Optimal Planning of Workplace Electric Vehicle Charging Infrastructure with Smart Charging Opportunities

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Abstract— **We analyze the decision problem of a workplace manager determining the optimal number of electric vehicle (EV) charging stations to install in order to supply employees with adequate charging service and take advantage of EV smart charging opportunities, while also considering the investment costs of installing additional infrastructure. To optimize smart charging revenues, we introduce assignment methods that designate specific charging spots to arriving EVs. This includes two heuristic packing methods and an offline oracle. Under each assignment method, we perform a cost-benefit analysis that determines the optimal number of chargers to install on-site. Our results highlight the importance of considering revenues from demand charge reduction to incentivize investment in additional infrastructure needed to tap into the smart charging potential of EVs, at least under current energy market prices.**

I. Introduction

Several countries and states have set ambitious goals to reduce their greenhouse gas (GHG) emissions by the year of 2050, and electrification of transportation plays a significant role in achieving these targets [1]. For example, California's zero-emission vehicle (ZEV) initiative aims to have 1.5 million ZEVs on its roadways by 2025. GHG reduction can be improved through *smart charging* strategies that consume more renewable energy resources [2]. Smart charging presents a significant opportunity to control electricity costs, along with other potential opportunities to manage distribution system protection, behind-the-meter renewable integration, or frequency regulation (e.g., [3], [4]).

As the EV penetration grows, so does the EV charging demand. Existing charging infrastructure must keep up with the growing charging demand to satisfy each EVs charging needs. Hence, EV charging infrastructure placement and expansion is an important problem faced with infrastructure owners and building managers. In this paper, we address this problem; specifically, we look into how planning additional infrastructure at a location creates decisions in choosing how many charge stations to install based on the expected charging demand and investment cost of a station. Typically, locations with a consistently large and low-varying number of EV arrivals are workplaces. Workplace charging can be done over the length of the entire workday. Hence, in theory, companies can capitalize on unique peak shaving and regulation opportunities that their EV fleet may provide [5], [6], [7]. Previous work has studied the amount and effectiveness of these potential savings based on historical evidence of vehicle arrivals and charge duration (see e.g., [8], [9]). However, to the best of our knowledge, there is no previous work that studies the trade-off between the number of installed charging stations and corresponding smart charging capabilities.

Hence, this paper attempts to address two challenges: 1) Given a certain number of available electric vehicle supply equipment (EVSEs) on site, how much benefit is gained if a workplace charging infrastructure operator assign different EVs to EVSEs in order to maximize their smart charging potential? Consider a workplace with abundant EVSEs installed on site. In the scenario in which there is no control over which EVSE a vehicle plugs into, and all drivers choose to plug into the stations closest to the buildings, the nearest stations will be required to charge vehicles over the entire workday while the furthest stations will have few or no charging requests. In this scenario, smart charging opportunities will be minimal, as the higher demanded stations won't have the ability to avoid peak electricity costs while also fulfilling all charge requests. To avoid this, vehicles can be routed, or assigned to specific parking spots, to distribute the charge requests and maximize the benefits of smart charging. Hence, we will discuss online and offline assignment methods and their respective smart charging potential; 2) Given a certain smart charging potential and its corresponding revenue streams, what is the optimal EVSE investment decision for a workplace? We perform a cost-benefit analysis based on historical EV charging sessions from workplaces in Northern California. We study the effects of realistic electricity price variations and EVSE costs on the cost-effectiveness of smart charging.

The authors in [8] study the effectiveness of smart charging in non-residential locations, using historical data of arrival and departure times to estimate the benefits of smart charging. Paper [8] is based on the observations that non-residential charging stations have a large amount of arrivals in the morning, when work begins, and a large amount of departures when working hours end. Our paper builds upon these findings by using the understanding of arrivals and departures to create a system model that allows us to find an optimal investment in charging infrastructure to tap into smart charging benefits. In [10], a method for managing the charging of EVs is explored, such that the cost of charging is minimized. In our work, heuristic routing methods are explored to determine their effectiveness in smart charging and each is compared to an optimal routing method; their effectiveness is determined using historical data of charging sessions in non-residential lots. In [11], the authors utilize pricing mechanisms to allow incoming EVs to solve for

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their own assignment. Online learning algorithms are used to determine prices that will accomplish smart charging objectives.

