Smart Charging Strategy for Electric Vehicle Charging Stations

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***Abstract*— Although the concept of transportation electrification holds enormous prospects in addressing the global environmental pollution problem, in reality the market penetration of plug-in electric vehicles (PEVs) has been very low. Consumer concerns over the limited availability of charging facilities and unacceptably long charging periods are major factors behind this low penetration rate. From the perspective of the electricity grid, a longer PEV peak load period can potentially overlap with the residential peak load period, making energy management more challenging. A suitably designed charging strategy can help to address these concerns, which motivated us to conduct this research. In this paper, we present a smart charging strategy for a PEV network that offers multiple charging options, including ac level 2 charging, dc fast charging, and battery swapping facilities at charging stations. For a PEV requiring charging facilities, we model the issue of finding the optimal charging station as a multiobjective optimization problem, where the goal is to find a station that ensures the minimum charging time, travel time, and charging cost. We extend the model to a metaheuristic solution in the form of an ant colony optimization. Simulation results show that the proposed solution significantly reduces waiting time and charging cost.**

***Index Terms*— Charging stations, charging strategies, plug-in electric vehicles.**

Nomenclature

t	Current time.
M	Total number of PEVs.
N	Total number of charging stations.
k	Type of charge at charging option ($k = 1$: swap battery, $k = 2$: dc fast charging and $k = 3$: ac level 2 charging).
$T^{\text{drive}}(s,\ j)$	Driving time from current location of PEV_i to the charging station j.
$T^{\text{drive}}(j,\ d)$	Driving time from the charging station j to the destination d.
$T_j^{\text{wait}}(k)$	Waiting time for charging option k at the charging station j.
$D^{\max}(t)$	Maximum driving distance with the remaining energy.
E^{ca}	Battery capacity of PEV.
E_j^{ca}	Maximum power capacity of each charging station j.
$E_g^{\max}$	Maximum capacity of grid g.
E^{Travel}	Energy consumption per unit driving distance for each PEV.
$\text{SoC}(t)$	State of the charge of the battery for a PEV.
λ_j	Arrival rate at the charging station j.
μ_j^k	Service time at the charging station j for charging option k.
$P_i(t)$	Power consumption of PEVs.
$L_j^k(t)$	Queue length at time t for charging option k at charging station j.
π_j^R	Probability transition matrix for R possible state at charging station j.
W_j^k	Waiting time at charging station j for charging option k.
d_i	Driving destination for PEV.
$\upsilon(s,\ j)$	Average speed between source to a charging station.
Pr_k	Price for charging option k.
$C_j^{\text{recharge}}(k)$	Recharging cost for charging option k at charging station j.
$T_j^{\text{max\_wait}}(k)$	Maximum waiting time for charging option k at charging station j.

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I. Introduction

PLUG-IN electric vehicles (PEVs) powered by electricity from low carbon emission grids can provide significant benefits in terms of reducing the climate impact from transportation and minimizing transport grid's reliance on oil-based fuels. PEVs provide a cleaner and quieter environment, and reduce operating costs at the same time [1]. Due to their usage pattern in urban areas, PEVs can potentially operate as flexible electric loads to support the operation of power systems and the integration of renewable energy sources [2]. The vision of using parked PEVs as storage devices for renewable energy has also attracted increasing interest in recent years [3]–[5]. Although PEVs are considered to be an important part of the next generation smart grid system [6], their market penetration is still relatively low and faces a number of challenges. First, drivers' range anxiety is a key issue which must be managed by organizing better communication with the smart grid interface, to facilitate timely and fast recharging at public charging stations. Second, uncoordinated charging strategies in a limited charging infrastructure can increase the average recharge time [7] and contribute to an increase in peak loads [8]. Currently, charging infrastructures are not widely available in all major cities, and because of long waiting times at charging stations, the recharging process can cause significant delays [9], [10].

The relevant industries consider this delay to be a major challenge and are exploring all available options to reduce the waiting time at public charging stations [11], commonly known as PEV networks. A smart charging strategy can make a major contribution to the efficient management of available resources in PEV networks. Recognizing the significance of smart charging in the context of PEV networks, researchers have investigated and presented various smart charging strategies in recent years, targeting the reduction of range anxiety and charging time [12]. However, a gap still exists in the literature since none of the existing works considers multiple charging and dynamic pricing options at the charging stations in their PEV networks [13], [14]. In practice, a charging station, like a traditional gas station (selling petrol, diesel, and LPG) can have multiple charging options with dynamic price information. A smart grid can collect important information about the current status (e.g., available number of sockets, queue status, price, etc.) of every charging station in a PEV network. The grid can then provide this information in real time to the individual PEV user [15], [16]. This information can be taken into account to calculate a path to the destination which would reduce the time and cost of charging. This provided the motivation for this research.

In this paper, we present a smart charging strategy for a PEV network that supports multiple charging options at its charging stations. We model multiple charging options as a multiserver queuing system in order to estimate the waiting time for each charging option at a charging station. The queuing system is presented in detail in Section III-A. We then model the optimal charging station finding problem as a multiobjective optimization problem where the objective is to minimize the travel time, waiting time, and charging cost. The optimization problem and related constraints are presented in Section III-B. Considering the industry demand for a robust solution, we extend and model the problem as a metaheuristic optimization problem. A detailed description of the metaheuristic solution is presented in Section IV. The main contributions of this paper can be summarized as follows.

1) We introduce a smart charging strategy that considers multiple charging options and relevant price information at each charging station in a PEV network. We model the research question as a multiobjective optimization problem, and reflecting the need for a real-time solution, we also present a metaheuristic solution.
2) We show that dynamic price variation at charging stations can be a useful mechanism to control the average charging time, which ultimately can prove pivotal in reducing the overlap extension between the PEV and residential peak load periods.

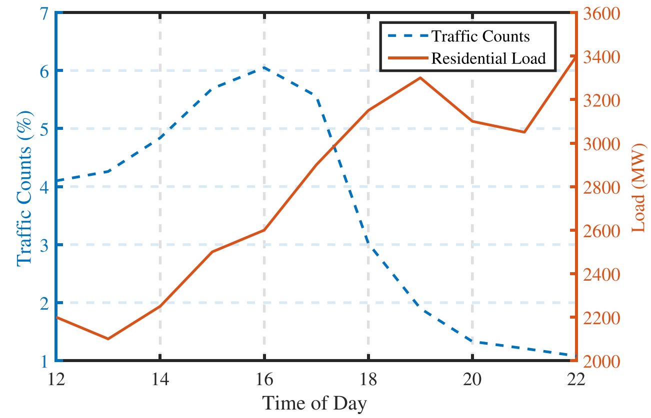

Fig. 1. Traffic counts and residential loads in NSW, Australia.

3) We verify the significance of the proposed solution using a computer simulation on a Washington City PEV network.

The remainder of this paper is organized as follows. Section II introduces previous work on PEV charging in urban areas. Section III describes a smart charging strategy for PEVs and presents a system model and the proposed method for solving the problem of the minimization of total travel time and recharging cost. Section IV presents the simulation results and discusses the introduced case study. Finally, SectionVI concludes with a summary of the study.

