An Optimal Spatial and Temporal Charging Schedule for Electric Vehicles in Smart Grid

Behzad Barabadi*, Farzad Tashtarian†, M.H. Yaghmaee Moghaddam‡
*‡Faculty of Computer Engineering, Ferdowsi University of Mashhad, Iran
†Department of Computer Engineering, Mashhad Branch, Islamic Azad University, Mashhad, Iran
* Behzad.Barabadi@mail.um.ac.ir† f.tashtarian@mshdiau.ac.ir‡hyaghmae@um.ac.ir

***Abstract*—In recent years, Electric Vehicles (EV) received many adaptation and improvements which make them suitable for real life. The popularity of them demands more electricity and consequently smart charge scheduling algorithms to reduce driving cost and peak loads in charge stations. To address this challenge, we propose a *smart charging scheduler* based on mathematical optimization to determine the optimal charging volume from charging stations in a given route. The addressed problem formulated as a Mixed Integer Linear Program (MILP) to choose the optimal charging points between an origin and destination. This problem takes predicted time slot price signals and vehicles information to calculate the optimal solution. To deal with NP-hardness of MILP formulation, the proposed model solved using a heuristic simulated annealing (SA) algorithm. In the end, we evaluate the benefit of such scheduling using the Southern California Edison average hourly price. The results show that this schedule can contribute to EV owners and charge stations interests.**

***Index Terms*—Smart Grid, Electric Vehicles, Smart Charging Schedule**

Nomenclature

W	A time window with known prices shared between charge stations.
T_v	Indicate time slots between origin and destination for $v \in V$.
V	Set of electric vehicles.
$\mathcal{S}$	Set of charge stations.
R	Set of energy packages for a time slot.
K	Set of road segments.
$P_{r,t}$	Electricity price for package $r \in R$ at $t \in W$.
ω_k^v	Discharging rate for $v \in V$.
γ^r	Charging volume for $r \in R$.
$\tau_k^v(\nu_k)$	Required time to traverse route segment $k \in K$.
ν_k	Vehicle speed mile per time slot in segment $k \in K$.
d_k	Length of segment $k \in K$.
E_0^v	Initial state of charge for $v \in V$.
SOC_k^v	State of charge for $v \in V$ at segment $k \in K$.
$a_{r,t}^{v,s}$	Binary variable to show selected charge package $r \in R$ in charging station $s \in \mathcal{S}$ for $v \in R$ at $t \in T$.
C	Positive variable equal to highest cost.
$\sigma_{s,t}^v$	An auxiliary binary variable.
θ_{init}	Initial temperature value.
θ_f	Final temperature value.

I. Introduction

Fossil cars consume the largest portion of gasoline in many big cities around the world. Therefore, they are the main source of air pollution in these cities. In recent years, with the adoption of electric vehicles, transportation sector can reduce greenhouse gas emissions. According to [1] the number of electric vehicles expected to rise to over 35 million by 2022 from the current number of 2 million cars at the end of 2017 [2]. This increase of EV usage has many environmental benefits. However, the transition to EV shifts the current weight of gasoline to the electricity industry. As a result, it threatens grid stability and quality. For instance, lacking in charging plans and organization among EVs can increase peak load and pressure producers as well as distribution networks [3]. Unlike gasoline, the time of charging and distance of generators from consumption points plays a significant role in electricity price. As in long distances, there is a transmission loss and in peak loads, the price might increase because of predicted peak load which demands the utilization of other energy sources like coal in generation facilities. The increasing trend on peak load convinces traditional power grid to transform its infrastructure to a smart power grid to leverage the benefit of demand response programs. In demand response, utilities employ various dynamic pricings such as Time-Of-Use to shift on-peak load to off-peak periods [4].

In the transportation industry, the vehicle mobility can play a significant role in EV charging cost due to lower EVs range compare to their counterparts. Their charging time is also longer than fossil cars refueling time. As a result, they might need several longer chargings before reaching their destination. Scheduling EVs charging can reduce owners cost while shifting consumption load to off-peak periods. Electric vehicles offer many opportunities in regulating their consumption in a stationary status where the owner put his/her car in a parking for a fixed duration in a day. However, as people start to use their car for longer trips, it is appealing for them to schedule their EV charging for the whole trip. Unlike stationary charging, this scheduling is affected by more entities including charging infrastructure availability, battery capacity, charging rate, driving patterns and other uncertainties like weather condition, and traffic pattern.

