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A multi-objective optimization model for EVSE deployment at workplaces with smart charging strategies and scheduling policies☆

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ABSTRACT

This study proposes a multi-objective optimization model to determine the optimal charging infrastructure for a transition to plug-in electric vehicles (PEVs) at workplaces. The developed model considers all cost aspects of a workplace charging station, i.e., daily levelized electric vehicle supply equipment (EVSE) infrastructure cost, PEV energy and demand charges. These single-objective functions are aggregated in a multi-objective optimization framework to find the Pareto optimal solutions. Smart charging strategies with interrupted and uninterrupted power profiles are proposed to maximize the use of EVSE units. The charging behavior model is developed based on collected workplace charging data. The model is tested with various scheduling policies to investigate their impact on the behaviors of EVSE types from different perspectives. Finally, a sensitivity analysis is performed to assess the impacts of battery sizes and onboard charger ratings on cost behavior. It is shown that the proposed model can achieve up to 7.8% and 14.6% cost savings as compared to single-objective optimal models and the current charging practice, respectively. The unit cost is found to be more sensitive to scheduling policies than the charging strategies. It is also found that the flexibility ratio policy gives the best PEV scheduling with the lowest unit cost and the most efficient use of the grid assets.

1. Introduction

The adoption of zero-emission plug-in electric vehicles (PEVs) is becoming an ambitious target for the decarbonization of the planet in the national mitigation plans of developed countries. One of the specific goals set out is to support the transition to smarter and more sustainable transportation. Enabling this transition to electrified transport can be achieved through a convenient and widespread charging network [1]. Workplaces are found to have the most charging points among non-residential stations that help increase the electric driving range for PEVs [2]. These stations are primarily available for use by employees or a commercial fleet of PEVs. The workplace charging process can be performed over most of a working hours, which can give flexibility. However, it is likely to coincide with the peak hours [3]. Workplace charging stations can then take the opportunity to co-operate with the utility grid to provide ancillary services (e.g., peak shaving) without violating overall charging requests when the PEVs are parked at workplaces [4]. To encourage charging at workplaces, utilities have started to implement PEV specific rates [5,6]. Given the expected growth in workplace charging networks, architecting and managing such a workplace charging station requires deep analysis. Planning should specify both optimal electric vehicle supply equipment (EVSE) type and unit number, while the managing process should include smart charging strategies to provide a cost-effective solution with efficient use of the grid assets.

With ever increasing numbers of PEVs, optimal planning of non-residential charging station deployment has been undergoing research [1,2]. The overall objective of this research is to ensure the techno-economic feasibility of charging stations while providing a charging service quality for PEV users [7]. Most of the studies formulate the planning problem as a single-objective with deterministic optimization models, such as linear [2,8–10] and nonlinear integer programming [1,11], or as meta-heuristic optimization models, such as a genetic algorithm [12]. In Ref. [2], the

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Nomenclature

$\mathcal{F}$	Aggregated objective function
μ, σ	Mean and standard deviation of normal distribution
ω_1, ω_2, ω_3	Weights of energy, demand charge, and levelized infrastructure cost functions
C_{DC}	Demand charge
C_{drate}	Demand charge rate
C_{EC}	Daily total PEV energy charge
C_{LIC}	Daily levelized EVSE investment cost
C_{unit}, C_{ins}, C_{main}	EVSE unit hardware, installation, and maintenance costs, respectively
$E_{available,s_j}$	Total energy in the available time slots of s_j^{th} EVSE unit
$E_{required,i}$	Required charging energy of the ith PEV
F	Electricity pricing vector
J	Set of EVSE charging levels
j	jth EVSE type
LC	Lifetime of EVSE unit
N	Set of PEVs
n	The number of PEVs
P_i^{rated}, η_i	Onboard charger rated power and efficiency of the ith PEV, respectively
P_J^{rated},η_J	Rated power and efficiency of DCFC, respectively
P_{base}	Base load
$P_{ch,i}$	Set of charging rates of the ith PEV
$P_{\lim}$	Distribution transformer capacity
r	Annual interest rate
S	Set of jth type EVSE unit
s	The number of EVSE units
SOC	State of Charge
T	The number of time slots of 1 min resolution
$t_{arr,i}$, $t_{dept,i}$,$t_{req,i}$	Arrival, departure and required charging times of the ith PEV, respectively
$t_{plug-in,i}$, $t_{plug-off,i}$	Plug-in and plug-off time of ith PEV, respectively
WD	Total number of working days per year
DCFC	DC fast charger
EVSE	Electric vehicle supply equipment
L2-1P	Single phase AC Level 2/Mode 3 charger
L2-3P	Three phase AC Level 2/Mode 3 charger
PEV	Plug-in electric vehicle
TOU	Time-of-use tariff

objective is set to minimize the overall cost of a workplace charging station that is sum of the levelized costs of EVSEs, installation, and operation. In Ref. [8], the optimization model maximizes the number of PEVs charged at different non-residential locations under a budget and substation transformer capacity constraints. In Ref. [9], the model is developed to maximize coordinated PEV charging energy at a workplace under constant and time-of-use (TOU) rates. While these studies focus on economics of charging stations to maximize the station owner's profit, technical aspects associated with charging station deployment such as network losses and the grid impact are not considered. However, some work address the effect of power grid constraints [10,12]. In Ref. [10], the siting and sizing of charging stations are optimized to reduce losses and improve the voltage profile in the distribution system. In Ref. [12], the profitability of DC fast charging (DCFC) stations with different sizes subjected to grid capacity constraint is analyzed through an optimal model that determines optimal locations and sizes for the DCFC.

While these single-objective optimization models provide an optimal charging infrastructure configuration through cost minimization, designing a charging station involves various objectives from different aspects in a workplace environment, such as charging infrastructure provider with profitability maximization, utility with peak demand reduction, business system operator with demand charge minimization, and PEV user with charging cost minimization. A workplace owner providing a PEV charging service as a benefit for the employees may have multiple conflicting cost objectives to achieve. Some of these objectives can be compromised in finding the optimal solution if considered independently as single-objective optimization. For instance, if only the energy charge is considered to reduce the electricity consumption, the peak demand can increase at the lowest cost time frames. This may result in higher demand charges for industrial and commercial customers, specifically with fast charging EVSE units. Therefore, optimality should be concurrently sought for each aspect considered that may result in multiple non-unique sets of solutions. The final subjective decision can then be made from the non-dominated solutions, i.e., the Pareto optimal set based on the decision maker's priority. In this respect, the multi-objective optimization (MOO) method can define a Pareto optimal set that provides a suitable compromise among all objectives without degrading any of them.

Only few works has applied the multi-objective optimization formulation to the planning of charging infrastructure [13–17]. In Ref. [13], two cost minimization objectives for charging service provider and PEV user, and an objective of maximizing charging unit utilization ratio are incorporated into a multi-objective optimization formulation. It is shown that the multi-objective optimization model provide better balanced solution as compared to the single-objective optimization. In Ref. [14], the siting and types of public charging infrastructure are optimized by a multi-objective optimization model with the objectives of minimizing the total cost and failed trips to the charging station. In Ref. [15], minimizing investment cost and energy losses with maximizing the number of PEVs served are considered for electric vehicle grid integration. The Pareto solutions obtained are used to make proper trade-off between the overall cost and the PEV charging service. In Ref. [16], the objectives of minimizing charging time and charging cost are set to find the optimal option among L2, DCFC, and battery swapping. In Ref. [17], the MOO model is set to minimize grid related objectives while maximizing the number of PEVs served with DCFCs. The Pareto solutions are found using a heuristic algorithm while a fuzzy based decision-making model is employed to select the best performing solution. A multi-criteria decision-making model is proposed in Ref. [18] to select the best performing Pareto solution meeting the charging station owner's perspectives at workplaces. The objectives in these studies have mainly focused on the energy charge and investment cost and excluded the demand charge as part of multi-objective optimization models.

In addition to the investment cost of charging infrastructure, PEV energy and demand charges are the other two main cost objectives in a workplace environment that need to be considered. These two objectives may contradict each other in finding the optimal charging infrastructure. In this respect, smart charging has been shown to have potential in terms of energy charge and peak demand reductions [19]. It is shown in Ref. [20] that demand charges can be a significant portion of the total electricity cost depending on the configuration of charging station. In Ref. [21], the impact of smart charging on cost behavior is found for different PEV assignments to EVSEs. It is proved that installing more EVSEs could enable a more distributed load assignment per EVSE that reduces total cost, in which the demand charge reduction is found to be significant. In Ref. [5], the studies on the smart charging strategies with different objectives suggest that either cost or peak minimization shows superior performance in maximizing utilization of existing infrastructure and supporting the maximum number of PEVs in a workplace, as they were shown to have nearly the same aging effect on the transformer. In Ref. [22], Munoz et al. develop a smart charging strategy based on PEV's load shifting flexibility that minimizes the number of EVSEs and reduces peak demand significantly. While these studies prove the benefits of smart charging strategies for only single EVSE type, the behavior of all EVSE options under various smart charging strategies needs to be evaluated for all aspects in a workplace environment. Moreover, many scheduling policies other than the current practice, i.e., first-come, first-served, can be implemented in a workplace environment. The behavior of EVSE types with various scheduling policies is largely unexplored.

