OPTIMIZING IMPACT ON POWER GRID FOR FUTURE ELECTRIC VEHICLE TRENDS

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Smart Grid In the Information Age

MS in Computer Science

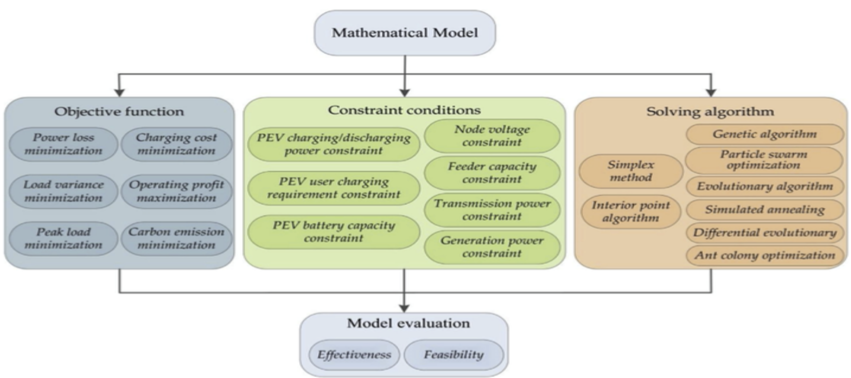
INTRODUCTION

An old Chinese saying goes, "***Make the best use of everything and give full scope to the talents***". The ultimate objective for V2G implementation could be considered to integrate all the available resources and fully exploit their respective advantages to fulfill the maximization of the overall energy efficiency.

In continuation with our previous presentation on "electric vehicle integrations and its impacts on the power grid", this report dives deeper into **OPTIMIZING IMPACT ON POWER GRID FOR ELECTRIC VEHICLE TRENDS.**

The current movement towards electric vehicle (EV) usage would require high power consumption in future due to large scale EV charging. At a time when the number of EVs charging demand gets high, the total load of the grid may rise at a sudden peak, especially at the busy hours. If this exceeds the capacity of the substation it can cause damage to the grid system as well as load shedding. Thus, it is necessary to coordinate the EV charging and look for various other optimisations in the sector.

Inspired by improving the overall energy efficiency, all kinds of methods are explored to pursue the optimal charging patterns of EVs.



This report mostly talks in detail about the study of two pre-existing research works on optimising objective functions, namely **Peak Load Minimization** and **Load Variance Minimization** to improve energy efficiency in the EV Charging Infrastructure in the Smart Grid. The report also talks about the results from the case studies and extends insights around the future scope of optimisation algorithms. The report concludes with the short term and long term trends in the EV ecosystem.

ALGORITHM 1

Peak Load Minimization

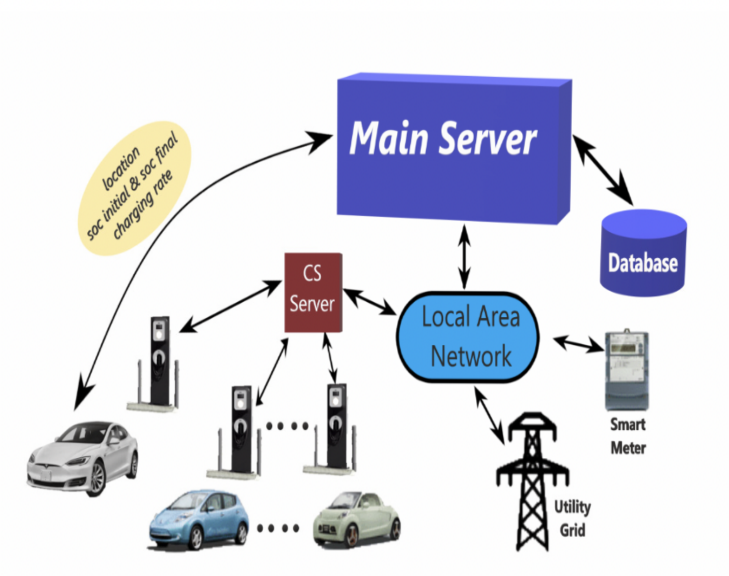
Peak load minimization is one of the potential ways to effectively integrate PEVs into the power system. The peak shaving strategy provides windows of opportunity to shift a part of the electricity demand to valley periods without increasing the grid capacity to the level of high peak loads.

In our report, the peak load shaving problem is solved by the proposal such that the allowable optimal loads of the charging stations at the different times of a day are determined for reducing the peak load of substations. This load information is used in selecting the charging station for a new EV.

Before we jump into the various parameters, let's look at the architecture which supports the proposal backbone.

SYSTEM ARCHITECTURE

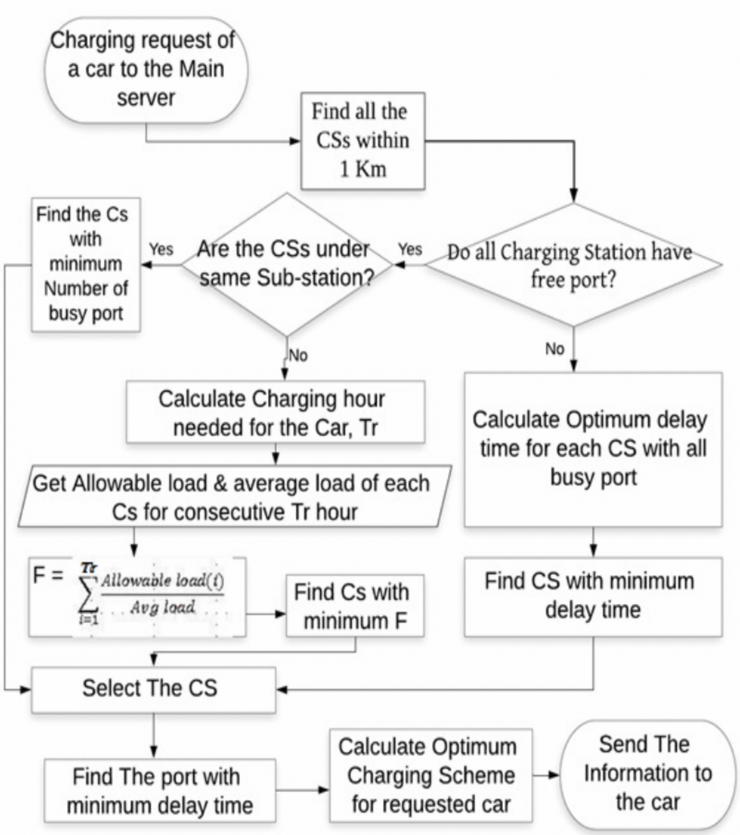
We consider an EV charging system consisting of a main server and S substations. The set of the substations is denoted by S. The number of charging stations in substation s ∈ S is Ns and their set is denoted by Ns. The number of ports to connect EVs in each charging station is M and their set is denoted by M. The system architecture is presented in Fig. 1. There is a local computing facility in each charging station to determine the charging schedule of the connected EVs. We assume that each substation has the knowledge of hourly electrical load demand on it and it informs the load information to the main server. The main server computes the allowable EV charging loads for each charging station of each substation which is referred to



