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An analysis the G2V scheduling of EVA in context of grid stability & EV Owners' Perception

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Abstract- There are advantages and disadvantages to incorporating electric vehicles (EVs) into power networks, particularly for Grid-to-Vehicle (G2V) charging. Examining the effects on grid stability and EV owners' perspectives, this study examines the scheduling tactics of EVAs for G2V operations. Economic and technical aspects of EVA's V2G scheduling will be covered extensively in the article. Focussing on grid stability via regulating services and the perspective of EV owners on charging cost reduction, this will be used to design an EVA static G2V scheduling algorithm. This is the static G2V charge scheduling case where EVA already knows the EV owners' charging profiles. Traditional, unregulated G2V charge scheduling is contrasted with the suggested method. Briefly discussing G2V scheduling approaches and related work in this area helps to keep things moving forward. In order to assess EVA's performance metrics, a comprehensive outline of the system architecture is given.

Keywords- Electric Vehicles, EV Owners', Perspectives, G2V Scheduling

INTRODUCTION

The energy management system in a smart grid allows for the seamless interconnection of electric vehicle charging networks, the power grid, and EVA. Using this information, EVA may develop efficient strategies for smart load aggregation, lowering customer costs, satisfying demand, & avoiding system overloading. Static, offline charging & dynamic, online charging are the two main categories into which data from the pre-G2V charge schedule setup falls. As part of the planned simplification effort, we take a static charging situation into consideration, where EVA already has all of the EV owners' entire charging profile data (including arrival & departure timings, starting state of charge upon arrival, and intended state of charge upon departure) stored. Once EVA arrives, each EV owner follows the charging plan it computes using the static G2V charge scheduling problem (SCSP) algorithm, which takes into account pricing and next driving information.

From the point of view of EV owners, EVA reduces the expense of charging. On the other hand, getting the most affordable charging option is no assurance of top-notch system efficiency. From SO's point of view, it's trying to maximise the grid's ancillary service benefits. As a for-profit organisation, EVA's goal in creating its own schedule is to maximise profits.

To rephrase, it discourages boosting regulation while simultaneously minimising charging costs. These issues are performance-uncertain & centred on the person, ignoring the needs of other entities. The combined worries of SO and EV owners might be alleviated by the co-optimization of techno-economic goals, such as minimising charging costs & ensuring grid stability through regulating services, through an ideally coordinated static G2V charge schedule of EVA.

The stability of the grid depends on equitable distribution of loads & frequency stability, both of which are necessary for SO. By charging electric vehicles with a lower POP when baseload is high and a higher POP when baseload is low, EVA can help achieve a generally fair distribution of loads by applying appropriate POP each hour according to baseload. In this way, EVA regulates the billing rate to prevent the system from being overloaded due to an increase in peak load caused by non-scheduled POP. So, when demand surges, EVA may help keep the supply and demand in balance by cutting power from the grid. The suggested solution optimises both EVA's income from grid stability support and the charging costs of electric vehicle owners at the same time through static G2V scheduling. An effective approach is devised to achieve a balance between the EVA's income & charging expenses after a thorough customer-centric analysis of EV charging is undertaken. Electric vehicle owners may also customise their charging needs using this approach. Not to mention that, in contrast to the heuristic charging scenario shown in similar research, the static charging scenario is easy to implement as a regular and correct manner, removing computing weight.

SYSTEM MODEL

A schematic representation of the proposed G2V charge scheduling architecture is shown in Figure 1. The main components of a G2V scheduling architecture are shown in this system model, which also shows how an EVA, a substation, and a set of related transformers integrate EVs into the grid. Electric vehicles are connected to a leaf node transformer, which is located on the node's lateral. To avoid transmission line & equipment overload, this design connects the aggregated EVs to the leaf node transformers in a way that controls the EV charging rate so it doesn't exceed the delivery capability of each transformer. During off-peak hours, an EVA can charge the EVs at a higher pace than during peak hours, depending on the battery capacity & load circumstances. While attending to these duties, EVA is also making an effort to optimise income.