II. Related Work

Fig. 1 shows the average afternoon traffic distribution as a percentage of the total vehicle counts, and a typical residential load profile in an urban area in New South Wales (NSW), Australia [17], [18]. It is evident that the period between 2 P.M. and 6 P.M. is the busiest, when most of the vehicles are on the streets. The load profile for a PEV charging network is expected to follow a similar trend, as most of the PEVs are also expected to be on the roads during this period and would need to recharge. This is analogous to traditional gas stations, where the load is generally high in the late afternoon. Fig. 1 also demonstrates that there is an overlap between the daily residential peak load and the PEV load. This overlap would be a major challenge for the power industry since an extended period of overlap can put significant stress on both the generation and distribution sides of the energy industry. An uncoordinated charging strategy can result in a long queue at hotspot areas during busy period, which would increase the charging time (i.e., waiting time at a station plus time to recharge) and the overlap period between the PEV and the residential load. This challenge can be mitigated by introducing a smart charging strategy, where the smart grid can collect real-time information about loads at various charging stations and pass this information to individual PEVs, enabling PEVs to come up with their charging plans (i.e., the optimum charging station along the route to the destination). Most of the research [19]–[22] on PEV charging strategies has focused on controlling residential charging patterns to avoid the potential overloads, stresses, voltage deviations, and power losses that may occur in distribution systems from domestic

PEV charging activities. Some researchers [23], [24] have also investigated the simultaneous utilization of distributed renewable resources and PEVs to improve the performance of smart power distribution networks. Most recently, researchers have started to investigate charging strategies for public charging stations.

Amini and Karabasoglu [25] proposed a framework for interdependent power and electrified transportation networks that utilized the communication of PEVs with competing charging stations to exchange information such as electricity price, energy demand, and time of arrival. While the framework solves an important problem in the area of optimal power flow and vehicle routing, Amini *et al.* [25] do not consider multiple charging options and associated queuing models to address the problem of longer waiting times at charging stations. Yang *et al.* [26] investigated the PEV charging problem and proposed two types of charging station selection algorithms: the first solution utilized only local information (e.g., SoC, geographical position, etc.) relating a PEV and the second solution utilized the global information obtained through the interaction between the PEVs and the charging station server using a mobile telecommunications network. Their work showed that the performance of the charging algorithm that used global information was better than the performance of the charging algorithm that used local information. However, their work focused on waiting time and did not consider the multiple charging option, cost, and travel time.

Pourazarm *et al.* [27] solved a path-finding problem within a graph of charging station nodes using a dynamic programming solution. They applied a grouping technique based on traffic flows with multivehicle routing to achieve the shortest path. This paper, however, did not consider the waiting time and recharging cost at charging stations. Similar to the work presented in [27], Sweda and Klabjan [28] introduced a recharging plan for PEVs to find a charging station with the shortest path. Their model was designed for an urban environment where the number of routes can be very large and the number of charging stations is limited. They proposed a preprocessing approach to save computations in an urban environment. Their work, however, focused on finding the shortest path based on the minimum travel time only. In [29], a distributed charging scheduling protocol was proposed to minimize waiting times in the charging stations. The authors used a theoretical approximation model which was based on the arrival rate of PEVs at each charging station and achieved a high performance in terms of waiting time. However, they did not consider a multiserver queuing system for different charging options. In addition, they did not consider the minimization of total travel time and recharging cost in their objective function. Gusrialdi *et al.* [30] proposed an optimized charging strategy using a stochastic model for controlling the PEV arrival rate at charging stations in order to minimize the demand flow and the waiting time. However, they did not consider the impact of variable price and multiple charging options at a charging station.

Razo and Jacobsen [31] proposed a smart charging approach to plan charging stops on highways with limited charging infrastructure. Using the coordination between the charging stations and PEVs, their approach focused on minimizing the waiting time at charging stations and the overall travel time. Considering the complexity of the optimization problem, they adopted a metaheuristic (A* search) approach to find a solution. However, this paper did not consider multiple charging options and price variation among charging stations in their model.

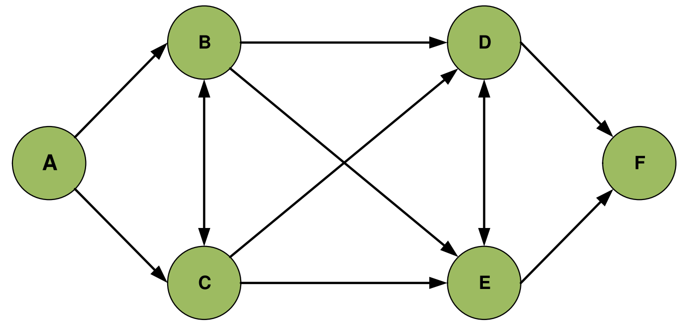

Fig. 2. Graph representation of a PEV network.

As discussed above, while researchers have introduced a number of smart charging strategies for PEVs, none of the existing work presents an integrated solution that considers multiple charging options, waiting time, travel time, and recharging cost. In this paper, we introduce a smart charging strategy, focusing on total travel time reduction, with different charging options at charging stations and also taking into account various prices for each charging option.

III. Smart Charging Strategy

A. System Model

A PEV network can be considered as a weighted undirected graph $G = (V, E)$, where V is the set of charging stations which is denoted as $j : (j = 1 \ldots N)$ and E is the set of connecting paths between the nodes as shown in Fig. 2. Each charging station provides three charging options: 1) dc fast charging; 2) ac level 2 charging; and 3) battery swapping facilities [32]. Each charging option has a queue, and each queue has a specific service rate, waiting time, and price. The queue length is influenced by factors such as PEV arrival rates and service times (i.e., time to fully recharge). The queue length is an important parameter as it determines the waiting time before the actual service is offered. The PEV arrival rate is also partially influenced by price information. In our system model, each PEV indexed by i at a time instant t can be attributed by its current state of charge $\mathrm{SoC}_i(t)$, current location S_i, and intended destination d_i. All charging stations and PEVs are connected to the smart grid and can exchange information in real time. If a PEV plans to go from a source to a destination node and its current SoC suggests that it will not have enough stored energy, it will have to recharge at a charging station. A PEV driver may also prefer to charge at a faster rate from a fast charging station instead of using the slow charging facility at his/her accommodation. The research question then translates into finding the optimum charging station that does not significantly increase the travel time to the destination and offers the best price for recharging.

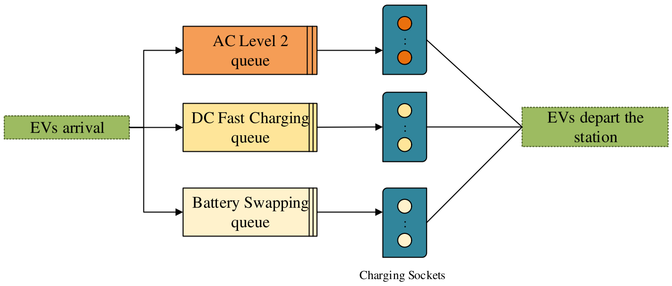

Fig. 3. $M/M/s/C$ queuing model for a charging station.

