2, and 3: 0.2, 0.3, 0.5; 0.1, 0.4, 0.5; and 0.3, 0.2, 0.5 as shown in Table 3. While the first setting is referred to as the balanced arrival ratio (BAR), the second and third settings are defined as the lower first tier (LFT) and the higher first tier (HFT) scenarios.

The performance of a system's operation can be measured using various parameters [14, 15]. The simulation study compared the following performance measures for a total of nine combinations with three overall arrival rates (10 veh/hour, 12 veh/hour, and 14 veh/hour) and three vehicle tier ratios (BAR, LFT, and HFT):

- Number of rejected vehicles (overall and per tier) out of 1000 arrivals;
- Utilization of pumps (overall and per tier), i.e., a ratio of pumps' usage duration to the duration of 1000 arrivals.

In addition, a calendar-based schedule (further denoted as "scheduling calender") is presented to visualize the operation of the charging station over time [15].

IV. Simulation Results and Analysis

The results for BAR with the arrival rate of 10 veh/hour have shown a negligible dependence of the analyzed performance measures on the number of shareable pumps in tier 2. Whereas, sharing of tier 1 pumps has led to significant growth in the overall number of rejections with a negligible increase in the utilization of pumps. Hence, sharing pumps should be avoided for this scenario. The overall results for

BAR with arrival rates of 12 veh/hour and 14 veh/hour are shown in Fig. 3 and Fig. 4, respectively. The corresponding tier-specific results are provided in Fig. 5 and Fig. 6.

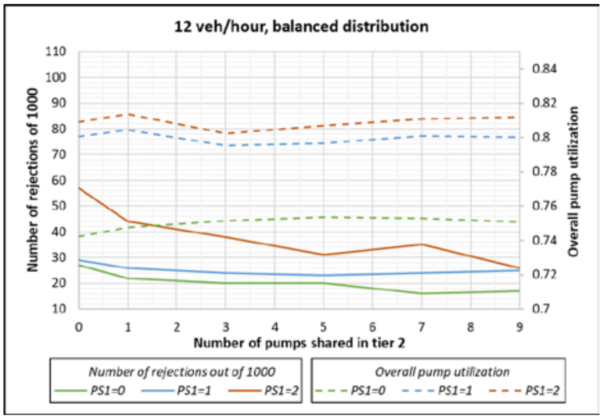

Figure 3 Dependence of the overall number of rejections and pump utilization for 12 veh/hour arrival rate with BAR on the number of pumps shared in tiers 1 and 2. Each color corresponds to a certain number of pumps shared in tier 1 (PS1).

It can be seen from Fig. 3 that sharing tier 1 pumps has a higher impact on both, number of rejections and pump utilization, than sharing tier 2 pumps. Sharing only one pump in tier 1 results in the minimum number of rejections for any level of sharing in tier 2. On the other hand, sharing of both pumps of tier 1 results in the highest number of rejections by an increase of 56 vehicles, and in the highest pump utilization by an increase of 5% to 6% when compared to the results of the non-shared scenario. If all pumps in tier 1 are not shared, it can also be noticed that sharing of up to 5 pumps in the second tier minimizes the overall number of rejections.

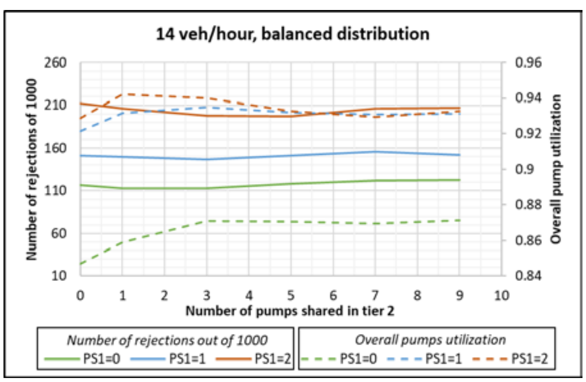

Figure 4 Dependence of the overall number of rejections and pump utilization for 14 veh/hour arrival rate with BAR on a different number of pumps shared in tiers 1 (denoted by PS1) and 2.