The motivation of this study is to explore the techno-economics performance of EVSE configurations at workplace charging stations against smart charging strategies and scheduling policies. As such, the optimal workplace charging infrastructure configuration that satisfies the workplace owner's multiple objectives simultaneously is identified. This is particularly important for commercial and industrial customers that are subject to paying additional fees such as demand charges, unlike residential customers. The following research questions were developed in this study: (*i*) Does the optimal charging infrastructure configuration differ from the perspective of a workplace setting?, (*ii*) What is the impact of the smart charging strategy on the optimal charging infrastructure configuration?, (*iii*) What is the impact of charging scheduling policies on the optimal charging infrastructure configuration?, (*iv*) How does the optimal charging infrastructure configuration differ from EV battery sizes and onboard charger ratings? To investigate the above-mentioned research questions, this study proposes a MOO model to find the trade-off among three conflicting single objectives. These are described as cost functions of daily levelized EVSE investment, PEV energy, and demand charges. To find the Pareto optimal solutions, three cost functions are aggregated using the weighted sum method. Two smart charging strategies with interrupted and uninterrupted charging profiles are studied to solve the optimization problem using linear programming. The model is tested with prioritizing scheduling policies. All workplace EVSE configurations are studied. These are AC single-phase (7.36 kW) (L2-1P) and three-phase (22 kW) (L2-3P), dual-port AC L2-3P (22 kW) (L2 MP), DCFC (50 kW) and dual-port DCFC (50 kW) (DCFC MP). Dual-port EVSEs allow two PEVs to connect and charge simultaneously. Based on collected charging data from the field, case studies are performed for a research institution. The findings will be critical in the installation of cost-effective workplace charging stations, which show the contributions of each cost element to the total cost to avoid a possible subsidization among PEV users while also being grid-friendly charging stations at workplaces. The rest of the paper is organized as follows. Section II describes the development of the MOO model with the Pareto solution. Section III presents smart charging strategies and charging scheduling policies. Case studies are presented in Section IV. Finally, concluding remarks are given in Section V.

2. Multi-objective optimization model for workplace charging station

2.1. Multi-objective optimization problem formulation

The framework for the proposed workplace charging station design optimization is shown in Fig. 1. Herein, a MOO model is proposed to determine the optimum EVSE configuration in which workplace PEVs are scheduled with optimal charging power rates. A charging station operator first sorts EVs and assigns them to available EVSE units based on a scheduling policy. The proposed MOO model is then solved only once for each EV when it is plugged in by considering available PEVs at the station. Once it has been scheduled, it is not updated when new PEVs arrive at the charging station. The MOO model entails identifying the trade-off among several objectives through optimal charging processes for candidate PEVs at the station. Several objectives can be defined from the perspective of a workplace environment, depending on whose optimality is sought. From a charging station owner perspective, the objective can be to minimize EVSE infrastructure costs over its life cycle [2], while the objective becomes to minimize operational energy charges for PEV users [19]. Peak demand reduction is always desirable from the grid perspective [23]. This, however, may conflict with energy charges that occur at the lowest TOU intervals. That can be defined as minimizing demand charges at workplaces as the demand charge is proportional to the peak load over a billing period [20]. Hence, the problem can be formulated as a Multi-Objective Linear Programming problem with three objective functions that results in global minimum as follows:

$$\min_{\substack{P_{ch,1}\ldots P_{ch,n} \\ S_j}} \left[C_{EC}(P_{ch,i}) \quad C_{DC}(P_{ch,i}) \quad C_{LIC}(S_j) \right]^T, \tag{1}$$

with,

$$\begin{cases} C_{EC} = \displaystyle\sum_{s_j=1}^{S_j} \sum_{i=1}^{n} \sum_{t=1}^{T} \left(F(t) \times (P_{ch,i,s_j}(t) \cdot \frac{\Delta t}{60}) \right), \\ C_{DC} = C_{drate} \cdot \left(max \left(\displaystyle\sum_{k=1}^{96} \sum_{t=1}^{15} mean \left(P_{base}((k-1) \cdot 15 + t) + \sum_{s_j=1}^{S_j} \sum_{i=1}^{n} P_{ch,i,s_j}((k-1) \cdot 15 + t) \right) \right) \right), \\ C_{LIC} = AF \cdot s_j \cdot \left(C_{unit} + C_{ins} + C_{maint} \right). \end{cases} \tag{2}$$

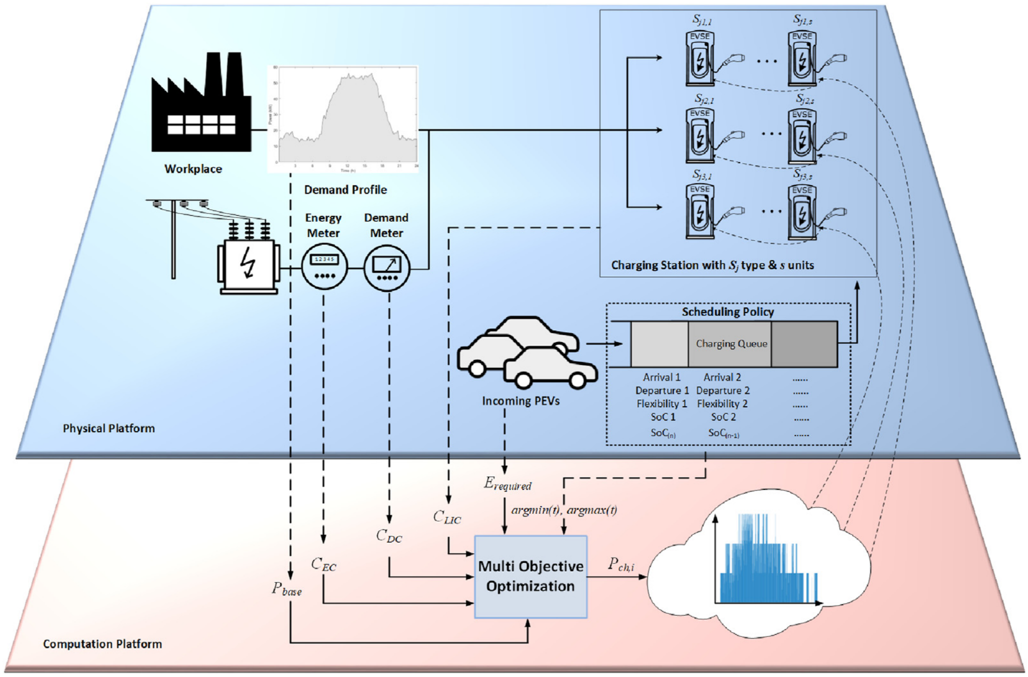


Fig. 1. A schematic overview of the proposed workplace charging station design optimization framework.

(1) is composed of three objective functions. The first objective is to minimize operational energy charge, C_{EC}, referring to daily total PEV energy charge as defined in (2). Minimizing the operational energy charge is achieved by optimizing the charging power rates of PEVs, $P_{ch,i}$. The second function in (1) is to minimize demand charge, C_{DC}. Minimizing the demand charge is achieved by minimizing the peak load in 15 min resolution as expressed in (2) through optimizing the charging power rates of PEVs. The last function in (1) is to minimize EVSE infrastructure cost, C_{LIC}, referring to daily levelized investment cost (LIC) of EVSE units. Minimizing the LIC is achieved by optimizing the number of charging units installed, S_j as given in (2). The objective functions are subject to following constraints:

$$\text{subject to} \sum_{t=1}^{T} P_{ch,i}(t)\cdot\eta_i\cdot\frac{\Delta t}{60}=E_{required,i},\ \ \forall t\in[t_{arr,i},t_{dept,i}],i=1,\ldots,n \tag{3}$$

$$\begin{cases} 0 \le P_{ch,i}(t) \le min\left(\eta_i P_i^{rated}, \eta_j P_j^{rated}\right), \forall J\in\{1,2,3\} \\ 0 \le P_{ch,i}(t) \le \eta_j \cdot P_j^{rated}, \forall J\in\{4,5\} \end{cases} \quad \forall t\in[t_{arr,i},t_{dept,i}], i = 1,\ldots,n \tag{4}$$

$$P_{ch,i}(t) = 0, \quad \forall t \notin [t_{arr,i}, t_{dept,i}], i = 1,\ldots,n \tag{5}$$

$$t_{req,i} \le (t_{dept,i} - t_{arr,i}), \quad i = 1,\ldots,n \tag{6}$$

$$\sum_{t=1}^{T}\left(P_{base}(t)+\sum_{S_j=1}^{s_j}\sum_{i=1}^{n}P_{ch,i,s_j}(t)\right)\le P_{lim},\ S_j=1,\ldots,s_j,i=1,\ldots,n. \tag{7}$$

Eq. (1) always seeks optimal charging rates for each PEV with satisfying the constraints simultaneously, while the smart charging algorithms employed guarantee the minimization of the number of charging units. The details of each objective function are expressed in the followings. The smart charging algorithms are defined in the next section.