In Section II, we introduce the problem setting and our structure for determining the cost of electricity when using smart charging opportunities. In Section III, various vehicle routing methods are introduced and their impact on the EV load distribution among EVSEs is explained. In Section IV, we use real EV charging data at a California bay area company to perform a cost benefit analysis for various EVSE installment strategies and their associated cost savings. We highlight the importance of considering savings from demand charges under current energy market conditions

II. Preliminaries

We consider the decision-making problem of a company that provides its employees with workplace EV charging opportunities and faces the issue of determining the optimal number of EVSEs to install. Installing more EVSEs could bring in revenues due to smart charging strategies and more flexibility to employees that want to charge their vehicle. To study this problem, we first need to provide a model for the usage patterns of a given number of installed EVSEs. We assume the existence of a customer guidance mechanism that would assign customers to EVSEs at the beginning of the work day. This can be achieved either through a reservation mechanism (e.g., a mobile application that receives information about charge requests from the EVs and returns a designated spot) or through newer multi-plug EVSEs, where one EVSE can connect to multiple vehicles at the beginning of the day and subsequently switch between cars, charging them one at a time. Different assignment methods would result in different electricity costs and infrastructure requirements, which would affect our cost benefit analysis in determining the optimal infrastructure investment.

Given the sequential nature of EVs' arrival at work, as well as the random nature of the number of charging requests per day and their respective charge lengths, the assignment problem of EVs to EVSEs at the beginning of the day is an online stochastic assignment problem. Theoretically, this class of problems can be solved using dynamic programming (DP) approaches. Specifically, assume that a random number of N vehicles arrive each day, each requesting to charge their batteries for a certain time duration $S_i,\ i \in \{1,\ldots,N\}$, which we consider to be independent and identically distributed. The assignment algorithm would determine the EVSE j that vehicle i plugs into, captured through the binary variable $D_{i,j}$. Hence the total charge duration that each EVSE $j \in \{1,\ldots,M\}$ will allot to the vehicles that are assigned to it during a work day of C discrete time epochs is given by:

$$Y_j = \sum_{n=1}^{N} D_{n,j} S_n. \tag{II.1}$$

The variable Y_j is also referred to as the level of EVSE j. The number of daily time epochs C represents the most charging time an EVSE can supply and is referred to as the capacity of the EVSE. Because only a constant rate of charge for EVs is considered, capacity can also be described in units of electric energy for a given rate of charge. In a feasible assignment, we have $Y_j \leq C$. The receding horizon problem of assigning EVs to EVSEs can be formulated as:

$$\begin{aligned}
&\min_{D_{i,j}\in\{0,1\}} \sum_{n=1}^{N} [c_n(D_{n,1},\ldots,D_{n,M})] + C_F(Y_1,\ldots,Y_M) \\
&\text{s.t. } \ Y_j = \sum_{n=1}^{N} D_{n,j} S_n, \quad \forall\ j \in \{1,...,M\} \\
&\qquad Y_j \leq C, \quad \forall\ j \in \{1,...,M\} \\
&\qquad \sum_{j=1}^{M} D_{n,j} = 1,\ \forall\ n \in \{1,...,N\},
\end{aligned} \tag{II.2}$$

where the first term in the objective function captures the running cost of assigning each incoming EV n to EVSE j. This can capture the preferences of users for different stations. The second term captures the electricity cost of serving the charging requests as the final stage cost $C_F(Y_1,\ldots,Y_M)$, and is a convex function of the EVSE levels. In this paper, we focus solely on the final stage electricity cost and do not consider user preferences or strategic service denials in favor of future charge requests, assuming a first come first serve service discipline. Hence, the running cost functions $c_n(.)$ are assumed to be zero. Moreover, as we will see, in our case, $C_F(Y_1,\ldots,Y_M)$ is symmetric in the Y_j's.