When the aggregate arrival rate increases to 14 veh/hour, the minimum number of rejections can be achieved when none of the tier 1 pumps is shared. Whereas, sharing of one and two pumps in tier 1 increases the number of overall rejections by about 35 and 50 vehicles, respectively, from the minimum. At the same time, it increases the overall utilization of pumps by about 7% (Fig. 4). Besides, sharing up to 3 pumps in the second tier reduces the number of overall rejections by about 3%, allowing to increase pump utilization by the same amount. On the other hand, sharing more than 3 pumps in tier 2 increases the number of overall rejections and reduces pump utilization (except for the scenario without sharing when the utilization stays constant).

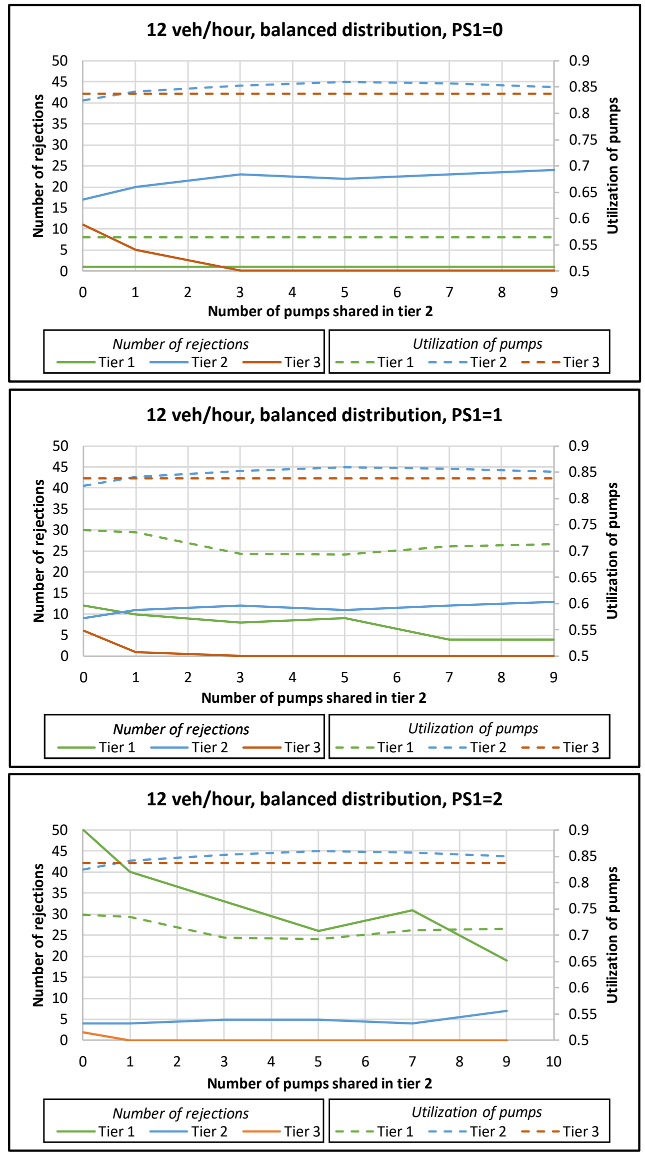

Figure 5 Dependence of the tier-specific number of rejections and utilization of pumps on the number of pumps shared in tier 1 (denoted by PS1) and tier 2 for 12 veh/hour arrival rate with BAR.

The effects of sharing pumps on different tiers for the arrival rate of 12 veh/hour can be observed from Fig. 5. It can be seen that sharing one pump in tier 1 allows increasing the utilization of tier 1 pumps by up to 18% with a corresponding increase in the number of rejections by 3 vehicles with respect to a non-shared scenario. Whereas, sharing two pumps in tier 1 results in the highest number of rejections in this tier, increasing it by at least 19 vehicles compared to a non-shared scenario, and 15 vehicles compared to sharing one tier 1 pump. At the same time, sharing 2 pumps in tier 1 increases the utilization of tier 1 pumps by about 2% only from that of the scenario of sharing one pump in tier 1. It can also be observed that the sharing of tier 2 pumps provides a trade-off between an increase in the number of rejections in tier 2 and a decrease in the number of rejections in tier 3 and increases the utilization of tier 2 pumps by about 3%.

