ISSN: 2449 – 0539
BAYERO JOURNAL OF ENGINEERING AND TECHNOLOGY (BJET) VOL.15 NO.1, JANUARY, 2020 pp30-38

A PRICE BASED CHARGING STRATEGY FOR ELECTRIC VEHICLE MANAGEMENT IN DISTRIBUTION GRID

Gaddafi Sani Shehu*, Abdullahi Bala Kunya[1], Mukhtar Fatihu Hamza[2]

[1,*]Department of Electrical Engineering, Ahmadu Bello University Zaria, Nigeria
[2]Department of Mechatronics Engineering, Bayero University Kano, Nigeria
*Corresponding author: gsshehu@abu.edu.ng

ABSTRACT

The growths of electric transportation and advancement toward smart grids, large-scale placement of smart charging infrastructure for electric vehicles (EVs) becomes necessary. This leads to prospects of diverse market parties to utilize the flexibility of EVs for various objectives such as optimal shifting of peak demands for the distribution grids and demand response. Electric vehicle charging in distribution grid brings a new set of the loads profile, causing significant power quality related problems, creating grid congestions, and converting distribution operator from facility manager to congestion manager. To mitigate these problems a number of methods are presented in literature, from renewable energy integration to price control regulation. In our approach, a new set of algorithm based on flexible price control for electric vehicle charging are proposed depicting typical real world scenarios. The algorithms are designed to support the existing grid infrastructure and contribute in reducing charging burden on the grid. The proposed approach is tested on IEEE 33-bus distribution grid test system using Matlab environment. The efficient approach is found to accommodate 50% of EVs penetration.

Keywords: Charging strategy, Electric vehicles; Distribution grid; Smart price control

1. INTRODUCTION

Distribution grid is normally medium and low voltage power delivery to consumer rated capacity and its expected electric vehicle (EV) charging will mostly be carried out at those voltage level. With load profile varies depending on weather condition over time of the day, it is expected EVs load will bring a new peak demand profile. One smart way to control EV charging is to allow the customer to participate in the activities that exist within the grid i.e. EV owner understand the price signal at the time of the day or incentives attached, so they charge at a low price with kind of restrictions and incentives. Based on the statistics and mathematical tools, the residential power consumption historical data can be analyzed and fitted to predict their probability distribution, so that the models of EVs charging schemes are developed. Developed countries are proposing initiative of reducing greenhouse emission effect due to climate change impact. Currently, the world realized EVs and renewable energy potentials capabilities of decreasing carbon emission from both transportation and power generations. In the context of this work EVs includes internal combustion engine with a limited range in all-electric mode Plug-in-hybrid electric vehicle (PHEV), and battery electric vehicle (BEV) having no combustion engine, however an electric motor with ability to be charge from a stationary electrical source or an outlet in the home garage is also consider as EV (Kempton and Tomic, 2005).

Research indicates that EVs offers potential to decrease carbon emission from both transportation and power generation, electricity generations and transportations consume over 60% of global energy demand (Richardson, 2013). The integration of EVs to power grid sector will lead to various challenges, for example grid loads during the EV charging process at peak period. With high potentiality impacts of a large share of EVs in power network, many research works on related directions but with wider perspective in (Zhang et al., 2010; Hota et al., 2014). Details related review of issues, solutions approach detailing integration using agent-based different control model, optimization problems, and the computational tools employed is presented in (Hota et al., 2014). A robust emphasis on network effects by EVs and suitable method on how charging is to be controlled so as to reduce potentially maximum impacts detailed reported in (Hota et al., 2014; Green II et al., 2011; Bessa and Mato, 2011). Optimal charging of EV in the deregulated market based on a forecast of electricity price to reduces grid overloading and allow efficient energy flow at the reduced cost of electricity, taking into account incentive for EV owner to participate in providing ancillary services is presented in (Rotering and Ilic, 2011). Due to many distribution grid constraints, an EV fleet based on grid-aware charging plan in an optimal manner to shift peak loads demand, significantly reduced grid-overloading in (Rahbari-Asr and Chow, 2014). Agent-based EVs charging aggregation model with the involvement of an agent bidding electricity price, the optimized approach decreased charging cost and avoiding dumb charging (Bessa et al., 2012). A smart flexible charging plan based on individual EV owner to avoid grid congestions is presented in (Sundstrom and Binding, 2012). Distributed price charging framework to regulate user demand and balance gird loads is reported in (Fan, 2012). Coordinated EV charging cost for congestion prevention is reported in (Hu et al, 2016), the coordination took into consideration of three actors i.e. EV owner, Fleet operator and DSO decision in EV charging at the lowest cost, but the conflicting interest of different actors can hamper optimal charging cost. A vehicle-to-grid optimal spot price charging model in a microgrid concept presented, the design integrates battery state-of-charge and renewable energy capacity in obtaining reduced charging cost, and otherwise, the completely optimal strategy is bound to charge at a high cost (Tushar, 2017). Management pricing of EVs charging with a more flexible system perspective consider key input; travel pattern, the self-charging interest of EV owner, and traffic congestion as input to game theory algorithm model design, failure in one of the input responds convert the model into normal charging (Rahbari-Asr et al, 2013). A heuristics and metaheuristics method of EVs charging based on spot pricing algorithm suffer from local trapped problems, which occasionally does not guarantee optimal reduced cost and overloading reduction (Liu et al, 2017; Kang et al, 2016).