as first layer problem. Assumption is that at a time request from only one EV reach to the main server to know the charging station for itself. The main server has the facility to determine the physical distance of an EV from each of the charging stations through GPS and road maps. An EV also sends the present state of charge (SOC) and required SOC when it sends a request for a charging station to the server through wireless cellular communication. The local computers of the charging stations are also connected to the main server through a local area network. Each charging station also sends the updated information of EV connection status of its different ports to the main server, i.e., whether an EV is connected to a port or not.

FLOW CHART

The flow chart for selecting a charging station by an EV requested by the main server is shown here. When an EV sends a request to the main server, it finds the charging stations within 1 km distance from the EV. In the selection process, the main server selects one of these charging stations. To select a charging station, at first, the main server checks if all the charging stations have free ports. If any of the charging stations does not have free port, the main server calculate delay of the EV for each charging station considering all the ports of the charging stations are busy. The charging station with the minimum delay is selected in this case. It's assumed that the main server knows the present SOCs for all the connected EVs in all the charging stations. It also knows the required charge for all the connected EVs. From this information, the main server can calculate when a port of the charging station will be free.



Assuming travel time delay to a charging station is negligible compared to the required time for getting connection to a port, for simplicity, the charging station whose port becomes free earlier is considered as the charging station with the minimum delay.

If all the charging stations in 1 km have free ports and all of them are in the same substation, then the charging station with the maximum number of free ports is selected. However, if all the charging stations are not connected to the same substation, then a functional value for each of the charging stations is calculated as described below. The charging station with the minimum functional value is selected for the EV. Before calculating the functional value of a charging station, the charging hour required to achieve the required charging state by the requested EV is calculated. Let Ci and Cf are the existing and required SOC values for the EV. Note that SOC of an EV equal to 1 means that the battery of the EV is fully charged. The required continuous charging hour for the EV is given as $T_r = \frac{B_c(C_f - C_i)}{Q_e}$ where, Bc is the battery capacity in watt-hour and Qe is the charging rate in watt/hour. The functional value for a charging station n ∈ Ns of the substation s ∈ S is calculated as $F_{n,s} = \sum_{h=1}^{T_r} \frac{P_{n,s}^h}{\tilde{P}_{n,s}}.$

OBJECTIVE FUNCTION & CONSTRAINTS

The main server computes the allowable loads at the charging stations for EV charging for 24 hours of day by solving the optimization problem below. The main objective of this problem is to reduce the peak loads at the substations by configuring the allowable loads at the different charging stations for EV charging for the 24 hours of a day. Let the average load of the substation s ∈ S be L̃s. At the h-th hour of a day the electric load except load of the charging stations at the substation s is Qh which is know to the main server. Denote by Ph the allowable load at the h-th hour of a day for EV charging to the charging station n ∈ N of the substation s. Let Lh be the total load at the substation s at the h-th hour of a day which can be obtained as

$$L_s^h = \sum_{n \in \mathcal{N}_s} P_{s,n}^h + Q_s^h. \qquad (1)$$

Note that the average load L˜s is given by

$$\tilde{L}_s = \frac{1}{H}\sum_{h=1}^{H} L_s^h. \qquad (2)$$

where, H = 24. Let P˜s,n be the average load for EV charging at the charging station n ∈ Ns of the substation s. Let the matrix for the Ph variables be P. Let P and P be the lower and upper bounds on the allowable EV loads at different hours of a day. The optimization problem to determine the allowable EV charging load at the h-th hour of a day for the charging stations of the substation s is formulated as follows.

Problem $\mathcal{P}_1$:

$$\min_{\mathbf{P}} \sqrt{\sum_{h=1}^{H} \left(L_s^h - \tilde{L}_s\right)^2} \qquad (3)$$

$$L_s^h = \sum_{n \in \mathcal{N}_s} P_{s,n}^h + Q_s^h \qquad \forall h \in \{1, 2, \ldots, H\} \qquad (4)$$

$$\tilde{P}_{s,n} \le \frac{1}{H}\sum_{h=1}^{H} P_{s,n}^h \qquad \forall n \in \mathcal{N}_s \qquad (5)$$

$$P_{lb} \le P_{s,n}^h \le P_{ub} \qquad \forall n \in \mathcal{N}_s, \forall h \in \{1, 2, \ldots, H\}. \qquad (6)$$

In the optimization problem P1, the objective is to minimize the root mean square of the differences of the total load at different hours of a day to the average load of a substation. Thus, the objective function tries to minimize the peak loads at different hours of a day. The constraints in (4) are used for calculation of total load for each hour of day. The constraints in (5) state that allowable EV loads at different hours of a day should maintain a minimum average allowable EV load. The constraints in (6) present the bound of the allowable EV loads at different hours of a day. The optimization problem P1 is a non-linear optimization problem due to the non-linear objective function.

