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Smart Charging and Discharging of Electric Vehicles to Support Grid with High Penetration of Renewable Energy

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Abstract: High penetration of renewable energy to the grid may cause a number of problems such as supply and demand mismatch, voltage fluctuations and even network instability. Electric Vehicles (EVs) with on-board batteries are capable of supporting the grid with large integration of renewable energy sources by absorbing (charging) the excessive amount of energy and returning it (discharging) to grid when needed. This paper proposes a new smart control algorithm using the idea of Certainty Equavilent and Adaptive Control and a "customer participating program" to coordinate both the charging and discharging of EVs to achieve the above objective. The advantages of the proposed algorithm come from its simplicity, robustness and hence a promising opportunity for real-life applications in future smart grid. The effectiveness of the proposed scheme is evident by the numerical simulations on a micro-grid system with high penetration level of wind energy

Keywords: Optimal Control, Smart Grid, Electric Vehicle, Renewable Energy

1. INTRODUCTION

Renewable energy has become increasingly important in our fight against climate change and energy crisis. However, it has a major disadvantage of being an intermittent resource which limits its integration to the power grid. It is generally accepted that under current conditions, the maximum amount of renewable energy that the power system could accept without risk of instability is only 20-25% (EWEA, 2005). Among a number of solutions that have been explored in order to increase the renewable energy penetration to the grid, one feasible approach is to use electric vehicles (EVs) as energy storage or demand response tool to deal with the variation in renewable energy generation, provided that the scenario of EV proliferation becomes reality (Wade, 2010).

This potential benefit of EVs has recently attracted the attention of many researchers. While most of the prior work has focused on controlling only the charging of EV (Sortomme and El-Sharkawi, 2011), (Deilami, 2011), (Linni, 2013), (Richardson, 2012) (Grid to Vehicle - G2V), few have explored the discharging aspect (Vehicle to Grid-V2G). Although the infrastructure for V2G might not be commercially feasible in the near future, it is our belief that V2G has a crucial role in tackling the problem of intermittent renewable energy sources. Therefore, it is necessary to develop a control algorithm that addresses both the G2V and V2G .

Among the works examining both G2V and V2G, the most recent ones could be generally divided into two main trends. In the first trend, the Load Frequency Control (LFC) technique is employed to adjust the charging or discharging rate of EVs according to the frequency deviation signal, which is a measure of power imbalance in the system (Ota, 2012a) (Ota, 2012b) (Yunfei, 2013). Although LFC technique has the advantages of simplicity and easy implementation, it only considers EV as a normal demand response equipment rather a smart energy storage unit. Hence, LFC has not yet exploited all of the benefits of EV. Moreover, there is also a possibility that under the LFC scheme, some EVs may not be fully charged before their time of departure since the customer requirements are normally traded off for the network stability.

As for the second trend, researchers such as (Saber and Venayagamoorthy, 2012) and (Khodayar, 2012) use dynamic programming optimisation to find the optimal charging or discharging schedules for all EVs for a day ahead that minimises the total expected cost of the power system. With the dynamic programming approach, charging plans for all EVs are actively and optimally scheduled, which can provide a much better result than that of LFC. However, since there are different uncertainties involved in the problem such as the error in renewable energy, load demand forecasting and even the availability of EVs themselves, the dynamic programming approach requires comparatively overwhelming computation work (Bertsekas, 2005). Although advanced solving methods, such as Particle Swarm Optimization (PSO), have been applied to the problem above, it still takes hours or even days to compute the result, which might not be feasible for real applications.

In our work, we do not attempt to find a final solution from a large complex dynamic programming considering all kinds of uncertainties at the beginning of the control period (i.e. a day). Alternatively, we propose a novel approach in which at each time step, we only solve one deterministic optimisation problem that minimises the cost objective from that time step till the end, using forecast information about renewable energy resources and load demand as if there were actual value. This produces optimal charging or discharging control sequences for all EVs; however, only the first components (the solution for the current time step) are used while the rest are discarded. Such control process is repeated continuously with updated information to obtain a new control solution for each new time step until the end of the whole control period, and the fundamental concept is based on the principle of Certainty Equivalent and Adaptive Control (CEAC). As a result, the optimal solution of the proposed algorithm is simple and efficient in computation and is robust subject to system uncertainties. (Bertsekas, 2005).