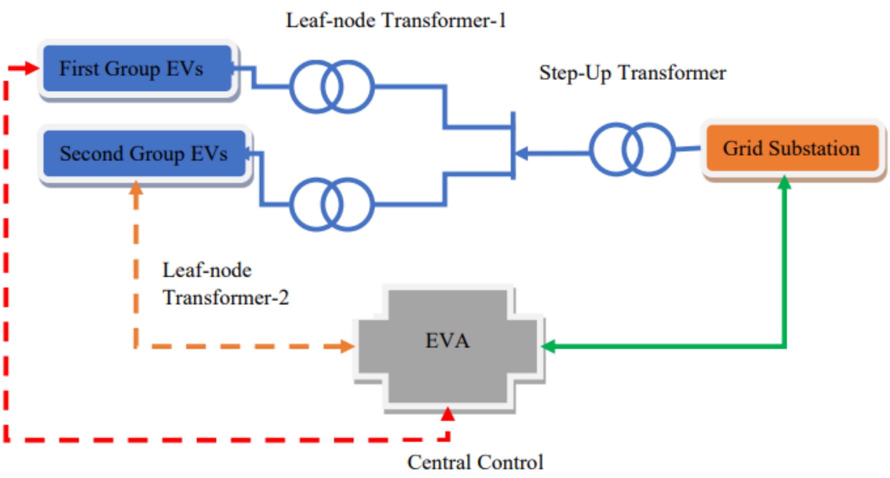

Figure 1: EV Charging Network Architecture

In a typical day, EVA pays the grid a wholesale price for electricity that changes hourly. During the day's peak hours, this purchase cost is significant in a dynamic pricing situation, but during off-peak hours, it's quite cheap. In order to mitigate its exposure to fluctuations in the market, the EVA adds a margin to the wholesale price before selling it to consumers. The mark-up price is the extra profit margin. The EVA collects data from the SO in addition to the EV owners. EV customers are presumed to have the freedom to come and go at their convenience in the model under consideration in this study.

A single charging session can be represented by five data sets: the i-index for the EV number, tai the arrival time of i^{th} EV, tdi departure time of ith EV, $SOCi^{INI}$ initial SOC of i^{th} EV and $SOCi^{DES}$ desired SOC of i^{th} EV. The current electric vehicle charging schemes are not particularly complicated, and the majority of them rely on advance information based on a regular vehicle movement pattern. Despite the fact that some charging tasks may not have available information in advance, this assumption seems reasonable to begin with. Many automobiles prefer to charge exclusively throughout the night because the load is lower then. Assumption: the electricity market under consideration operates on an hourly basis. Going forward, the G2V charge schedule horizon will be 24 hours, spanning the entire day from noon on the current day to noon the following day. Every interval lasts for an hour.

REGULATION CAPABILITIES OFFERED BY A SINGLE EV

The SO is responsible for maintaining a steady frequency and a level or evenly distributed load to guarantee the system's stability & dependability. To achieve a more fair distribution of loads, the EVA can adjust the charging rates of the linked EVs $POP_{i,t}$ such that they are lower during peak hours and greater during off-peak hours. In case the SO contacts EVA to request more power during an emergency, EVA will temporarily adjust the charge rates to meet the increased or decreased demand. Providing this kind of service is known as regulation in the power market. Regulation capacity describes the extent to which an EVA may alter its charging rate in reaction to grid demand.

The utilization of EV capacity for up/down regulation is shown in Fig. 2. Put another way, it shows how much regulation capacity the SO can get from only one EV. Because it is the maximum power that an electric vehicle's battery can absorb, the maximum charging rate is dependent on the battery itself. The following equation takes into account the maximum charging rate limit $POP_{i,t}^{max}$, which is the power needed to charge the ith electric vehicle to its desired SOC in a one-time slot t:

$$POP_{i,t}^{\max} = \frac{\left(SOC_i^{DES} - SOC_{i,t}\right) \cdot BC_i}{Ef_i} \qquad (1)$$

Here, $SOC_{i,t}$ is the SOC level, BCi is the battery capacity (kWh) and Ef_i is the charging efficiency of i^{th} EV battery. The maximum charging rate for an EV cannot be exceeded within any given time window. When there is a shortfall in generation and the system needs to make up the difference by slowing down charging rates to lower the load from electric vehicles, this is called regulation up capacity $uc_{i,t}$. To calculate $uc_{i,t}$, subtract the electric vehicle's lower charging rate limit—the amount by which it can reduce its charging rate to assist increase the system frequency—from its scheduled charging rate limit. An rise in the charging energy consumption of electric vehicles at a given time t necessitates a regulation-down capacity it, dc, which occurs when the system experiences surplus generation and must balance this amount by increasing the charging rate for i^{th} EV. The difference between the upper charging rate limit or maximum charging rate limit (whichever is smaller) and the scheduled charging rate is the $dc_{i,t}$. Furthermore, once charging a cluster of EVs, the overall regulation down capacity should be additionally limited by the transformer delivery capacity TDC. EVA governs whether the aggregated charging rates $POP_{i,t}$ (kW) and regulation down capacities $dc_{i,t}$ (kW) of entire plugged-in N EVs is within TDC (kW) i.e. guaranteeing $\sum POP_{i,t} + dc_{i,t} \le TDC$. Regulation capacity $rc_{i,t}$ is thus the total of regulation down capacities $dc_{i,t}$ and regulation up $uc_{i,t}$. This is one way EVA might back keeping the system's frequency stability while also providing SO with regulating services. As a result, SO is open to paying for EVA's regulatory services.

