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Real-Time Control for Charging Discharging of Electric Vehicles in a Charging Station with Renewable Generation and Battery Storage

Ubaid Qureshi
Department of Electrical Engineering
Indian Institute of Technology, Delhi &
University of Kashmir
ubaidqureshi4209@gmail.com

Arnob Ghosh
Department of Mechanical Engineering
Indian Institute of Technology, Delhi &
Imperial College of London
arnob.ghosh@mech.iitd.ac.in

Bijaya Ketan Panigrahi
Department of Electrical Engineering
Indian Institute of Technology, Delhi
Delhi, India
bkpanigrahi@ee.iitd.ac.in

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***Abstract*—Charging of electric vehicle in an uncontrolled manner can seriously impact the power distribution grid and make the large scale adoption of electric mobility non viable. In this paper we propose an online charging discharging decision sequence for electric vehicles in a commercial charging station to minimize the overall cost of charging the electric vehicles while satisfying the number of constraints. The control problem has been formulated as a multi-objective optimization problem, which aims to reduce the cost of charging the electric vehicles, reducing the frequent change in charging rates, flattening the load profile subject to equality and inequality constrains of the chargers and the grid. The decision sequence is capable of handling both the homogeneous as well as heterogeneous charging requirements with random arrival times and deadlines. The problem is transformed to a convex optimization problem which can be solved using any standard convex optimization toolbox. We empirically demonstrate that our proposed decision reduces the cost of charging and frequent changes in charging rates while reducing the peak loading on the grid.**

***Index Terms*—electric-vehicle, charging , commercial charging station, optimization, smart grid**

I. INTRODUCTION

The growing concern for the environmental degradation among other measures has given the much needed impetus to the use of electric vehicles over conventional internal combustion engine based vehicles [1]. In addition to helping reduce the emission of green house gases, these electric vehicles have higher efficiency, better aesthetics, lower noise levels, less maintenance and no reliance on the crude oil.

However large scale use of electric vehicles could cause problems to the distribution grid as it could lead to network congestion, new peaks in load curve, demand side uncertainties, increase in maximum demand, overloading and power quality issues [4] which will push the already stressed grid to further limits. It has also been studied that the uncontrolled electric vehicle charging can severely impair the voltage profile as well [2] [3]. In order for the successful integration of electric vehicles on a large scale, it is imperative that the charging of electric vehicles should not go random and uncontrolled.

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On the other hand optimized or controlled charging of electric vehicles considering different constraints have the potential to fulfil different objectives without impairing the functionality of distribution grid. Electric vehicle charging can be scheduled to minimize the cost of charging [5] [6] [7] , valley filling of the load profiles [11], maximum demand reduction [15] [16], minimizing the cost of charging to electric vehicles owners [5], maximizing the profit of charging station or aggregator [5] [13] or reducing the distribution system losses [4] [8].

In addition, electric vehicle load being schedulable and deferrable can provide demand response functionality to grid. Electric vehicle load can thus play a significant role in smart grid [1] [20]. Energy can be stored in the battery of Electric vehicle and can be pumped back into the grid (V2G) at other time thus making the demand flexible and schedulabe. Electric vehicle can also be used to provide auxillary functions to the grid like frequency regulation [17] [18] [19], reactive power support [21] [22] [23] and volt var control (VVC) [24].

There exists a fair deal of literature that addresses the problem of electric vehicle charging scheduling. [9], [10] have proposed the centralised charging scheduling while the authors of [11], [12] have put forward the decentralised or distributed control for making the charging decision. Centralised charging scheduling algorithms need the bidirectional communication between the centralised controller and the household chargers. Also the complexity of problem becomes difficult to handle with the increasing number of electric vehicles to be scheduled. However the centralised scheduling algorithms have the potential to give the optimal solutions. The authors of [25], [26] have proposed the time-of-use pricing as the method of controlling the electric vehicle charging. [27] [28] [29] have addressed the scheduling problem from the residential household charging point of view.