The following are the definitions of the sets used in the model: $N = \{1, 2, \ldots n\}$ is set of PEVs, T is the number of time slots of 1 min each, $P_{ch,i}(t) = \{Pch, i(1) \ldots Pch, i(T)\}$ is set of charging rates of the ith PEV, $S = \{1, 2, \ldots s\}$ is set of EVSE units, $J = \{1, 2, 3, 4, 5\}$ is set of charging levels of the EVSE types considered. {1, 2, 3, 4, 5} denotes L2-1P, L2-3P, L2-3P MP, DCFC and DCFMP charging units, respectively. The electricity price vector is $F(t) = \{f(1) \ldots f(T)\}$.

2.1.1. Energy charge function

The energy charge represents operational cost as daily electricity consumption cost to charge all PEVs at the workplace. It can be expressed by (2). The pricing vector, $F(t)$, considers a TOU tariff. While (2) minimizes total daily energy charge with optimal charging rates, the PEV user requirements are satisfied by Constraints (3) through (6). Herein, $E_{required,i}$ is the required charging energy of the ith *PEV* to achieve the desired state of charge (SOC) at departure time. $t_{arr,i}$, $t_{dept,i}$, and $t_{req,i}$ are the arrival, departure, and required charging times of the ith *PEV*, respectively. P_i^{rated} and η_i are the onboard charger rated power and its efficiency of ith *PEV*, respectively. P_J^{rated} and η_J are the rated power and the efficiency of DCFC EVSE unit, respectively. The equality constraint (3) guarantees every PEV has a desired SOC by departure time. Constraint (4) states that the charging power can be between zero and maximum rated value in compliance with the standards IEC 61851/SAE J1772 [24,25]. Constraint (5) imposes that the charging process happens within the arrival and departure times. Constraint (6) states that the required charging time cannot be longer than the plugged-in time.

2.1.2. Demand charge function with TOU tariff

The demand charge is calculated by (2). It is product of a demand charge rate and peak of aggregated load averaged in 15 min time intervals. The aggregated load is the sum of base load, P_{base}, and total charging loads, $\sum P_{ch,i,s_j}$. The demand charge rate, C_{drate}, in (2) is a part of the demand metered rate schedule for general service customers of Pacific Gas and Electric Company (PG&E) [26]. The rate of 13.27 $/kW for winter season is considered in demand charge calculations. In this study, a demand profile in 15 min interval for a research institution was collected for typical five working days throughout a year and daily average load of these five days was used as the base demand profile. The base profile was then interpolated to 1 min intervals to be used in the model. The charging power rates of each PEV in the charging time horizon are optimized such that the peak of aggregated power of 15 min intervals is minimized. The aggregated load is dynamically updated after each PEV's scheduling. According to Ref. [26], the rate schedule limits the total power demand at 499 kW that a customer can demand in three consecutive months. Therefore, the constraint in (7) states that the aggregated load after charging all the PEVs shall not exceed the peak power limit, $P_{\lim}$ of 500 kW. In addition, the rate schedule offers TOU rates used in (2) as $F(t)$ rate of electrical energy. The three time frames during a day are described as peak, part- and off-peak for winter. Fig. 2 depicts the daily average base power and TOU rate used.

2.1.3. Levelized EVSE infrastructure cost function

The EVSE infrastructure cost includes unit hardware, C_{unit}, installation C_{ins}, and maintenance costs, C_{maint} [27], as in (2). It is assumed that the cost term associated with operating the EVSE unit (e.g., charges for electricity) is considered in the energy charge while the installation cost includes the maintenance cost. The capital cost should be levelized to consider the time value of money since the infrastructure cost includes total length of lifetime of EVSE [28]. Since the energy cost is calculated in 24 h time horizon, the infrastructure cost is converted to daily levelized cost figure using the annuity factor, AF in (2) [2] as

$$AF = \left(\frac{1}{\text{WD}} \cdot \frac{(1+r)^{LC} \cdot r}{(1+r)^{LC} - 1}\right), \tag{8}$$

where, WD is total number of working days per year, r is annual interest rate, and LC is lifetime of an EVSE unit.

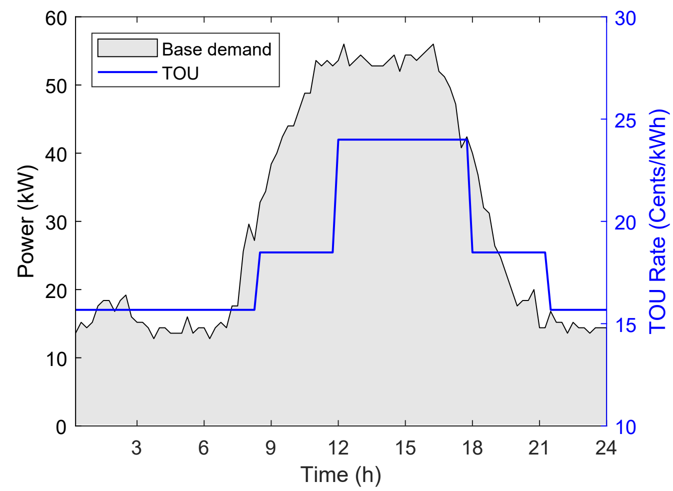


Fig. 2. Daily average demand profile in 15 min resolution with TOU tariff considered.

2.2. Pareto optimal solutions with the weighted sum method

For the multi-objective problem, it is highly unlikely to have a single solution which minimizes each objective function simultaneously [29]. The solution is defined in terms of Pareto optimality and a set of points on the Pareto frontier is therefore sought. The unique optimum solution is identified from the Pareto frontier depending on the decision-maker preference [17]. The Pareto set includes all feasible solutions in the objective space representing alternative designs. One intuitive way to find Pareto points is to combine all the design objectives into a single aggregate function ($\mathcal{F}$) in a way that it should represent the user's preferences and objectives. As such, the Pareto solutions are obtained by optimizing $\mathcal{F}$. The most common way of aggregate objective function formulation is the weighted sum approach that presents weighted linear combination of all objective functions [30]. For the proposed multi-objective optimization problem, the aggregate objective function can be expressed as

$$\mathcal{F}(P_{ch,i}, S_j) = (\omega_1 \cdot C_{EC}(P_{ch,i}) + \omega_2 \cdot C_{DC}(P_{ch,i}) + \omega_3 \cdot C_{LIC}(S_j)), \tag{9}$$

with,

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad \forall \ \omega \in [0,1], \tag{10}$$

where (ω_1, ω_2, and ω_3) represents weights of energy and demand charges, and levelized infrastructure cost functions, respectively. This results in all possible solutions including the single-objective solutions. An increment of 0.1 for the weights' iterations is used in simulations to evaluate the range of weights that makes up 66 wt sets. By setting possible weight sets, minimizing $\mathcal{F}$ yields a series of Pareto points that shows a feasible objective space with a trade-off among the three objective functions. Among the 66 solutions, the optimal solution is more subjective and depending on the user's design preferences. In this study, unit cost is given priority.

Algorithm 1. Uninterrupted PEV charging algorithm

1. Generate mobility data
2. Load pricing data and base demand profile
   for i = 1:N do
    Compute $E_{required,i}$
    S = 1
    Calculate $E_{available,s_j} = f(min(P_i^{rated}, P_J^{rated}), t_{arr,i}, t_{dept,i}, \sum P_{ch,(i-1)})$
    if $E_{available,s} <= E_{required,i}$ **then**
     Calculate $t_{req,i}$
     Find idle time slots t_{idle}
     for k = 1:size(t_{idle}) **do**
      if $t_{req,i} <= t_{idle}(k)$ **then**
       Set constraints Eqs. (3)-(7)
       Solve Eq. (1)-(2)
       Update demand profile $\sum_{t=1}^{T}(P_{base}(t)+\sum_{i=1}^{n}P_{ch,i}(t))$
      end if
     end for
     else
     S = 2
     ...
     else
     if $i == N$ **then**
       break;
     end if
     end if
     end for

3. Smart charging strategies and scheduling policies

3.1. Smart charging strategies with interrupted and uninterrupted charging profiles

In order to maximize the use of EVSE units, the proposed MOO model implements a smart charging algorithm that utilizes either uninterrupted or interrupted charging profiles. To address the current charging practice, an uninterrupted charging profile is first proposed in which each PEV is plugged-in and continuously charged until the desired SOC is reached. With the existing charger technology, this employs an uninterrupted charging profile between plug-in and plug-off times that occurs at either variable or fixed charging rates [3]. Second, in order to investigate the impact of future EVSE features, an interrupted charging profile is proposed in which the PEV is charged at discrete time slots separated by idle slots (t_{idle}). Interrupted charging requires that multiple PEVs be connected to the same charging unit while only one PEV can be charged at a time. This can be implemented on Octopus chargers that have built-in more cables but only one active cable at a time [22]. One advantage of the uninterrupted charging profile is the potential to allow the battery some cool off time and mitigate rapid temperature rise, which is an important factor for battery lifetime longevity due to the on/off switching behavior of the discrete charging process [31].