RESULTS

In order to simulate the results two substations were considered: SS1 and SS2. The number of charging stations in SS1 and SS2 are taken to be 2 and 3, respectively. The number of charging ports in each charging station is taken to be 15. In a substation, the

EV load is taken to be 30% of the total load of the substation, i.e., EV penetration is 30%. Arrival of the requests for charging from the EVs is modelled as a Poisson Process with an arrival rate 5 EVs per hour. Charging rate of the EVs is taken to be varying in the range of 10 to 15 kW/hour. The average charging load (P˜s,n) of the EVs are taken to be 15 kW. For the two substations, hourly electric loads, i.e., Qhs are taken from the electric loads of two cities: a city of Italy and Dhaka city which are shown in **Fig. 3**. The lower and upper bounds on loads, i.e., bounds on Plb and Pub are set to 90 kW and 225 kW. The values of parameters a and b are chosen as 5 and 3, respectively by iteration method. The study assumes, Tma = 1.5Tm.

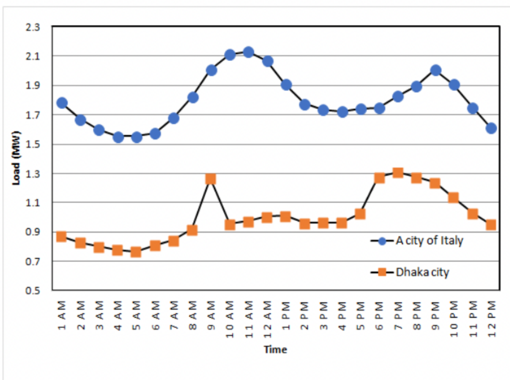


Fig. 3. Substation loads of two different cities

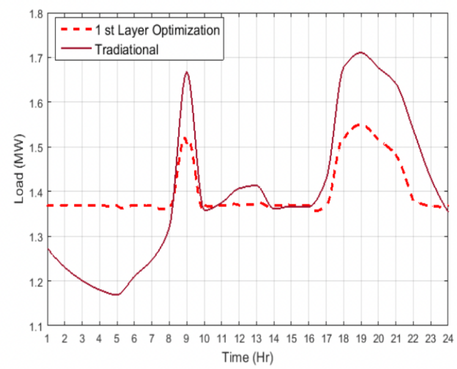


Fig. 5. The total load of the substation SS_1 with and without optimizing the allowable load at the charging stations.

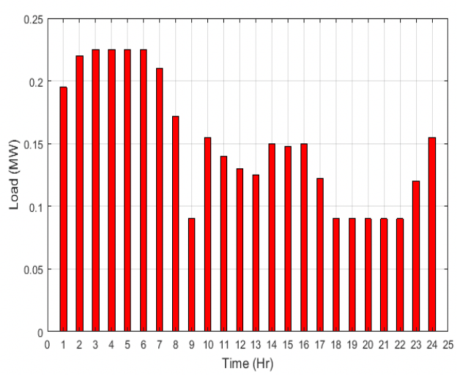


Fig. 4. Allowable hourly loads for the first charging station of SS_1.

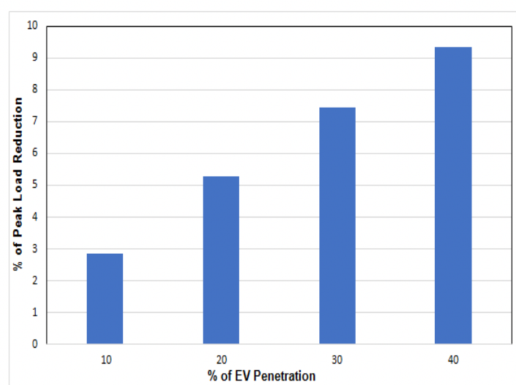


Fig. 6. Reduction of peak load of the SS_1 with increasing EV penetration.

Optimization problem P1 is solved by using MATLAB tools and the loads at the substation S S1 and S S2 are determined. In Fig. 4, the allowable loads of the first charging stations of the substation SS1 for the 24 hours of a day are shown. The results clearly show that the allowable loads of a charging station are lower at the busy hours such that the peak load in the substations becomes lower. Similar results were also obtained for the other charging stations of the both substations.

Next, the total load of the two substations for the 24 hours of a day was determined. In addition, the total load of the two substations if optimization is not performed, i.e., if the loads of the charging stations are taken equal to the average value was found. For both cases, the results of total load of the substation SS1 for the 24 hours of a day are shown in Fig. 5. The results show that under the proposed method the total load of a substation increases at the off-peak hours and decreases at the peak hours. As a result, the peak load of the substations decreases. Similar results was obtained for the other substation. It was found that the peak load reductions under the proposed method are roughly 7.5% and 5.5% for the SS1 and SS2, respectively.

The peak load reduction by the proposed method depends on the EV penetration. To investigate the effect of EV penetration on peak load reduction, further, the percentage of peak load reduction is determined for 10%, 20% and 40% EV penetra- tion. The percentage of peak load reduction for the SS1 for different EV penetration is shown in Fig. 6. The results show that peak load reduction significantly increases with increasing the EV penetration.

CONCLUSION ON ALGORITHM 1

With increasing the integration level of EVs into the grid, un- coordinated charging of EVs will greatly increase the system peak load and have a significant effect on safe and reliable operation of the power system. It was found that the proposed method simulates to decrease peak load about 14% with respect to the traditional uncoordinated charging as per the simulations. Obviously, there are multiple other factors into play which might pop up with the practical implementation of it. Nevertheless, it's quite meaningful to develop models with lower computation cost for the practical implementation of V2G technology in the future.

ALGORITHM 2:

Minimization of Load Variance in Power Grids

Bidirectional sharing of energy has opened new opportunities for the power grids to improve in terms of the system reliability and sustainability. Grid to Vehicle technology has always been the usual norm. Adoption of Vehicle-to-Grid (V2G) technology has helped to improve the reliability of the power grid. It has also facilitated the large scale integration of renewable and different forms of Energy.