For a PEV, the total travel time depends on the time required to reach the charging station, the time spent waiting in the queue for the preferred charging option, service/charging time, and time required to reach the destination. As such, in the following sections, we show how to model and calculate the total travel time takings, the queuing delay, and charging cost for each charging option into account.

1) Driving Time From Source to Destination: For a PEV at a time instant t, if $T^{\text{drive}}(s, d)$ indicates the driving time from its current location s to the destination d and j indicates the charging station along the way, then $T^{\text{drive}}(s, d)$ can be obtained by

$$T^{\text{drive}}(s, d) = \frac{D(s, j)}{v(s, j)} + \frac{D(j, d)}{v(j, d)} \tag{1}$$

where the first term of the above equation is the time required for the PEV to travel from its current location to the charging station and the second term states the travel time from the charging station to the specific destination. Here, $D(s, j)$ and $D(j, d)$ indicate the route distance from the source to the charging station and the charging station to the destination, respectively. $v(s, j)$ and $v(j, d)$ indicate the average moving speed of the PEV from its source to the charging station and the charging station to the destination, respectively. To make sure that the PEV does not run out of charge before reaching the charging station, $D(s, j)$ must be less than $D^{\max}$, and the maximum distance that the PEV can travel based on its current SoC. The maximum distance that the PEV can travel based on its SoC at a current time t, can be given by

$$D^{\max}(t) = \frac{E^{\text{ca}}\text{SoC}(t)}{E^{\text{Travel}}} \tag{2}$$

where E^{ca} is the total capacity of batteries in PEV, and E^{Travel} represents its energy consumption per unit of traveling distance. In addition to the net driving time as indicated by (1), the PEV would have to wait in the queue at a charging station before it obtains access to the desired facility. The waiting time in the queue at a charging station can be estimated using a queuing system, which is presented in the next section.

2) Queuing Model for a Charging Station: Fig. 3 shows the queuing system used for charging stations with multiple charging options in our model. To estimate the waiting time for each charging option at a station, we use the $M/M/s/C$ model [7], [33], where the letters have the following meaning:

1) the first M (Markov): Markovian (exponential) PEVs arrival time distribution;

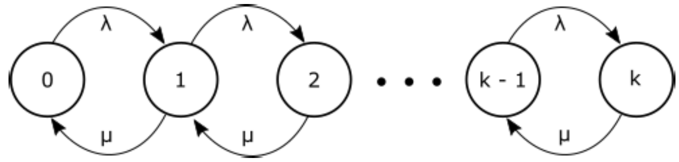

Fig. 4. State transition diagram of the $M/M/s/C$ queuing system.

2) the second M (Markov): Markovian (exponential) charging time distribution;
3) s: the number of servers;
4) C: the system capacity (the number of PEVs that can be parked at the station).

Every PEV that arrives at a station can immediately recharge if there is an available socket in the charging station. If all the sockets are busy, the PEV needs to wait in a queue until a socket becomes available. Each charging station has three queues, one for each charging option. PEVs in each queue are served by s servers. Each server operates with an exponential service rate μ_j^k facilitated by a socket. The PEV arrival process at a charging station follows a Poisson distribution with a mean arrival rate λ_j. The service rates are constrained by the infrastructure (i.e., sockets and charging rates), whereas the mean PEV arrival rate during various hours of the day can be derived from historical data. A smart charging strategy that influences the route selection decision can have an impact on arrival rates at a charging station. However, the traffic/load analysis based on the data collected over a period of time is expected to capture this impact. Based on the principle of Markov chains [34], the state transition diagram for the $M/M/s/C$ queuing process can be derived and depicted as shown in Fig. 4, where each state of the chain corresponds to the number of PEVs in the queue. When new PEVs arrive or a PEV recharges and departs the station, the queuing process moves to a different state. This state transition is essentially a stochastic process with X_r being the random variable that represents the value of the chain at step r. This stochastic process with state space $\xi = \{1, 2, 3, \ldots\}$ exhibits the property of a Markov chain because of the $P(X_{r+1} = j | X_r = i, X_{r-1} = x_{r-1}, \ldots, X_0 = x_0) = P(X_{r+1} = j | X_r = i)$ attribute.

The state transition probability matrix P for the above-mentioned stochastic process can be given as [35], [36]

$$P = \begin{bmatrix} -\lambda & \lambda & 0 & \ldots & 0 & 0 \\ \mu & -(\lambda+\mu) & \lambda & \ldots & 0 & 0 \\ 0 & 2\mu & -(\lambda+2\mu) & \ldots & 0 & 0 \\ \ldots & & & & & \\ 0 & 0 & \ldots & & \lambda & 0 \\ 0 & 0 & \ldots & & -(\lambda+c\mu) & \lambda \end{bmatrix}. \tag{3}$$

Definition 1: In the probability matrix P, $P^T \cdot \pi^T = 0^T$, where π is the row vector that contains the stationary distributions. Assuming the occupancy rate with $\rho = \lambda/c\mu$, we can obtain the rth stationary distribution

$$\pi_r = \pi_0 \frac{\lambda^r}{n!\mu^r} = \frac{(c\rho)^r}{r!}\pi_0 \tag{4}$$

and reaching the system capacity C, we obtain the capacity for each station which is shown by c

$$\pi_{c+r} = \rho^r \pi_c = \rho^r \frac{(c\rho)^c}{c!} \pi_0 \quad r=0,1,2,\ldots,c+r=C. \tag{5}$$

Now if we consider $\sum_{p=0}^{\infty} \pi_p = 1$, we can obtain the π_0 stationary distribution

$$\pi_0 = \frac{1}{\sum_{i-0}^{c}(\frac{1}{i!}\left(\frac{\lambda}{\mu}\right)^i + \sum_{j=c+1}^{R} \frac{1}{C^{j-c}})(\frac{1}{c!})\left(\frac{\lambda}{\mu}\right)^i}. \tag{6}$$

Using this formula, we can also obtain the mean queue lengths for each queue

$$E(L_q) = \sum_{k=c}^{R} (p-c) \cdot \pi_p \tag{7}$$

where π_p is the pth stationary distribution. After substituting the proper values and simplification of the equation, queue length can be given as

$$E(L_q) = \pi_0 \cdot \frac{\rho(c\rho)^c}{c!(1-\rho)^2}[1-\rho^{R-c}-(R-c)\rho^{R-c}(1-\rho)]. \tag{8}$$

Using the Little law at each charging station for three types of charging options, the mean waiting time at each queue can be given as [37]–[39]

$$\forall k:(k=1,\ 2,\ 3)$$
$$E\left(W_j^k\right) = \frac{E\left(L_j^k\right)}{\lambda_j\left(1-\pi_j^R\right)}. \tag{9}$$