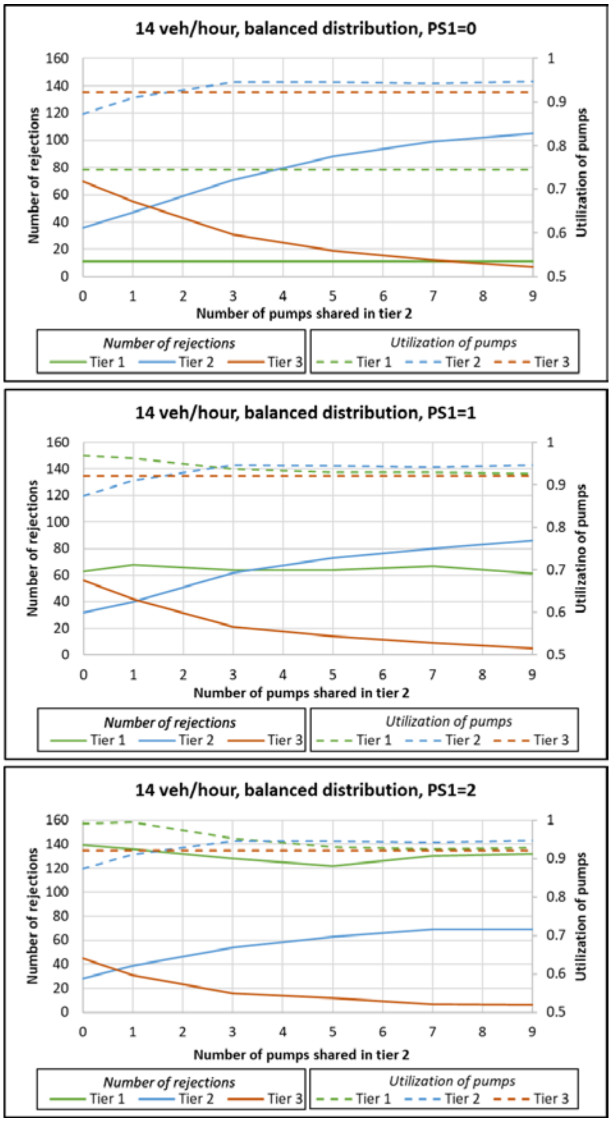

Figure 6 Dependence of the tier-specific number of rejections and utilization of pumps on the number of pumps shared in tier 1 (denoted by PS1) and tier 2 for 14 veh/hour arrival rate with BAR.

The tier-specific results for the arrival rate of 14 veh/hour follow similar trends with a significant increase in the number of rejections and the corresponding growth of pumps' utilization. In addition, a stronger dependence of the number of rejections and pumps' utilization on the number of shared pumps in tier 2 has been observed.

There are several general recommendations can be stated from the obtained results. As a well-known rule of thumb, if there is a shortage of pumps in a certain tier, sharing them with the other tiers should be avoided. This rule is confirmed by the results of sharing tier 1 pumps and tier 2 pumps for HFT and LFT arrival distributions, respectively. Since highest tier vehicles can be charged at the same tier pumps only, sharing tier 1 pumps has been beneficial for only LFT arrival distribution when 10 veh/hour arrival rate is considered. In this case, the number of overall rejections has been reduced from 37 to 14, with the respective 10% increase in overall pumps' utilization rate in comparison with the non-shared scenario when both pumps of tier 1 are shared. A similar trend with sharing pumps of tier 1 for LFT arrival distribution can be observed when 12 veh/hour and 14 veh/hour arrival distributions are considered.