While problem II.2 can be theoretically cast in the framework of dynamic programming (DP), it is clear that for large numbers of EVs and EVSEs, the state space will be high-dimensional and hence it would be computationally difficult to solve the exact DP (note that even the offline version of the problem is NP-hard). Hence, approximate or heuristic assignment methods are considered in this paper. The first approximation we consider is the certainty equivalent controller (CEC) with no knowledge of the charge length of the current or future incoming requests. CEC replaces all uncertain parameters by their expected values at each stage. In our assignment problem, this would mean that all future arrivals will be modeled through a number of EV charge requests of equal size $E[S_i]$.

Proposition II.1. *The assignment determined by the CEC is equivalent to that of the Worst Fit assignment heuristic.*

The proof simply follows from the convexity of $C_F(.)$ and its symmetry in the Y_j's. Inspired by this observation, we propose to use two well-known online packing heuristics (Next Fit and Worst Fit) and compare their performance against the optimal assignment found through an offline oracle assignment optimization (as an unattainable baseline). Since we focus on workplace locations, we can assume that the maximum amount of charging energy that can be delivered by each EVSE is limited by the length of the workday, and that all users are available during this time. We further assume that the inter-arrival and inter-departure times are significantly shorter than the workday.

A. Electricity Costs

We assume the parking lot operator is under a dynamic electricity pricing tariff. The prices corresponding to each time slot are denoted as $A_1, A_2, A_3, \ldots, A_C$ and are provided to the operator at the beginning of each day. A feasible charging strategy, leading to a certain electricity cost $C_F(.)$ consists of choosing what time periods an EVSE should be actively charging the vehicles connected to it. As long as the total number of active charging periods for EVSE j is equal to Y_j, all charging demand will be satisfied.

In this paper, we consider both energy and demand charges in determining the optimal strategy to charge the vehicles. We assume demand charges are calculated according to the company's highest recorded demand during each monthly billing cycle [12]. The demand charge per unit power is denoted as α. Note that the time at which the monthly peak demand happens is not known in advance to the assignment method at any given day d. Hence, we can only assume that the assignment method has access to the statistics of the peak demand for the month. On the first day of a new month, the current peak demand for the month will be the peak demand of that day. To allow the charging controller to operate effectively on early days of the month, the facility manager can start the month with a target peak demand $\hat{p}$ that is likely to occur with probability $(1-\epsilon)$. On any given day, if the observed peak surpasses the target peak, the target peak is updated to reflect the new highest observed peak in the month. It is assumed that the charging controller has a good forecast of the facility's base load (i.e., non-EV load) for the day, denoted as $u[t]$. Hence, to minimize costs on any given day, the charging plan can be determined by solving:

$$\begin{aligned}
\min_{G_{j,t},K} \quad & \sum_{t=1}^{C} A_t \sum_{j=1}^{M} G_{j,t} + \alpha K \\
\text{s.t.} \quad & \sum_{t=1}^{C} G_{j,t} = Y_j, \\
& 0 \le G_{j,t} \le \rho, \ \forall\, t \in \{1,...,C\}, \\
& K \ge u[t] + \sum_{j=1}^{M} G_{j,t} - \hat{p} \ \forall\, t \in \{1,...,C\}, \\
& K \ge 0,
\end{aligned} \tag{II.3}$$

where $G_{j,t}$ is the decision variable describing the energy supplied by EVSE j in hour t. This decides the optimal hours to charge in based on costs for energy and demand, for a given set of levels, Y_j, of M EVSEs.

The level of individual EVSEs Y_j, and hence the electricity cost per EVSE, would depend on the assignment algorithm as well as the number of EVSEs installed on site. We will study this in Section III.

B. EVSE Infrastructure Investment Costs

Installing a higher number of EVSEs on-site could enable a more distributed load assignment per EVSE and hence, it could lower electricity costs. Therefore, we plan to use real charging data to systematically study this cost-benefit trade-off for different assignment algorithms, reliability metrics mirroring whether we can accommodate all requests, and different dynamic pricing tariffs.

III. Vehicle Assignment Methods

We denote the number of EVSEs *needed* to satisfy *all* incoming charge requests as L. It is important to distinguish the difference between the number of EVSEs needed to serve all incoming EVs and the number of EVSEs actually used, as given a lack of enough investment in infrastructure, there can be occurrences in which the number of EVSEs *needed* is greater than the number actually used, in which case some charge requests will go unserved.