In this work, we intend to determine the optimal charging stations and charging volume procurement to reduce driving cost. Our motivation is to devise a *Smart Charging Scheduler* using recent smart grid bi-directional communication capabilities [5] between EV and utility that delivers electricity. A *Smart Charging Scheduler* states how we should charge the EVs to satisfy certain objectives and constraints at both users and utility side [6]. As such, our design balances the load among a group of charge stations to reduce peak load in each station and meanwhile decreases users consumption cost by selecting the best charging time slots.

The paper main contributions are summarized as follows:

- We formulate the problem of EV charging schedule in a route as a MILP to select the best charge stations and charge volume to reduce charging cost.
- Our objective function jointly reduces peak load and overall system cost.

II. RELATED WORKS

The prevalence of EVs in near future motivated many research groups in academe and industry to work on EV charging schedule. These efforts divided into two areas according to its results whether upon power grid or users [7].

Among the paradigms that consider vehicles mobility, the work in [8] divides a city into different regions containing charge stations. Their solution assigns EVs to the charge stations with the minimum distance to the source to reduce transmission loss. They have used ToU pricing to schedule EVs temporally to reduce the peak-valley difference in each region and hence reduce users cost. In [9], a smart scheduling method proposed based on an improved version of A* algorithm to minimize end-to-end travel time on a highway. The scheduling occurred for each EV while there is a coupling variable to make a loose connection between EVs. In this algorithm, given the individual EV information, the total time of driving, waiting and charging minimized subject to EV energy constraints. However, no cost consideration suggested for EVs. The authors realized three entities in their model specifically EV's, highway and charging stations. Each of these entities has their own physical characteristics. When an EV enters the highway if the highway length is longer than its range it will stop on at least one charge station. This stop is based on the EV strategy, where in this article is minimizing the overall travel time (driving, waiting and charging). Each EV explore charging stations to book the best charge stations according to its strategy.

To reduce taxies charge waiting time in Shenzhen, China, authors in [10] devised a recommendation system using large-scale GPS data mining. In this system, drivers recharging behavior are intercepted and combined with charging station constraints to obtain the suitable stations for charging. Furthermore, an Optimized Charge and Drive Management (OCDM) methodology proposed in [11] which selects the optimal driving route and schedules daily trips. It optimizes the EV charging process based on drivers timing preference.

A highway with a fixed number of entrance and exits considered in [12]. The authors assumed that EV charging stations are close to these entrance and exits and then they modeled vehicles mobility using M/M/C queue model. Their purpose was to schedule charging in order to achieve a uniform utilization of the charging infrastructure in the network. This program needs coordination between network, drivers, and drivers themselves.

For stationary charging scenarios where electric vehicle parked in a single location, the work in [13] considered a workplace parking lot where EVs advertise their charging requirement and departure time to the station control center. The control center then decides whether to admit or decline EVs charging request. The goal here is to maximize providers total profit. In [14], the author analyzed a fleet of EVs with predefined plugged time into the grid. The goal is to completely charge each EV at the end of this period using a control center responsible for charging schedule. This center can interrupt the connection remotely or set a power level for each EV during the connection period. In [15], a TOU price plan imposed by the government. Users should set the expected end time of charging. A scheduling module is embedded in the charger to calculate optimize charging considering SOC curve. The goal is to get minimum cost and reduce peak and fill valleys. In [16] the authors hypothesize a situation where both EV and charge stations are mobile. EVs send charging service requests along with their demand volume and locations to the operator. The operators then will make the optimal decision by considering EV users cost. Additionally, based on the information provided by EVs, the optimal placement of Mobile charging station is taking place. As for dynamic charging assignment, the authors in [17] propose an algorithm using centralized Simulated Annealing to optimize CS utilization. The result has shown a lower waiting time for EV owners.

Moreover, in [18] peak-to-valley differences reduced through a multi-objective particle swarm optimization based on weight aggregation strategy. Nonetheless, their study only includes stationary PHEVs that use home charging piles. More EV scheduling methods surveyed in [19] and [20]. A similar problem studied in [21] where authors used Model Predictive Control (MPC) to indicate charging volume in a time horizon. They present an interesting system model where allows an EV to switch between gasoline and electricity to decrease driving cost. However, their formulation did not consider charge station locations, therefore EVs have access to a plug whenever it is required.

The rest of paper organized as follows. Section III introduces system components and then formulates the problem of EV charging schedule in a trip. In section IV, we solve the formulated problem using a heuristic algorithm based on simulated annealing. The numerical evaluation results demonstrated in section V where we compare four charging scenario. Finally, in section VI we drawn our conclusion.