Goal: Investigating an Optimal Vehicle-to-Grid/ Grid-to-Vehicle Power Scheduling

In very simple terms, the above mentioned goal can be achieved by allowing electric vehicles to charge (grid-to-vehicle) whenever the actual power grid loading is lower than the target loading. On the contrary, conducting electric vehicle discharging (vehicle-to-grid) whenever the actual power grid loading is higher than the target loading.

ASSUMPTIONS

The performance of the optimization algorithm depends heavily on the setting of the target load, power grid load and capability of the grid-connected electric vehicles. Target load is the average load which is expected in the system to have at any given time. Power Grid Load is the load which the grid is having at any given time. Capability of grid-connected vehicles depends on the number of the vehicles around the power grid with a sufficient charge level at any given time. Hence, the performance of the proposed algorithm under various target load and electric vehicles' state of charge selections were analysed.

PROCEDURE

As the above mentioned goal goes, G2V/V2G optimization algorithm is focused on the minimization of grid load variance by performing load levelling and peak load shaving using the available grid-connected EVs.

When the actual power grid loading is lower than the target loading, EVs are allowed to receive charging power from the power grid. This G2V operation falls under the load leveling scenario. Meanwhile, when the actual power grid loading is larger than the target loading, EVs are encouraged to discharge for power grid support. This V2G operation is called the peak load shaving scenario.

The V2G algorithm instructs Electric Vehicle charging and discharging operations with the aim of minimizing the difference between the actual power grid loading and target loading.

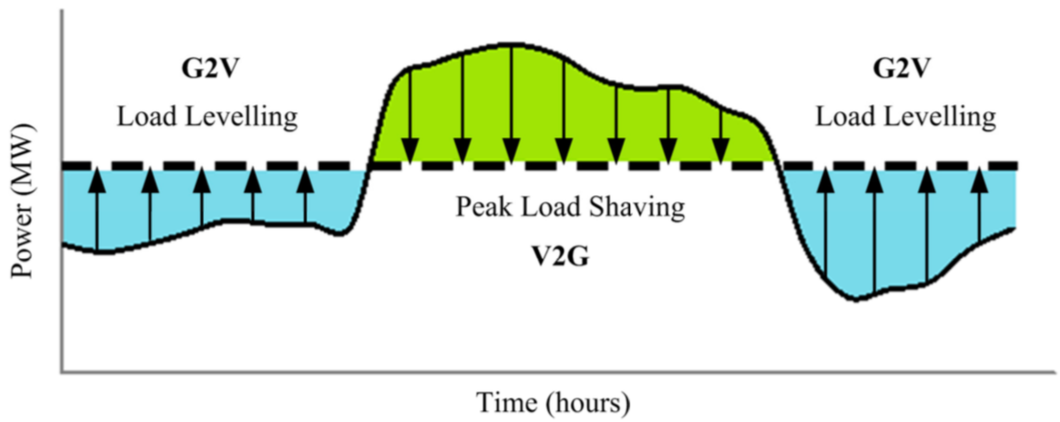


Fig: Generalised daily power load curve showcasing concept of peak load shaving and load levelling

CONSTRAINTS

Optimization algorithm includes thorough consideration of both power grid and EV constraints. Some dynamic constraints which can affect the V2G scheduling includes uncertain mobility characteristics of EVs, which have random initial State of Charge (SOC) and grid connection duration, as well as the dynamic grid connection probability.

State of Charge (SOC):

The charge in the EV battery must be kept within certain limits during the V2G operation. It is important for a couple of reasons:

1. The first reason is to protect the health of the battery. Studies show that a lithium ion battery should best be limited to a 60% swing (between 30% and 90% or 25–85%) to minimize the battery health degradation.
2. The second reason to keep the SOC level of the EV battery within certain limits is to reserve a certain amount of energy for the EV travel usage.

Therefore, by taking both reasons into consideration, each EV is prevented from discharging if the battery SOC is lower than the minimum SOC . Meanwhile, the EV charging process is only allowed if the SOC level of each EV battery is below the maximum SOC, to prevent the battery overcharging issue. Both of the EV charging and discharging processes are allowed if the battery SOC is within the minimum SOC and maximum SOC:

$$SOC_n \leq SOC_{\min}\text{, allow for charging only}$$

$$SOC_{\min} \leq SOC_n \leq SOC_{\max}\text{, allow for charging and discharging}$$

$$SOC_n \geq SOC_{\max}\text{, allow for discharging only}$$

where SOC_n is the battery SOC for nth EV.

EV Grid Connection Probability:

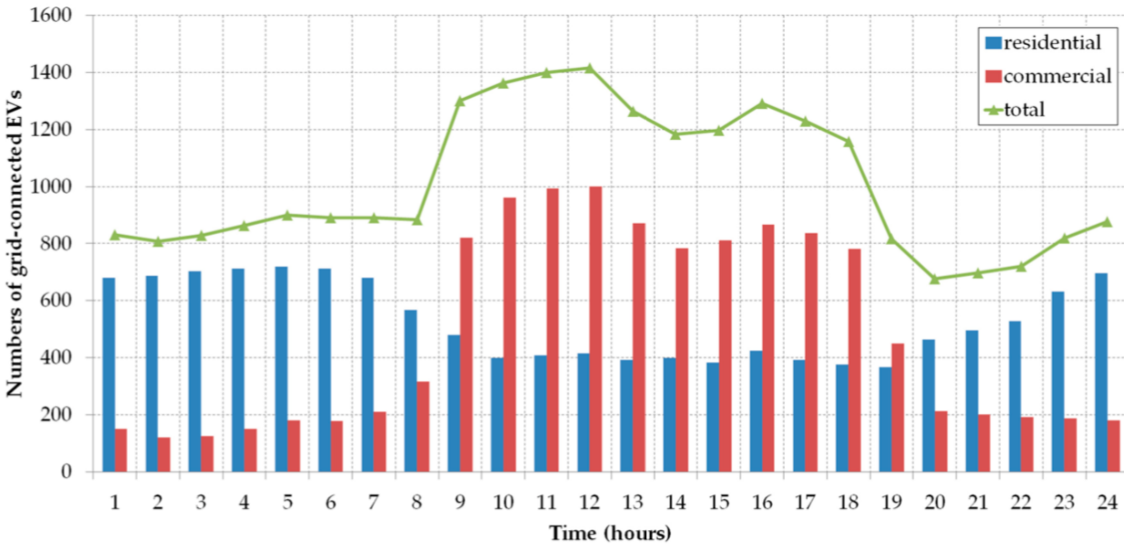


Figure: Electric Vehicle (EV) grid connection probability of the township

In the above figure, most of the EV owners are away from their workplaces and schools around 9:00 o'clock. From 18:00 o'clock onwards, the residents started to return home and occupied the residential car park. On the other hand, the EV grid connection probability of the commercial car parks depicted that most of the parking spaces are occupied during the daytime office hours. Other than these periods, the commercial car park is almost empty. The combination of the EV grid connection probability of the residential and commercial car parks gave the total EV availability in the proposed generic township.

EV Power Exchange Rate

In order to protect the safety and health of EV batteries throughout the power exchange periods, the power exchange rate between the EV batteries and power grid shall be restricted within a safe margin.

$$P_{\mathrm{EV,charging}} \le P_{\mathrm{EV,max}}$$

$$P_{\mathrm{EV,dischargin\ g}} \le -P_{\mathrm{EV,max}}$$

where $P_{\mathrm{EV,max}}$ is the maximum EV exchange rate.

Planning

The number of Electric vehicles around the power grid is crucial for the practicality of V2G technology. This is to ensure an average distributed amount of EVs shall be accessible within the V2G location throughout the day. Therefore, it is expected that a large enough township is considered, which consists of both residential and commercial areas to ensure a sufficient and consistent EV mobility throughout the day. This power balance between the grid generation and demand becomes a very important constraint for the feasibility of this algorithm.

The supplied power from the generation plants and distributed EV battery sources must satisfy the power grid load and EV charging demands:

$$P_{\mathrm{grid}}(t) + \sum_{n=1}^{N} A_n K_n P_{\mathrm{EV,discharging}}(t) = P_{\mathrm{load}}(t) + \sum_{n=1}^{N} A_n K_n P_{\mathrm{EV,charging}}(t)$$

where P_{grid} is the active power from the generation plant.

Below, a Genetic Algorithm (GA) optimization technique is discussed that is employed to solve the V2G optimization problem.

Objective Function

Equation 1 shows that the optimization algorithm has the goal to optimize the grid-connected EV charging and discharging power in order to minimize the power grid load variance.

Equation 2 shows that the proposed V2G optimization algorithm is performed by enabling the EV charging during the period where the power grid loading is less than the target loading (G2V operation). On the contrary, EVs are required to discharge the energy from the batteries when the power grid loading is larger than the target loading (V2G operation). No power flows between the EVs and power grid when the target loading is equal to the power grid loading.

Equations (1) and (2) express the objective function in terms of grid load variance, target loading, charging and discharging rate:

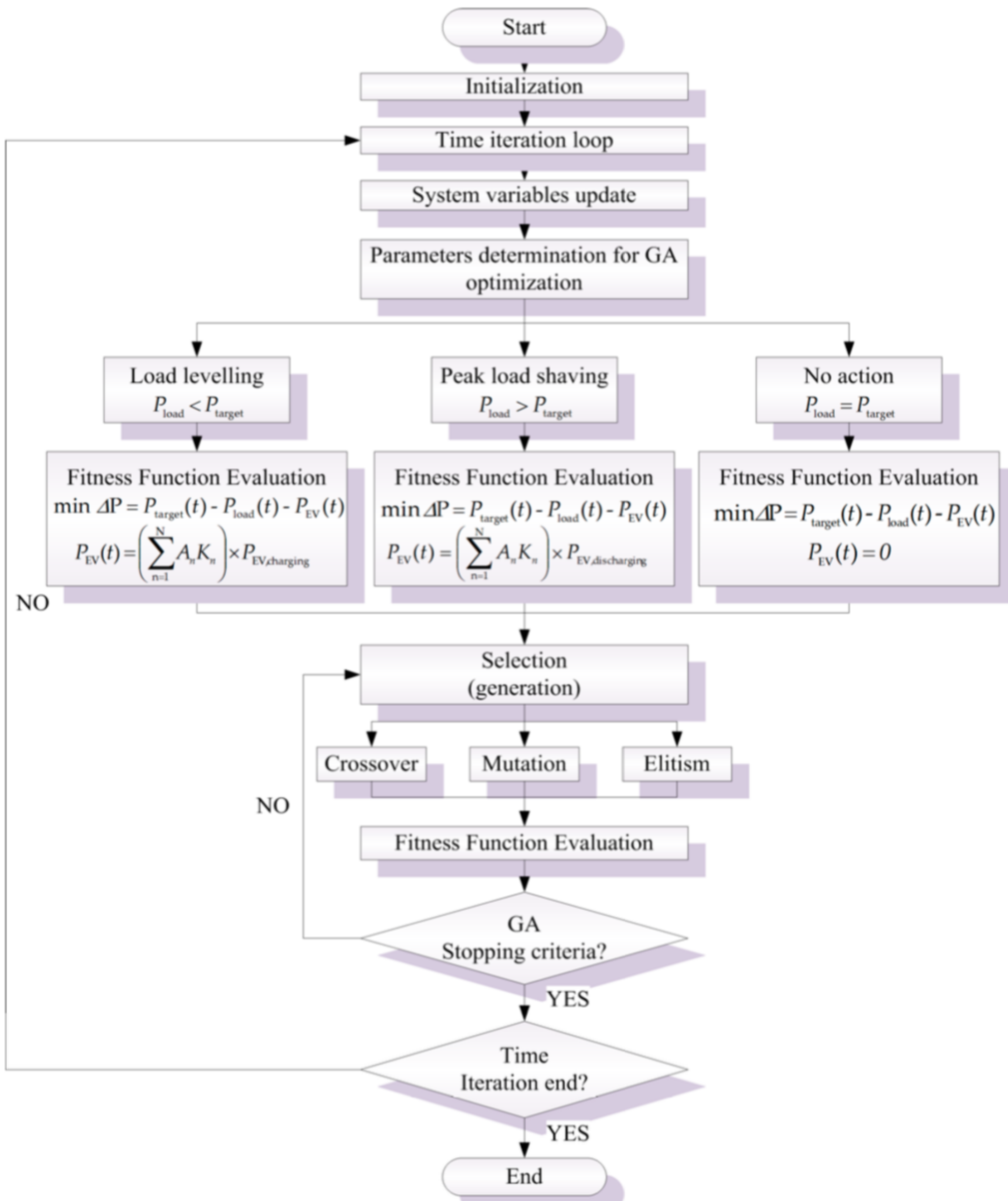
$$\min \Delta P = P_{\text{target}}(t) - P_{\text{load}}(t) - P_{\text{EV}}(t) \tag{1}$$