Note that L changes daily and due to the random nature of the daily number of charge requests N, as well as the i.i.d. distributed charge length of each EV $S_i,\ i \in \{1, \ldots, N\}$, it is a random variable with a distribution $p_L(l)$. Though charge requests can be more closely represented with a continuous random variable, we make S_i a discrete random variable with probability mass function, or pmf, $p_{S_i}(s)$ as our data source is already discretized. The statistics of the number of EVSEs needed is driven by the assignment method. For example, an assignment method that assigns one vehicle per EVSE would clearly result in a much larger expected number of needed EVSEs. The assignment method also determines the statistics of EVSE levels, Y_j, where $j \in \{1, \ldots, M\}$. The pmf of levels $p_{Y_j}(y)$ can be used to determine the expected electricity costs that the workplace will incur due to EVSE j. Together with the statistics of L, these two pieces of information can help us perform a cost-benefit analysis to determine the optimal number of EVSEs in which the workplace should invest.

Hence, in this section, we will present our assignment heuristics as well as the offline oracle used to provide a point of comparison, and we will discuss methods we use to determine the pmfs $p_L(l)$ and $p_{Y_j}(y)$.

A. Next Fit Routing

One approach to assign EVs to EVSEs is the so-called Next Fit packing heuristic [13]. The Next Fit heuristic involves placing a series of items into the same bin sequentially, until an incoming item doesn't fit in the current bin; when an element doesn't fit, the current bin is closed and a new bin is opened, and the items continue to be placed in the new bin until it is filled. This algorithm is unidirectional, meaning once a new bin is opened, the previous ones will no longer be used for subsequent items even if they can be accommodated. This heuristic is feasible for EV parking as it doesn't depend on the order in which elements arrive. Note that while it might initially seem odd that users are declined access to a charging station that has space to accommodate them, the extra idle time for each EVSE is required to perform smart charging services and hence could have more benefits than serving an extra user.

Note that if C is equal to the actual length of the working day, the Next Fit algorithm is the closest to the status-quo.

This would leave the parking lot operator with little to no smart charging opportunities in some EVSEs while other EVSEs deliver no charge at all. By virtually restricting C to be shorter than the length of the entire working day, the Next Fit algorithm would lead to a more distributed workload among EVSEs. However, decreasing C would result in a need to install higher number of EVSEs to accommodate all charging requests. This is the trade-off between minimal investment in infrastructure and smart charging opportunities that we will investigate in Section IV.

B. Worst Fit Routing

Another well-known routing method inspired by the bin packing literature is the Worst Fit heuristic, which involves placing elements into bins sequentially, similar to the Next Fit heuristic; however, with the Worst Fit heuristic, elements are placed into the bin with the most available space. If an item cannot be accomodated by any bin, it will be rejected.

Proposition III.1. *The Worst Fit algorithm is an optimal online assignment algorithm to minimize total electricity costs (i.e., it is an exact solution to the DP) if all charge requests have equal size ϵ.*

Proof idea: The solution of the Worst Fit algorithm for the case of N vehicles and M EVSEs will lead to $N - M\lfloor\frac{N}{M}\rfloor$ EVSEs with level $(\lfloor\frac{N}{M}\rfloor + 1)\epsilon$ while the rest of the EVSEs will have a level of $\lfloor\frac{N}{M}\rfloor\epsilon$. In any other solution, at least some EVSEs $\mathcal{X}$ have a level higher than $(\lfloor\frac{N}{M}\rfloor + 1)\epsilon$ and at least some EVSEs $\mathcal{Y}$ have a level less than $\lfloor\frac{N}{M}\rfloor\epsilon$. The optimality of the Worst Fit outcome then follows from the convex nature of the electricity cost function, ensuring that for any other solution, by moving users from EVSEs in $\mathcal{X}$ to EVSEs in $\mathcal{Y}$, the cost can be decreased, and hence proving that such a solution cannot be optimal.