III. SYSTEM MODEL

We considered the problem of optimal charging of an electric vehicle denoted by $v \in V$ en route to the destination with the lowest cost. Initially, we describe our time horizon model and its related variables. The whole system has a general timeline denoted by W which we call it a time window from now on. In each time slot $t \in W$, the electricity price is known for electricity package $r \in R$ and denoted by $P_{r,t}$. This time window is shared between available charge stations in the road, hence, they have equal prices in the same time slots $t \in W$. Next, we have a set of time slots denoted by $T_v \subset W$. Since vehicles driving pattern might be different, the set T_v defined for each vehicle $v \in V$. This set contains all time slots that a vehicle spends in the system from origin to destination including scheduled charging time slots. Employing Time-Of-Use tariffs is a popular program for electricity distributors using diffrent time slot granularities [22].

Now that we defined a time window we can continue defining other parts of the system. As we state earlier we have several charge stations shown by $s \in \mathcal{S}$. The location of charge stations are fixed in the road and the road segment between two charge stations denoted by $k \in K$. As a result, the number of road segments between origin and destination is $|K| = |S|+1$. These charge stations offer electricity packages $r \in R$ with volume γ^r to the electric vehicles with the price $P_{r,t}$. No restriction imposed on charge stations capacity. Therefore, several EV can charge simultaneously in a single charge station. In this manner, we can evaluate maximum profit available using our model.

An electric vehicle starts its journey from origin with an initial state of charge denoted by E_0^v. Variable SOC_k^v is also defined to reflect the vehicle state of charge for each $k \in K$. We suppose EVs have enough battery capacity to store all their energy demand for a trip. Electric vehicles have a discharging rate to cross a road segment denoted by ω_k^v which is a constant function of speed denoted by ν_k. The number of time slots a vehicle spends to traverse a segment $k \in K$ with the length d_k denoted by $\tau_k^v(\nu_k)$ and calculates as $\frac{\nu_k}{d_k}$. It is crucial to state that in our model, EVs either are moving stop for charging in a charge station. In Fig. 1, we illustrate notions described above.

In our system, we also have a System Operator (SO) which performs scheduling as a central entity using information collected from the utility and electric vehicles. Utility provides price signals $P_{r,t}$ and electric vehicles send their initial state of charge, origin, destination, average speed, and discharging rate to receive a charging schedule from the system operator. The communication link required to exchange information between EVs, SO, and utility provided by smart grid infrastructure [19].

Based on the aforementioned model, the system schedules a single or group of EVs to determine charge stations $s \in \mathcal{S}$ and electricity packages $r \in R$ such that charging volume meets electricity demand for the trip. Note that the concept of windowing we have used allows scheduling of EVs irrespective of time and location restrictions. They can enter the system at any time slot and place of origin as long as price signals are available for their complete trip duration.

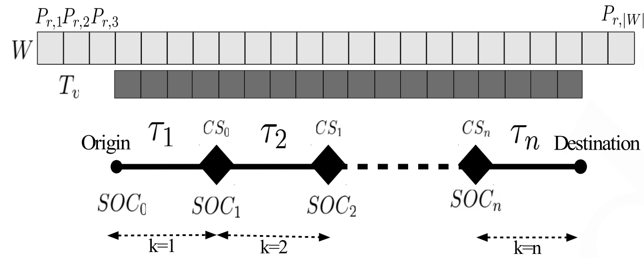

Fig. 1. System Model.

A. Problem formulation

In the previous section, we introduced our system model and its entities. In this section, we formulate the problem as a MILP to extract optimal time slots and charging packages for each EV that participates in scheduling program. In our formulation, we defined a set of energy packages denoted by $r \in R$ where each one resembles a different charge rate comparing to the chosen timeslot duration. As a result, continuous charge rate adapted as discreet variable based on standard charge rates in the industry. To satisfy requirements discussed previously, in the following a set of constraints described for each restriction.