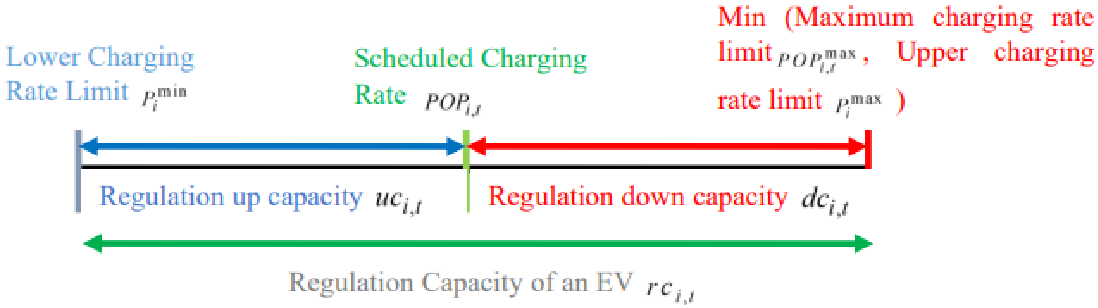

Figure 2: Regulation Up/Down Capacities Offered by a Specific EV

PROBLEM FORMULATION

The suggested static G2V charge scheduling problem takes into account two competing goals, each limited by its own set of technical & economic constraints: minimizing the charging cost to EV owners and maximizing the revenue to the EVA. Over the complete scheduling horizon, the best outcome includes charging schedules, regulating capacity, and SOC of linked EVs with a specific charging task. The charging cost for electric vehicle owners should not go over the top limit while the EVA's revenue is being maximized. When the system load is met & demand from EV owners (as indicated by charging jobs) is also met, then any charging plan can be considered practical.

UNCONTROLLED BASELINE CHARGE SCHEDULING PROBLEM

When an electric vehicle is connected to the grid, EVA charges it in a single time slot under the uncontrolled charging type. So, this kind of pricing doesn't take prices into account. Electric vehicles are charged at the maximum allowed charging rate, $POP_{i,\,t}^{max}$ (kW), in the baseline or uncontrolled charging configuration.

There is no economic basis for decision-making in unregulated charging. Unregulated charging may, therefore, constitute a cost upper bound in terms of overall charging energy cost. The price structure determines this limit on expenditure. When calculating costs, charging energy, & regulation capacities, it's important to keep in mind that an EV could not be accessible for a specific slot. The plug-in availability of EV i in the time interval t is given by the binary variable $Av_{i,t}$ according to Eq. (2). In particular, the $Av_{i,t}$ representing the availability or lack thereof of an EV can take the value 1 in cases where the time interval is longer than the arrival time but shorter than the departure time, or the value 0 in all other cases. Equation (3) states that the higher value charging cost that corresponds to the availability of EVs is the upper bound of the charging cost (CB).

$$Av_{i,t} = \begin{cases} 1 & ta_i \le t \le td_i \\ 0 & otherwise \end{cases} \qquad (2)$$

$$CB = \sum_{t=1}^{T}\sum_{i=1}^{N} POP_{i,t}^{\max} \cdot \left(M_t + EP_t^{TOU}\right) \cdot Av_{i,t} \qquad (3)$$

PROPOSED STATIC G2V CHARGE SCHEDULING PROBLEM (SCSP)

Prioritizing EV owner satisfaction & SO benefit, the suggested static G2V charge scheduling problem (SCSP) takes into account two competing goals: minimizing charging costs for EV owners & maximizing EVA revenue, all within the bounds of a) system restrictions and b) EV limits. A feasible charging task takes into account the system's technical limitations as well as the monetary constraints of EVs. Over the complete scheduling horizon, the best outcome includes charging schedules, regulating capacity, and SOC of linked EVs with a specific charging task. The charging cost for electric vehicle owners should not go over the top limit while the EVA's revenue is being maximized. Two statements can be used to define the suggested problem:

Problem 1: With respect to the specified charging tasks, the EVA's revenue $\sum_{i=1}^{N}\sum_{t=1}^{T} REV_{i,t}^{SCSP}$ should be maximum amongst all the feasible charging tasks in SCSP.

$$\mathrm{Re}v^{SCSP} = \sum_{t=1}^{T}\sum_{i=1}^{N} RP_t \cdot rc_{i,t} + \sum_{t=1}^{T}\sum_{i=1}^{N} \left(M_t + EP_t^{RTP}\right) \cdot POP_{i,t} \cdot Av_{i,t} \qquad (4)$$

The regulation pricing ($/kWh) is represented by RPt, the mark-up price ($/kWh) is denoted by Mt, and Avi,t, indicates if the EV is available or connected. According to Equation (4), there are two components that make up EVA's revenue. The SO's regulation service comes first. SO receives both upstream and downstream regulation services from EVA. With regard to the New York Independent System Operator (NYISO), a market that is thought to be symmetrical, EVA offers both services for the same price. Thus, regulating revenue is calculated by multiplying the total regulation capacity offered by EV i at time t by the regulation power price at time t. Moreover, EVA buys energy on the wholesale market at a price EPt RTP that is updated in real-time and then sells it at a premium Mt over EPt RTP. Profit from selling energy to meet the charging needs of available EVs is denoted by the second term, which is calculated as the product of the markup price over the charging rate of EV i at time t, and EPt RTP.