The smart charging algorithm with uninterrupted and interrupted charging profiles is summarized in Algorithms 1 and 2, respectively. It expects three parameters: arrival time ($t_{arr,i}$), charging energy need ($E_{required,i}$) and departure time ($t_{dept,i}$). The algorithm assigns PEVs into an EVSE unit sequentially depending on the prioritizing scheduling policy until an incoming PEV does not fit into the current unit. Then, a new EVSE unit is added, and the incoming PEV is placed in the new unit. The algorithm is bidirectional in the sense that the available EVSE units are used for subsequent PEVs if any of available units can accommodate any subsequent PEV. That is controlled by checking available time slots and energy, $E_{available,s_j}$, for every existing EVSE unit sequentially. The $E_{available,s_j}$ is calculated based on the arrival and departure times of the incoming PEV and the total charging power of previous PEVs.

Algorithm 2. Interrupted PEV charging algorithm

1. Generate mobility data
2. Load pricing data and base demand profile
   for i = 1:N do
    Compute $E_{required,i}$
    S = 1
    Calculate $E_{available,s_j} = f(min(P_i^{rated}, P_J^{rated}), t_{arr,i}, t_{dept,i}, \sum P_{ch,(i-1)})$
    if $E_{available,s} <= E_{required,i}$ **then**
     Set constraints Eqs. (3)-(7)
     Solve Eq. (1)-(2)
     Update demand profile $\sum_{t=1}^{T}(P_{base}(t)+\sum_{i=1}^{n}P_{ch,i}(t))$
    else
     S = 2
     ...
    else
     if $i == N$ **then**
      break;
     end if
    end if
    end for

3.2. Charging scheduling policies

Charging requests for a group of PEVs can be ordered using heuristic prioritizing policies [32]. The station owner can apply rational policies to take decisions about matching charging requests and available resources. This study exploits five scheduling policies as benchmarking criteria to provide a basis for assessing the performance of the proposed model. The impact is explored in terms of the station owner, PEV users, and grid perspectives. These policies can be rational in a workplace setting since PEV users are typically required to provide some information about their mobility, such as daily commute, dwell times, and required charging energy in accordance with an employer-prepared policy.

The first policy is the current charging practice which is first-come, first-served (FCFS) basis. It sorts PEVs according to their arrival times and assigns the first PEV with the earliest arrival time by

$$\ell = \underset{i \in \mathcal{N}}{\arg\min}\left(t_{arr,i}\right). \tag{11}$$

The second policy is the earliest deadline first (EDF) [32]. PEVs are sorted according to their departure times and the PEV with the earliest departure time is scheduled first as

$$\ell = \underset{i \in \mathcal{N}}{\arg\min}\left(t_{dept,i}\right). \tag{12}$$

The flexibility ratio (FR) policy considers the ratio of parking duration to required charging time and sorts PEVs with respect to their flexibility ratios. The PEV with the least flexibility is scheduled first as

$$\ell = \underset{i \in \mathcal{N}}{\arg\min}\left(\frac{t_{dept,i} - t_{arr,i}}{t_{req,i}}\right). \tag{13}$$

The longest job first (LJF) policy sorts PEVs with respect to their amount of required energy. The PEV with the highest required charging energy is scheduled first by

$$\ell = argmax_{i \in \mathcal{N}}\left(E_{required,i}\right). \tag{14}$$

The final policy is the shortest job first (SJF) [32] which PEVs are sorted with respect to their amount of required energy and the PEV with the lowest required charging energy is scheduled first by

$$\ell = \arg\min_{i \in \mathcal{N}} \left(E_{required,i} \right). \tag{15}$$

4. Case studies

4.1. Modeling workplace charging behavior

A workplace charging behavior model is developed using collected data from a charging station based in a research institution. Currently, 27 PEVs, including 3 PEV fleet cars, are registered and 10 charging units are installed in the station. The charging units are available on a FCFS basis for only the registered PEVs. The specifications of the charging infrastructure and the registered PEVs are summarized in Table 1 and 2, respectively. Note that L2 type (3-Phase) EVSEs have 2 ports that share the supply of 22 kW across the 2 sockets, depending on the onboard charging rates of the PEVs plugged-in. Even though the charging station does not include any DCFC units, it is considered in the study.

To form a charging behavior, the daily charging energy and duration with a timestamp were collected through each station transaction for a period of 6 months. In evaluating the collected data, the charging activities of the fleet PEVs are not considered to have realistic arrival/departure times as these cars dwell most of the time at the workplace. Since battery SOC information is not registered, the changes in SOC (%) are calculated based on each PEV's battery capacity and its recharged energy. The following assumptions were made to fit the distributions of arrival/departure times and charging energies into a Gaussian curve: Arrivals after 12.00PM and departures before 12.00PM are not considered as arrival and departure times, respectively. Also, any charging energy of less than 1 kWh is ignored. It is observed that the histograms of exploited data can be represented by a Gaussian distribution. The normal distributions are N(8h40, 1h05), N(16h10, 2h28), and N(45.44%, 17.87%) for workplace arrival and departure times and percentage change in SOC, respectively, with $N(\mu, \sigma)$ indicating a normal distribution with mean μ and standard deviation σ. Finally, the PEV mobility and charging behavior are generated based on the obtained Gaussian probability density functions.

4.2. Simulation settings

To represent the field implementation, a set of 5 different PEV types listed in Table 2 are selected in the model. The set of PEVs is composed of (12 kWh, 3.7 kW), (24 kWh, 6.6 kW), (30 kWh, 6.6 kW), (34 kWh, 11 kW), and (64 kWh, 7.2 kW). The selected PEV models are homogeneously distributed to all PEV users considered. The onboard chargers are assumed to operate at 90% efficiency whereas an efficiency of 97% is taken for DCFC. A lifetime of 15 years is assumed for AC EVSEs while a lifetime of 10 years is taken for the DCFC EVSEs. The sum of unit and installation costs are taken as follow: \$5000 and \$12,000 for L2-1P and L2-3P, respectively, from the field implementation while a cost figure of \$50,000 for DCFC EVSE at 50 kW is taken from Ref. [28]. A fixed interest rate of 5% is used in (8). The numerical simulations are run for 100 PEVs for 100 times to cover a considerable different randomly generated mobility scenarios. The presented results are average values among 100 trials. The model is implemented in MATLAB and the solution is obtained using the linear programming in optimization toolbox [33]. The resolution is assumed to be a time interval of 1 min.

Table 1
Specifications of EVSEs in the study area.

EVSE Type	Charging power [kW]	Connector type	No of charging stations
L1 (1-Phase, 16A)	3.68	Type-2	2
L2-1P (1-Phase, 32A)	7.36	Type-2	6
L2-3P (3-Phase, 32A)	22	Type-2	2

Table 2
Specifications of PEVs in the study area.

Onboard Charger Rate [kW]	No of PEVs	Battery Capacity [kWh]	No of PEVs
3.3	7	11−12	4
3.7	3	24	10
6.6	12	27−30	8
7.2	4	33−40	4
11	1	64	1

4.3. Charging infrastructure analysis

4.3.1. Analysis of Pareto solutions

To demonstrate the superiority of the MOO over the single-objective approach, each component of the MOO are individually run as single-objective optimization. These are energy charge (ECO), demand charge (DCO) and EVSE cost (EVSEO) optimizations. Table 3 presents the comparison results for DCFC unit with interrupted charging strategy as an example. It is shown that each single optimization achieves its objective by minimizing the value. However, their solutions result in higher unit cost figures than that of the MOO approach since optimizing a single objective can compromise other objectives. The MOO achieved further unit cost savings up to 7.8% as compared to the single-objective approaches depending on the charging strategy and scheduling considered. Cost savings differ from both the charging strategies and scheduling policies. The Pareto solutions of the MOO are therefore, further investigated below. Pareto optimal points have been found for five EVSE types under two charging strategies and five

Table 3
Comparison of MOO results with various single-objective optimization results for DCFC unit.