In order to formulate the problem as a MILP, we introduce an auxiliary binary variable denoted by $\sigma_{s,t}$. This variable defined for time slots a vehicle spends in a station, we call this time slots a charging session. To ensure we have a continuius charging session as the model satated we should have:

$$\sigma_{s,t}^v \geq \sigma_{s,(t+1)}^v \quad \substack{\forall s \in \mathcal{S}, \forall t \in T \\ \forall v \in V} \tag{1}$$

In addition, at the start of a journey, no previous EV status is available, as a result we should set the time slots each EV needs to reach the first charge station $s \in \mathcal{S}$. Following constraint initialize the variable. $\sigma_{s,t}$ to take care of it.

$$\sum_{t \in T} \sigma_{s=1,t}^v = \tau_{s=1} \quad \forall s \in \mathcal{S}, \forall v \in V \tag{2}$$

Next, our model considers several available charge rate for a vehicle. So, it is not possible to use more that one rate at the same time slot, the variable $a_{r,t}^{v,s}$ should be mutually exclusive. Following constraint reflect this restriction in our formulation:

$$\sum_{r \in R} a_{r,t}^{v,s} + \sigma_{s,t}^v \leq 1 \quad \substack{\forall s \in \mathcal{S}, \forall t \in T \\ \forall v \in V} \tag{3}$$

At a charging session, although an EV can use different charge rates, it is not possible for it to switch to a previously used charge rate. Therefore, it can start charging with any available rate and then switch to other rates. This will allow us to formulate the problem as a MILP.

$$\sum_{r \in R} a_{r,t}^{v,s} + \sigma_{s,t}^v \geq \sum_{r \in R} a_{r,(t+1)}^{v,s} - \sigma_{s,(t+1)}^v \quad \substack{\forall s \in \mathcal{S}, \forall t \in T \\ \forall v \in V} \tag{4}$$

Constraint 5 validates final solution. In this constrain, the auxiliary variable $\sigma^v_{s,t}$ denotes the summation of assigned time slots for all EVs.

$$\sum_{t \in T} \sigma^v_{s,t} = \sum_{i=1}^{s} \tau^v_i + \sum_{p=1}^{s-1} \sum_{q \in R} \sum_{t \in T} a^{p,v}_{q,t} \quad \forall s \in \mathcal{S}, \forall v \in V \tag{5}$$

The next two constraints are related to EVs SOC in the path. First, to ensure that vehicles have enough energy for each segment of the road we should have:

$$\omega^v \tau^v_k \leq SOC^v_{k-1} \quad k \in K, v \in V \tag{6}$$

Second, to address the EVs energy balance between road segments, charging volume, and energy demand we define following constraint

$$SOC^v_k = SOC^v_{k-1} + \sum_{r \in R} \sum_{t \in T} a^{k,v}_{r,t} \gamma^r - \omega^v_k \tau^v_k \quad k \in K, v \in V \tag{7}$$

where $SOC^v_0 = E^v_0$. Now we define our objective function as

$$C + \epsilon \sum_{\substack{v \in V, s \in \mathcal{S} \\ r \in R, t \in T}} a^{v,s}_{r,t} \gamma^r P_{r,t}$$

It minimizes the total cost for all vehicles. In this function variable C equals to the vehicle with maximum electricity cost and the constant ϵ works as a balancing factor to make a tradeoff between reaching global minimum cost and individual vehicle costs. Adding variable C provides an additional benefit to jointly optimize load between charge stations and cost.

Finally, we have following problem. It solves the problem to achieve global minimum cost when $\epsilon = 1$

$$\begin{aligned} & Minimize \quad C + \epsilon \sum_{\substack{v \in V, s \in \mathcal{S} \\ r \in R, t \in T}} a^{v,s}_{r,t} \gamma^r P_{r,t} \\ & Subject\ to: (1) \ldots (7) \end{aligned} \tag{8}$$

The above formulation solves the problem for variables $a^{v,s}_{r,t}, SOC^v_k$, and C. Since the objective is linear, the problem contains both integer and continuous variables, and the constraints are linear, it is a MILP problem [23]. As a result, it belongs to the *NP* class of problems and as a scheduling problem it is NP-complete. Having an NP-hard difficulty makes solving it hard for a large number of vehicles. In order to tackle this problem, a heuristic algorithm devised using simulated annealing in the next section.

IV. A HEURISTIC ALGORITHM USING SIMULATED ANNEALING

Simulate Annealing [24] is a metaheuristic method that applied to many complex systems. The algorithm starts with a high temperature and a random feasible solution. Following the cooldown procedure, the algorithm discovers neighbor solutions with a probability threshold until it reaches either a predefined condition or a specified temperature. Although it cannot guarantee an optimal solution, it will converge to a global optimum in a finite number of iterations with high probability [25]. There is three main component in a simulated annealing algorithm namely cost function, neighbor exploration, and cooling scheduling. Algorithm 1 shows the procedure for our scheduling problem.