[5], [6], [13] have addressed the electric vehicle scheduling from the commercial charging station point of view. Electric vehicles are assumed to be charged from a commercial or a workplace charging station and the charging station operator uses intellegent decisions to charge the electric vehicles while

optimizing various parameters subject to equality and inequality constraints. The authors in [5] have proposed the menu based pricing to control the electric vehicle charging where in upon arrival at the charging station the electric vehicle owner is provided with a menu of prices for various energy-level and deadline combinations.

The work closest to ours is in [13] and [14]. In [13] the authors have considered the centralised scheduling of large scale electric vehicle charging by a charging station. The arrival time and deadline of electric vehicles is considered to be of random nature. The authors of [14] have formulated the problem as a deadline scheduling problem to control the charging of electric vehicles. Our work is diffrent from that of [13] and [14] in that we are considering bidirectional charging station with vehicle to grid (V2G) control and having on-site renewable generation. Our scheduling algorithm optimizes charging and discharging of elctric vehicles with vehicle to grid (V2G) support, the problem is formulated as a multi-objective real-time online scheduling at the commercial charging station. Contrary to residential charging,in a commercial charging station the user do not have the luxury to charge their vehicles at each interval of time. In our work, electric vehicles arrive at the charging station at random times with random energy demands to be fulfilled with in a certain deadline (random). The scheduling is updated everytime a new vehicle arrives at the charging station to minimize the cost of charging to electric vehicle owners, minimizing the running cost to charging station, reducing the frequent change in charging rates while ensuring that the peak loading on the distribution grid is reduced and satisfying the charging constraints.

II. MODEL

We consider a commercial charging station having on-site renewable energy generation, battery storage and bi-directional chargers. In order to perform the scheduling, total time T is discretized into smaller time intervals of equal duration Δt i.e $t = [1, 2, ...T]$. The scheduling policy has the following components.

A. Electric Vehicle Arrival

Let the user $k_e = 1, 2, \ldots, K_e$ arrives at a charging station at time interval t_k demanding energy $Q_{k_e,max}$ with the deadline t_{dead,k_e}. The charging requests of the arriving electric vehicles are assumed to be random. However, whether the k_e^{th} vehicle is connected to charger or not depends on the decision sequence. The electric vehicle can only be charged when it is connected to a charger.

B. Charging Station

The charging station is assumed to have energy available from both conventional and renewable sources. Let $q_{k_e,t}$ and $w_{k_e,t}$ be the amount of conventional and renewable energy used to charge the k_e^{th} vehicle from time interval $[t_k, t_{k+1})$. The Energy stored in the Vehicle can also be used to supply it back to the grid during the peak times to reduce the cost further by taking the advantage of difference in prices. We denote the energy supplied by vehicle k_e to the grid during time interval $[t_k, t_{k+1})$ by $g_{k_e,t}$. Thus the net energy drawn from the grid to charge k_e^{th} vehicle during time interval $[t_k, t_{k+1})$ is:

$$q'_{k_e,t} = q_{k_e,t} - g_{k_e,t} \tag{1}$$

C. Battery Storage and Renewable Energy Harvesting

charging station is assumed to have battery storage of maximum capacity B_{max} to store the energy harvested from the renewable energy generation and to take advantage of time-of-use (TOU) pricing for making profit. Let the cost of conventional energy be c_t, and the marginal cost of harnessing renewable energy is assumed to be zero. We have assumed c_t to be time-of-use pricing, however our algorithm is independent of the nature of pricing and will adapt well for different type of pricing mechanisms. The battery energy level at any instant t_{k+1} is:

$$B^{t_{k+1}} = B^{t_k} + \hat{E}^t - w_t + \left(q'_t - \sum_{i \in \kappa_0} q_{i,t} \right) \tag{2}$$

$$0 \leq B^{t+1} \leq B_{max} \tag{3}$$

where B^{t_k+1} and B^{t_k} are the battery energy levels at time instant t_{k+1} and t_k respectively, $\hat{E}^t$ the renewable energy harvested by the charging station during time interval $[t_k, t_{k+1})$, w_t is the total energy drawn from storage and q'_t the net energy drawn from the grid for all the vehicles in the interval $[t_k, t_{k+1})$. κ_0 is the set of all the Electric Vehicles being charged during interval $[t_k, t_{k+1})$.