Proposition III.2. *As $\epsilon/C \to 0$, the distribution of number of EVSEs L needed to satisfy all demand is $p_L(\ell) = p_N(\frac{C\ell}{\epsilon})$.*

However, in reality, none of the above cases will hold. Accordingly, the Worst Fit heuristic will not be optimal.

C. Offline (Oracle) Routing

To comparing the heuristic routing methods to a lower bound on EVSE infrastructure planning, an oracle routing method is explored. The oracle uses an offline optimal routing algorithm to minimize the cost of charging for a given number of charging stations and known set of charge requests.

IV. Infrastructure Recommendation

Having studied the cost associated with each assignment method, we are now ready to perform a cost benefit analysis that determines the optimal number of EVSEs that the company should invest in to minimize the total cost of serving the EV population. This analysis would involve a numerical study of the electricity and infrastructure investment costs for varying number of EVSEs and finding the number of EVSE installments with minimum total operational costs. In

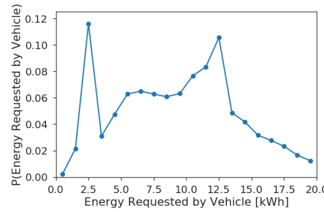


Fig. 1: Distribution of Vehicle Energy Request: $p_{S_i}(s_i)$

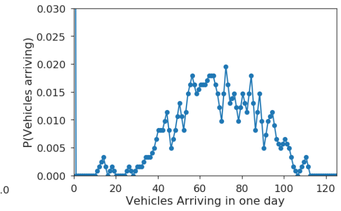


Fig. 2: Distribution of Vehicle Arrivals per Day: $P_N(n)$

performing our analysis, we will associate a constant daily cost that represents both the normalized long run cost as well as the short run costs of installing each EVSE on site.

A. Reliability Metric

In order to ensure that the company provides good quality of service to its employees, we only consider infrastructure investment strategies that can provide statistical guarantees of serving almost all the employees every single day. Hence, we adopt a reliability metric that sets a lower limit on the number of stations to be installed. The reliability metric, denoted as r, is representative of the percentage of days in which all vehicles are accommodated; equivalently, $(1 - r)$ gives the percentage of days in which at least one vehicle is denied charging accommodations. The number of bins needed to reach a specified reliability can be determined from the distribution of bins at a location by solving for M in $r = \sum_{l=0}^{M} p_L(l)$.

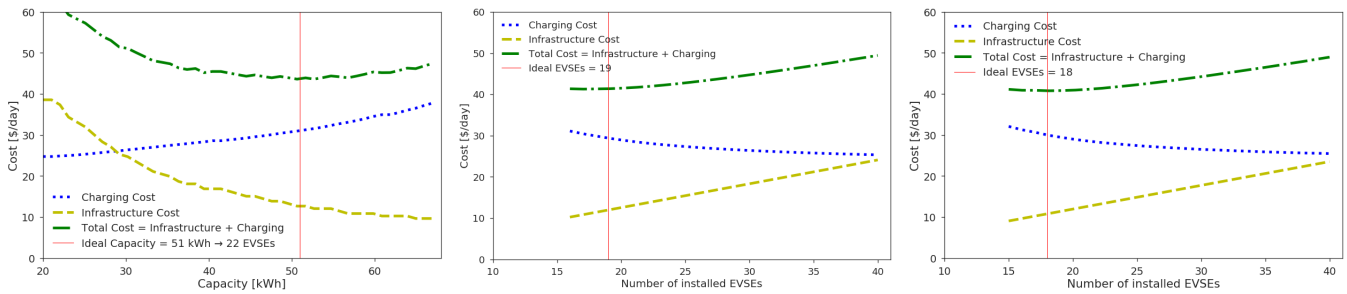
B. Test Case Setting

To test the different vehicle assignment methods proposed in this paper and to investigate the trade-off of installing additional EVSEs, the expected daily costs are calculated using Monte-Carlo simulations based on historical data.

The parking structure specific information, including the distribution of daily vehicle arrivals, fig. 1, and distribution of charge requests, fig. 2, are gathered from charging sessions at a company located in Mountain View, California and only considers vehicles that arrived between 6:00 am and 9:00 am and were charged during daytime. When needed in the simulations, we generated daily scenarios of charge requests based on the statistics shown.