In order to further improve the performance of the algorithm, a "customer participating" scheme is proposed which requires information from EV owners about their charging plans. This scheme on the surface seems impractical in reality as it would probably affect customersćomfort. The true reality is however the opposite. Based on a survey conducted in Victoria, Australia on load control response project, up to 80% of the participants would accept charge-management of their EVs only if their vehicles are fully charged when they need them. Interestingly, nearly 40% are willing to do so if this could "provide a better environment outcome" even though "there is no financial benefit for them" (Goverment, 2013).This result of government survey indicates the feasibility of the customer participation scheme proposed in this paper

The paper is organised as follows. Section II describes the control scheme and Section III presents the simulation data and results. Conclusion is provided in Section IV.

2. OPTIMAL CONTROL SCHEME FOR ELECTRIC VEHICLES

Consider a micro-grid system which consists of 5 main components (Figure 1): a conventional power plant (P_G), a renewable energy source (P_{RE}), a load (P_D), a group of EVs (P_{EV}) and a standby generator (P_A) to provide ancillary service.

The stability of the system requires that, the total net power injected and consumed in the system must be balanced at any time, which means:

$$P_G(t) + P_{RE}(t) + P_D(t) + P_{EV}(t) + P_A(t) + P_{Loss}(t) = 0 \quad (1)$$

Where:

- $P_G(t)$: *power output of the conventional power plant at time t. P_G provides the base load demand and normally is constant with only a small amount of variation for spinning reserve.*
- $P_{RE}(t)$: *power output of the renewable energy source at time t*
- $P_D(t)$: *load demand at time t*
- $P_{EV}(t)$: *total charging or discharging demand of all the EVs*

$$P_{EV}(t) = \sum_{i=1}^{N} P_{EV}i(t) \quad (2)$$

(With N is the number of participating vehicles). $P_{EV}i(t)$ can be negative or positive representing charging or discharging power, respectively.

- $P_A(t)$: *power output of stand-by generator at time t*
- $P_{Loss}(t)$: *loss in the system at time t. P_{loss} generally depends on the power flow of the system and is hence partly correlated to the location of EV's charging points and their current charging power.*

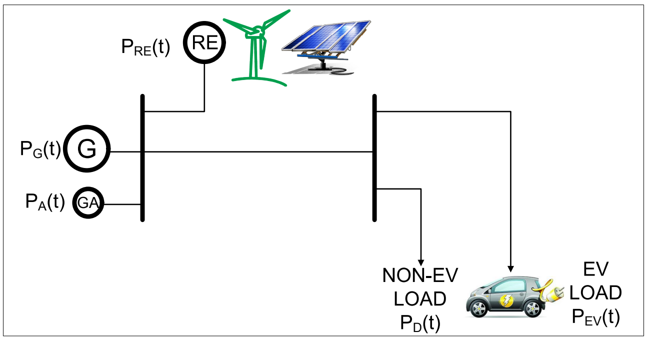

Fig. 1. A Micro-grid system with 5 main components

If there is no control over the power consumed by EVs, there can be a mismatch between the supply and demand due to the fluctuation of both renewable energy and load demand. In order to keep the system in balance, the grid operator must require expensive ancillary service from stand-by generators or import power from other area. This is partly the reason why high renewable energy penetration is generally not favoured by grid operator.

A centralised control scheme based on linear optimisation is proposed in this paper to coordinate the charging and discharging of all participating EVs. Assume that a group of vehicles is controlled within a window of time (for example one day) which is divided into M small time steps $[t_1, t_2, ..., t_M]$. At each time step $t_m \in [t_1, t_2, ..., t_M]$, the central controller will solve the optimisation problem to find the optimal charging or discharging schedule $[P_{EV}i(t_m), P_{EV}i(t_{m+1}), ..., P_{EV}i(t_M)]$ for all the participating vehicles with the objective of minimising the power imbalance $F(t) = P_G(t) + P_{RE}(t) + P_D(t) + P_{Loss}(t) + P_{EV}(t)$ in the system from time t_m to time t_M (cost-to-go from t_m to t_M).

$$\underset{P_{EV}(t)}{\text{minimize}} \quad \| F(t) \|, \quad t \in [t_m, t_{m+1}, ..., t_M] \quad (3)$$

where $P_{RE}(t_m)$ and $P_D(t_m)$ are actual value measured at the current time step $t = t_m$. From $t = t_{m+1}$ to $t = t_M$, forecast data are used, which is normally provided from network operator for a period of time ahead. For example, in Australia, AEMO (Australia Energy Market Operator) normally publishes predicted information about a-day-ahead load demand for different states. Prediction data is generally subjected to error.