$$P_{\text{EV}}(t) = \begin{cases} \left(\sum_{n=1}^{N} A_n K_n\right) \times P_{\text{EV,charging}} & \text{, when } P_{\text{load}} < P_{\text{target}} \\ \left(\sum_{n=1}^{N} A_n K_n\right) \times P_{\text{EV,discharging}} & \text{, when } P_{\text{load}} > P_{\text{target}} \\ 0 & \text{, when } P_{\text{load}} = P_{\text{target}} \end{cases} \tag{2}$$

where ΔP is the grid load variance, t is time, P_{target} is the target loading, P_{load} is the existing load of the power grid, P_{EV} is the total power of EV loads/sources, n is the EV index, N is the maximum EV index, A_n is the availability of nth EV for the V2G application, K_n is the indicator of nth EV for V2G application, $P_{EV,charging}$ is the EV charging rate, and $P_{EV,discharging}$ is the EV discharging rate. In Equation (1), the grid load variance (ΔP) was minimized by optimizing the number of grid-connected EV to charge or discharge during valley load and peak load period, respectively. In the condition where K_n and A_n are available, the nth EV will be instructed to charge or discharge the battery.

Optimization Algorithm

The Genetic Algorithm is an iteration method that evaluates a global optimal solution within an execution time limit. In the initial stage of the proposed V2G algorithm, the system parameters are obtained and updated into the database. With this information, the GA algorithm gets the perfect fitness function of the grid load variance minimization, which later produces the next generation of solution. The evaluation is repeated itself until the iteration converges to an optimal EV charging or discharging power.



RESULTS

According to the research paper, various values for average initial SOC of EV batteries (average SOC) and target load curve in percentage (TLC) were considered to examine the performance of the proposed V2G optimization algorithm. TLC were set at 50%, 55% and 60%, respectively. In each scenario, different average SOC of 40%, 50%, 60%, 70% and 80% were applied.

Observation:

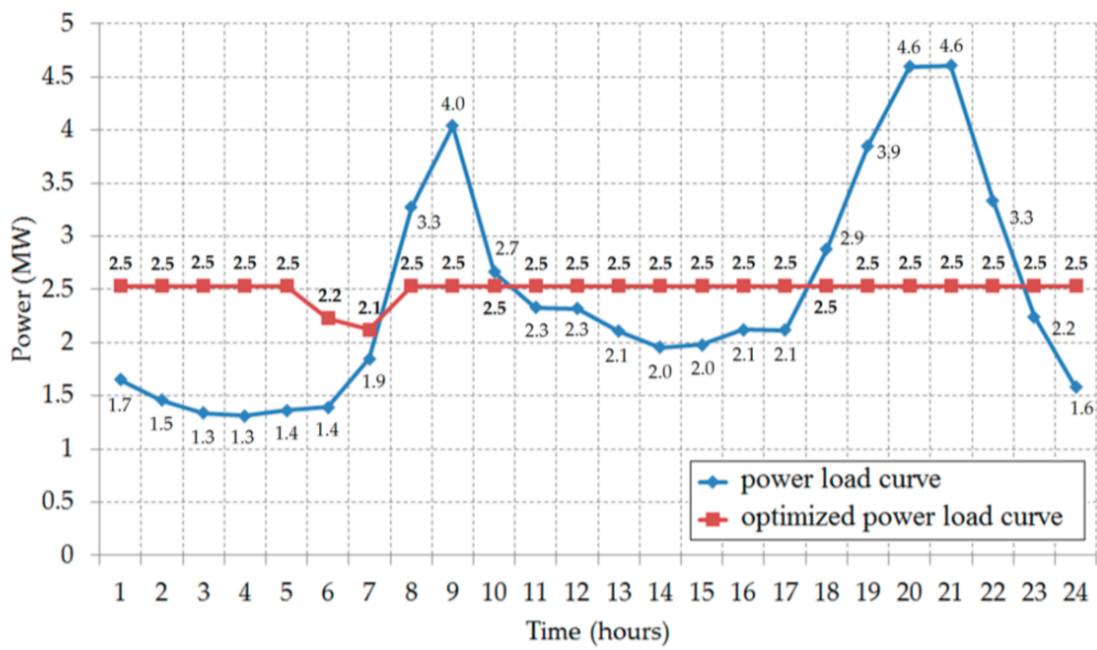
It was observed that when average SOC was low, the proposed V2G optimization algorithm can perform the load levelling service by the EV charging operation. In contrast, EV discharging operation for the peak load shaving service was more for scenarios due to higher average SOC and target load curve percentage TLC. In certain scenarios, EV batteries cannot supply or absorb the required energy for the minimization of grid load variance. Therefore, an index denoted as Performance Index was introduced to allow better comparison among the optimized power load curves. The Performance Index indicated the percentage of successful operations of the peak load shaving, load levelling or combination of both to achieve the preset target load curve over a day. The Performance Index can range from zero to one, where greater value indicates higher successful rate. Three sets of the Performance Index were calculated for peak load shaving, load levelling and both services together.