In order to determine the recommended number of EVSEs to be installed, the expected daily cost of electricity and the infrastructure investment need to be determined and their total should be minimized. Both the daily electricity cost and daily infrastructure cost will vary with the numbers of EVSEs installed; however it is expected that electricity cost will decrease as the infrastructure cost increases. We do not limit the number of vehicles that can connect to an EVSE, instead the only limit on the number of requests an EVSE can serve is its capacity.

For the purposes of this paper, the daily cost of an EVSE was set at \$.603 per day. For our first experimental setup, we chose a relatively high variance set of dynamic



(a) Next Fit vehicle assignment method (b) Worst Fit vehicle assignment method (c) Offline vehicle assignment method

Fig. 3: Cost analysis of various EVSE installation numbers under each vehicle parking assignment method

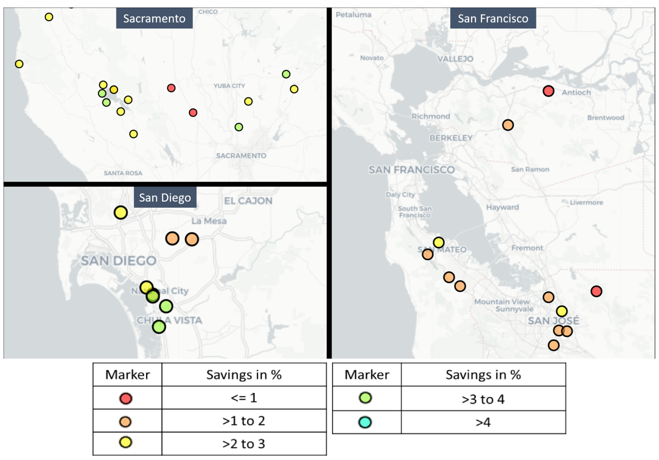


Fig. 4: Annual savings of implementing the Next Fit heuristic given historical locational marginal prices for electricity at various California nodes.

electricity prices that remain constant for the various scenarios that we consider. Electricity prices were determined using historical locational marginal pricing (LMP), where rates are determined by local transmission congestion in the electricity grid. These prices were found from [14] at the LMP node AMESDST_1_N001, located in Mountain View; A = [\$44.92/MWh, \$55.61/MWh, \$69.92/MWh, \$85.21/MWh, \$116.32/MWh, \$134.69/MWh, \$61.68/MWh, \$48.81/MWh, \$39.31/MWh] for each hour between 8:00 am and 5:00 pm. We note that such prices would be considered outliers in today's energy markets. However, as we will demonstrate in a separate experiment, we make this choice because on days with lower and less volatile prices, electricity costs will be lower and the current cost of infrastructure will take over in determining an EVSE recommendation, resulting in relatively negligible savings under current market conditions. We note that while this seems like a negative conclusion, higher variance prices are more representative of future market conditions with higher levels of renewable energy integration. Moreover, as we will see, the inclusion of demand charges will more than justify the investment in extra infrastructure to harness smart charging opportunities even under current average expected energy market prices.

For each assignment method, the electricity and infrastructure costs vary with the number of installed EVSEs. For the Worst Fit and Oracle assignment methods, the simulation was repeated over the same 365 charging scenarios, only changing the number of installed EVSEs to observe its effect on the total cost of operation. In figures 3(b) and 3(c), the average daily operational costs across the scenarios are plotted versus the number of installed EVSEs. Both plots abruptly start at 16 and 15 EVSEs respectively, as no fewer EVSEs are feasible when considering a reliability of $r = 97\%$. With both these assignment methods, few additional EVSEs are recommended to achieve the minimum cost of operation. For the Next Fit routing method, in the same 365 charging scenarios, the number of EVSEs needed to satisfy the reliability of $r = 97\%$ was found for different artificial capacities. In figure 3(a), the operational costs are plotted versus the artificial capacity. To minimize the total cost of operation, the Next Fit assignment method recommends a capacity that elicits several more EVSEs than when the full capacity is allowed. In all three assignment methods, not many additional EVSEs are recommended and savings from installing additional EVSEs is insignificant. For these, the electricity cost was determined using only energy, and fully ignored demand charge.