	MOO	ECO	DCO	EVSEO
Unit cost (\$/kWh)	0.487	0.525	0.521	0.488
Energy charge (\$)	226.89	220.82	223.35	227.30
Demand charge (\$)	62.17	70.98	52.59	62.34
EVSE cost (\$)	74.96	100.11	113.06	74.96

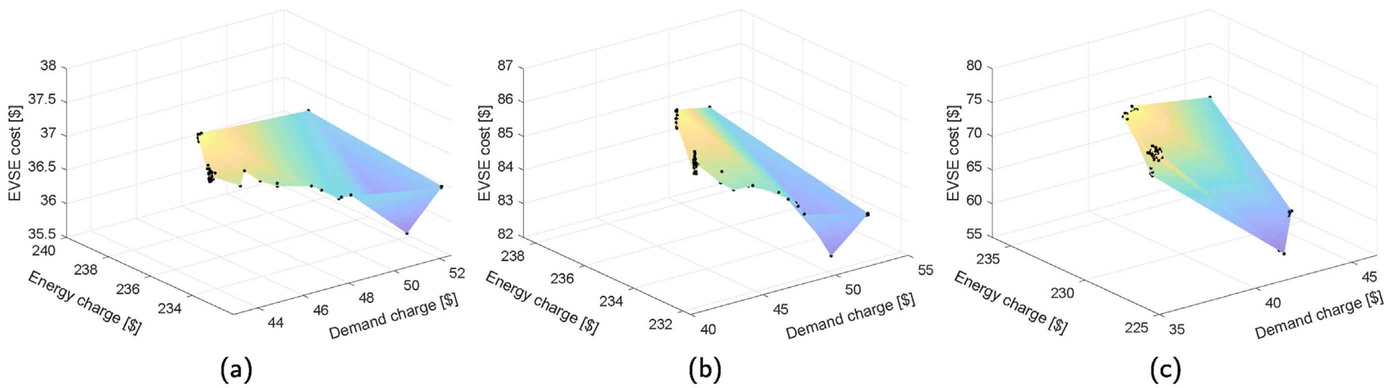


Fig. 3. Design objective values of the Pareto solutions with interrupted charging strategy for EVSE types (a) L2-1P, (b) L2-3P, (c) DCFC.

scheduling policies. As an example, Fig. 3 presents the Pareto points for L2-1P, L2-3P, and DCFC with interrupted charging strategy. Due to page limitation, all design objective values are not presented. The discussions below are made through presenting the Pareto solution making the unit cost the lowest.

As expected, the MOO increased the computational time by approximately 50 fold for an increment of 0.1 in weights as compared to optimizing the single-objective case. The computational burden can be even exacerbated for increased number of set of weights. However, the scheduling time to solve the problem per vehicle is found to be ranging from 5.98 s to 11.6 s depending on the charging scheduling considered. This proves that the MOO approach does not violate its real-time implementation as it is solved only once at the time the PEV is plugged-in.

4.3.2. EVSE unit cost analysis

The cost behavior of an uncontrolled charging scenario is given in Fig. 4a to provide a basis for assessing the performance of the proposed model. In the uncontrolled charging scenario, all PEVs are charged at their rated power with the FCFS policy. Fig. 4b through Fig. 4f present the unit cost behaviors of the optimal model with the uninterrupted charging strategy for each EVSE type. The unit cost is the ratio of total cost to total charging energy where the total cost is the sum of three cost components. When compared to the uncontrolled charging scenario, the optimal model with the uninterrupted charging strategy saves between 7.9% and 14.6% of the cost. DCFC units offer the greatest cost savings. L2-1P displays the best unit cost performance with a mean value ranging from 0.278 to 0.309$/kWh whereas the highest cost figures are obtained with L2-3P EVSE type with a mean value of 0.314—0.368 $/kWh. This is due to the inefficient use of L2-3P capacity (i.e., 22 kW) which is much larger than the onboard charger rates of the PEVs. In this perspective, multi-port L2 shows similar performance to that of L2-1P with the best mean value of 0.282 $/kWh. Multi-port option decreases the number of charging units needed, which reduces the EVSE cost component significantly. The best mean unit cost values for single and multi-port DCFCs vary between 0.286 and 0.388 $/kWh, respectively. Although the charging capacity of DCFC types is high, higher infrastructure costs make them less cost-effective compared to L2-1P and multi-port L2. The impact of scheduling policies on unit costs differs from EVSE types. Among the scheduling policies, FR policy has the best mean unit cost figure for each EVSE type considered, ranging from 0.278 $/kWh and 0.314 $/kWh. On the contrary, EDF policy shows the worst unit cost performance. It is observed that EDF may increase unit costs compared to the uncontrolled charging case since peak demand and thus higher energy charge periods overlap with departure times.

As shown in Fig. 5, the cost behaviors of the optimal model with the interrupted charging strategy are further reduced for all EVSE types by 2—3%. Similar to the uninterrupted charging strategy, L2-1P type returns to the lowest unit cost with a mean value of 0.272 $/kWh, while L2-3P has the highest unit cost value of 0.307 $/kWh. The lowest unit cost is still obtained by FR policy. As compared to the uncontrolled charging, FR policy achieves a cost savings of 3—5 Cents/kWh depending on the EVSE type. It has been found that unit cost is more sensitive to scheduling policy than the charging strategies.

4.3.3. Impact of EVSE types on aggregated load profile

The impact of the optimal model on the grid is quantified and evaluated in terms of the peak of 15-min intervals and the variance of the aggregated load profile. The variance of the distribution system load profile is a measure to evaluate load fluctuation that increases power system operational cost and transmission level operation [34]. Herein, the peak and variance values for each charging strategy and scheduling policy, reported in Table 4, provide a measure of the impact of EVSEs on the grid. Note that the peak values are the maximum of the aggregated load. The interrupted charging strategy achieves further peak reduction, while both smart charging strategies significantly reduce the peak demand as compared to the uncontrolled charging scenario. DCFC has the highest peak reduction, up to 27.4%. The scheduling policies have more influence on the grid behavior of EVSEs than the charging strategies. Among the scheduling policies, FR displays the best peak power performance, while EDF could increase peak demand. As an example shown in Fig. 6, L2-1P and L2-3P exhibit similar characteristics for the both charging strategies, while L2-3P achieves slightly less peak power. It is found that DCFC can be the most grid friendly configuration with both smart charging strategies and scheduling policies. This is because DCFC can take advantage of the off-peak periods efficiently with higher power charging rates. It is also noticed that the load variance follows the peak and exhibits similar relationships. For all charging strategies and scheduling policies, multi-port DCFC helps further reduce the peak power due to lower charging powers as compared to the single unit.

4.3.4. Performance evaluation of EVSE types from different perspectives

Table 5 presents a comparative analysis of the EVSE types from a station owner's perspective. The number of charging units can be of interest as it might require parking space depending on the EVSE type. Since the presented values are average values among 100 trials, the EVSE unit numbers in the table are found to be fractional.

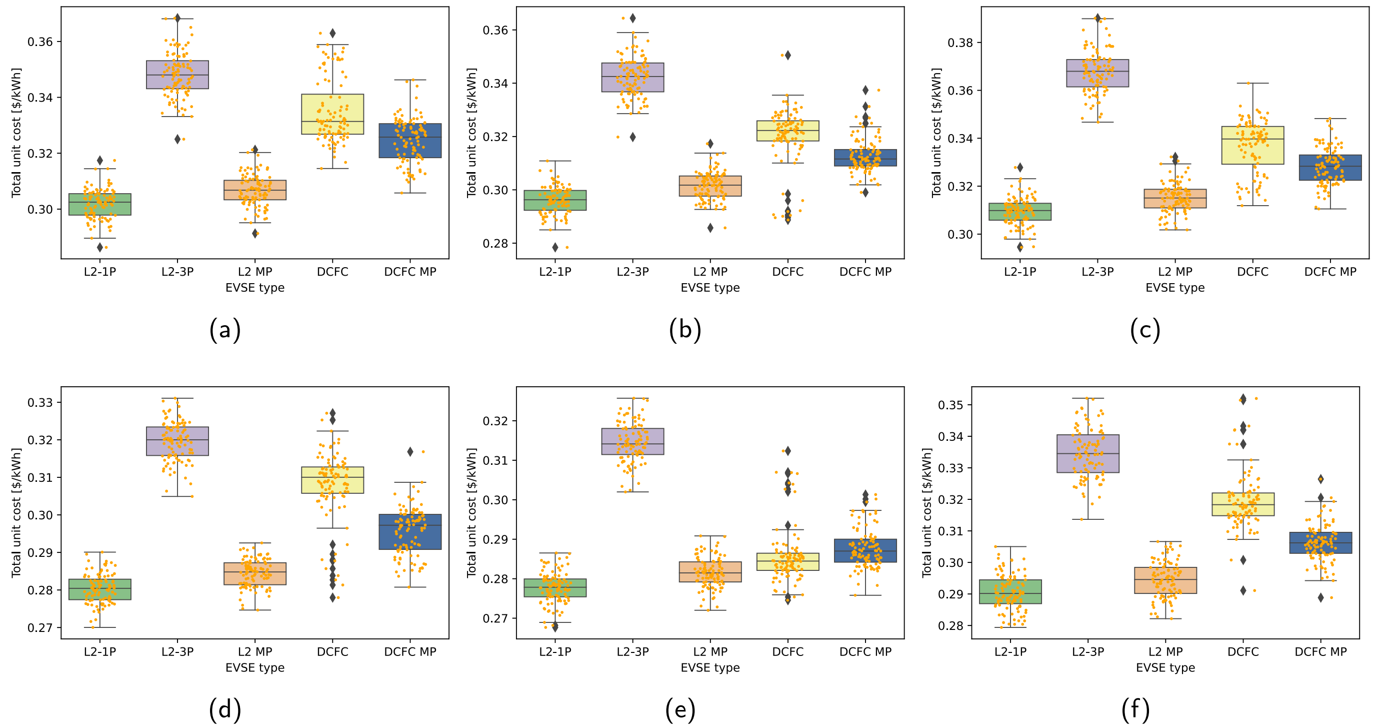


Fig. 4. Unit costs of EVSEs for 100 PEVs with uninterrupted charging strategy: (a) uncontrolled, (b) FCFS, (c) EDF, (d) LJF, (e) FR, and (f) SJF scheduling policies.