Table 1. Performance Index of the V2G optimization algorithm under various scenarios.

Region	Percentage of Target Load Curves (TLC_{pct})	Average Initial SOC of EV Batteries ($SOC_{i,ave}$)				
		40%	50%	60%	70%	80%
Peak load shaving	50%	0.429	0.496	0.724	0.870	0.872
	55%	0.571	0.590	1.000	1.000	1.000
	60%	0.751	0.809	1.000	1.000	1.000
Load levelling	50%	1.000	1.000	1.000	0.956	0.713
	55%	0.953	0.950	0.937	0.818	0.623
	60%	0.830	0.826	0.791	0.694	0.526
Overall	50%	0.667	0.706	0.839	0.905	0.806
	55%	0.785	0.792	0.965	0.898	0.789
	60%	0.805	0.821	0.858	0.793	0.679

With reference to the Performance Index in Table 1, with the increase of average SOC, the capability of peak load shaving was enhanced while the capability of load levelling was reduced. These situations were due to the increase in the available EV energy to be discharged for the peak load shaving, as well as the reduced need of EV batteries to receive charging from the power grid and thus limited the load levelling. Likewise, the occurrence of similar trends can be determined with the increase of the target load curve percentage TLC, where more peak load shaving service can be accomplished while fewer load levelling can be achieved using the proposed optimization algorithm. The reason was due to the required EV discharging energy for the peak load shaving was greatly reduced when the set point of TLC_{pct} was increased. However, the load levelling became more difficult to achieve due to the significant increase of energy required to be charged into the EV batteries.

According to the research paper, the figure below shows the results of implementation of the proposed V2G optimization algorithm for the category of 60% of $SOC_{i,ave}$ and 55% of TLC_{pct}. The optimized power load curve has almost met all the target loadings throughout the day, except during the periods from 05:00 to 08:00 o'clock.



In summary, the contributions of this algorithm include:

(i) the development of an algorithm to minimize grid load variance via peak load shaving and load levelling

(ii) a performance analysis of the proposed optimization under various target load and average initial SOC of EV batteries.

CONCLUSION

The load variance based objective function provides an alternative option for coordinated charging of PEVs regardless of the network topology. Evidently, minimizing the overall load variance will smooth out the fluctuation in the load profiles. As a result, it will inevitably reduce the system losses to a great extent. The literature has presented many potential benefits for the power grid by adopting V2G technology. These benefits include peak load shaving, load levelling, grid voltage regulation, improvement in energy efficiency and mitigation of renewable energy intermittency

From the economic standpoint, further studies have emphasized on the maximization of power utility profit while developing the V2G algorithm. Meanwhile, the minimization of power system losses is also a popular topic in the V2G application. V2G technology was also utilized to maximize the renewable energy generation by solving the renewable energy intermittency issue

Outline and evaluation among seven typical programming models.

Model Outline		Model Evaluation	
Objective	Main constrains	Effectiveness	Feasibility
Minimize power loss [42]	(a) Charging demand limit (b) Charging power limit (c) Voltage limit	(a) Reduce power loss (b) Improve voltage profile	(a) High computation cost (b) Depend on grid topology
Minimize load variance [79]	(a) Battery SoC limit (b) Charging power limit (c) Charging demand limit	(a) Fill load valley (b) Shave load peak	(a) High computation cost (b) Topology independent
Minimize system peak [85]	(a) Battery SoC limit (b) Voltage limit (c) Current limit	(a) Reduce load peak (b) Improve three-phase unbalance	(a) Very high computation cost (b) Depend on grid topology
Minimize PEV charging cost [90]	(a) Charging power limit (b) Battery SoC limit (c) Charging demand limit	(a) Fill load valley (b) Reduce charging cost (c) Demand response	(a) Low computation cost (b) Topology independent
Maximize aggregator profits [100]	(a) Battery SoC limit (b) System load limit (c) Charging demand limit	(a) Achieve load shifting (b) Provide ancillary services (c) Reduce charging cost	(a) Low computation cost (b) Topology independent
Minimize system operating costs [110]	(a) Voltage limit (b) Current limit (c) DGs load limit (d) Charging demand limit	(a) Reduce operating costs (b) Improve voltage profile (c) Improve load unbalance	(a) Very high computation cost (b) Depend on grid topology
Minimize generation cost and carbon emissions [47]	(a) Charging demand limit (b) Charging power limit	(a) Mitigate impact of PEV charging (b) Reduce generation cost and carbon emission	(a) Low computation cost (b) Topology independent

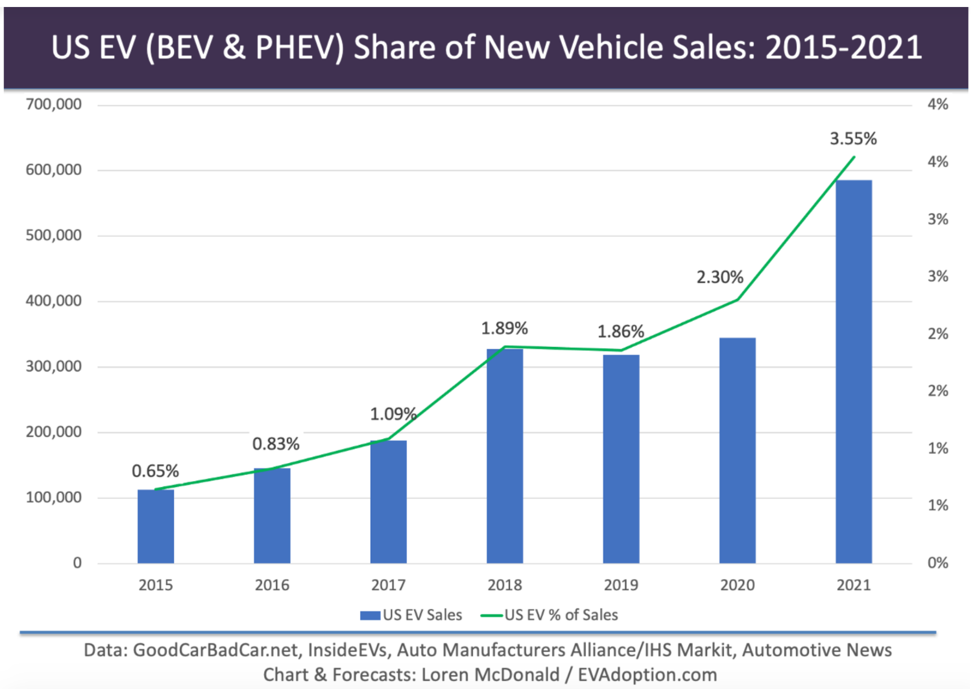
It is evident both the effectiveness and feasibility of a model are the key factors for the V2G successful implementation. Therefore, it is valuable to make an overall evaluation for these models on the basis of effectiveness and feasibility. Comparatively speaking, the electricity market environment is open and flexible with fierce competition. The electricity price level will encourage more efficient use of energy, and market prices will encourage more demand response. As a consequence, the economic index is likely to be taken as the objective function of the mathematical description for charging scheduling optimization. EV cost needs to be reduced significantly in order to have higher EV adoption in the marketplace.