Although the outcome of the optimisation is a control sequence $[P_{EV}i(t_m), P_{EV}i(t_{m+1}), ..., P_{EV}i(t_M)]$ (with $i \in N$), we only use the result at the current time step t_m by ordering all participating vehicles i to charge with their particular power $P = P_{EV}i(t_m)$ and forget about the rest. Moving to the new time step, new information is updated to the central controller, and the optimisation is processed again with the new cost-to-go objective from this current time step till the end. This process is repeated until the end of the control window.

In order to improve the performance of the controller, the proposed owner participation scheme requires information from the EV owners about their charging plan at the beginning of the day, such as number of charging processes per day, arrival and departure time for each charging process, the State of Charge (SOC) or energy level at the beginning and desired state of charge at the end. For the SOC at the beginning of the planned charging period, customers may alternatively provide information about their travelling distance or even their next charging location. Then computer will estimate the SOC based on the average energy consumption per miles of their cars. This information needs not to be precise; however, once the car is actually plugged into the charging point and sends out a charging request to the control centre, the owner is required to provide accurate information about the time of departure and the desired SOC. This information acts as a commitment or contract of the car owner to the grid operator.

The set of information that a vehicle owner number i needs to provide is as follows:

- The number of charging jobs required: n_i
- The starting SOC of each charging no. n : $E_s(i,n)$ with $n = [1...n_i]$
- The desired SOC of each charging job: $E_d(i,n)$ with $n = [1...n_i]$
- The commence time of each charging job: $T_s(i,n)$ with $n = [1...n_i]$
- The departure time of each charging job: $T_d(i,n)$ with $n = [1...n_i]$

In return for customers' contribution, all the charging requirements from vehicle owners will be fulfilled if only 1. they are not physically infeasible [1], and 2. the cars remained plugged in during their committed period.

The details of optimisation algorithm are formulated as follows:

- **The objective of the algorithm is:**

$$\underset{P_{EV}(t)}{\text{minimize}} \quad \|F(t)\|, \quad t \in [t_m, t_{m+1}, ..., t_M] \tag{4}$$

Here it is assumed that the power loss is constant and relatively small compared to the load demand and supply. Since RE and load are forecast values, the objective function of (4) becomes: $F(t) = P_G(t) + \widetilde{P}_{RE}(t) + r(t) + \widetilde{P}_D(t) + d(t) + P_{EV}(t)$, where $r(t)$ and $d(t)$ are error or noise signals,respectively, and $\widetilde{P}_{RE}(t)$, $\widetilde{P}_D(t)$ are forecast values. To deal with the uncertainties or errors in the prediction, the algorithm solves the problem in the worst case scenario, when the wind power is lowest and the load demand is highest, which is:

$$\begin{gathered}\underset{P_{EV}(t)}{\text{Minimize}} \; \underset{|r(t)|,|d(t)|}{\text{Maximize}} \|F'(t)\| \\ t \in [t_m, t_{m+1}, ..., t_M]\end{gathered} \tag{5}$$

with $F'(t) = P_G(t) + \widetilde{P}_{RE}(t) - |r(t)| + \widetilde{P}_D(t) + |d(t)| + P_{Loss}(t) + P_{EV}(t)$

This is a robust mean square linear optimisation under uncertainties (El Ghaoui, 1997), which makes sure that the control algorithm is stable and that all the charging requests are guaranteed to be met.