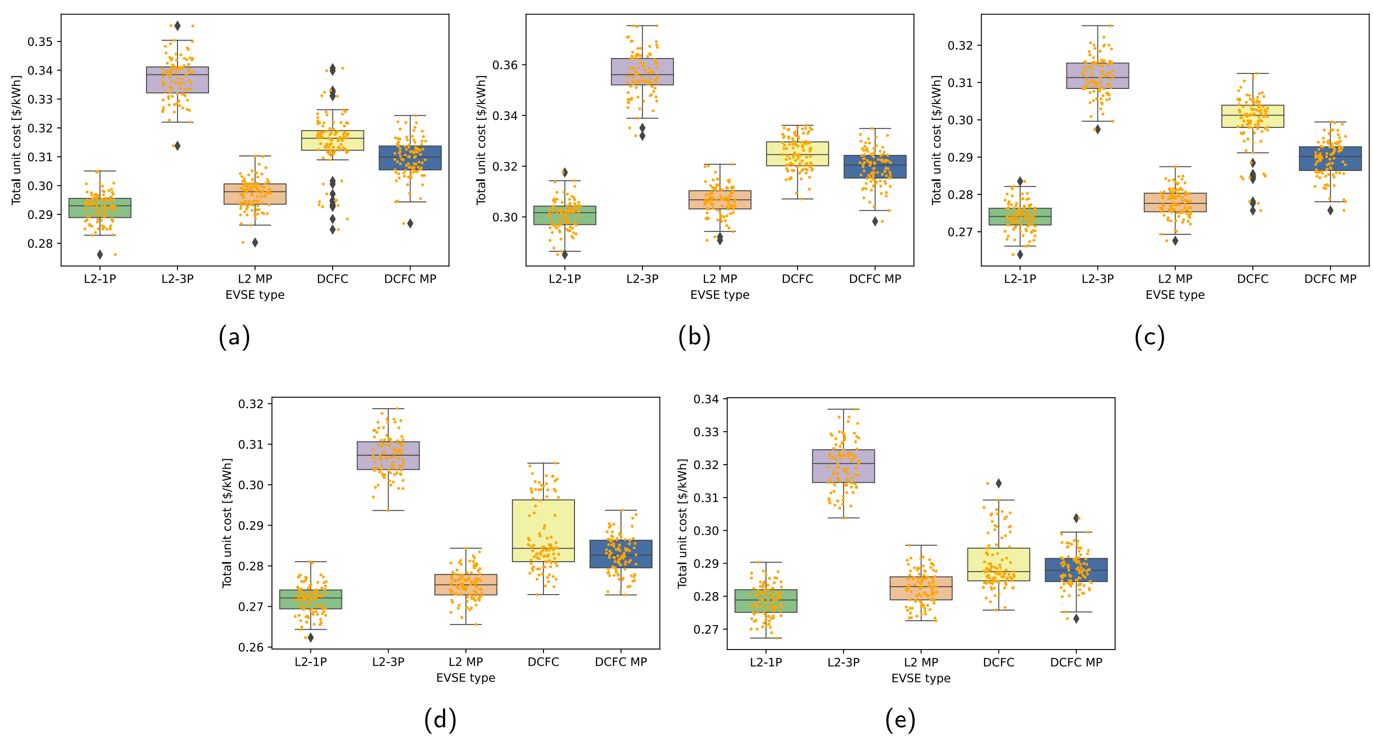


Fig. 5. Unit costs of EVSEs for 100 PEVs with interrupted charging strategy: (a) FCFS, (b) EDF, (c) LJF, (d) FR, and (d) SJF scheduling policies.

The unit numbers for the L2 types are found to be approximate, while 3–5 DCFC units can charge all PEVs. The highest EVSE infrastructure costs happened for L2-3P types due to their higher unit numbers, even though DCFC has the highest infrastructure cost. It is found that the number of EVSE units is affected significantly by the scheduling policies, but less sensitive to the charging strategies. FR policy returns to the lowest charging unit numbers, while EDF policy gives the highest numbers.

In terms of total cost, L2-1P type is found to be cost effective for all charging strategies and scheduling policies. The EVSE cost is the

Table 4
Impact of EVSE types on the grid in terms of charging strategy and scheduling type.

Charging	Scheduling	L2-1P		L2-3P		L2 Multiport		DCFC		DCFC Multi-port	
Strategy	Type	Peak [kW]	Variance [kW]^2	Peak [kW]	Variance [kW]^2	Peak [kW]	Variance [kW]^2	Peak [kW]	Variance [kW]^2	Peak [kW]	Variance [kW]^2
Uncontrolled	**FCFS**	183.97	4456.2	181.50	4355.5	181.5	4355	192.36	4208.97	178.2	4035
Uninterrupted	**FCFS**	174.15	4058.9	174.33	4047.7	177.7	4043	169.29	3,2212.0	166.3	3494
	EDF	203.09	4868.9	201.18	4809.4	200.5	4812	181.45	3672.5	186.8	4128
	LJF	157.80	3564.2	155.91	3520.8	155.8	3519	147.15	2929.2	147.3	3022
	FR	152.24	3468.6	151.54	3415.3	150.9	3419	145.16	2833.2	142.5	2905
	SJF	168.66	3714.9	169.15	3665.2	167.6	3669	152.46	3005.6	155.4	3135
Interrupted	**FCFS**	167.03	4038.5	167.75	3991.3	166.5	3995	156.02	3482.2	161.6	3566
	EDF	190.21	4612.5	190.22	4555.4	189	4567	191.63	3674.9	185.1	3994
	LJF	149.49	3466.9	148.77	3417.5	148.6	3424	139.59	3009.1	142.9	2975
	FR	146.72	3397.7	146.40	3359.2	145.7	3363	139.90	2856.7	139.1	2898
	SJF	152.27	3539.5	152.04	3483.6	151.3	3490	145.83	2916.4	144.6	3013

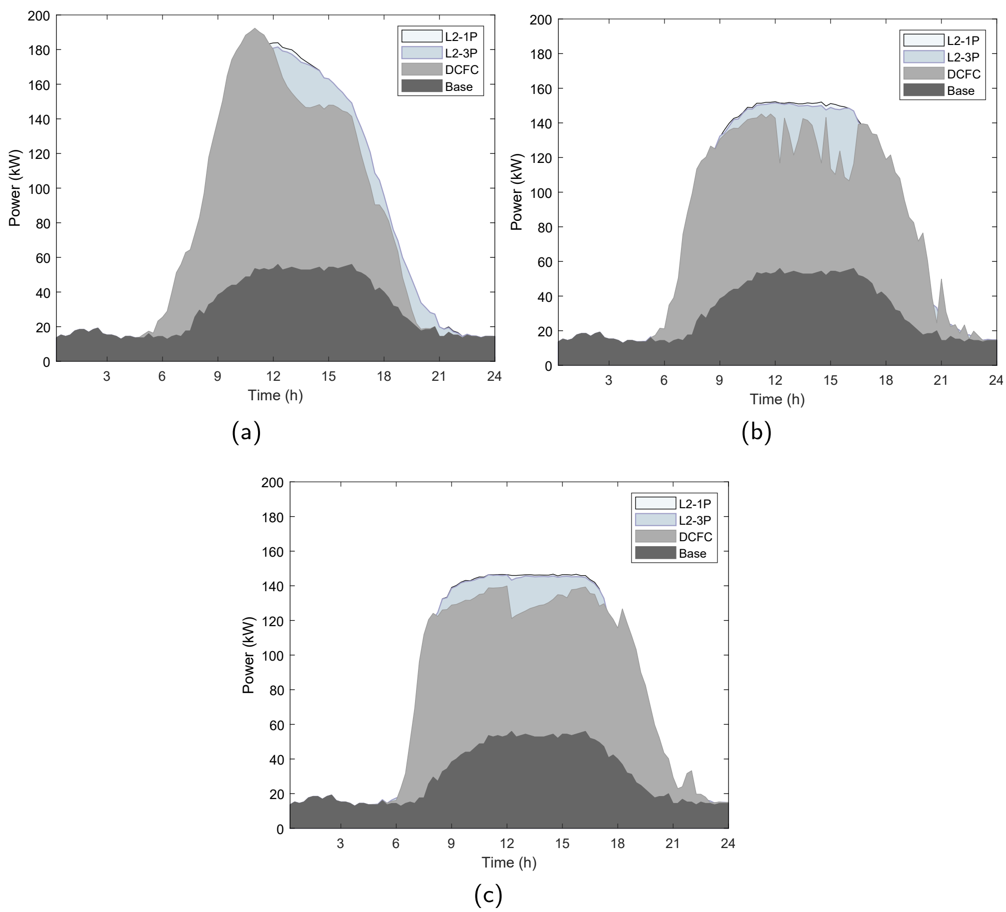


Fig. 6. Aggregated load profiles with 100 PEVs for (a) uncontrolled, (b) uninterrupted, (c) interrupted charging profiles.