Current Trend for 2021

1. Government Initiatives and Incentives

- Tax credits for EV purchases and EV charging infrastructure
- Rebates
- Reduced vehicle registration fees
- Research project grants
- Alternative fuel technology loans

2. Surge in EV sales



Source: https://cleantechnica.com/2020/10/30/forecast-2021-us-ev-sales-to-increase-70-year-over-year/

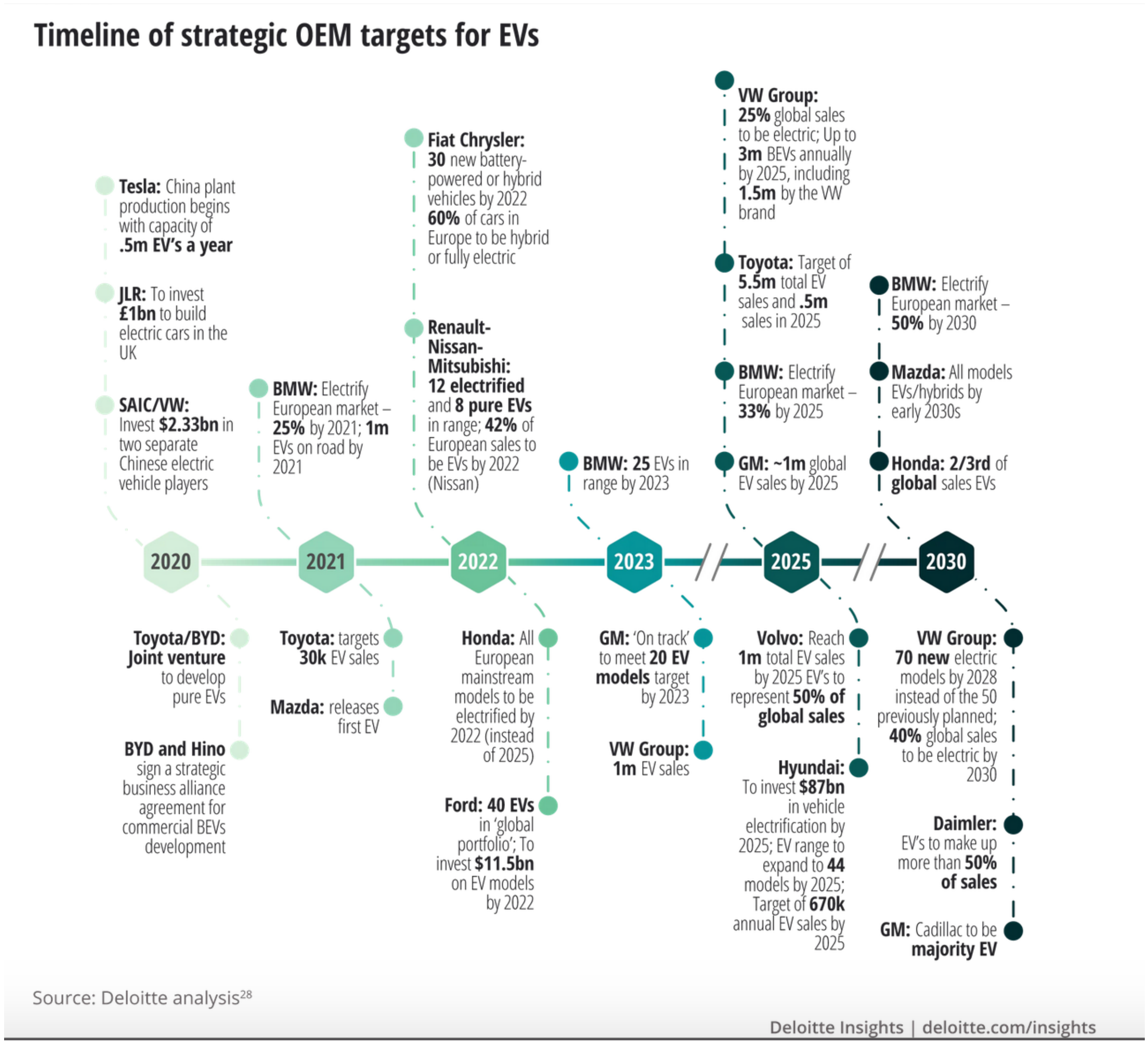
3. Improving Range and Charge for new EVs

4. Expanding EV Charging Station Infrastructure

- Supporting transportation electrification via EV programs
- Directly owning charging equipment
- Funding portions of the charging installation
- Conducting consumer education programs
- Offering special electricity rates for EVs

5. Home EV Charging Stations More Efficient Than Ever

Future



Author Contributions

All authors contributed equally for the decimation of the report article in current form.

Conflicts of Interest

The authors declare no conflict of interest.

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