If sharing pumps is required, it should be started from the lowest available tier. Sharing of more than 50% of pumps in the highest tier results in a relatively high number of rejections in this tier for all arrival distributions with 12 veh/hour and 14 veh/hour arrival rates and, hence, is not recommended as a sharing solution. However, sharing less than 50% of pumps in the highest tier for these scenarios results in a more robust sharing solution, which provides an observable trade-off between the number of rejections and pumps' utilization. Hence, such an approach can be recommended to maximize pumps' utilization with the lowest rejection rate. Specifically, this level of sharing results in the increase of pump utilization by about 15% and 20% in comparison with the non-shared scenario for arrival rates of 12 veh/hour and 14 veh/hour, respectively.

A detailed scheduling calendar illustrating the timeline of each pump's utilization within the duration of the simulation is shown at Fig. 7. The arrival rate of 12 veh/hour with BAR and charging station's design with non-shareable pumps are considered in this scenario. Each line of this calendar shows the ordered sequence of time intervals when the corresponding vehicles have been scheduled at the particular charging pump based on the information obtained from the historical vehicle status matrix (Vaggr) described in section II. The number of each time interval corresponds to the order, at which a particular vehicle was scheduled for charging at a given pump. The beginning and end of each time interval correspond to start and completion times of charging vehicles as per the mathematical formulation described in section II. Recall that the default online scheduling problem considers minimizing the total completion times without considering penalties (section II). This platform can alternatively consider the makespan as its objective function. It has been noticed that the application of the sum of weighted completion times as an objective function results in several additional empty time slots (non-utilized for charging) with respect to the utilization of makespan as an objective function (Fig. 7).

As defined in section II, power consumption information is important for optimized integration of an ACS to the smart grid. Such information can be presented through a power consumption profile of an ACS [7, 8]. Power consumption profile for the arrival rate of 12 veh/hour with BAR and charging station's design with non-shareable pumps is shown in Fig. 8. Its shape is purely defined by the corresponding traffic pattern and a certain design of the charging station (number of charging pumps in each tier), which also determines its maximum capacity (Fig. 8). Largest increases and decreases in power consumption correspond to the moments of connections and disconnections of tier 1 vehicles to their charging pumps. Due to the significant difference in charging rates between tier 1 and tiers 2 and 3, similar