Therefore, for the queue corresponding to the battery swapping facility at a charging station j, the mean waiting time is calculated as follows:

$$E(W_j^1) = \frac{\mu_j^1}{\lambda_j\left(\mu_j^1-\lambda_j\right)\left(1-\pi_j^R\right)} \tag{10}$$

for the dc-fast charging queue, the mean waiting time is calculated by

$$E\left(W_j^2\right) = \frac{\mu_j^2}{\lambda_j\left(\mu_j^2-\lambda_j\right)\left(1-\pi_j^R\right)} \tag{11}$$

and for the ac-normal charging queue, the mean waiting time is calculated by

$$E\left(W_j^3\right) = \frac{\mu_j^3}{\lambda_j\left(\mu_j^3-\lambda_j\right)\left(1-\pi_j^R\right)}. \tag{12}$$

3) Charging Cost for a PEV With a Specific Charging Option at the Charging Station: The charging cost of each PEV depends on its associated charging option and the associated charging rate at the station j. For a PEV, the charging cost is calculated through the formula below

$$C_j^{\text{recharge}}(k) = ((d_{\text{charging}}\text{Pr}_k) \quad j \in J \tag{13}$$

where d_{charging} is the charging demand of each PEV, which depends on the remaining and target SoC for each PEV

$$d_{\text{charging}} = \sigma \text{E} - \text{SoC}. \tag{14}$$

Here, σ is the coefficient for partial charging, which can vary from the current SoC to the maximum SoC (e.g., 90% battery capacity). Under normal circumstances, most users would prefer full charging (i.e., $\sigma = 0.9$). However, during peak hours, a preference for full charging would lead to longer waiting times. Longer waiting times can stretch the PEV peak period and make it overlap with the residential peak period. Partial charging (i.e., $\sigma < 0.9$) can encourage users to postpone their full charging process and depart the queue early. Partial charging can be influenced by a suitable dynamic pricing model, and together, these measures can provide an effective solution to the problem of longer waiting times during peak hours.

B. Proposed Model

The objective of the proposed charging strategy is to find a charging station along the path such that the total travel time—including driving time from current location to destination, waiting, and charging time at a charging station—and the charging cost are minimized. Mathematically, considering (1), (9), and (13), the objective of our charging strategy can be modeled as: for $\forall i \in I$ find a charging station j that minimizes total travel time and recharging cost, as below

$$\min\left[x(T^{\text{drive}}(s,\ d)) + yT_j^{\text{wait}}(k) + zC_j^{\text{recharge}}(k)\right] \tag{15}$$

where x, y, and z are the positive coefficients of the objective function

$$\text{s.t. } T^{\text{drive}}(s,\ d) \le ((E^{\text{ca}}\text{SoC}(t))/E^{\text{Travel}}) \tag{16}$$
$$T_j^{\text{wait}}(k) <= T_j^{\text{max\_wait}}(k) \tag{17}$$
$$\text{SoC}_{\min} \le \text{SoC}(t) \tag{18}$$
$$\forall j \in J \sum_{i=1}^{M} E^{\text{ca}} \le E_j^{\text{ca}} \tag{19}$$
$$E_j^{\text{ca}} < E_{\text{ca, grid}}^{\max}. \tag{20}$$

In the optimization problem, the summation of driving time from source to destination, waiting time at the station for a specific queue, and charging cost for each PEV_i at a charging station j should be minimized. Constraint (16) shows the constraint for the driving time from the current source to a charging station, which is explained in (2). In constraint (17), the maximum waiting time for each queue at charging stations is presented. This should be less than the maximum waiting time at each charging station for different charging options. Constraint (18) indicates that initial amount of SoC for a PEV at charging station j should be greater than $\text{SoC}_{\min}$. An additional constraint is defined in (19), which states that the summation of the charging power capacity for all PEVs at a charging station should be less than the maximum capacity of that charging station, and constraint (20) considers the maximum grid capacity for each charging station.

IV. Smart Charging Strategy Using Metaheuristic Algorithm

In the previous section, we have shown that the proposed smart charging strategy can be formulated as a classical optimization problem. However, the optimization solution is NP-hard due to the path discovery mechanisms [37]. This motivated us to further investigate the research problem and find a heuristic solution.

A. Ant Colony Optimization

Ant Colony Optimization (ACO) is a category of swarm intelligence that analyzes the survival behavior pattern of the insects in solving complex optimization problems [38]. ACO is a widely recognized metaheuristic approach and has been successfully used across diverse domains, including vehicle routing and scheduling [39]–[42]. The main characteristic of ACO is that every single ant in a colony can construct a possible solution by considering both heuristic and stochastic information and exchanging that information with the ants and the environment [38]. The collective intelligence gathered from a group of ants traveling along alternate routes leads to the identification of an optimal route [28], [43]. As a description of the ACO algorithm, consider a colony with m ants that iteratively exploits the graph and searches for feasible solutions to the problem. At each iteration u, an ant k moves stochastically, based on a constructive decision policy which uses the information of pheromone trails and attractiveness to obtain the probability for choosing the next node, as below

$$P_{ij}^{k}(u) = \frac{\tau_{ij}(u)^{\alpha}\eta}{\sum_{l \in N_i^k} \tau_{il}(u)^{\alpha}\eta} \quad \text{if } j \in N_i^k. \tag{21}$$

Here N_i^k is the set of feasible neighborhood nodes in the graph. For a node i, a set of feasible neighborhood nodes indicates that the list of nodes are directly accessible from node i and candidates for searching based on the heuristic information. Nodes that are in the feasible neighborhood set offers a better chance of finding the optimum solution [41], [44], $\tau_{ij}(u)$ is the sum of pheromones deposited between nodes i and j which denotes the desirability of the move between the nodes; η_{ij} is heuristic information which specifies the attractiveness of that move, and α and β are parameters which control the relative weight of pheromone and heuristic information. During the completion of a tour, each ant deposits the pheromone information on the respective edges of its path. There is a rule for updating pheromone information, as below

$$\tau_{ij}(u+1) = \rho\tau_{ij}(u) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(u) \quad \forall(i,\ j) \tag{22}$$

where $0 \leq \rho \leq 1$ is the pheromone evaporation rate, which causes the pheromone value to decrease over time to prevent a local optimum, and $\Delta\tau_{ij}^{k}(u)$ refers to the inputs of ants between nodes i and j. Consequently, each ant moves through those nodes similar to its partial solution. Although the convergence properties of the ACO algorithm have been proven, the probabilistic decisions depend on the problem-definition and user preferences [38]. For the proposed objective function, the routing algorithm should consider the lowest travel time, the lowest recharge cost, and the lowest waiting time at each station, as the heuristic information.

ACO is not only sensitive to the number of variables but also runs faster, which is an important ability in relation to solve dynamic vehicle routing and refueling problems. ACO is a probabilistic search algorithm which has specific characteristics, considering the problems in terms of the heuristic information in the probabilistic decision, and the strategy of updating the pheromone trail in the path is based on the search objectives [39], [43].