$$q_t = \sum_{k_e \in \kappa_0} q_{k_e,t} \tag{4}$$

$$w_t = \sum_{k_e \in \kappa_0} w_{k_e,t} \tag{5}$$

D. EV Chargers

When the k_e^{th} vehicle is connected to a charger, depending on the scheduling policy it is either charged or is supplying energy back to the grid during the time interval $[t_k, t_{k+1})$. However owing to the inherent limit of chargers, there is maximum and minimum charging and discharging rate constraints. Let R_{min} and R_{max} be the minimum and maximum charging rates and D_{min} and D_{max} be the minimum and maximum discharging rate constraints. The charging and discharging rate constraints can be translated into the constraint on the energy that can be supplied to the electric vehicle or pumped back to the grid during each time interval, by multiplying the charging rates by the duration of time interval. Thus,

$$R'_{min} \leq q_{k,t} \leq R'_{max} \tag{6}$$

$$D'_{min} \leq g_{k,t} \leq D'_{max} \tag{7}$$

where

$$R'_{min} = R_{min}[t_k - t_{k-1}] \qquad \& \qquad R'_{max} = R_{max}[t_k - t_{k-1}]$$

$$D'_{min} = D_{min}[t_k - t_{k-1}] \quad \& \quad D'_{max} = D_{max}[t_k - t_{k-1}]$$

R'_{min} and R'_{max} are the minimum and maximum amount of energy that can be supplied to the electric vehicle during each time interval and D'_{min} and D'_{max} are the minimum and maximum amount of energy that can be pumped from vehicle to grid during each time interval.

III. PROBLEM FORMULATION

The problem has been formulated as multi-objective optimization to minimize the charging cost to electric vehicle owners, maximize the profit of charging station, reduce the frequent change in charging rates, reducing the peak load on the distribution grid and simultaneously minimizing the total energy mismatch (energy demanded - energy supplied) at the deadline while satisfying the constraints of the chargers and the battery storage.

Let $k_e \in K_e$ be the vehicle being connected to the charging station at time $t_k \in T$ where K is the collection of all the vehicles connected to the charging station including at $t = t_k$. Let $q'_{k_e,t}$ be the net amount of energy being supplied to the battery of Electric Vehicle k_e during each time interval. Then

$$\sum_{t=t_k}^{T-1} c_t q'_{k_e,t}$$

gives the total cost of charging k_e^{th} Electric Vehicle and the summation

$$\sum_{k_e=1}^{K_e} \sum_{t=t_k}^{T-1} c_t q'_{k_e,t}$$

gives the total cost of charging all the Electric Vehicles $k_e \in K_e$.

In addition to minimizing the cost of charging, we also intend to prolong the life of lithium-ion batteries of electric vehicles and thus saving on the future cost. Studies from [30] suggest that the frequent changes in charging rates reduces the effective life of battery. Thus to increase the life of battery, we have penalized the frequent changes in charging rate by adding the term

$$\sum_{t=t_k+1}^{T} \gamma \left| q'_{k_e,t} - q'_{k_e,t-1} \right|$$

to the objective function.

where γ is the penalty factor corresponding to changing charging rates and $q'_{k_e,t}$ and $q'_{k_e,t-1}$ are respectively the charging rates during intervals $[t, t+1)$ and $[t-1, t)$. It is assumed that the charging rates remain constant through a particular time interval. Thus Penalizing the change in energy supplied is equal to penalizing the rate of charging rates multiplied by a constant (Δt).