Problem 2: With respect to the specified charging tasks, the EV owners' charging cost $\sum_{i=1}^{N}\sum_{t=1}^{T} CC_{i,t}^{SCSP}$ should be minimum among all the feasible charging tasks in the SCSP.

$$CC^{SCSP} = \sum_{t=1}^{T} EP_t^{RTP} \left(\sum_{i=1}^{N} POP_{i,t} \cdot Av_{i,t} \right) \tag{5}$$

The purchase cost CCSCSP should be least according to Eq. (5), while the revenue of EVA should be greatest among all possible charging jobs for the defined tasks set, as described before. This study attempts to quantify the dynamics of SCSP by framing it as a profit maximization problem of EVA, where EVA is defined as the difference between its revenue & costs. Given this, we may declare (6) to define the scheduling problem:

$$\max_{SOC_{i,t}, \mathrm{POP}_{i,t}, rc_{i,t}} \Pr ofit = \mathrm{Re}\, v^{SCSP} - CC^{SCSP} \tag{6}$$

All of the charging profile details for ith EV, including tai, tdi, $SOCi^{INI}$, and $SOCi^{DES}$, are known to EVA in a static charging environment. We can anticipate the ith EV's arrival time tai and departure time tdi by looking at its mobility pattern history. Based on the equations in (7) and (8), it is presumed that they adhere to the pdf, which is a probability distribution function. The mean is represented by μtai & μ tdi standard deviation of the variables with normal distributions, respectively, is σ tdi and tai.

$$pdf(ta_i) = \frac{1}{\sigma_{ta_i}\sqrt{2\pi}} \exp\left(-\frac{(ta_i - \mu_{ta_i})^2}{2(\sigma_{ta_i})^2} \right) \tag{7}$$

$$pdf(td_i) = \frac{1}{\sigma_{td_i}\sqrt{2\pi}} \exp\left(-\frac{(td_i - \mu_{td_i})^2}{2(\sigma_{td_i})^2} \right) \tag{8}$$

The SOC of every linked EV is given a value per hour in this constraint (9). $Av_{i,t}$, is availability status for i^{th} EV during a time slot t . The computation of regulation capacity, charging energy, and cost would be significantly affected by the availability of EVs.

$$SOC_{i,t} = \begin{cases} SOC_i^{INI}, & \text{if } t = ta_i \quad \forall i \\ SOC_i^{DES}, & \text{if } t = td_i \quad \forall i \\ SOC_{i,t-1} + Ef_i Av_{i,t-1} POP_{i,t-1} / BC_i, & \text{otherwise} \end{cases} \tag{9}$$

For electric vehicles to be able to charge, EVA is necessary. Hence, the fuel efficiency of an EV i is used as a time limit at the time of departure (10),

$$POP_{i,t} = \left(SOC_i^{Des} - SOC_{i,t-1}\right) \cdot \frac{BC_i}{Ef_i} \cdot Av_{i,t} \quad \forall \mathrm{t} \in \mathrm{td}_i \tag{10}$$

$$P_i^{\min} \leq POP_{i,t} \leq P_i^{\max}, \qquad \forall i,t \tag{11}$$

$$\sum_{t=1}^{T}(M_t + EP_t)\left(\sum_{i=1}^{N}(\mathrm{POP}_{i,t}\ Av_{i,t})\right) \leq CB \tag{12}$$

$$rc_{i,t} = uc_{i,t} + dc_{i,t} \qquad \forall i,t \tag{13}$$

$$uc_{i,t} = \begin{cases} \left(POP_{i,t} - P_i^{\min}\right) \cdot \mathrm{Av}_{i,t} & \forall i,t \ \ s.t. \ \ \mathrm{Av}_{i,t} = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

$$dc_{i,t} = \begin{cases} \left(\min\left\{POP_{i,t}^{\max}, P_i^{\max}\right\} - POP_{i,t}\right) \cdot \mathrm{Av}_{i,t} & \forall i,t \ \ s.t. \ \ \mathrm{Av}_{i,t} = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

$$\sum_{i=1}^{N}(\mathrm{POP}_{i,t} + dc_{i,t}) + l_t^b \leq TDC \qquad \forall \mathrm{t} \tag{16}$$

For each time slot t in $POP_{i,t,}$ the charging rate of the i^{th} electric vehicle is limited by the lowest charging rate limit (in kW) & highest charging rate limit (in kW) in restriction (11). The maximum allowable cost ($) to charge an electric vehicle is denoted as CB in constraint (12). The total cost of charging the vehicles under an unregulated scenario, where the maximum potential charging rate is applied, is shown in (.3). In order to determine the regulatory capacity, constraints (13–15) are derived from the system model described in the preceding section.