In order to use SA we should define solution space of problem 8. That is, an EV can charge itself in time slots and CSs that:

$$\begin{aligned} & \sum \tau^v_{k-1} * \omega^v \leq E^v_0 + \sum a^{k,v}_{r,t} * \gamma^r && \forall k \in K, \forall v \in V \\ & a^{k,v}_{r,t} \geq a^{k,v}_{r,t+1} && \forall v \in V, t \in T \end{aligned} \tag{9}$$

Algorithm 1 Simulated Annealing Algorithm

```
Initialisation:
Generate solution space
Set initial random solution s
Set initial temperature (θ = θ_init)
Set final temperature (θ_f)
LOOP Process
for i = 1 to maxIter do
    s' := SelectNeighborSolution()
    Δc = cost(s) − cost(s')
    if Δc > 0 || exp(−Δc/θ) ≤ rand[0, 1] then
        s := s'
    end if
    θ' := CoolingSchedule(θ)
    if (θ' ≤ θ_f) then
        stop
    end if
end for
```

A. Neighbor exploration

As illustrated in algorithm 1, a function is needed to explore solutions in each iteration. In this problem, we consider any other solution in solution space as a neighbor as long as the solution is feasible. To create such solution space, consider two set A and R. The first set denoted by $A = \{0, 1, 2, 3, \ldots, i\}$ shows the number of times a particular electricity package should be selected in a charge station. The second set is R which is the same as rate packages defined in the system model. If $n = |S|$ denoted as the number of charge stations, the problem is to choose $n * |R|$ terms like $a_i r, a \in A, r \in R$ such that

$$\sum_{i=1}^{n} a_i \gamma^r = \sum_{k=0}^{|K|} \omega^v_k \tau^v_k - E^v_0 \quad \forall v \in V$$

As a result, a depth-first search is applicable to generate all integer solutions. Note that since a charging session has consecutive time slots, we can calculate cost as $\sum_{s \in S} \sum_{i=1}^{n} a_i \gamma^r P_{r,t}$ having the number of time slots in previous and following charge stations in a feasible solution.

B. Cooling schedule

Different cooling schedules are available. Nevertheless, each method includes at least three main parameters namely initial temperature, temperature cooling function, and cool down duration to determine the number of states in each temperature. In this paper, a variant of exponential cooling schedule known as geometrical cooling schedule is used [25]. Therefore, new temperature in each level calculates through $\theta' = \theta\alpha$ where α is the reduction parameter and calculated from following formula:

$$\alpha = 1 - \ln(\theta) - \ln(\theta_f)/i \tag{10}$$

V. Numerical evaluation

In this section, we apply our formulation to two other scenarios and compare it with each other. First, we describe our simulation setting and then we present the results.

A. Simulation Setting

We set the time window as $W = \{1, \ldots, 150\}$ with a group of EVs enters the system. The electricity price is known in advance through a price vector and synchronized between 2 charge stations in the road [26]. As a result, we have $k = 3$ road segments. Additionally, charge stations provide a single charge service transferring up to 30 kWh energy in a single time slot. The initial state of charge assigned randomly enough for reaching the first CS in the trip. The EV speed is the mean speed of an EV through the route segment and measured through the average passing time of a road segment. Alike to charging rate, we map this speed to the number of time slots an EV needs to reach its destination. The number of time slots in the system is $|T| = W = 150$, that is if an EV enters the route at $t = 0$, it can only schedule the trip for following 100 time slots. The discharging rates are between $(0.33, 0.37)$ kWh/mile based on average speed. The number of EVs are between 25 and 200 and three charging scenarios assumed:

Smart Charging (SC): This scenario uses our model to determine the optimal volume of charge procured from a charge station.

Next Segment Energy Need (NSEN): In this scenario, when an electric vehicle reaches a charge station, it charges a minimum amount of electricity to reach the next station.

First Available Charge Station (FACS): This scenario evaluate the system when a vehicle charges all its need at the first available charge station.

B. Evaluation results

Three parameters used to assess the performance of our work. Initially, the total cost of the system evaluated in order to show how much we can save using an optimal charging plan. The second measure is the influence of scheduling on the total load of the system in each time slot.