In order to ensure that the Electric Vehicles are charged to level demanded by the owners $Q_{k_e,max}$, at the deadline, another soft constraint

$$\eta^{t-t_{dead},k_e} \, \mathbb{1} \left(\sum_{t=t_k}^{t_{dead}} q'_{k_e,t} < Q_{k_e,max} \right)$$

has been added to the objective function to penalize the mismatch between the energy demanded and the energy supplied, where $\mathbb{1}$ is the indicator function giving output as 1 only if the condition inside the parentheses satisfies otherwise giving output as 0.

$$\begin{cases} 0 & \left(\sum_{t=t_k}^{t_{dead}} q'_{k_e,t} < Q_{k_e,max} \right) = 0 \\ 1 & \left(\sum_{t=t_k}^{t_{dead}} q'_{k_e,t} < Q_{k_e,max} \right) \neq 0 \end{cases}$$

η is a penalty factor, t_{dead}, k_e the deadline and $Q_{k_e,max}$ the demand of the k_e^{th} Electric Vehicle. In order to transform this to a convex problem, the indicator function is approximated as:

$$-min \left(0, \left(\sum_{t=tk}^{t_{dead},k_e} q'_{k_e,t} - Q_{k_e,max} \right) \right)$$

In order to keep the loading on the distribution grid under limits, we have added another term

$$\zeta \left| \sum_{k_e=1}^{K_e} q_{k_e,t} \right|^2$$

to the objective function, to minimize the energy drawn from the grid at each time interval so that the charging station does not overload the Electric power distribution system.

In order to compensate for the additional wear and tear of electric vehicle battery for utilizing it to provide vehicle to grid (V2G) services, we add another term to objective function proportional to the energy supplied by Electric Vehicle to the grid.

$$\beta \left| \sum_{k_e=1}^{K_e} g_{k_e,t} \right|^2$$

Thus the overall objective function becomes:

$$\begin{aligned} & minimize \\ & \sum_{k_e=1}^{K_e} \Bigg(\sum_{t=t_k}^{T-1} c_t \, q_{k_e,t} - \sum_{t=t_k}^{T-1} c'_t \, g_{k_e,t} + \sum_{t=t_k+1}^{T} \gamma \left| q'_{k_e,t} - q'_{k_e,t-1} \right| \\ & \qquad - \eta^{t-t_{dead},k_e} \, min \left(0, \left(\sum_{t=tk}^{t_{dead},k_e} q'_{k_e,t} - Q_{k_e,max} \right) \right) \Bigg) \\ & \quad + \zeta \left| \sum_{k_e=1}^{K_e} q_{k_e,t} \right|^2 + \beta \left| \sum_{k_e=1}^{K_e} g_{k_e,t} \right|^2 \end{aligned} \tag{8}$$

Subject to:

$$B^{t+1} = B^t + \hat{E}^t - w_t + \left(q_t - \sum_{i \in \kappa_0} q_{i,t} \right) \tag{9}$$

$$0 \leq B^{t+1} \leq B_{max} \tag{10}$$

$$R'_{min} \leq q_{k,t} \leq R'_{max} \tag{11}$$

$$D'_{min} \leq g_{k,t} \leq D'_{max} \tag{12}$$

where $q_{k_e,t}$, $g_{k_e,t}$ and $w_{k_e,t}$ are the optimization variables. The weights of penalty factors are tuned depending on the relative importance of the objectives using pareto optimality. This convex optimization problem is solved every time a new electric vehicle arrives at the charging station to update the scheduling policy.

Theorem 1: The optimization problem in eq. (8) above is a convex optimization subject to constraints eq. (9) to eq. (12). We have used disciplined convex programming [31] optimization toolbox CVX with MATLAB to solve this problem.