In equation (13), the total regulation capacity, denoted as $rc_{i,t,}$ is equal to the sum of the regulation up & regulation down capacities, denoted as $uc_{i,t}$ and it, dc, respectively. With the help of Eqs. (14) and (15), we can calculate the regulation up/down capacity for ith EV at a given time t, $uc_{i,t,}$ / $dc_{i,t.}$ For every time slot t, EVA checks to see if the total of all connected EVs' charging rates ($POP_{i,t}$) & regulation down capacities ($dc_{i,t}$) (in kW) is less than or equal to the delivery capacity (TDC) of the distribution transformer. This prevents the transformer from being overloaded due to the charging of EVs and ensures that the EVs are charged within the acceptable range of its delivery capacity. Equation (16) expresses this congestion control constraint, which guarantees that TDC is always honored. The baseload at time slot t is represented here by lbt. It should be mentioned that any EV that isn't available for a specific hour will not be counted towards the overall regulation service delivered by the EVA to the SO, as the projected market for regulation service is hourly.

Using constraints (1)–(3) and (10)–(16), this paper explains mathematical optimization that was done to maximize (3.6). As an example, for a certain time slot t, we have the total cost of charging all electric vehicles ($) and the cost of electricity ($/kWh) as EPt. In addition to maximizing (4), it minimizes (5). What follows is a description of the results as well as the mathematical formulation in depth. In order to get a trade-off solution & conduct multi-objective optimization using the objectives specified by equations (4) and (5), an optimization framework is established in Matrix Laboratory (MATLAB). The full optimization issue is mixed-integer linear since it incorporates both binary or continuous variables; this is revealed by examining the objective functions and constraints. If the availability is not seen as a binary variable but as something that is predicted based on the communicated arrival & departure times, the problem can be simplified to a linear one. Next, we will go over the specifics of how we used MATLAB's Simplex technique to solve the Linear Programming Problem (LPP).

RESULTS AND DISCUSSIONS

We test the suggested static G2V charge scheduling approach using real data from the baseload & battery systems, as well as actual prices from the power market. The NYISO hourly market is precisely where the power & regulation prices are sourced. For the purpose of this simulation, the 30-day average of power & regulation prices (January 1–30, 2015) is utilized. Realistic information on µtai, µtdi, σ tai & σ tdi, and TDC is recorded. The load profile is used to determine the base loads at each hour, with the battery capacity efficiency and charging rate limit being taken into consideration as references. Table 3.1 details the various constants utilized in the simulations. It is believed that the EVA will charge EV owners a markup price of 0.05 $/kWh. Each EV's DES SOCi is set at 0.9, and the SOCi INI is dispersed between [0.3, 0.9]. The range of the charging rate POPi,t is from zero to four and a half kilowatts. This study employs a ten-run Monte Carlo simulation to produce ten different sets of randomly generated input data, and the numbers below provide the average values from all ten iterations. To find the best compromise, we multiply EVA's performance metrics—its income & total cost of charging the EVs—by each other. Various values of N and Pimax are simulated to compare their effects on the performance characteristics, which are affected by the number of electric vehicles (N) & maximum charging rate (Pimax).

Table 1: Simulation Parameters

Mean of t_{a_i}	Mean of t_{d_i}	Standard Deviation of t_{a_i}	Standard Deviation of t_{d_i}
7	19	2 hours	2 hours
T	TDC	E_{f_i}	BC_i
24	200 kW	0.9	16 kWh

Determining the Effects of EV Population on EVA Efficiency Measures

Integrating electric vehicles into the grid depends on the number of vehicles in a given area. The majority of relevant parties are hesitant to implement G2V charge schedule management systems & services for electric vehicles unless the number of EVs in a given area reaches a certain saturation point. To rephrase, from a cost-benefit perspective, it is not reasonable to set up EV battery loading services if there are few pluggable EVs. This is because efforts and costs remain constant irrespective of the number of plugged vehicles, whereas benefits are dependent on vehicle stock. As a result, the quantity of electric cars shows the saturation point of the stock of conventional automobiles. Figure 3 shows the financial performance indicators of EVA, including revenue, charging cost, & profit, for a range of EV numbers (5–200) and an upper charging rate limit of 4.4 kW, optimised using Eq. (6). With a high number of customers having EVs, the overall charging cost per customer dramatically decreases, as the number of cars increases. In other words, the minimum total charging cost for consumers is lowering. Having a big number of EV users also means greater income for the EVA.