The work on this paper focus on EVs charging control in smart manner depending on the scenario the EVs is set for charging, with the aims of flexible control for EV to charge anytime during the 24-hr period of the day. A flexible price control allowed unrestricted charging over a 24-hr period, meaning that the EV are allowed to charge and discharge depending on the price for a particular time, the aims are not only for profit to the EV owner rather a control pattern of how optimal electricity price can shift overloading effect. A linear programming model price index based on the objective function is developed for the optimal parameters configuration. A case of uncontrolled charging, a reactive power discharge control, and a flexible price control are well treated. Therefore, the work considers EV as a load in one scenario and a source giving back to the grid (V2G) in another scenario. The methodology and network model presented in Section 2, charging scenarios presented in section 3; Results and discussion are presented in Section 4, while Conclusions are presented in Section 5.

2. METHOD AND FORMULATION

Presently charging are normally expected to be taken place at residential feeder especially with type I charger. EV owner is expected when returned home plug EV and commence charging, preparing for next trip, the plug and play attitude will lead increasing power demand even at the off-peak period. To ascertain the how many EVs require to be connected for a charge at any given time and maximum power delivery for continues charging in the distribution a grid depicting practical scenario, a steady-state analysis is performed using load flow calculation to determine how the change in electricity price will shift and another control scheme can reduce grid stress.

2.1. Test system model

The test network based on a low voltage is IEEE 33-bus system, with 32-branch line, 12.66 kV radial distribution network has active and reactive power demand capacity of 3.715 MW and 2.305 MVAr respectively, the single line diagram shown in Figure 1, the system has an inherent power loss of 210.89 kW (Zulpo et al, 2014; MATLAB R2014a). The simulation analysis of EV charging at each node is considered to have a lump sum of customer demand loads, while the EV is model separately, each node is treated individually, and EVs are distributed evenly. Its pertinent main power supply is coming from a single transformer connected to node 1. The distribution voltage deviation tolerance in this work is assigned at ± 10% of

ISSN: 2449 – 0539
BAYERO JOURNAL OF ENGINEERING AND TECHNOLOGY (BJET) VOL.15 NO.1, JANUARY, 2020 pp30-38

nominal voltage. A typical 24 hour for residential loads distribution demand and electricity price obtained by Monte Carlo simulation with mean load demand of 1.225 kW and standard deviation of 0.1021 kW, these are the typical residential load demand shown in Figure 2. For electricity price considering deregulated market is determined between the balance of generation and demand, usually following power demand profile with a mean price of 38.4 $/kWh and standard deviation of 3.423$/kWh (Urkmez and Nurettin, 2010; 20. Richardson et al, 2012a).