IV. SIMULATIONS

A. Simulation Setup

In this section we study and show the efficacy of proposed scheduling policy over the benchmark Earliest-deadline-first (EDF) algorithm. The scheduling algorithm was tested on the simulated data for 24 hours divided into 96 intervals of 15 minutes each. Similar to [5], we have assumed that Electric Vehicles can be charged at any rate from 0 to 3.3 kW. The average amount of energy consumed per electric vehicle was taken as 6.9 kWh with standard deviation of 4.9 kWh [5] in the interval [2,20]. The time spent by an Electric Vehicle in the Charging station is assumed to be exponentially distributed with mean of 2.5 hours [5]. Also from [5] the arrival process of Electric Vehicles is considered to be a non-homogeneous poison process with arrival rate of 28 Vehicles per hour during peak period (08 A.M to 5 P.M) and 12 vehicles per hour during off-peak period. In numerical simulations we take the value of penalty factors in the ratio:

$$\beta : \zeta : \gamma : \eta = 1 : 10 : 100 : 1000$$

B. Simulation Results

Fig. 1 clearly shows that the cumulative cost of charging electric vehicles to commercial charging station is considerably lower than in the earliest deadline first (EDF) algorithm. The two curves starts almost parallel to each other but proposed algorithm takes the advantage of price difference to pump in energy back to the grid during the time of peak pricing and thus earn significant profit. Fig. 2 shows the price of conventional energy as a function of time in dollars. As illustrated by Fig. 3 in proposed algorithm there is a considerable amount of energy being pumped back into the grid during the peak pricing.

Fig. 4 gives the clear picture of the energy demanded from the grid during various intervals. We have divided this figure into three intervals, two off-peak and one peak period. During off-peak periods Fig. 4(a) and Fig. 4(c) in proposed algorithm the demand is greater than the demand in the EDF algorithm. This is because by proposed algorithm, during non-peak periods the charging station should store additional energy in the battery of charging station as well as the battery of those electric vehicles which have larger deadlines to take the advantage of price differences. However during peak period Fig. 4(b) the demand of charging station is negative, which implies that during peak times the charging station is supplying energy back to the grid and increasing its profit.

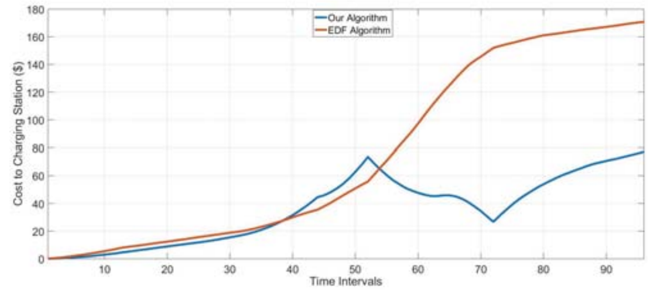


Fig. 1. Cumulative cost of charging to station.

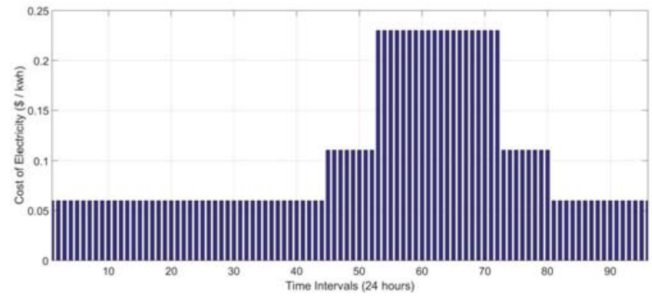


Fig. 2. Electricity prices as a function of time

Fig. 5 shows the number of charging slots required by proposed algorithm and the EDF algorithm. Though proposed algorithm requires some chargers more than in the EDF algorithm, but the cost : benefit ratio is still less in proposed algorithm.

Electric vehicle owners also benefit a great deal from proposed algorithm. Fig. 6 show the comparative cost analysis for charging electric vehicles between proposed algorithm and the EDF algorithm from the electric vehicle owners point of view. As is evident from the figure that vehicle owners will have to spent less in proposed algorithm and in fact a number of vehicle owners will recieve payments from the charging station for letting the charging station use the battery of electric vehicles for providing vehicle to grid (V2G) services.