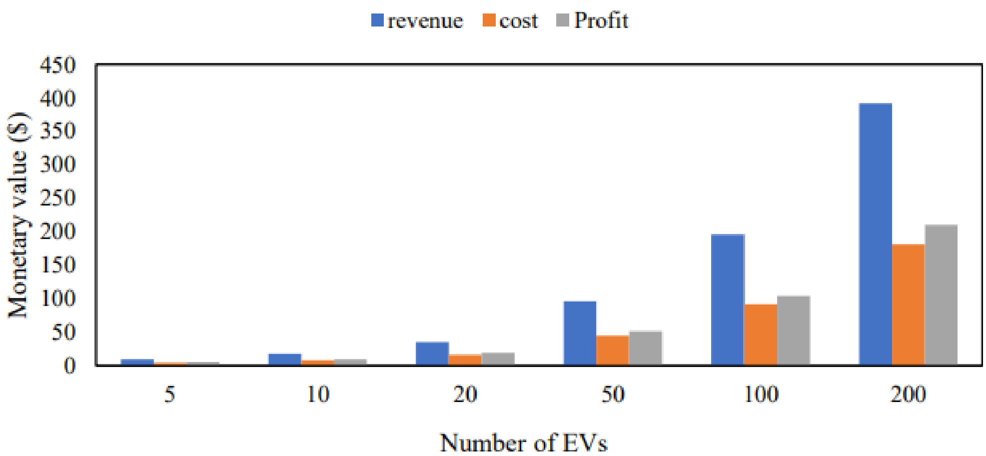

Figure 3: Performance Parameters of EVA Versus the Number of EVs

In G2V charge scheduling, Figs. 4 and 5 display the comparison of monetary values with the amount of EVs for two methods: the baseline (unregulated) scenario & suggested way after optimising Eqs. (5) and (4), correspondingly. The effectiveness of the suggested approach is confirmed. The graphs show that the suggested plan using the simplex solution method produces superior outcomes. Additionally, in comparison to uncontrolled baseline charging of EVs, regulated charging schedule provides substantially lower minimum total charging cost & bigger maximum EVA income. The overall charging cost per customer drops dramatically when there are a lot of customers with EVs, as shown in Fig. 4, which shows summarises that the minimum total charging cost for clients is lowering as the number of cars increases. Figure 5 shows that the EVA's income increases as the number of EV consumers increases.

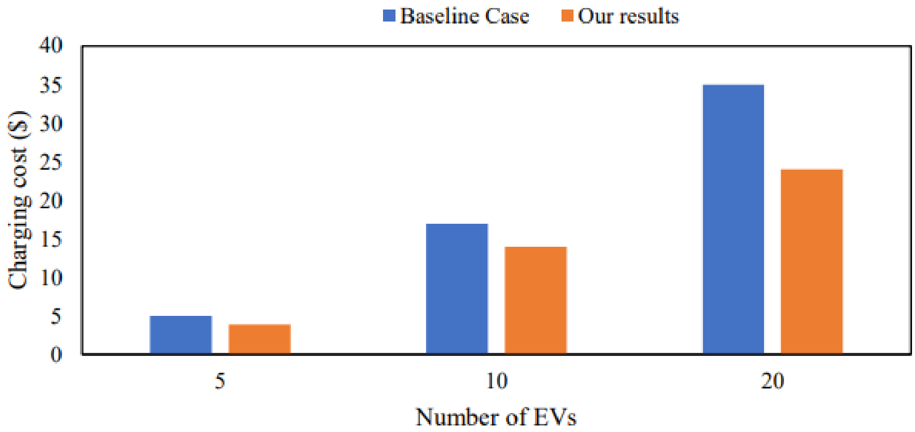

Figure 4: Minimizing the Total Charging Cost by Electric Vehicle Count

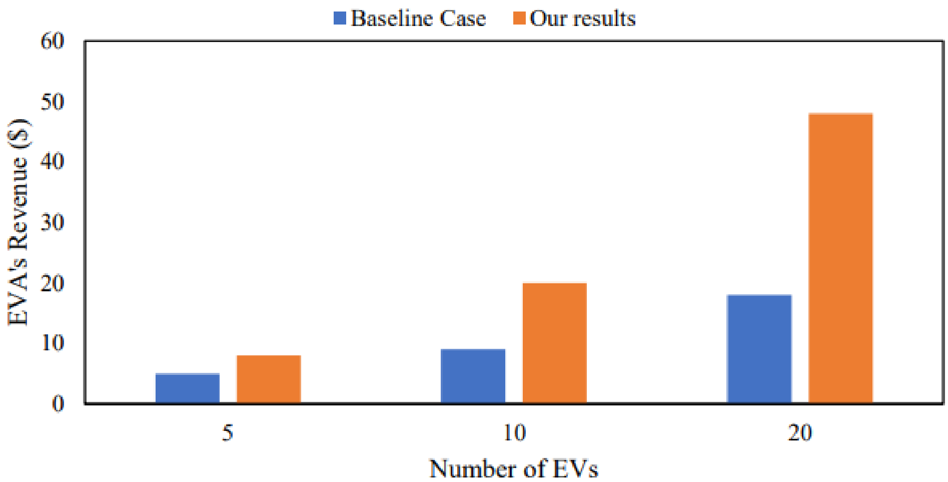

Figure 5: Maximal EVA Revenue as a Function of EV Count

Analyzing the Effects of the Maximum Charging Rate on EVA Performance Characteristics

Figure 6 shows how EVA performance parameters including maximum revenue, minimum total charging cost, and profit are impacted by the increased charging rate constraint. By adjusting the maximum charging power from 3.3 kW to 8.8 kW in increments of 1.1 kW, simulations are performed for N = 200 EVs. Figure 6 shows that increasing the maximum charging rate does not significantly benefit EV owners. However, as this restriction enhances the regulating capability, the income of maximum EVA grows approximately linearly with the upper charge rate limit. That is why enhancing the EVA framework is the only way to make increasing the charge rate feasible and achieve it successfully. On the other hand, if the charge rate is significantly greater, the system may experience overheating, loss of power, and a rise in peak load demand from EV charging. Increasing the maximum charging rate won't help electric vehicle owners much, as demonstrated in Figs. 7 and 8 for a smaller group of EVs N = 5, when considering the influence of the restriction on maximum EVA's income or minimum total charging cost. However, when the highest charging rate limit approaches, the income of maximum EVA grows practically linearly.