- **The constraint set of the optimisation algorithm is presented as follows:**

$$P_{EV}(t) = \sum_{i=1}^{N} P_{EV}i(t) \tag{6}$$

Constraint (6) requires that the total EV power must equal to the sum of power from each individual electric vehicle.

$$\begin{gathered}P_{EV}i(t) = 0; \\ i \in N; \; t \notin [T_s(i,n), T_d(i,n)]; \; n = [1, ..., n_i]\end{gathered} \tag{7}$$

Constraint (7) requires that the charging power $P_{EV}i(t) = 0$ when car i is not plugged in.

$$\begin{gathered}-P_{max}(i,n) \leqslant P_{EV}i(t) \leqslant P_{max}(i,n) \\ i \in N; \; t \in [T_s(i,n); T_d(i,n)]; n = [1, ..., n_i]\end{gathered} \tag{8}$$

Constraint (8) requires that the charging or discharging power must not exceed the maximum power of the charger. The value of P_{max} depends on the charging facility.

$$\begin{aligned}\int_{T_s(i,n)}^{T_d(i,n)} \eta \times P_{EV}i(t)dt &\geqq E_d(i,n) - E_s(i,n) \\ &\quad - a \\ \int_{T_s(i,n)}^{T_d(i,n)} \eta \times P_{EV}i(t)dt &\leqq E_d(i,n) - E_s(i,n) \\ &\quad + a \\ i \in N; \; n = [1, ..., n_i]\end{aligned} \tag{9}$$

Constraint (9) makes sure that all EVs are charged up to their desired state of charge at the end of the charging period. When providing the charging plan, customers may arrive late or early at the charging point and with their SOC different from estimated value. To deal with this uncertainty, a fuzzy approach is employed, which accepts the planned charging task , as long as the result is within a bounded interval [-a; a]. For committed jobs in which an EV has actually arrived and send the accurate data, the constraint (9) becomes equality constraint $\int_{T_s(i,n)}^{T_d(i,n)} \eta^{2} \times P_{EV}i(t)dt = E_d(i,n) - E_s(i,n)$ (with a = 0), and this job is guaranteed to be completed. It should be noted that during the actual charging period, the starting energy level is the energy level at the end of the previous step $E_s(i,n) = E_i(t_{m-1})$ [3] and the starting time is the current time step $T_s(i,n) = t_m$

$$E_{min}i \leqq E_i(t) \leqq E_{max}i; \; i \in N \tag{10}$$

[1] An example of physically infeasible requirement is fully charging an empty car battery within a minute

[2] Charging efficiency

[3] $E_i(t)$ - Energy level of car i at time t

Constraint (10) *makes sure that the maximum and minimum capacity is never breached to prolong the battery life.*

The block diagram of the whole control process is displayed as in Figure 2. Furthermore, it is worth mentioning that although the above control algorithm is developed for a finite period of time, it could be easily modified to formulate an infinite control problem by means of using a sliding window of time as long as new information is continuously fed into the central controller.

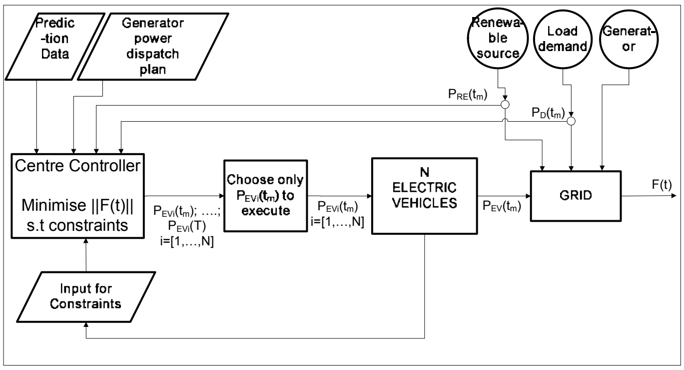

Fig. 2. The block diagram of the proposed control scheme

3. SIMULATION AND RESULT

3.1 *Description of simulation model*

A test system is modelled in Matlab environment to evaluate the performance of the proposed control scheme. In this system, there are two conventional power plants G_1 and G_2 with capacity of 4,250 kW and 750 kW, respectively. During the day, both generators are scheduled to run in parallel while during night time, G_2 is shut down.The renewable source is a wind farm representing all the large scale wind generators in Victoria region, Australia scaled down by a factor of 100. The total rated power of the wind farm is 3,770kW so the wind penetration level is around $\frac{P_{wind}}{P_{G1}+P_{G2}} = 43\%$ which is relatively high. The load source is also modelled from history electricity demand of Victoria region being scaled down to kW unit. A set of wind and load demand data is randomly selected on a day with 5-minute interval from the historical database and used them as the forecast values. In order to model the inaccuracy in the prediction, errors of 3% and 5% are introduced to the load and wind data, respectively (Figure 3 and Figure 4).