Algorithm 1 ACO Algorithm for the Smart Charging Strategy

Require: Graph Of Charging Stations, Charging Station Specifications, PEVs Specifications, SoC , Destination Coordination;
Ensure: optimum path, P

SetAdjustableParameters (G, PEV, t, α, ρ, τ, β, SoC, η, CS);
Initialize (t,$counter$,$iteration$);
// t: time slot;
Set $t \leftarrow 0$;
while maximum iteration is not met **do**
  $t \leftarrow t + 1$;
  Initialize τ_{global};
  for each node j of graph G **do**
    if j is in graph G's selected path **then**
      Call function of driving time;
      Call function of waiting time;
      Call function of charging cost;
      $P_g \leftarrow 0$;
    else
      for each ant n **do**
        Initialize τ_{local} ;
        for $P \leftarrow 1$ to G **do**
          while constraints are not met **do**
            $g \leftarrow \eta_{Pg}$(t);
            $x_{Pg}^{n} \leftarrow link(Pg)$;
          end while
          Update τ_{local};
        end for
      end for
      Sort (RouteSolution(N)) ascendingly;
      $I_{best}^{p}(t)$= RouteSolution(1);
      Update τ_{global};
    end if
  end for
end while
Update Information ($PathInfo$, $\mathcal{P}$);

B. Proposed Smart Charging Strategy Using Ant Colony Optimization

The main reason for choosing ACO in our proposed scenario is that using the heuristic information in the ACO algorithm our model can estimate the minimum travel time and charging cost at every node of the graph to accelerate the computation. With the arrival of a new PEV, every neighbor exploration allows us to test for the defined constraints and exclude nonfeasible alternatives at the first stage. However, the conventional ACO algorithm keeps track of the variable it aims to minimize along the entire search. In the proposed model, the smart-strategy in Algorithm 1 is iteratively called up to provide up-to-date information to the PEV driver. As information is shared between the smart grid and a PEV driver, the following processes occur.

1) *Loading Initial Information:* The modified ACO algorithm receives as input a graph describing all possible paths, the current SoC of the PEVs battery, the maximum energy consumption of the PEV, the coordination of the source and destination, the colony number, the number of ants in each colony, the initial pheromone level, and the coefficient of the creation and evaporation of the pheromone.

2) *Selecting Specific Heuristic Information to Obtain the Probability Distribution Function:* In a conventional ACO algorithm, for calculating the probability distribution in (21), only the pheromone and one heuristic value (distance) are considered. In the smart charging strategy, since PEVs look for an optimum path in terms of minimum travel time and charging cost, we introduced a modification where we maintained the driving time, waiting time, and charging cost as a set of heuristic information. Considering the three objectives in the aforementioned objective function, the ACO algorithm for each $j \in N_i^k$ can be implemented with the below equation

$$P_{ij}^k(u) = \frac{\tau_{ij}(u)^\alpha \left[(T^{\text{drive}}(s,d))T_j^{\text{wait}}(k)C_j^{\text{recharge}}(k)\right]^\beta}{\sum_{l\in N_i^k}\tau_{ij}(u)^\alpha \left[(T^{\text{drive}}(s,d))T_j^{\text{wait}}(k)C_j^{\text{recharge}}(k)\right]^\beta} \tag{23}$$

where the variables $\tau_{ij}(u)$, $T^{\text{drive}}(s,\ d))$, $T_j^{\text{wait}}(k)$, and $C^{\text{recharge}}(j,\ k)$ are the pheromone intensity, driving time, waiting time, and charging cost of a path. The parameters α and β are constants, which determine the relative influences of the pheromone and heuristic parameters on the PEV's decision. For the probability distribution, there is a tradeoff between the three objectives. The process of finding an optimum path is described in the following.

a) *Pheromone Initialization:* Collect the possible solution at each iteration and update the pheromone values using the general (22), $\tau_{ij}(u+1)$ symbolizes the pheromones of a vehicle moving from the current location s to a destination d or stopping at node j for charging during time period $(u+1)$ with the objective of minimizing travel time. Here, the updated value of the pheromone is a function of time and is controled by the number of PEVs on each route.

b) *Generate the Best Possible Path:* This step uses the modified ACO algorithm which is described in algorithm 1 for the PEV network, which receives as input a graph describing all possible paths including charging stations, the source, and destination nodes, and the SoC of the PEVs. Each time a neighboring node is explored, the function Feasible_nodes is responsible for selecting feasible

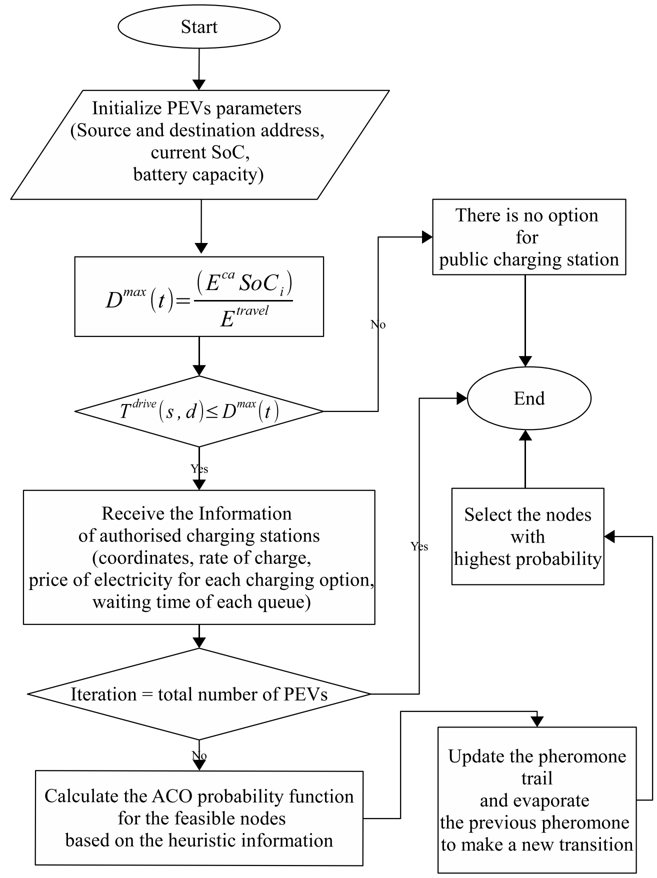

Fig. 5. Flowchart of the proposed smart charging strategy.

nodes from the graph with a calculation of the distance from each current location to all charging stations, then using the output of this function (which is a set of feasible nodes, with function get_nodes and using sub functions w-time and cost-to-charge) the heuristic values can be obtained for calculating the probability function of the modified ACO. As illustrated in Fig. 5, the first step is exchanging information between PEVs and charging stations using the smart grid panel in real time. For planning and managing the charging strategy, the smart grid needs PEV components and the charging station's specifications. The next step uses our proposed algorithm to implement a charging strategy for PEVs along their trip. During this process, the algorithm needs to consider the capacity of each charging station and the lengths of the queues which are updated for all the iterations in the simulation. The analytical and numerical results are explained in Section V.

c) *Local Pheromone Update:* While constructing the path decision solution, a local pheromone update is executed so that the visited path becomes less attractive, allowing the next PEV to explore other paths. This local update can be defined as

$$\tau_{ij}(u+1) = (1-\rho)\tau(u) + \tau_{ij}^l \quad \forall(i,\ j) \in \text{iter}^l \tag{24}$$

where based on the ACO algorithm, for the local best solution at each local iteration, only the PEV which constructed the best solution is allowed to deposit the pheromone information. τ_{ij}^{l} is the incremental amount of the local updating phase for the local iteration.

