TOU Pricing Based Energy Management Of Public EV Charging Stations Using Energy Storage System

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Abstract—Adoption of EVs on large scale is greatly dependent on electricity price. Energy storage system (ESS) can bring down cost of EV charging using time of utilization (TOU) pricing of wholesale electricity market. In this study, analysis of energy management using energy storage deployed at public EV charging stations is done to find benefits of TOU pricing of wholesale electricity using uncontrolled EV charging model. The objective of this analysis is to minimize the cost of EV charging. Heuristic algorithm proposed in this study performs real time energy management by analysing wholesale electricity price (WEP) trend over past 30 days. It minimises the power imported from grid during high price hours and charges the battery at low price hours while continuously feeding the dynamic EV charging load demand. Results obtained show the significant reduction in cost of EV charging due to ESS in utilization of TOU pricing of WEP.

Index Terms—Electric vehicles, electricity price, energy management, energy storage system, time of utilization.

I. INTRODUCTION

In Singapore, government has set to increase the deployment of electric vehicles (EVs) to meet the transportation needs of its citizens. The government has planned to encourage the EV public charging infrastructure, preparing Singapore for the future possibility of widespread adoption of EVs [1]. In a result, increased number of EVs have started to come on road. Large number of EVs connecting to the grid simultaneously creates a significant challenge to the quality and stability of the overall power system [2]. Authors in [3] have also mentioned that without an appropriate energy management system at the charging infrastructure, large numbers of electrical vehicles have the potential to threaten the stability of the grid.

To overcome these problems, EV owners can be encouraged to shift their charging loads to off-peak hours. This can be achieved by offering price incentives to consumers for off-peak hours charging and introducing dynamic electricity prices. In [4], authors suggests a solution to reduce the impact of EVs on the grid by coordinating and optimizing their charging profile so that they are not charged at the same time. Authors in [5] presents an optimized EV charging model considering TOU price and SOC curve enabling EVs to adjust their charging power and time. But in real time scenario it is very difficult because consumer level management requires the active consumer involvement, which is not very effective [6].

In real time scenarios, uncontrolled charging behavior of EV users is possible due to lack of coordination amongst the EV users. Literature [2]–[4], [6] indicates that large number of uncoordinated EV charging will have unfavorable effects on grid performance and efficiency.

The energy storage systems (ESS) are becoming an important solution in minimizing load impacts on distribution grid [7]–[10]. Unfavorable impact of EV charging on distribution grid can be reduced if ESS is applied between the grid and the EVs. The problem of uncoordinated EV charging due to less involvement of consumers can be solved with ESS. It can be integrated with transportation system, making the grid ready for vehicle to grid scenario mentioned in [11]. The major benefit of deploying ESS is to utilize benefit of Time of utilization (TOU) pricing without relying on EV coordination. Electricity price is crucial parameter in the deployment of EVs on large scale.

In electricity market, wholesale consumer can get the benefit of ups and downs in electricity price. In Singapore wholesale electricity market, electricity price changes every half hour. The price varies between $350/MWh during peak to as low as $54/MWh [12]. This creates an opportunity for deploying ESS at distribution side and take the benefits of TOU pricing. Public charging stations equipped with suitably sized ESS can save considerable amount of money. In this study, an uncontrolled EV charging model at public charging station is considered to analyze impact of ESS for TOU pricing benefits.

The objective is to minimize the charging cost of EVs at public charging station using TOU pricing which changes at half hourly basis. The algorithm focuses on energy management using heuristic approach by analyzing statistical data from past 30 days and uncontrolled EV charging model while not violating the constraints on ESS and EVs. The rest of the paper is organized as follows. Section II discusses the model for EV charging, ESS and TOU pricing which are used for applying energy management strategy. Section III describes proposed heuristic algorithm based on energy management strategy. In Section IV, proposed algorithm is applied on uncontrolled EV charging scenario using real data and results are discussed. Conclusions are summarized in Section V.
II. MODEL FOR EV CHARGING, ESS AND TOU PRICING

With the analysis of trend in electricity pricing of previous 30 days it is possible to plan the energy consumption on upcoming days in advance to take benefit of TOU pricing. Initial state of charge (SOC) and battery capacity are read by charging system. Desired final SOC and preferred mode of charging will be set by EV owner. Based on EVs available at charging station with their respective SOC, energy supplied by charging station will be managed through grid and ESS. Energy storage is used for providing power during high price hours and also to deal with the sudden peak power requirements during low price hours to cap the maximum load demand from distribution grid.