As far as the EVs are concerned, there are 600 cars in total, of which 280 are Mitsubish i-MiEV and the rest are Nissan Leaf (the proportion of Mitsubishi and Nissan cars resemble the actual proportion of these two types in Victoria (Goverment, 2013)). Each vehicle is scheduled with a charging plan including the number of charging jobs per day, and information about energy level as well as charging period for each charging request. The energy level at the beginning and the end of each charging job (2) are created based on the information of EV driving history in Victoria, Australia - for example mean and standard deviation of EV travelling distance per day (Table 1).

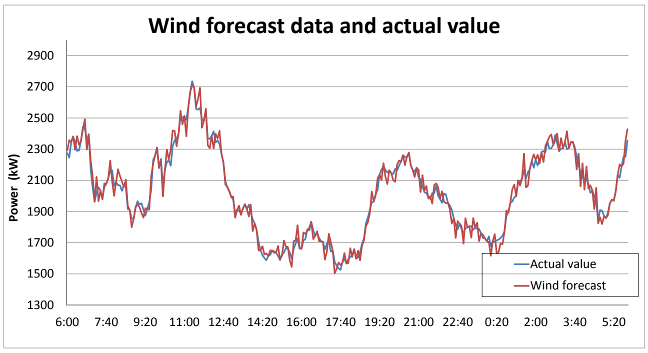

Fig. 3. Wind prediction data and error (Miskelly, 2013)

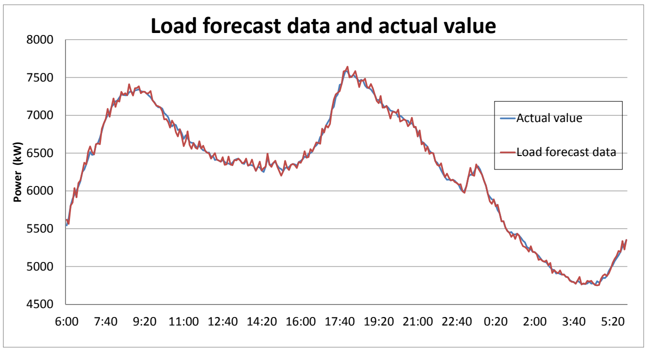

Fig. 4. Load prediction data and error (Operator, 2013)

Table 1. Electric Vehicle Usage data in Victoria, Australia (Goverment, 2013) (With AV-Average, SD-Standard deviation)

Vehicle use attribute	**Mitsubishi iMiEV**		**Nissan LEAF**	
	AV	SD	AV	SD
Distance travelled per day(km)	24.5	12.7	32.8	15.3
SOC at plug in %	57.5	10.2	52.0	9.4
Average energy economy (kWh/km)	0.150		0.179	

Table 2. An example of energy level at the beginning and at the end of each charging jobs from Vehicle no. 1 and 2

Vehicle no.	**Charging job 1**		**Charging job 2**		**Charging job 3**	
	E_s kWh	E_d kWh	E_s kWh	E_d kWh	E_s kWh	E_d kWh
1	14.57	14.57	14.28	14.28	12.85	16
2	13.73	13.73	13.28	13.28	11.01	16

For the timing of each charging events, it is assumed that vehicle owners leave home for work in the morning, and as soon as arriving at their offices at the mean time of 8:30am, they start to charge up their EVs. The car will remain plugged in until around 5:30pm and re-plugged at about 7:00pm after retuning back to home. For 10% of the electric vehicle population, owners will disconnect their cars to go for lunch at 12pm and return at around 1pm to continue their charging (Table 3). The standard deviation for the above mean value is 30 minutes. Similar to the prediction data for wind and load values, errors are introduced to model the inaccuracy in the charging plan information provided by customers. In other words, customers can possibly arrive at the charging point later or earlier than their proposed plans (Table 4).

In this case study, we adopt a control policy in which if an EV arrives earlier than its plan, the central controller, upon receiving the early charging request, will run two off-line optimisation problems to determine whether it should let this vehicle start charging at the next time step or defer the charging until the original time. In the case when a car does not arrive on time, the central controller will create a new arrival time with 15-minute delay. There can be some penalty measures to discourage late arrivals, but at this stage, this is out of the scope of this paper.