3) *Evaluation of the Tour:* When the PEV arrives at the destination, for each PEV tour the optimization function value (total travel time), denoted as drive-time in Algorithm 1 is calculated. The PEV tour that utilized the optimum path with the minimum travel time and charging cost among all the PEV tours that are found in the previous iterations is selected as the best tour.

4) *Global Pheromone Update:* After a few iterations, each node is then able to estimate the potential path, regardless of the varying conditions of the model topology and the PEV traffic. In fact, the global pheromone update rule is only employed by a PEV that has constructed the best global solution so far and this update gives the PEVs more opportunities to explore the search space, thus balancing the need for exploration and PEV exploitation. The global pheromone update at each global best solution can be defined as

$$\tau_{ij}(u+1) = (1-\rho)\tau(u) + \tau_{ij}^{g} \quad \forall(i,\ j) \in \text{iter}^{g} \tag{25}$$

where τ_{ij}^{g} is the incremental amount of global updating phase for the global iteration.

V. Simulation and Results

A. Simulation Model

In the simulation, we implemented a PEV network for the Washington City road network along the driving route from Oregon to Vancouver, as shown in Fig. 6. The PEV network consisted of 28 charging stations, each equipped with two charging options (CHAdeMO Fast charger and ac level 2 charger) and a battery swap facility. We considered up to 1000 PEVs comprising Nissan Leaf (30 kWh), BMW i3 (22 kWh), and Smart Ed (16 kWh), with their SoC modeled as a uniform distribution in the 10%∼90% range. The PEV arrival at each charging station was modeled as a Poisson distribution. The number of sockets for a charging option at a station was distributed uniformly in the 1∼10 range. For the fast dc charging option, each socket was assumed to supply 20-kW power [46]–[48]. For the ac level II option, each socket supplied 7-kW power [49] and the average time to swap a battery was considered as 3 min [50]. PEVs were assumed to travel at a maximum speed of 60 miles/h, consuming 0.12 kWh/mile [51]. The time of use (i.e., dynamic) tariff was modeled using an exponential function [52] with the minimum and maximum rate set as \$0.24 and \$0.46 [53]–[55], respectively. Price variation at different charging stations was implemented using a uniform distribution within the −10% to +10% range of the standard time of use tariff rate. We used MATLAB to perform the simulation.

B. Results and Discussion

In this paper, we analyzed the average waiting time, travel time, charging cost, and charging station queue occupancy.

Fig. 6. Washington green highway PEV network [45].

The waiting time results from the time spent waiting in the queues plus charging time, whereas the travel time is made up of driving time plus waiting time. The queue occupancy parameter indicates the current occupied queue length expressed as a fraction of the maximum queue length at a charging station. We compared the proposed solution with the active scheduling, known as the AS model in the literature. In the AS model [31], the smart charging strategy is modeled as a metaheuristic optimization problem (A^{*} search algorithm) where the goal was to find charging stations that reduced the travel time. The AS model, however, does not consider multiple charging options (i.e., does not include a queuing model) and the costs associated with recharging at a charging station. To the best of our knowledge, for a PEV network, the AS model is the most relevant and best performing smart charging solution available in the literature.

The discussion of the results begins with Fig. 7, which shows the normalized average waiting time for PEVs at charging stations. We normalized the average waiting time over the travel time, i.e., the period of time a PEV has to wait at a charging station on average expressed as a fraction of the travel time. As the figure suggests, the average waiting time increases with the increasing volume of traffic. This is because

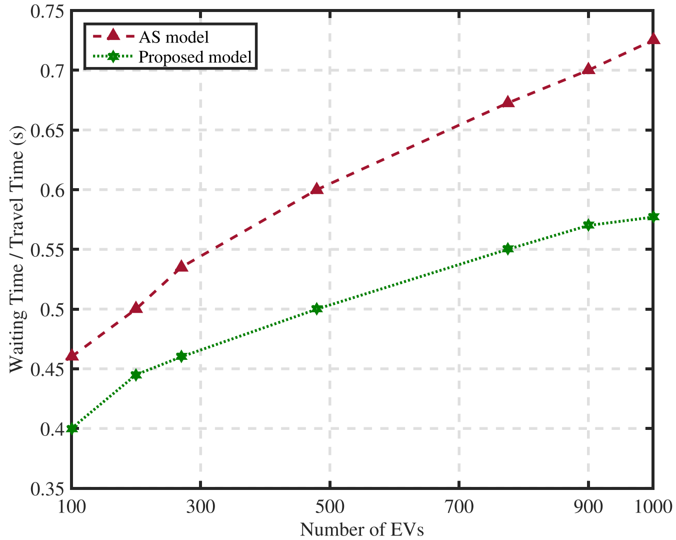

Fig. 7. Normalized waiting time for different number of PEVs.

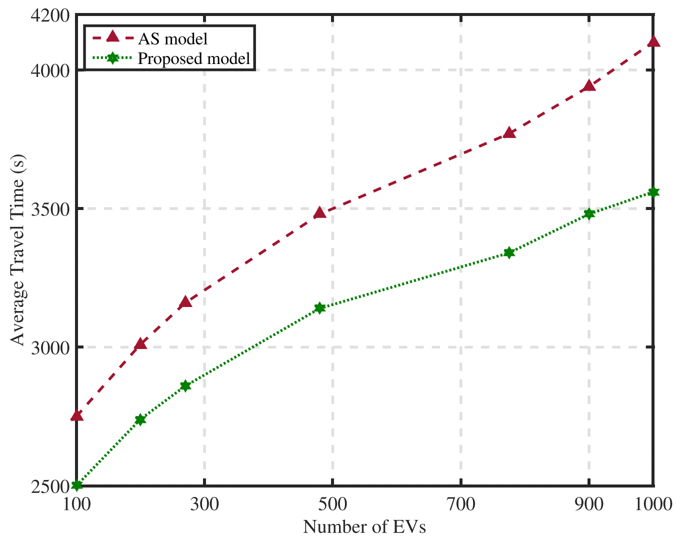

Fig. 8. Average travel time for different number of PEVs.

for a bigger fleet of PEVs, more PEVs are required to share the limited charging facilities. The result, however, shows that the waiting time is significantly lower in the proposed solution compared to the AS model. This is because in our model, we implemented multiple charging options as a queuing model and considered the queuing delay for each charging option while selecting the best charging station for a PEV, which was missing in the AS model. In our model, information in relation to the queuing delay for each charging option at every charging station was communicated to a PEV, which allowed the PEV to make an informed decision while choosing the best charging station. Fig. 8 presents a comparison of the average travel time in the proposed and AS models. It is evident that compared to the AS model, the proposed model reduces the average travel time. This is because in the AS model, many PEVs show up at charging stations (e.g., hotspot areas) where the queue lengths corresponding to their preferred charging options are too long, and PEVs are required to wait for a longer period before they can be served. In our proposed model, the waiting time corresponding to each charging option at a