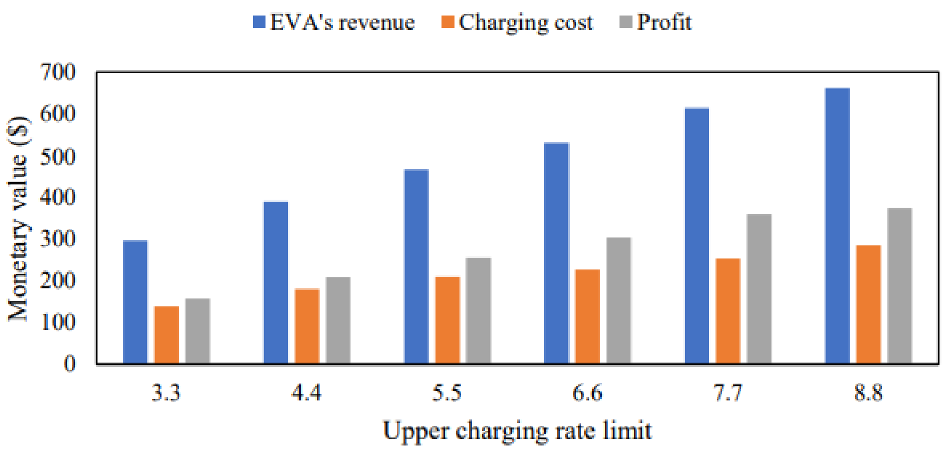

Figure 6: Performance Parameters of EVA Versus Upper Charging Rate Limit

In addition, the expansion & contraction of the transformer is increased daily due to EV charging, which shortens its lifespan, because it creates new load peaks that exceed the service transformer's rated delivery capability. It puts a financial strain on SO and speeds up the ageing of equipment. Overloading the transformer is a critical issue that has to be addressed in order to slow down the increase in the charging rate. By coordinating intelligently with SO, EVA is able to get the value of the transformer's delivery capacity and adhere to loading constraints while scheduling G2V.

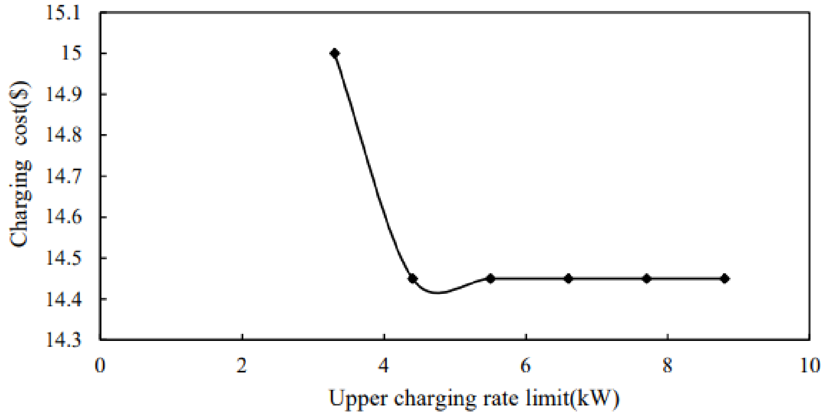

Figure 7: Minimal Total Charging Costs vs. Maximum Charging Rate

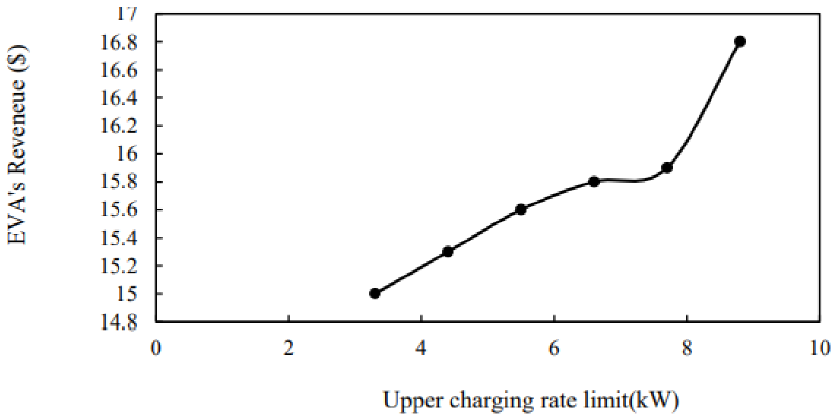

Figure 8: Comparison of the Upper Charging Rate Limit to the Maximum EVA's Revenue

EPILOGUE

In this chapter, we look at the possibility of coordinated regulated EV charging & suggest static G2V scheduling of EVA to minimise the effects of new load peaks caused by large-scale EV integration, accommodate EV charging while maintaining peak demand, and maximise grid utilisation. The expense to EV owners and income to EVA have been included into a mathematical optimisation issue concerning the creation of a controlled EV charging infrastructure. The scenario is based on a static charging schedule. The LPP has been resolved by employing MATLAB's simplex approach. We exhibit the revenue increases & cost reductions brought about by optimal static G2V charge scheduling based on simulation findings that are based on real power pricing and load data. We compare the EVA income and charging expenses for both regulated & uncontrolled charging situations. They are also examined for their sensitivity to changes in the maximum charge rate and the number of cars. Interesting trends in grid reliability, charging rate regulation, & the economics of EV charging emerge from the results.