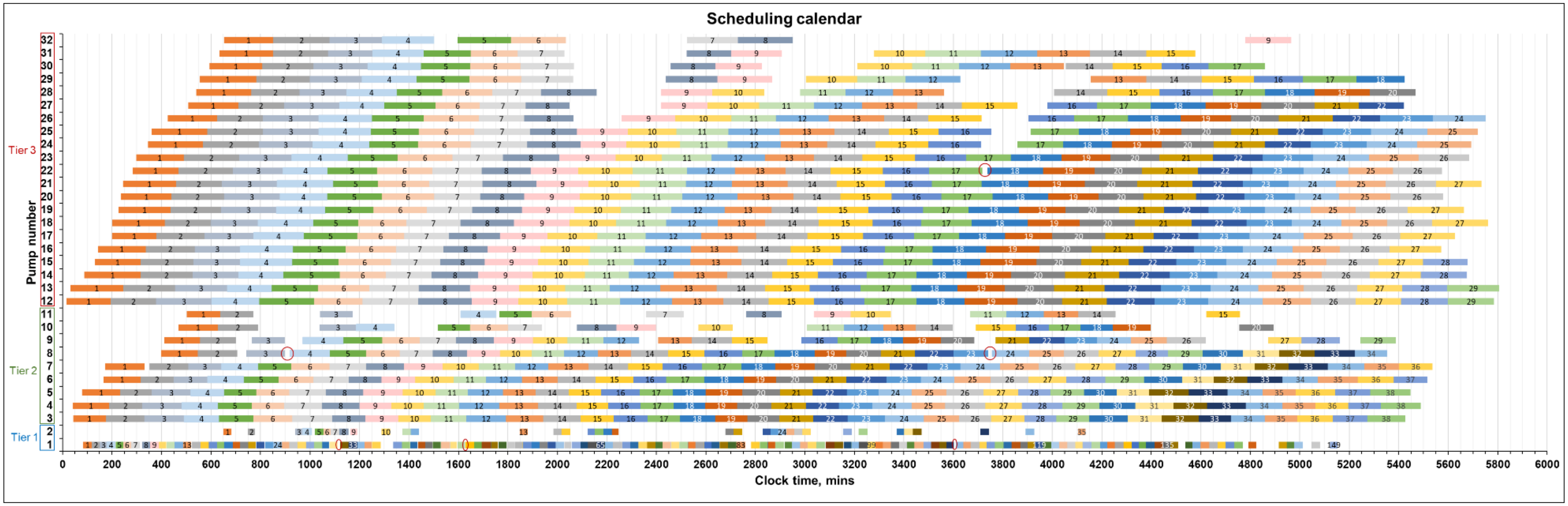

Figure 7 Scheduling calendar for BAR with 12 veh/hour arrivals. Extra empty slots (marked by red circles) take place when the sum of weighted completion times is used as the objective function vs. makespan.

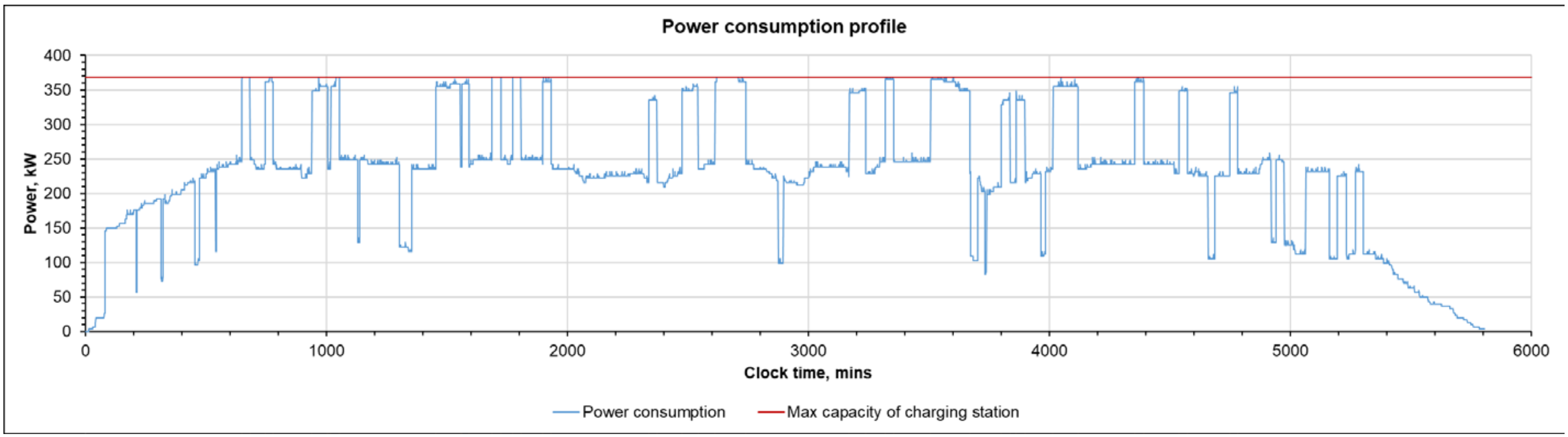

Figure 8 Power consumption profile for the arrival rate of 12 veh/hour with BAR and charging station's design with non-shareable pumps only.

connections and disconnections of vehicles belonging to the last two tiers result in considerably smaller increases and decreases of power consumption profile. On one side, such a profile is utilized to estimate the requirements for energy generation. On the other side, it is used for energy consumption management, e.g., reduction of peak-to-average ratio, shifting of energy load from peak to off-peak hours, etc.

There are several possible ways to apply the obtained results for the optimization of ACS operation. The simulation results can lead to the development of rules for dynamic pump sharing, which can be used to assign a different number of shareable pumps over time. For example, a time period of 1 hour can be considered for sharing. In this case, the developed model can be utilized to ascertain the expected number of rejections and pumps' utilizations (both overall and for each tier) for the next hour along with a predictive data analytics for the arrival rate in each tier. Comparing the expected performance for sharing alternatives, the number of pumps to be shared in the next hour can be determined. Another avenue that the simulation platform can be utilized is risk-aware business decision-making under uncertain environment: changes in vehicle population, variations or bursts of traffic, etc., which can lead to exhaustion or under-utilization of charging pumps. For instance, the decision about overprovisioning the number of pumps in each tier can be based on such parameters as a number of rejections and utilization of pumps per tier calculated for a given scenario.