A. Problem Description

With the analysis of trend in electricity pricing of previous 30 days it is possible to plan the energy consumption on upcoming days in advance to take benefit of TOU pricing. Initial state of charge (SOC) and battery capacity are read by charging system. Desired final SOC and preferred mode of charging will be set by EV owner. Based on EVs available at charging station with their respective SOC, energy supplied by charging station will be managed through grid and ESS. Energy storage is used for providing power during high price hours and also to deal with the sudden peak power requirements during low price hours to cap the maximum load demand from distribution grid.

B. Objective Function

The cost of charging all vehicles at charging station is to be minimized using TOU based electricity pricing. Hence the objective function is stated as,

$$\arg \min C, C = \int_{t_i}^{t_i + t_c} R(t) P_g(t) dt.$$  \hspace{1cm} (1)

In (1), $t_i$ is starting time of charging, $t_c$ is time required by EV for charging, $R(t)$ is the electricity price and $P_g(t)$ is total charging power supplied by the grid to all EVs available for charging, $t_c$ is minimum of all charging time of EVs and is updated at every time interval $\Delta t$.

Here $\Delta t$ is considered as 1 minute. Therefore, $P(t)$ and $t_c$ required for each EV is calculated each minute and power from ESS is planned to change at any time interval based on the proposed algorithm.

C. Parameters for EV charging

1) Target Vehicle category: Public charging stations will be utilized by commercial vehicles more than private car owners since they cannot afford to charge for longer hours at home chargers which has lower power ratings. Taxis are the emerging EVs in commercial vehicles category in Singapore. Total no. of taxis in Singapore in 2014 was 28736 [13]. Number of taxis in Singapore is around 3% of the vehicle population [12]. Despite their small numbers, they account for 15% of the total distance covered by all vehicles in Singapore [14]. Assuming the penetration rate of EVs in Singapore taxis between 10% and 15%, estimated no. of electric taxis entering each year on road will be around 3000.

2) Initial SOC ($SOC_i(t)$): This parameter is estimated based on the average daily ridership, average distance per passenger-trip and total no. of taxis in Singapore. The average daily distance travelled by taxis in Singapore considering two shifts working pattern is 355km. Considering the maximum range of EVs available in the market, taxis will need to be charged at least twice per day. It is assumed that the average distance travelled by the vehicles follows a normal distribution [15]. Typical probability density function (PDF) and cumulative probability function (CPF) of an average travel distance of 350km and standard deviation of 50km are shown in Fig. 1. $SOC_{ik}$ is calculated as

$$SOC_{ik} = (1 - \frac{D_k}{D_{max,k}}).$$ \hspace{1cm} (2)

In (2), $D_k$ is distance travelled by the kth EV for charging after last charge in a day estimated with previous vehicle travelling data and probability distribution from above figure, $D_{max,k}$ is maximum range of kth EV out of N EVs available for charging.

3) Final SOC ($SOC_f(t)$): Since target vehicles are mainly dependent on public charging stations to get a full charge as
quickly as possible, the $SOC_f(t)$ required by EVs is assumed to be a random variable between 80% and 100% of EV battery capacity.

4) Battery capacity of EV and charge characteristics:
For this study we have chosen BMW i3, Nissan Leaf and Kia SoulEV for generating test cases. BMW i3 has 18.8kWh capacity [16] whereas Nissan Leaf has 24kWh capacity [17]. Kia Soul EV has 27kWh battery [18]. All the three EVs are capable of fast charging and can be connected to 50kW DC fast chargers [16]–[18]. Power and time required for each EVs for charging is estimated from the data available on EV manufacturers web portals. The estimated values as shown in Fig. 2 shows resemblance with actual battery characteristics stated by the EV manufacturers. EVs show similar charging pattern when changed from normal charging mode to fast charging mode but in fast charging mode, $d(SOC(t))/dt$ i.e. slope of SOC curve increases, indicating higher power consumption of battery every minute than normal mode of charging. Battery life and performance are governed by ambient temperature, number of cycles as well as charge/discharge rates. Also chemistry of two batteries will not be same for all times. Hence percentage increment in SOC of EV batteries of same make will not be same in real time fed with same charging power every minute.

To account for this variability, a random factor $\alpha$ is introduced while deciding the charging power required for each EV every minute. In the proposed algorithm, $\alpha$ gets calculated every minute and gets added or subtracted randomly from total charging power

$$P_c(t) = \sum_{k=1}^{N} \left[ \frac{P_{e v k}(t)}{\eta_{e v}} \pm \alpha \frac{P_{e v k}(t)}{\eta_{e v}} \right]$$  \hspace{1cm} (3)

In (3), $P_{e v k}$ is the calculated charging power for each $k$th of N vehicles, $\eta_{e v}$ is efficiency of EV chargers [19] at each charging instant.