Any scheduling policy would aim to full fill the energy demand as much as possible before deadline. Fig. 7 shows that the proposed algorithm was able to meet charging requests upto 95 percent while EDF algorithm was able to full fill upto 94 percent charging requests. Finally Fig. 8 shows the fractional change in charging rates. it is clearly evident that the proposed algorithm perform better than EDF algorithm in this parameter as well.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

we considered the electric vehicle scheduling problem at the commercial bidirectional charging station with on-site renewable energy generation, battery energy storage and vehicle to

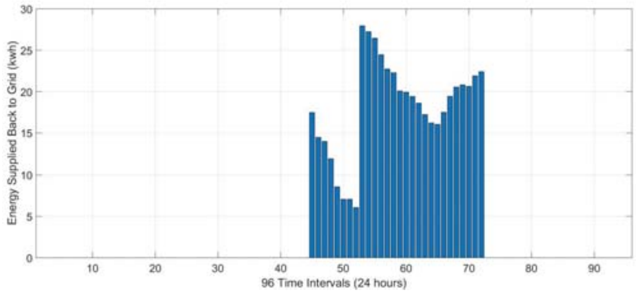
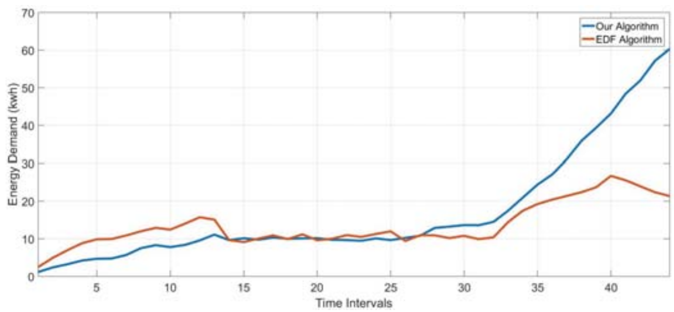
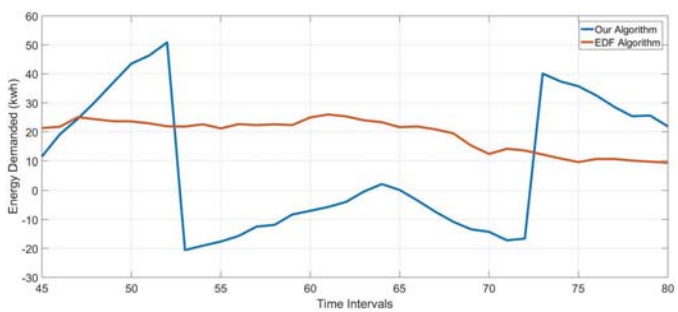


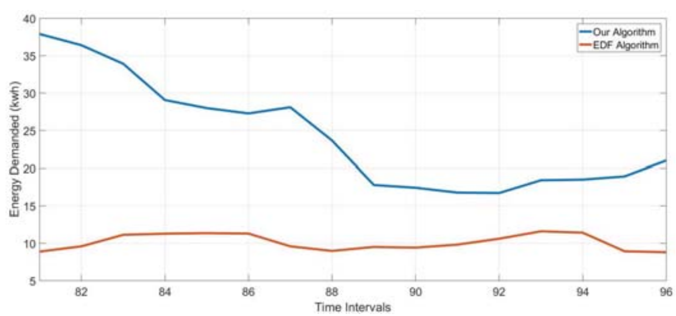
Fig. 3. Energy pumped back to the grid as a function of time.