V. Discussion

The major features of the demonstrated analytical platform are flexibility in the initialization of vehicle arrival rate and tier distribution and scalability of energy consumption profiles of vehicles. As fast chargers (450 kW, 550 kW, etc.) become available; one can use this platform to perform various analyses of charging station's operation with state-of-the-art vehicles and chargers. Within such analyses, decisions are made at the operational level so that the performance of the charging station can be optimized. In addition, the number of charging pumps can be optimized based on the traffic patterns of a certain area serviced by the analyzed charging station in the strategic level. In addition to that, priority charging lines feature can be simulated using completion times' penalties, which are described in the mathematical formulation and included in the developed platform. Moreover, this analytical platform can be applied at multiple sites in a hierarchical way to analyze a network of charging stations within a certain city, state, etc.

The other extension can be achieved by the inclusion of pricing parameters, which can be based on such factors as time of charge, operating cost, generation cost, etc. The analysis of each of these factors can lead to the development of a dynamic pricing scheme that enables us to analyze the charging station from a business perspective.

The developed framework can also be extended by "opportunistic charging", "three-stage charging", and "reject & referral" approaches, which will be applied when a charging station is unable to service the initial request. The "opportunistic charging" approach considers the utilization of two separate time slots for vehicle charging. In this case, a minimum threshold can be assigned for the selection of such time slots, e.g., based on a tier or a certain percentage of the total charging time. The "three-stage charging" approach considers an extension of the charging process with two additional stages. In these stages, an extension of charging deadline and reduction of the required amount of energy can be offered to service a vehicle. "The reject and referral" approach can be utilized for a search of another charging station that can serve the initial request. Thus, the application of these approaches can decrease the number of rejected vehicles and increase the utilization of charging pumps.

VI. Conclusion

This study proposes an analytical framework that can be utilized to evaluate the performance of decisions made at the design and operational phases of an autonomous charging station (ACS). At the design phase, the capacity of ACS (i.e., the number of charging pumps in each tier classified by various charging rates) is determined, while tactical utilization of charging pumps from another tier is considered at the operational phase (sharing pumps). The framework simulates traffic scenarios of autonomous vehicles (AVs) with various arrival rates as well as battery acceptance rates for serving a given number of vehicles. Results of an extensive numerical study for an ACS with 32 pumps that serve 1000 vehicles are reported and analyzed. The 32 pumps are partitioned into tiers 1, 2, and 3 with the respective numbers of pumps as 2, 9, and 21. As for the arrivals of vehicles, the arrival rate is set to correspond to the ratio of the arrival rate to the service rate equal to 0.83. Performances are measured by the number of rejected service requests out of 1000 requests.

In the scenario where the arrival rates were accurately estimated, the tested design of the ACS has shown the best performance with 15 rejections and pump utilization of about 0.76 if seven pumps in tier 2 were shared and no pumps in tier 1 and 3 were shared. When the arrival rate was increased by 17%, the same design of ACS displayed the best performance with 110 rejections and pump utilization of about 0.87 when two pumps in tier 2 are shared. In both scenarios, no pumps in other tiers were beneficial. In fact, it was concluded that, unless the arrival rate of tier 1 vehicles is significantly low, sharing tier 1 pumps is not recommended.

The obtained results demonstrate how the developed simulation platform can be used to analyze the performance of ACS's operation, develop recommendations for operational decisions given a traffic pattern (aggregate arrival rate and distribution ratio among charging tiers) and current charging parameters (power acceptance rate and battery capacity), and estimate energy consumption of an ACS. The results indicate that the demonstrated analytical platform will be useful for businesses and stakeholders to optimize the operation of charging stations: by the development of rules for dynamic pump sharing and by risk-aware business decision-making on ACS design defining the number of pumps in each tier.