For the purpose of comparison, two additional methods of EV charging are analyzed, both of which assign vehicles with respect to the status-quo, i.e., parking in the first available station that is closest to the entrance of the building. However, one method utilizes no smart charging strategies, while the other does. An expected daily cost of charging and infrastructure were found for the two status-quo scenarios.

For the purpose of clarifying the expected savings under current market conditions, and not under the outlier price chosen in the previous experiment, the reader can see fig. 4. Here, we showcase the annual average savings of the total cost of operation when using the Next Fit assignment method compared to the status-quo without any smart charging at various different LMP nodes in California using real LMP data. In this map, the highest observed savings are in the range of less than 5%. Seeing this, one may conclude that installing additional EVSEs and adopting a vehicle assignment method results in negligible savings and is unnecessary; however, these electricity costs do not include

Savings in Daily Cost of Operation								
	EV Energy Cost	EV Demand Cost	Total EV Charging Cost	EVSEs	Daily Infra. Cost	Total Daily Cost	Savings from Case 1	Savings from Case 2
Without Demand Charge:								
Case 1- No Routing Without Smart Charging	$43.15	NA	$43.15	16	$9.65	$52.80		
Case 2- No Routing With Smart Charging	$40.75	NA	$40.75	16	$9.65	$50.40	4.55%	
Case 3- Next Fit Routing With Smart Charging	$30.79	NA	$30.79	22	$13.27	$44.06	16.56%	12.58%
Case 4- Worst Fit Routing With Smart Charging	$32.43	NA	$32.43	19	$11.46	$43.89	16.69%	12.72%
Case 5- Oracle Routing With Smart Charging	$29.92	NA	$29.92	18	$10.85	$40.77	22.77%	19.10%
With Demand Charge:								
Case 1- No Routing Without Smart Charging	$42.49	$25.91	$68.40	16	$9.65	$78.05		
Case 2- No Routing With Smart Charging	$39.02	$9.71	$48.73	16	$9.65	$58.38	25.20%	
Case 3- Next Fit Routing With Smart Charging	$31.02	$0.22	$31.24	22	$13.27	$44.51	42.98%	23.76%
Case 4- Worst Fit Routing With Smart Charging	$30.60	$0.48	$31.08	19	$11.46	$42.54	45.50%	27.14%
Case 5- Oracle Routing With Smart Charging	$27.49	$0.01	$27.50	23	$13.87	$41.37	47.00%	29.14%

TABLE I: Comparison of savings under various scenarios considered in this paper.

demand charges that fall upon larger electricity consumers.

In Table I, the costs of electricity and infrastructure are recorded for each assignment method, and the savings in reference to the status-quo with and without smart charging are noted. This was done initially without including the demand charge the building would incur. It can be observed that the savings from operating under any of the heuristic charging methods is modest when compared to the status-quo with or without smart charging capabilities, even when using an LMP with relatively high volatility. The reader should note that this cannot be further improved upon as the unattainable savings found through the oracle routing method are still not as noteworthy when only energy costs are considered. However, the savings are significantly improved when we consider on demand charges as well, as we showcase next. For our simulations, a demand charge of $8.03/kW was used. Furthermore, the non-EV load was randomly generated for each day around a typical load shape for commercial customers. The lower half of table I shows the associated costs of electricity and infrastructure for each of the assignment methods when demand charges are considered on top of energy costs. The simulations are carried out in the same manner as previously described, however the smart charging controller makes decisions with respect to (II.3), and the demand charge is factored into the cost of electricity. When the demand charge is considered, the heuristic and oracle assignment methods result in considerably higher savings than the status-quo. Hence, considering demand charges can significantly affect the decision to install additional EVSEs.

V. Conclusions & Future Work

In this paper, we proposed three methods of assigning EVs to charging stations at workplaces and analyzed the resulting EVSE requirement and potential for smart charging. We found that installing additional charging infrastructure, particularly while utilizing smart charging strategies that consider demand charges, can create sizable savings in EV charging costs. In future work, we will include the effects of smart charging to integrate behind-the-meter solar generation and the effects of user preferences for specific charging spots for others in the assignment method.

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