(a) Off-peak period



(b) Peak load period



(c) Off-peak period

Fig. 4. Energy demand of charging station as a fuction of time.

grid control. The control problem was formulated as a multi-objective convex optimization problem with various equality and inequality constraints where the arrival and deadlines of electric vehicles was assumed to be random together with the renewable energy generation. Using simulations we have shown that the proposed control offer significant advantages compared to benchmark algorithm like Earliest-Deadline-First

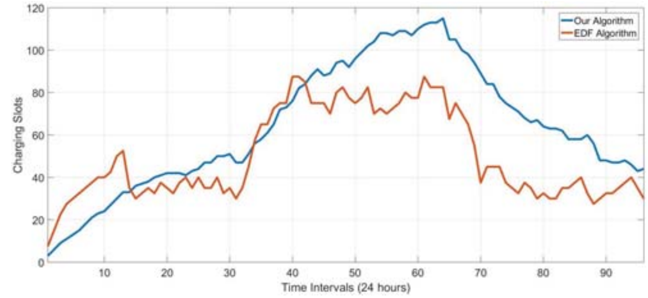


Fig. 5. Charging slots requirement comparison

(EDF) for randomly generated charging requests.

B. Future Works

In this paper we have scheduled the electric vehicle charging from the commercial charging station point of view. In future we consider that scheduling from the household charging perspective and extend the commercial charging scheduling to the joint vehicle charging and transportation optimization. Also some deep neural networks can be used to forecast the renewable energy generation and electric vehicle load so as to improve the performance of the algorithm further.

Finally we consider in future to study the system wide effects of commercial charging station scheduling on the distribution grid, like its effects on voltage profile, harmonics and reactive power support.

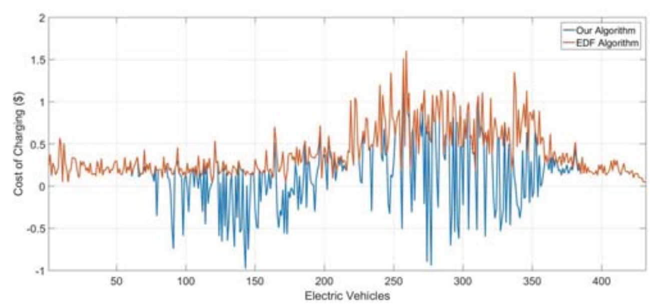


Fig. 6. Charging cost for different electric vehicles

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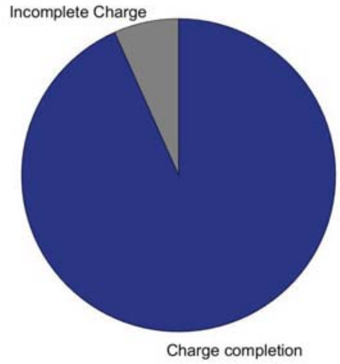
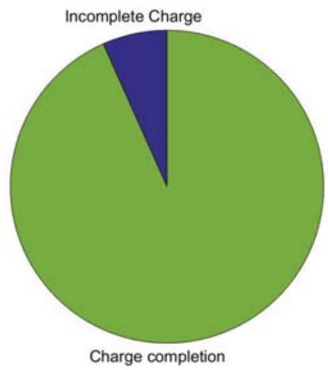


(a) Earliest Deadline First Algorithm



(b) Proposed Algorithm

Fig. 7. Percentage charge completion comparison

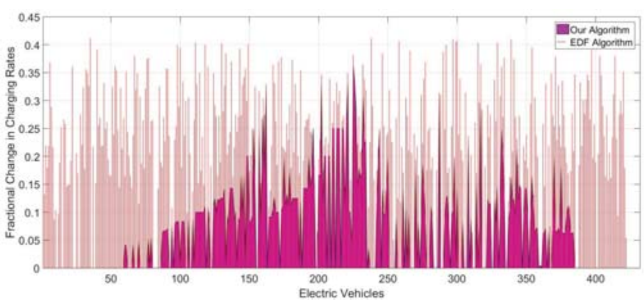


Fig. 8. Comparison of fractional change in charging rates

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