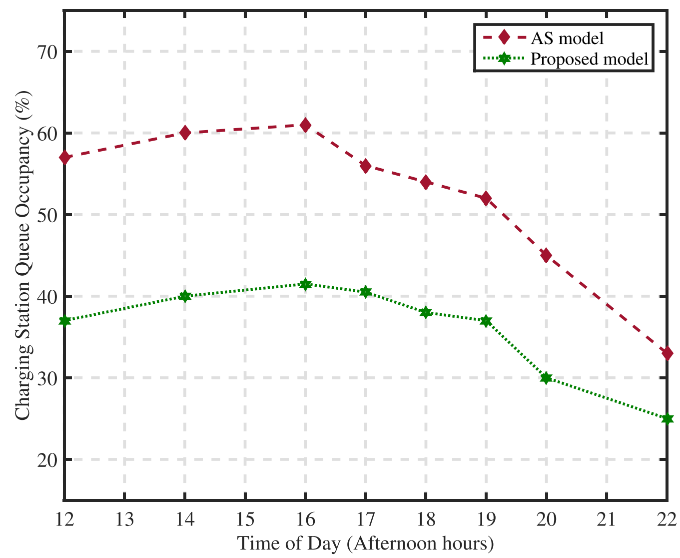

Fig. 9. Charging station queue occupancy in hotspot areas.

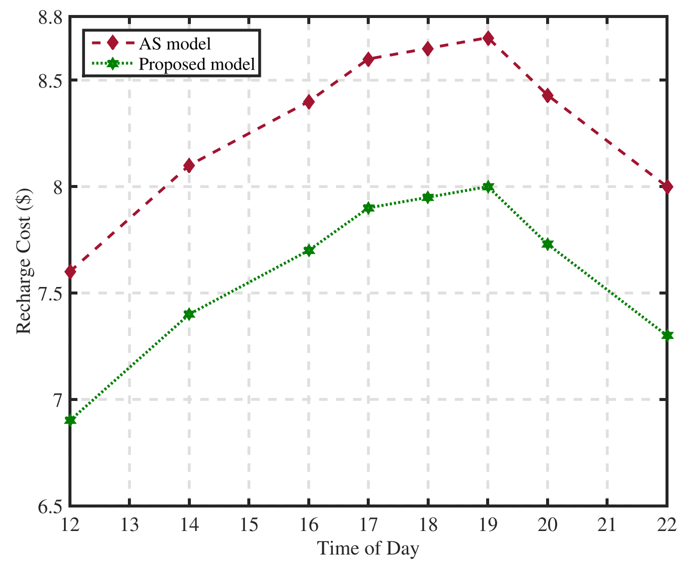

Fig. 10. Average charging cost in AS and proposed model.

charging station is calculated based on the queuing model, which when communicated to the PEV users, and can help them to make a better decision.

In Fig. 9, we present the comparison of average queue occupancy at charging stations in hotspot areas (i.e., nodes with a greater number of edges) for both models. It is apparent that the AS model results in higher average queue occupancy because the model does not use queue information specific to an individual charging type. In our proposed model, PEVs tend to distribute themselves more uniformly among the available charging stations, thereby reducing the pressure on charging stations in hotspot areas.

Just as gas/petrol prices vary from place to place, prices per charging option can vary between charging stations. In the proposed model, we therefore considered the price per charging option at various charging stations, which ultimately generated a lower average charging cost. In Fig. 10, we present the average charging cost during various hours of the day. It is

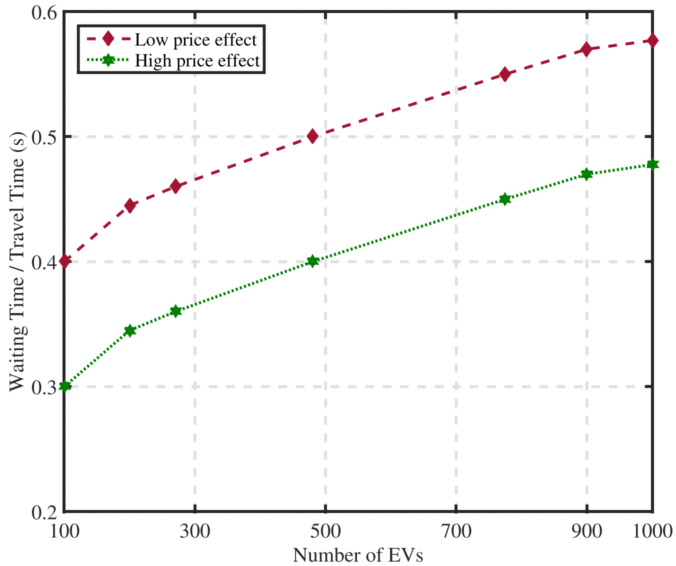

Fig. 11. Improvement in waiting time with price variation.

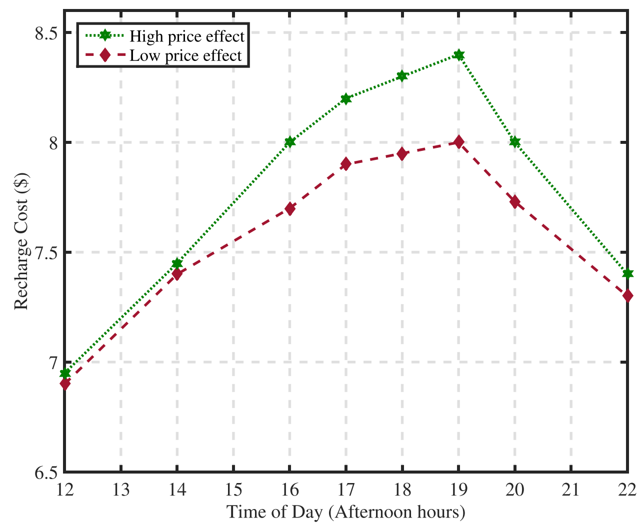

Fig. 12. Average charging cost for the proposed model with price variation.

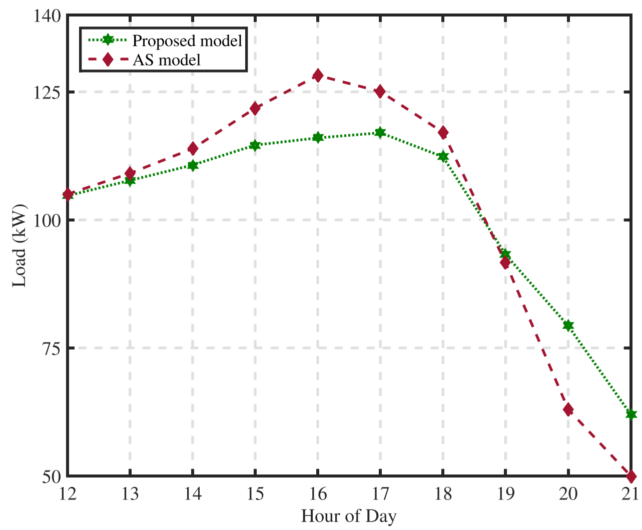

Fig. 13. PEV load with AS model and proposed model.

evident that because the price information is not taken into account while calculating the route in the AS model, the average charging cost in the proposed model is significantly lower than the average cost in the AS model.