There are measurable metrics that determine the algorithm's behaviour & performance, such as EVA's income and overall charge cost. A sort of performance indicator utilised by businesses to monitor and evaluate how well their optimisation strategy is doing. One way to demonstrate the possible benefits of regulated charging is to utilise the optimal solutions provided by static charge scheduling methods as a baseline for evaluating performance. When compared to the uncontrolled baseline instance, effective charge scheduling results in significant income gains & expense savings. Because the cost of charging is lower than in the previous example. Additionally, EVA yields a higher profit than the baseline situation.

When compared to the uncontrolled baseline strategy, EVA may achieve an average revenue improvement of 139% and a total billing cost reduction of 18.5%. Therefore, the suggested method is superior since it allows EVA to earn more money while meeting the needs of EV owners through cheaper charging. So, reducing network congestion & increasing grid support regulatory services for SO are both facilitated by the proposed effort. By lowering the billing cost burden, the outcomes are better reflecting the customer's opinion.

CONCLUSION

This paper provides a high-level overview of how to add a customer-centric viewpoint to an already established method of charge scheduling. In a practical sense, EV owners are free to come and go whenever they choose, and EVA isn't informed about the charging schedule of EVs in advance. With this setup, the EVA is not privy to EV arrival details before to their actual arrival, making the local/online/dynamic G2V charge scheduling issue (DCSP) more realistic. Furthermore, demand-side management techniques can further minimise the charging cost for EV owners. Because of the value they add to regulatory services, incentives for EV owners are spreading. The computational cost is increased due to the incorporation of EV mobility uncertainty in a dynamic scenario in the issue formulation. Future work should focus on leveraging emerging technologies like artificial intelligence and data analytics to further refine scheduling strategies, ensuring a more resilient and adaptable power grid in the face of increasing EV adoption.

References

1. A. Hernández-Arauzo, J. Puente, R. Varela, and J. Sedano, "Electric vehicle charging under power and balance constraints as dynamic scheduling", Computers & Industrial Engineering, vol. 85, pp. 306-15, 1 Jul. 2015.

2. B. Han, S. Lu, F. Xue, and L. Jiang, "Day-ahead electric vehicle aggregator bidding strategy using stochastic programming in an uncertain reserve market", IET Generation, Transmission & Distribution, vol. 13, no. 12, pp. 2517-25, Apr. 2019.

3. Charging infrastructure for electric vehicles: Guidelines and standards, https://powermin.nic.in/sites/default/files/webform/notices/scan0016%20%281%29.pdf.

4. D.B. Richardson, "Encouraging vehicle-to-grid (V2G) participation through premium tariff rates", Journal of power sources, vol. 243, pp. 219-24, 1 Dec. 2013.

5. Frade I, Ribeiro A, Gonçalves G, Antunes AP. Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal. Transportation Research Record. 2011;2252(1):91-98. doi:10.3141/2252-12.

6. G.V. Kumar, R.K. Sarojini, K. Palanisamy, S. Padmanaban, and J.B. HolmNielsen, "Large Scale Renewable Energy Integration: Issues and Solutions", Energies, vol. 12, no. 10, pp.1996, Jan. 2019.

7. H. Hashemi-Dezaki, M. Hamzeh, H. Askarian-Abyaneh, and Haeri-Khiavi, "Risk management of smart grids based on managed charging of PHEVs and vehicle-to-grid strategy using Monte Carlo simulation", Energy Conversion and Management, vol. 100, pp. 262-76, Aug. 2015.

8. H.M. Chung, W.T. Li, C. Yuen, C.K. Wen, N. Crespi, "Electric vehicle charge scheduling mechanism to maximize cost efficiency and user convenience", IEEE Transactions on Smart Grid, vol. 10, no. 3, pp. 3020-30, Mar. 2018.

9. M. Esmaili, and M. Rajabi, "Optimal charging of plug-in electric vehicles observing power grid constraints", IET Generation, Transmission & Distribution, vol. 8, no. 4, pp. 583-90, 2 Dec. 2013.

10. N.I. Nimalsiri, C.P. Mediwaththe, E.L. Ratnam, M. Shaw, D.B. Smith, S.K. Halgamuge, "A survey of algorithms for distributed charging control of electric vehicles in smart grid", IEEE Transactions on Intelligent Transportation Systems, 2 Oct. 2019