D. Energy storage systems (ESS)

The charging model considered for this study is run to get power requirement for 7 days of week with $\Delta t = 1$ min. and graphs from simulation results are plotted as shown in Fig. 3, to identify minimum power requirement at all time instant for all days. This will serve as a minimum energy storage capacity selection criterion. Also it is observed that apart from base load requirement there are significant peaks in power requirement throughout the day lasting from 30 minutes to 60 minutes. These peaks should also be taken into consideration for ESS capacity planning. From Fig. 3 we observed that minimum power delivering capacity of ESS for our study including significant peak power requirement should be 150kW. From Fig. 3, high price hours last for maximum of 4 continuous hours in a day hence, it is sufficient to select battery capacity as 150kW for 4 hours which comes out to be 600kWh. Therefore, we select 620kWh as a nearest standard battery capacity available in market [20]. In our study, the maximum charge rate $P_{bc0}$ is taken as 200kW which is at $C/3$ rate [20] while maximum discharge rate $P_{bd0}$ is taken as 150 kWh which is at $C/4$ rate [20]. Both values are lower than maximum allowable charging / discharging rates specified by the battery manufacturer [20]. This will reduce stresses on batteries and increase their life.

E. Electricity market in Singapore

Singapore’s Energy Market Authority has progressively opened the retail electricity market to competition to give consumers more options to manage their energy cost. Instead of buying electricity at the regulated tariff, eligible consumers can choose to buy electricity from the wholesale electricity market at prices [12] that fluctuates every half-hour. From WEP changing every half hour as shown in Fig. 4, it is observed that though there are two significant peaks of high prices occurring on each day, the one in the morning between 9 am and 1 pm and another between 7:30 pm and 11 pm. Maximum continuous time for high price is around 8 time intervals in which algorithm should minimize the cost of EV charging. Also we observed that there are other significant peaks of higher prices present in some days which do not last more than 1 hour in which algorithm should perform peak shaving so that power imported from grid at high price is reduced. Hence we will also incorporate the peak shaving in our algorithm so that power taken from grid at high price hours will be reduced.
Step 3: Calculate charging power required for each EV

Step 2: Collect SOC

heuristic approach.

price which varies over the time we design the algorithm with the pattern for WEP for each day of week.

WEP. After doing data analysis it is observed that typical WEP are charged only in this time period. These time intervals are in 3 categories:

Off-peak - This time period is continuous low price period

Neutral - This time period contains intermittent peaks of station at

charging characteristics of battery at

charging power of ESS

SOC falls

SOC falls

SOC falls

Step 5: Calculate the SOC of energy storage system battery

SOCb(t) at each time instant

Step 6: Check the day and time of the day at t=j. Decide whether j th time interval is in peak, neutral or off-peak period from the previous 30 days statistical data available.

Step 7: Get the value of SOC of ESS battery at previous time interval

SOCb(t−1), at 

Step 8: If time interval at

is in peak period, Always set charging power of ESS

Pbc(t)=0.

If

SOCb(t−1)>25% and if

Pc(t)/ηc<Pb0d, set discharge power of ESS

Pbd(t)=Pc(t)/ηc and

Pb(t)=0.

If

Pc(t)/ηc>Pb0d, set

Pbd(t)=Pb0d and

Pb(t)=Pb(t−1).

If

SOCb(t−1)<25%, set

Pbd(t)=0 and

Pb(t)=Pc(t). 

Step 9: If time interval at

is in off-peak period, Always set

Pbd(t)=0.

If

SOCb(t−1)<90%, set

Pbc(t)=Pb0d, 

Pb(t)=Pc(t) +

Pbc(t)/ηc

If

SOCb(t−1) > 90%, set

Pbc(t)=0, 

Pb(t)=Pc(t).

Step 10: If time interval at

is in off-peak period, Always set

Pbd(t)=0.

If

SOCb(t−1) < 90%, set

Pbc(t)=Pb0d, 

Pb(t)=Pc(t)+Pbc(t)/ηc

If

SOCb(t−1) > 90%, set

Pbc(t)=0, 

Pb(t)=Pc(t).

Step 11: Update value of

SOCb(t). Increase value of j by 1 and start from step 1.

III. ALGORITHM

In our algorithm we have classified time periods in following 3 categories:

Peak - It is continuous high price period which lasts up to 4 hours. Batteries will discharge into load demand by EVs.