Table 3. Scheduled starting time and departure of each charging job from Vehicle no. 1 and 2

Vehicle no.	Charging job 1		Charging job 2		Charging job 3	
	T_s	T_d	T_s	T_d	T_s	T_d
1	7:50	12:10	13:05	17:15	19:20	5:40
2	8:00	12:10	13:05	17:05	19:10	5:35

Table 4. Actual starting time and departure of each charging job from Vehicle no. 1 and 2

Vehicle no.	Charging job 1		Charging job 2		Charging job 3	
	T_s	T_d	T_s	T_d	T_s	T_d
1	7:55	12:20	13:00	17:15	19:30	5:40
2	8:10	12:10	13:00	17:10	19:05	5:35

Finally, we assume that during the day, EVs have access to fast charging facilities with $P_{max1} = 7.68kW$ at their workplace car park (equivalent to level II charging standard), while during their charging period at home, the maximum power is only $P_{max2} = 2.88kW$ (equivalent to level I charging standard) (International, 2013)

The model is simulated in two different scenarios - with and without the central controller to compare the impact of the proposed optimal control scheme for EVs.

3.2 Scenario 1 - Without the central controller (free charging policy)

In this scenario, it is assumed that all the vehicle owners return home at around the mean time of 7pm and immediately start charging their cars with maximum power until the battery tanks are full. The energy levels or SOC at the beginning of the charging period are created based on the EV driving history in Victoria region. The result of this simulation is presented in Figure 5 and Figure 6.

It could be clearly seen from the result that the system is constantly out of balance (Figure 3) due to the fluctuation of wind energy. On top of that, additional imbalance is added to the system during the night when all of the vehicles are being charged at the same time (Figure 4). With this level of power imbalance, the grid operator must require costly ancillary services to keep the whole system stable or even have to upgrade the physical infrastructure for additional peak demand from EVs.

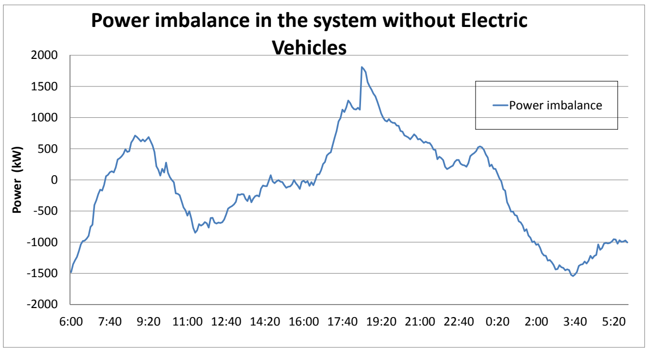

Fig. 5. Power imbalance in the system without the presence of EVs

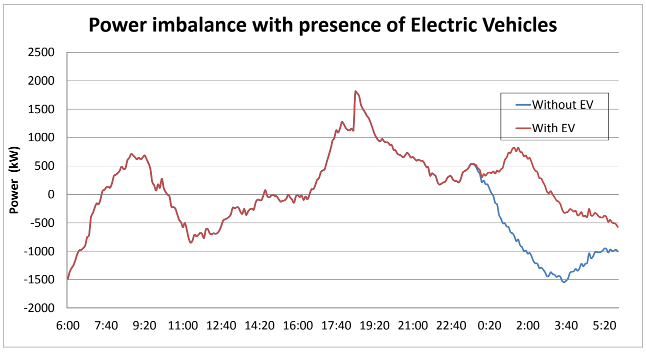

Fig. 6. Power imbalance in the system with the presence of EVs

3.3 Scenario 2 - With the central controller

In the second scenario, the central controller will coordinate the charging and discharging power of 600 EVs. The result of the simulation is presented in Figure 7. It shows that during the early morning (from 6:00 to 7:15) or late afternoon (17:15 to 19:20), most cars are on the road. Without their support, there is a large mismatch between supply and demand, which is similar to scenario 1. However, from 7:15 to 16:00 and from 19:20 to 4:30 (next day)-when most of the cars are plugged in-they are instructed to charge or discharge optimally by the central controller. As a result, the gap between power supply and demand is significantly reduced to nearly zero. The trend is also flattened for most of the time, except for two short periods from 16:00 to 17:15 and from 4:30 (next day) to 5:55 (next day) when most EVs are nearly fully charged with little capacity in the car battery pool to utilise. A flattened power demand trend means that the grid operator can easily schedule power dispatch from base-load power plants to bridge the gap instead of having to mobilise costly emergency ancillary service from standby generators.