Due to the inevitable randomness of vehicles' arrival process, the simulated results serve as approximations providing ideas about achievable performances under developed scenarios and can be verified through additional analyses. For example, the achievable performance is dependent on the objective function, which is the sum of weighted completion time for all the conducted simulations. Several empty time-slots can be observed on pumps' scheduling calendar when this objective function is applied in comparison with a makespan one (Fig. 6). It can be beneficial to utilize the "opportunistic charging" approach for such time slots, e.g., to serve walk-in vehicles. Whereas, the application of makespan as an objective function reduces the number of empty time-slots and would be beneficial when a throughput of a certain pump needs to be increased.

The proposed analytical framework with its simulated implementation is the only approach in the literature to the authors' best knowledge. In spite of the fact that proprietary charging services are provided by several companies, such as Tesla, Chargepoint, etc., a fully automated one is not currently available. Hence, a complete validation is left for a future study until at least a prototype ACS starts operating and produces data about the traffic pattern, charging parameters, and system performances.

References

[1] K. Kazi, R. Bikmetov, C. Lim, M. Y. A. Raja, and A. Kelsey, "Secure, Resilient, and Safety Critical Architecture of Charging Stations for Unsupervised Autonomous Vehicles," presented at the 21st Int'l Conf. on Intelligent Transportation Systems, Maui, HI, USA, 2018.

[2] Statista. (2019, Mar). *Autonomous vehicle technology - Statistics & Facts*. Available: https://www.statista.com/topics/3573/autonomous-vehicle-technology/

[3] K. Kazi, R. Bikmetov, C. Lim, and M. Y. A. Raja, "Autonomous Charging Stations: Genesis of Machine to Machine Services Industry within Human Independent Ecosystem," Spring 2019 IAB Workshop, Raleigh NC, 2019.

[4] BI Intelligence. (2016, July). *10 million self-driving cars will be on the road by 2020*. Available: http://www.businessinsider.com/report-10-million-self-driving-cars-will-be-on-the-road-by-2020-2015-5-6

[5] Protiviti Inc., "The Evolution of Autonomous Vehicles," USA, 2017.

[6] R. Bikmetov, *Dynamic Energy Distribution in Smart Grids Enabled by Internet of Things Sensors and Hybrid Telecom Networks*. USA: UNC Charlotte, 2019.

[7] Z. Cao, C.-C. Chu, and R. Gadh, "An autonomous electric vehicle based charging system: Matching and charging strategy," in *2018 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference*, Washington, DC, USA, 2018.

[8] R. Bikmetov, "Dynamic Energy Distribution in Smart Grids Enabled by Internet of Things Sensors and Hybrid Telecom Networks," The University of North Carolina at Charlotte, Ed., ed. ProQuest Dissertations Publishing, 2019, p. 172.

[9] S. Gurumurthi and S. Benjaafar, "Modeling and analysis of flexible queueing systems," *Naval Research Logistics (NRL)*, vol. 51, pp. 755-782, June 2004.

[10] A. M. Law and W. D. Kelton, *Simulation Modeling and Analysis*, 5th ed. USA, 2014.

[11] A. Langer and S. McRaey, "Fueling Alternatives: Evidence from Real-World Driving Data," 2014.

[12] A. Cooper and K. Schefter, "Electric Vehicle Sales Forecast and the Charging Infrastructure Required Through 2030," ed. USA: Edison Electric Institute, 2018, pp. 1-18.

[13] Cadex Electronics Inc. (2017, Apr). *BU-504: How to Verify Sufficient Battery Capacity*. Available: https://batteryuniversity.com/learn/article/bu_504_how_to_verify_sufficient_battery_capacity

[14] R. W. Wolff, *Stochastic modeling and the theory of queues Englewood Cliffs*. USA: NJ: Prentice Hall, 1989.

[15] MIT, *Systems Engineering Fundamentals*: Department of Defense, Systems Management College, 2001.

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