major factor contributing to the main difference in the total cost figures for L2-3P and DCFC. This is because L2-3P requires a higher number of units while DCFC has the highest infrastructure cost. Following the EVSE cost, total cost is affected mainly by the demand charge. EVSE cost and demand charge are more sensitive to scheduling policy while energy charge display similar figures irrespective of charging strategies and scheduling policy. It is observed that the demand charges for L2-1P and L2-3P types are prominent compared to DCFC. This is due to need of longer charging times. In this case, the algorithm cannot avoid the peak times while minimizing energy charge. In terms of the station owner perspective, FR policy shows superior performance with benefits for all aspects considered. This shows the importance of charging flexibility in scheduling in terms of unit cost. Demand charge and EVSE cost become major cost components for L2-1P and L2-3P, respectively.

The analysis of the PEV user perspective is worth considering since energy charges can be reflected on PEV users. It is observed that the energy charge is more sensitive to scheduling policies than to charging strategies. All scheduling policies achieve energy cost savings with respect to the uncontrolled charging in which EDF policy shows the superior performance. However, EDF policy was shown to have the lowest performance of all the other aspects considered. This is because PEVs are sorted by their departure times under this policy, which shifts more charging loads towards peak times and increases the number of charging units needed. Thus, EDF policy results in the highest unit cost as explained above, even

Table 5
Performance of single unit EVSE Types in Terms of Station Owner and PEV User Perspectives.

Charging Strategy	Sche Type	L2-1P					L2-3P					DCFC				
		Num.of Units	EVSE Occ.	Energy Charge [$]	Demand Charge [$]	EVSE Cost [$]	Num of Units	EVSE Occ.	Energy Charge [$]	Demand Charge [$]	EVSE Cost [$]	Num of Units	EVSE Occ.	Energy Charge [$]	Demand Charge [$]	EVSE Cost [$]
Uncontrolled	**FCFS**	22.3	1	239.32	57.94	41.22	20.9	1	239.46	58.06	92.71	3.2	1	231.95	62.59	80.69
Uninterrupted	**FCFS**	21.6	1	238.4	53.70	39.91	20.4	1	238.41	54.73	90.54	2.92	1	230.82	55.73	72.72
	EDF	27.9	1	227.83	67.36	51.72	26.6	1	227.67	66.69	118.05	3.8	1	221.50	62.58	93.39
	LJF	18.5	1	233.85	46.36	34.21	17.7	1	233.56	46.30	78.45	2.92	1	227.22	45.60	72.72
	FR	17.4	1	234.42	44.72	32.30	16.6	1	234.03	45.13	73.43	2.1	1	227.39	40.90	51.8
	SJF	21.6	1	234.24	51.55	39.91	20.2	1	233.88	51.68	89.56	3.1	1	228.20	53.37	76.45
Interrupted	**FCFS**	21.2	3.1	239.04	49.37	39.33	20.1	3	238.87	49.98	89.11	2.91	9.3	235.19	45.77	72.47
	EDF	26.6	3.9	228	60.10	49.28	25	3.7	227.78	60.66	111.12	3	3	226.89	62.18	74.96
	LJF	17.8	3.6	232.57	41.64	33.04	16.9	3.6	232.38	41.62	75.25	2.8	13.6	228.36	37.85	69.73
	FR	16.9	3.2	232.86	40.56	31.33	16.1	3.5	232.58	40.68	71.34	2.24	8.8	227.96	38.21	55.78
	SJF	19.8	3.3	233.02	42.67	36.69	18.7	3.5	232.77	42.54	83.29	2.23	6.3	228.33	41.44	55.53

though it achieves the lowest energy charge. EVSE occupancy is proposed as another parameter to measure the charging time affecting the PEV user's convenience. Herein, the occupancy represents how much time PEVs are required to connect to EVSEs with respect to the required time to complete their charging needs. The EVSE occupancy is calculated by

$$\mathrm{EVSE}_{\mathrm{occupancy}} = mean\left(\frac{t_{\mathrm{plug-off,\ i}} - t_{\mathrm{plug-in,\ i}}}{t_{\mathrm{req,\ ii}}}\right) \quad i = 1, \ldots, n, \tag{16}$$

where, $t_{\text{plug-in, i}}$ and $t_{\text{plug-off, i}}$ are plug-in and plug-off time of ith PEV. With the interrupted charging, the occupancy rates increase significantly for DCFC while the charging times increase by 3–4 fold for L2-1P and L2-3P types. Since DCFC provides more charging flexibility thanks to its higher rated power, the algorithm seeks optimal time slots to minimize the cost function. His results in a reduction in the demand charge and a total cost even though the charging cost increases slightly.

Table 6 summarizes the performance of the optimal algorithm for multi-port EVSE types. As the number of port increases, the total cost decreases significantly. The major contribution to cost reduction differs from the EVSE type. Multi-port option reduces L2 EVSE costs almost by 2-fold. The cost reduction in multi-port DCFC is due to the contribution of reduced demand charges. As the number of DCFC units does not change significantly, the contribution of EVSE costs becomes limited. Energy charges do not change with the multi-port L2 type, irrespective of the charging strategies and scheduling policies. The energy charge with multi-port DCFC, on the other hand, increases slightly. Reducing charging power with multiple-port requires higher charging time. That can shift some of the charging process to part-peak or peak times. Since the charging flexibility decreases with respect to single port due to lower charging powers, the EVSE occupancy for multi-port DCFCs is reduced almost by 2-fold. As rated charging powers are not affected for the multi-port L2 type, the PEV user's convenience in terms of charging time does not change in this case.

4.4. EVSE PEV hosting capacity analysis

To evaluate the performance of charging services with each EVSE type, a new hosting capacity index (*HCI*) is introduced. *HCI* is a measure of actual PEV hosting capacity for a charging station and is calculated as the ratio of the total charging energy of PEVs to the total energy capacity for installed EVSE units in the available time horizon (e.g., between their plug-in and plug-off times) as follow:

$$HCI = \frac{\sum_{i}^{n} E_{required}(i)}{S_j(i) \cdot \int_{min(tplug-in(1:n))}^{max(tplug-off(1:n))} \left(P_j^{rated} \cdot \eta_j\right) \mathrm{d}t}. \tag{17}$$

The closer *HCI* is to unity, the better EVSE's performance. Fig. 7a and b demonstrate expected charging services for each EVSE type as a function of the number of PEVs for the interrupted and uninterrupted charging strategies with FCFS policy, respectively. As the total charging energy increases with the number of PEVs, *HCI* is becoming higher. Moreover, it is likely to be saturated after a specific number of PEVs that differ from the EVSE types. The L2-1P has the highest PEV hosting capacity index of 0.45 for around 150 PEVs (Fig. 7a). The L2-3P type has the lowest *HCI* of 0.15 even though the index of its multi-port option is bigger by 2-fold. This confirms that the capacity of L2 EVSE cannot be efficiently used due to the onboard charger specifications of PEVs on the market. As the number of PEVs increases, the hosting capacity of the multi-port DCFC is getting higher at a level of 0.44 for more than 250 PEVs, while it is slightly less for the single port option.

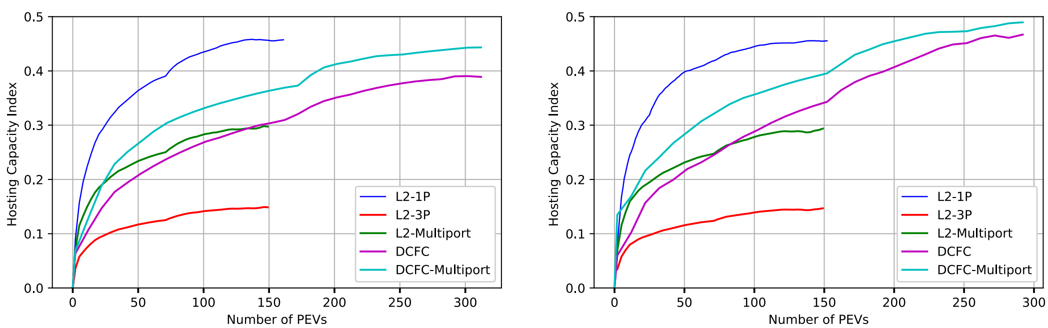
For the uninterrupted charging strategy, it is found that *HCI* for each EVSE types is slightly higher (Fig. 7b). The main factor is that the interrupted charging strategy turns out to have higher EVSE units as it uses a wider time horizon to fulfil charging requests at lower costs. The highest *HCI*s are found to be 0.48 and 0.46 for approximately 300 PEVs for the multi-port and single DCFCs, respectively. Similar to the interrupted charging strategy, L2-1P has the highest *HCI* among L2 types up to 100 PEVs. As a result, DCFC delivers the highest level of charging services as the number of PEVs increases significantly. However, L2-1P types has still have the best hosting capacity index for charging a lower number of PEVs. As expected, the multi-port EVSEs have better hosting capacities compared to their single-port counterparts.