The first diagram compares how overall system cost is affected by each scenario. As depicted, an optimal schedule results in lower cost giving the price vector depicted in Fig.3 for the entire time window W. Another criterion is overall system load in charge stations in each time slot. This parameter is in the interest of utilities. The results illustrated in Fig. 3 for each scenario and during the time window W. The continuous line in this figure denotes price of electricity. Before describing this figure, one should note that $|T_v| \le |W| \quad v \in V$, as a result, not all time slots used. In other words, from a particular time slot, the system has no load because every electric vehicle reached its destination. This figure shows that under smart charging, different time slots utilized, unlike FACS scenario which concentrates on initial time slots or a single charge station. When we have used NRSEN scenario, we achieve better load distribution but again this increased system cost. In our simulations, we observe a load peak in our proposed method, however, this is understandable due to the fact that in our simulation we set the vehicles' initial energy volume enough to reach the first charge station.

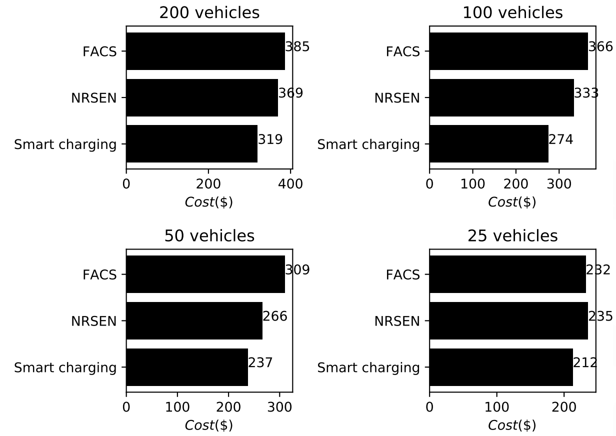

Fig. 2. Total system cost.

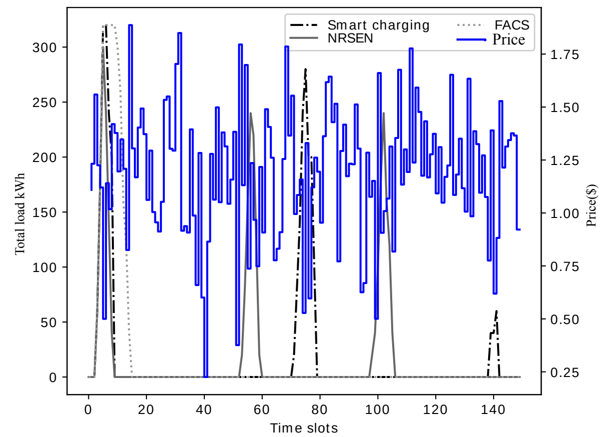

Fig. 3. Total system load vs. price.

Finally, simulated annealing performance compared in Fig. 4 using a core i7 host with 8 GB RAM and following algorithm configuration. The initial temperature (θ_{init}) sets to 1000 and algorithm stops when either it reaches maximum iteration 300 or when it cools down to minimum temperature (θ_f) 0. Initial variables and specifically cool down and neighbor exploration functions play a vital role in the performance of a simulated annealing algorithm. In Fig. 4 when the number of vehicles is low the algorithm performs faster and final system cost does not differ much. On the other hand, when the number of cars increases the algorithm become dependent on two aforementioned functions. For example, when the number of cars is equal to 50, our configuration stoped near 2100$. As a result, each number of vehicles have a set of parameters under which the algorithm perform better.

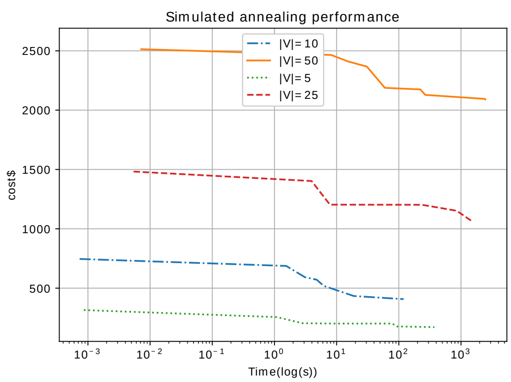

Fig. 4. Simulated Anealing performance.

VI. Conclusion and future works

In this paper, we present an algorithm to determine appropriate charge stations and charge volume to reduce EV owners cost during a trip. We have solved the problem in a centralized manner using a MILP solver and a metaheuristic simulated annealing algorithm. The obtained results of different scenarios show how it will benefit customers by decreasing their cost. In addition, load level distribution shows utility can also take advantage by reducing the peak to average ratio using price signals. In our future work, we will extend this framework by incorporating uncertain future prices, previous load in the system, and sporadic delays by vehicles. The current algorithm solved in a centralized manner. However, distributing the problem using a proper decomposition technique can improve scalability when there is a large number of electric vehicles.

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