Fig. 11 illustrates the average waiting time during the peak PEV load period in response to dynamic charging prices. As shown in the figure, the higher price option encourages many PEV users to go for either partial charging or to avoid charging during the peak load period, making the average waiting time shorter. Since the ultimate decision in relation to the choice of time to recharge PEVs belongs to owners, a service provider cannot enforce a policy to not to serve/charge a PEV, even when it creates a problem for the grid. But the behavior of PEV users can be significantly influenced by setting a suitable price so that both the users and grid can benefit. In our model, through the introduction of the recharge cost in the objective function, we capitalized on this potential. An extended overlap period between the PEV and residential peak periods can be avoided by setting a higher recharge price in our model, which would then encourage PEV users to perform partial charging at charging stations during busy hours and/or complete the charging process at home/charging stations during off-peak hours. It should be noted that an optimum dynamic pricing model, which would have the greatest benefit for both the grid and PEV users, can be modeled as an optimization problem. This, however, is not within the scope of this paper. We intend to investigate and develop an optimum dynamic pricing model for PEV charging stations in our next work. In this paper, in order to show the impact of pricing on partial charging and the average waiting time during the peak load period, we used two indicative maximum price levels, (i.e., US$ 0.46 vs. 0.56 per kWh as the maximum price). In response to the higher charging price during the peak load period, the partial charging coefficient value for a PEV was assigned a value in the range of its current SoC to the maximum SoC using a normal distribution. The mean value of this distribution was assumed to decrease exponentially with increasing charging price. For partial charging, there is a tradeoff between the recharge price and the delay at charging stations. As shown in Fig. 12, the average peak hour recharging cost with dynamic pricing is relatively higher.

We also investigated the impact of reduced average waiting time achieved by the proposed model on the charging load for the PEV network that we implemented in our simulation. As evident in Fig. 13, in the proposed model, the average PEV load per charging station is higher during the busiest hour compared to the AS model. This is because the proposed model efficiently uses the available PEV charging facilities by providing information in relation to the queue length and price for the preferred charging options to PEV users. The reduced average waiting time achieved by the proposed model also causes the PEV load curve to decline at a faster rate, making energy management for the residential load less challenging for the grid.

Since the smart charging strategy is intended largely for PEV users, it is important to have a solution that can be solved in real time. This motivated us to investigate the time complexity of the proposed ACO-based smart charging solution. Fig. 14 presents the convergence test result for the

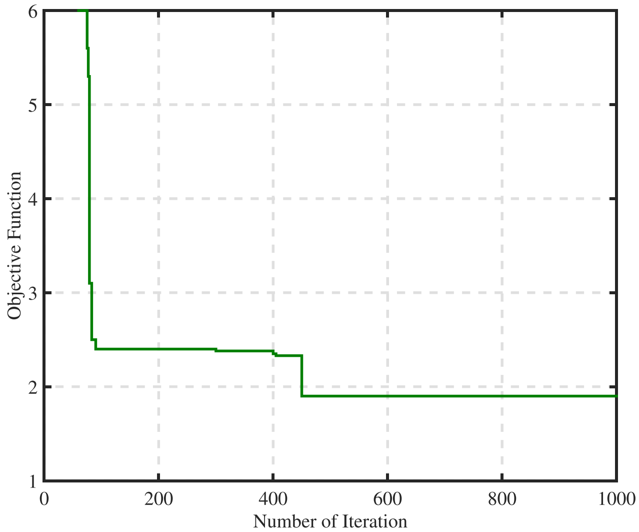

Fig. 14. Convergence graph with ACO for the optimal paths.

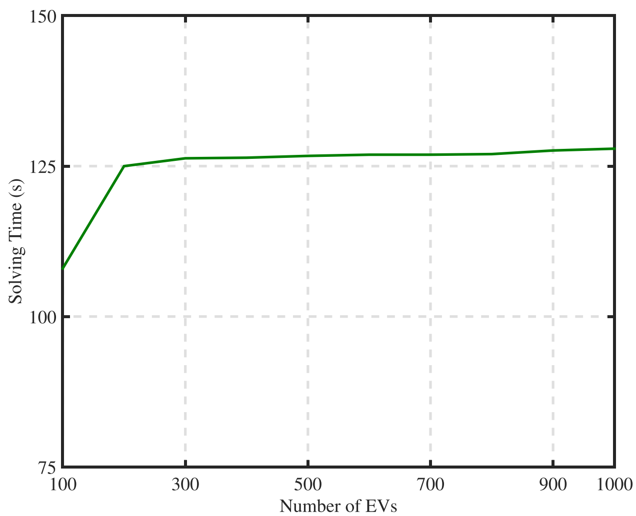

Fig. 15. Average computation time for PEVs.

TABLE I
SUMMARIZED SIMULATION RESULTS

Evaluation parameters	AS model	Proposed model	Improvement
Average waiting time (min)	48.5	36.2	25.3%
Average travel time (min)	68.3	58.2	15%
Charging cost (US$)	8.9	7.5	16%

proposed solution. This suggests that the ACO-based approach converges to the optimal solution after 440 iterations for a fleet of 500 PEVs. In real time, ACO-based approach requires around 127 s to find the best route for a PEV (Fig. 15). The computation time for each PEV remains relatively constant, even for a large fleet of PEVs.

Table I summarizes the performance improvements of the proposed model over the AS model for a fleet size of 1000 PEVs. The table clarifies the reduction in the average waiting time and the average travel time as well as the recharging cost.

VI. CONCLUSION

In this paper, we proposed a smart charging strategy for a PEV network that offers multiple charging options at charging stations. Just as traditional gas stations have different capacities and pricing options, charging stations can have different capacities and pricing options, and the recharge price for each option can vary from one station to another. In a scenario like this, it is important to adopt a charging strategy that identifies the most suitable charging station for a PEV user, so that the user can recharge at the minimum cost and reach his/her destination without a significant delay. We modeled the research challenge as a multiobjective optimization problem where the goal was to reduce the charging time, travel time, and charging cost. We used a queuing model to estimate the delay at various charging stations. To mitigate the challenge of longer waiting times and the potential overlap between the peak PEV and residential load periods, we also introduced the concept of partial charging. We showed that pricing could be used as a useful tool to encourage PEV drivers to choose the partial charging option during peak load hours. In light of the significant time complexity of the optimization solution, we solved the research problem by introducing an ACO-based metaheuristic solution. The simulation results confirm that the proposed solution significantly reduces the average charging delay (up to 25%) and cost (up to 15%). In our future work, we will investigate the optimum dynamic pricing model to minimize the overlap between the peak PEV and residential.

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