4.5. Sensitivity analysis

A sensitivity analysis has been performed to explore the impact of PEVs' battery sizes and their onboard charger ratings on unit cost behavior with respect to EVSE types. The battery sizes and onboard charger ratings were selected based on new PEV models on the market. According to the data in Ref. [35], among 128 new PEV models on the market, the distribution of battery sizes is as follow: 8.5% fewer than 30 kWh, 38% between 30 and 60 kWh, 45% between 60 and 90 kWh, and 8.5% greater than 90 kWh. The distribution of charger ratings varies as: 10% 7.2 kW, 10% 7.4 kW, 45% 11 kW, 17% 22 kW, and 18% other power ratings. For this sensitivity

Table 6
Performance of multi-port EVSE types in terms of station owner and PEV user perspectives.

		L2 Multi-port					DCFC Multi-port				
Charging Strategy	Sche Type	Unit #	EVSE Occ.	Energy Charge [$]	Demand Charge [$]	EVSE Cost [$]	Unit #	EVSE Occ.	Energy Charge [$]	Demand Charge [$]	EVSE Cost [$]
Uncontrolled	**FCFS**	10.4	1	239.46	58.06	46.36	2.8	1	236.13	57.02	70.73
Uninterrupted	**FCFS**	10.3	1	238.43	54.05	45.62	2.6	1	234.70	51.44	64.38
	EDF	13.3	1	227.70	66.54	59.07	3.3	1	223.93	61.81	82.43
	LJF	8.9	1	233.55	46.06	39.38	2.4	1	229.63	43.28	58.65
	FR	8.3	1	233.98	44.90	36.91	2.1	1	229.38	41.08	52.05
	SJF	10.2	1	233.94	51.04	45.11	2.6	1	230.11	48.21	65
Interrupted	**FCFS**	10.1	3.2	238.95	49.30	44.94	2.5	5	236.80	47.61	62.51
	EDF	12.7	4.1	227.70	59.62	56.25	2.9	3.7	226.35	58.80	72.97
	LJF	8.5	3.7	232.33	41.27	37.93	2.3	6.8	229.38	39.21	56.16
	FR	8.1	3.6	232.55	40.25	35.96	2	6.6	228.86	37.45	50.68
	SJF	9.4	3.5	232.73	42.27	41.91	2.1	5.7	229.52	40.23	53.29



(a) (b)

Fig. 7. PEV hosting capacity indices of EVSE types: a) interrupted, b) uninterrupted charging strategies.

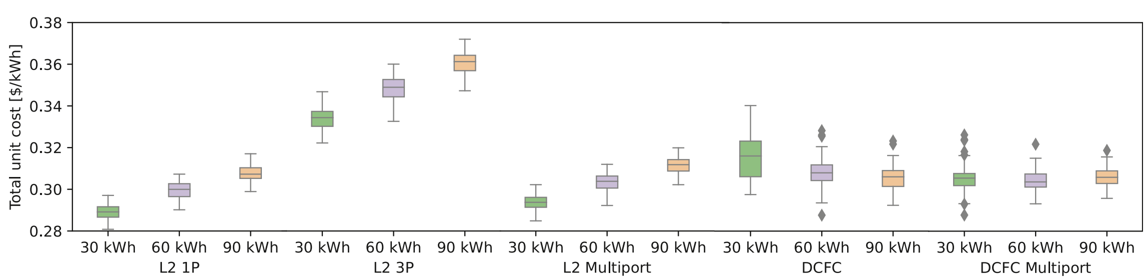


Fig. 8. Unit cost behaviors of EVSE types for battery sizes ranging from 30 kWh to 60 kWh.

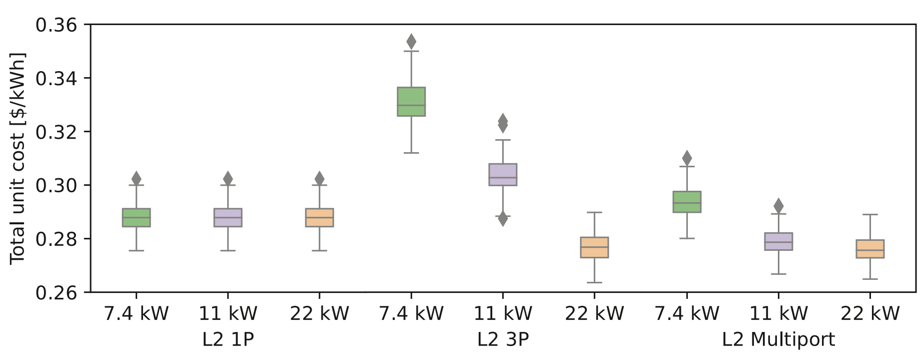


Fig. 9. Unit cost behaviors of EVSE types for onboard charger rates at 7.4 kW, 11 kW, and 22 kW.

analysis, three different PEV battery sizes and onboard ratings were selected.

Fig. 8 shows the unit cost behaviors of the EVSE types for selected battery sizes. DCFC is found to be the least sensitive to battery size. As the battery size increases, the unit cost for DCFC reduces while it increases in L2 types. The unit cost decreases slightly for multi-port DCFC. Among DCFC options, battery sizes up to 90 kWh are found to be the most economical for multi-port DCFC, in which the unit cost is getting higher than that of a single port option. The unit cost of L2 EVSE types increases with bigger battery sizes. However, L2-1P and multi-port L2 can still be cost-effective up to 60 kWh battery sizes. Among the L2 options, L2-3P has the highest unit cost due to the inefficient use of EVSE power ratings. The sensitivity analysis on the charger ratings is shown in Fig. 9. ince DCFC accesses the battery directly, it is not included in this analysis. As expected, L2-1P is the least sensitive to the power ratings since its rating limits the charging power. L2-3P is the most sensitive to the power ratings, and the unit cost for this type reduces significantly when increasing onboard power ratings. However, the multi-port option is still the most economical option for increased charger ratings up to 22 kW.

5. Conclusion

The optimal planning and management of a workplace charging station have been considered in this study. The multi-objective optimization model developed provides an optimum EVSE configuration that minimizes the unit cost of a charging station over its life cycle with an efficient use of the grid assets. From the perspectives of the station owner, PEV users, and the grid, the uninterrupted and interrupted smart charging profiles with various scheduling policies have been studied to explore their impacts on the behaviors of EVSE types.

It has been shown that the multi-objective model achieves up to 7.8% cost savings as compared to single-objective optimal models in which other cost aspects of a workplace charging station can be compromised. In addition, the developed model displays superior performance with reduced unit cost values of between 7.9% and 14.6% depending on the charging strategies and scheduling policies as compared to the current practice. Based on the workplace mobility pattern considered, it has been found that L2-1P has the best unit cost figure, whereas L2-3P displays the highest unit cost among the EVSE types considered. This has been supported by the introduced PEV hosting capacity index. As such, L2-1P and L2-3P have the highest and lowest index values at lower PEV numbers, respectively, while DCFCs outperform with an increased number of PEVs. However, higher EVSE infrastructure costs for DCFCs make their cost-effectiveness lower than that of L2-1P and multi-port L2 types.

The unit costs are found to be more sensitive to the scheduling policies than the charging strategies. In this regard, the impact of the scheduling policies on EVSE cost and demand charge can be dominant, whereas energy charge displays similar cost figures irrespective of charging strategies and scheduling policies. It was shown that knowing the charging flexibility gives the best PEV scheduling with the lowest unit cost and the most efficient use of the grid assets. Moreover, it is shown that the demand charge could play a major role in reducing unit costs even though the energy charge is dominant. As a result, when considering a charging station for workplaces, one should consider the impact of EVSE types on the grid in terms of peak power.

The sensitivity analysis has concluded that L2-3P is the most sensitive EVSE to both battery size and onboard power rating. As the battery size increases, the unit cost for DCFC reduces, while it increases significantly for L2 types. L2-1P and multi-port L2 can still be cost-effective for battery sizes up to 60 kWh. While multi-port options reduce unit costs compared to their single-port counterparts, the savings are lower for higher battery sizes and onboard power ratings.

Credit author statement

Nuh Erdogan: Conceptualization, Methodology, Software, Validation, Formal analysis, Data collection, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. Sadik Kucuksari: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. Jimmy Murphy: Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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