With respect to customer satisfaction, all of the charging requests from all of the participating vehicles are fulfilled. In other words, all EV batteries reached their desired energy level before their departure time. To illustrate, we examine the case of vehicle 1. During the day, when vehicle 1 is plugged in, its battery is charged up to the required energy level [4] at the end of each charging period (Figure

[4] Charging request of Vechile 1 is presented in Table 2 and Table 4

9), despite the fact that the central controller instructed it to charge or discharge with different power rate (within the maximum power constraint) (Figure 8) to support the network grid.

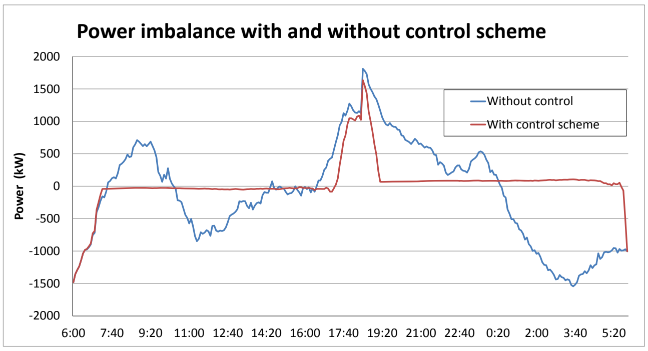

Fig. 7. Power imbalance in the system without and with an EV control scheme

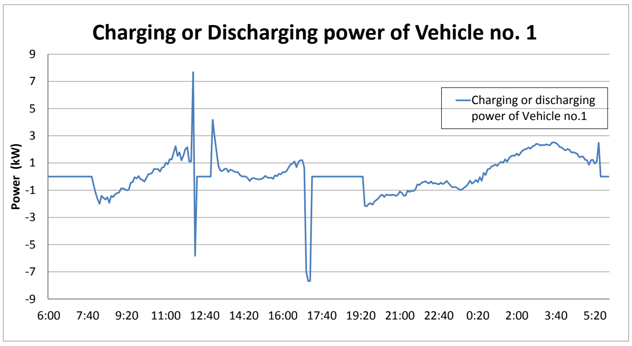

Fig. 8. Charging or discharging power of Vehicle no.1 during the day

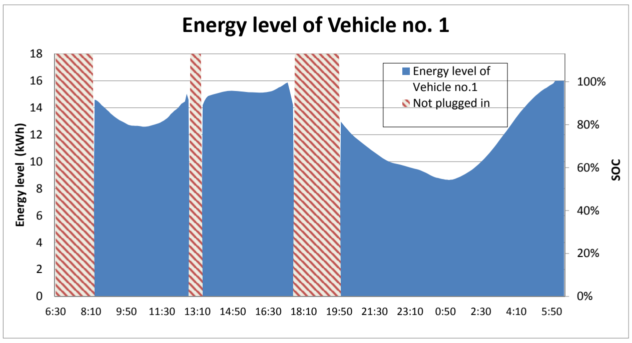

Fig. 9. Energy level of Vehicle no. 1 during the day

Finally, by using the interior-point method to solve the optimisation problem in this simulation, the longest computational process time is only 17s for 17 iterations on a normal desktop computer. The process time could be faster with a more powerful workstation.

4. CONCLUSION

In conclusion, the proposed control scheme has proved its ability to exploit EV battery in supporting a very high penetration level of wind energy to the grid, while at the same time customer satisfaction is always guaranteed. The computational process time is comparatively short, hence it is promising for real-life applications. Currently, power loss is ignored in this study, but it will be considered in future work to further enhance the efficiency of the system. Moreover, we will also look at the options of using aggregators as distributed controllers to extend the scale of the system as well as employing pricing scheme to stimulate favourable customer behaviour.

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