Neutral - This time period contains intermittent peaks of high price in it which lasts for 30 to 60 minutes. Batteries will be used only for peak shaving whenever EV charging power demand increases beyond set point

Since power supplied and consumed by energy storage as well as power imported from the grid depends on electricity price which varies over the time we design the algorithm with heuristic approach.

The optimization function is given as,

arg min C, C = ∑ R(t)Pb(t)Δ(t). (4)

Step 1: Sort previous 30 days of electricity pricing data on the basis of days and timing. Identify peak period, neutral period and off-peak period respectively. Get current day and time as input.

Step 2: Collect

SOCi k(t) ,

SOCf k(t), Capacity of EV battery

desired mode of charging e.g. normal or fast, from each kth of N number of EVs available at charging station at

Step 3: Calculate charging power required for each EV

based on

SOCi k(t),

SOCf k(t), mode of charging and charging characteristics of battery at

Step 4: Calculate charging time required for each EV based on

SOCi k(t),

SOCf k(t), mode of charging and power required at each time instant calculated at step 3, at

Step 8: If time interval at

is in peak period, Always set charging power of ESS

Pbc(t)=0.

If

SOCb(t−1)>25% and if

Pc(t)/ηc<Pb0d, set discharge power of ESS

Pbd(t)=Pc(t)/ηc and

Pb(t)=0.

If

Pc(t)/ηc>Pb0d, set

Pbd(t)=Pb0d and

Pb(t)=Pb(t−1).

If

SOCb(t−1)<25%, set

Pbd(t)=0 and

Pb(t)=Pc(t).

Step 9: If time interval at

is in off-peak period, Always set

Pbd(t)=0.

If

SOCb(t−1)<90%, set

Pbc(t)=Pb0d, 

Pb(t)=Pc(t) +

Pbc(t)/ηc

If

SOCb(t−1) > 90%, set

Pbc(t)=0, 

Pb(t)=Pc(t).

Step 10: If time interval at

is in off-peak period, Always set

Pbd(t)=0.

If

SOCb(t−1) < 90%, set

Pbc(t)=Pb0d, 

Pb(t)=Pc(t)+Pbc(t)/ηc

If

SOCb(t−1) > 90%, set

Pbc(t)=0, 

Pb(t)=Pc(t).

Step 11: Update value of

SOCb(t). Increase value of j by 1 and start from step 1.

IV. CASE STUDY

In order to test our algorithm, we have considered public charging station having 20 chargers. 5 chargers are considered as DC fast chargers and 15 chargers are considered as normal chargers. Initial SOC of ESS is kept at 90% Charging model for 3 different types of EVs with different battery capacity is created using MATLAB. Values of

SOCi k(t) and

SOCf k(t)

are created using random approach with existing statistical data about vehicles. Real time charging scenario through uncontrolled public charging behavior is created to replicate real time scenario closely to test algorithm. The cost of electricity with ESS and without ESS is calculated every half hour for the same scenario. The results after running simulation for all days of week with changing WEP for entire week are analyzed. Results for one of 7 days is shown in Fig. 6. It is observed that algorithm has successfully managed to shift all load requirement to ESS during peak period. Also ESS has operated in neutral period feeding all significant peaks until

SOCb falls
below 25% of its full capacity. Fig. 6 also shows that ESS was charged during off-peak hours having continues low price hours. Electricity cost with ESS is found to be than system without ESS. The graph in Fig. 7 shows cost reduction due to deployment of ESS for each day of week. Results also shows the percentage saving is significant as compared to electricity cost without ESS. However percentage saving obtained also shows wide variation. It is higher in the beginning of week and after a gradual fall it becomes stable. This has resulted because of high volatility in electricity prices on days where percentage saving is more and ESS has managed to reduce dependency on grid in that high price hours. Also ESS has clipped the load demand during sudden peak pricing hours during neutral time period.

V. CONCLUSION

From this analysis it is observed that proposed algorithm can effectively perform energy management between distribution grid and ESS without affecting EV load. The volatile pricing of WEP can be used to reduce electricity cost significantly. Proposed algorithm successfully minimizes the cost of EV charging at public charging station using TOU based ESS and in turn reducing dependency on grid. 20% to 50% cost reduction is possible on daily basis with suitably sized ESS under TOU pricing of WEP. This shows that the stress on power grid during peak demand can also be minimized without seeking active participation from EV owners and adding constraints on charging patterns of EV batteries mentioned in [5]. Hence, ESS at distribution side is found to be very advantageous for maximum utilization of TOU pricing benefits in wholesale electricity market.

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