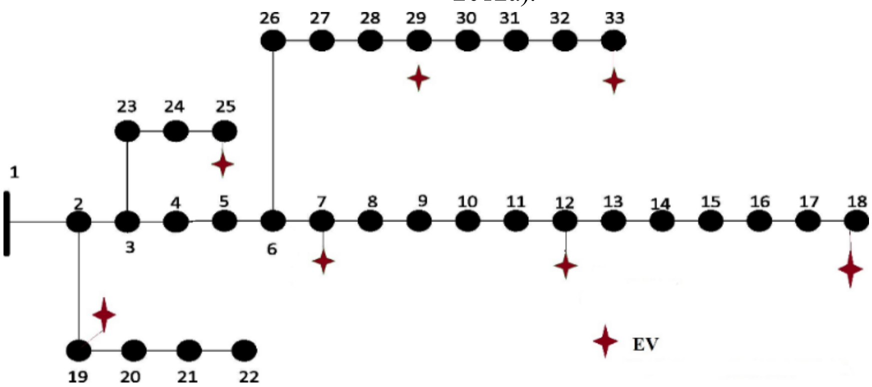

Figure 1: A 33-bus system with connected EV position level

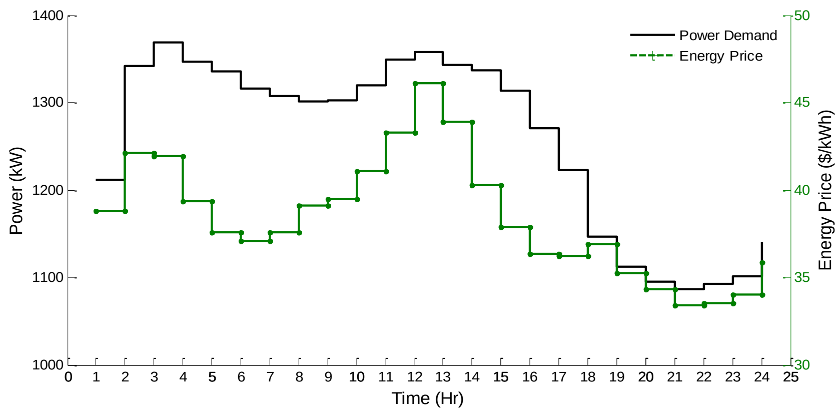

Figure 2: A typical load demand and price profile for a 24-hr period

2.2. Electric vehicle model

In the work, each individual EV is considered to charge at the same node with other residential loads demand appliances, the EV expected to be connected with single-phase type charger. The charging profiles for EVs can differ from the manufacturer of battery type, EV charger, and the network energy supply. For simplicity, the EV batteries are modelled based on lithium-ion battery technology with charging capability of 4 kW that is available at the low voltage level for battery capacity of 20 kWh (Richardson et al, 2012b). For general assumption, a single connected EV charge at a rate of 4 kW up to a battery state of charge of approximately 85%. After this point, the vehicle charges at a rate of less than 4 kW until the battery has reached its maximum capacity. To determine the total maximum power delivery to the EVs for a given period of time intervals, considering network constraint and assumptions. The total power delivers during a charging period of is given in (1). Our main constraint in relation to (1) is EV charger capacity, node voltage level loading and battery state-of-charge (SOC) to circumvent battery dilapidation and ensure full utilization of EVs number capable of participating in the charging process and grid services.

$$P_{ev} = \sum_{i=1}^{n} EV_i y_i \tag{1}$$

$$0 \leq EV_i \leq EV_i^{max} \quad (2)$$

$$V_{node}^{min} \leq V_{node} \leq V_{node}^{max} \quad (3)$$

$$85\% \geq SOC \leq 60\% \quad (4)$$

P_{ev} is power delivered to EVs in kW, n is a number of connected EVs, y_i a control variable for identifying the node with connected EVs, EV_i connected charge vehicle in a particular node, and assumed to vary between 0 to 4 kW maximum, charging at 4 kW increase power losses as in Fig. 3. Charging interaction are subject to network constraints from charging equipment, battery level, charging time, grid voltage level (Pillai, et al., 2012). The first constraint consider is that each individual EV cannot draw power more than $EV_{i.}$ (2). the voltage level at each node maintained at a specified value between ± 10% of nominal voltage V_{node}, (3). For any EV_i to participate in providing grid service grid services is to adapt to the constraint in (4).

3. ELECTRIC VEHICLE CHARGING SCENARIOS

. Three different charging scenarios are considered and are presented in this work for comparison. The first case considers uncontrolled charging (Dumb charging), the second case considers reactive power control charging, while in case three Flexible price control charging is presented.

3.1. Uncontrolled charging scenario

With no control string attached, any EV returned from a trip expected to begin charging immediately irrespective of the period of the day. This kind of charging is expected to be at a maximum charge rate of 4 kW, normally with this scenario grid stress will occur and will become more severe especially during peak periods with inherent maximum power losses as in power loss. In these scenarios, the following procedure is adopted: update residential load demand profile for selected node and EV is added. Identified connected EV status either full or continues charging. Perform load flow to calculate selected node voltage and power consumption. Determine the number of EVs and power deliver since there is no any control attached to this scenario the electricity price remain the same as the residential price. The procedure is repeated at the 30-minute interval during a 24-hr period.

3.2. Smart price control charging

A flexible charging control with the objective of maximizing incentive to EV owners charge at a lower price and participate in grid services including V2G at a high price. A linear programming algorithm is employed for optimizing the electricity price at 15-minute interval time, considering all the constraint attached. Linear programming algorithm requires a small amount of historical data; less computational techniques can easily be integrated into control scheme[24]. The scenario takes into consideration the demand profile at EV connected load. The objective function is formulated with decision variable of the 15-minute time interval of EV interaction (charging and discharging). Optimal EV charging schedule for connected EV follow equation (5) subject (6) to (10).

$$maximize \sum_i^{96}((P_{ri} - f) * h_1) - \sum_i^{96}(P_{ri} * h_2) \quad (5)$$

$$for\ f > 0$$

Subject:

$$b_i = b_{i-1} + h_2 - h_1 \quad (6)$$

$$SOC_{min} \leq b_i \leq SOC_{max} \quad (7)$$

$$0 \leq h_2 \leq h_{2max} \quad (8)$$

$$0 \leq h_1 \leq h_{1max} \quad (9)$$

$$b_1 = b_2 = \cdots b_{96} = 85 \quad (10)$$

Where P_{ri} is the price of electricity at a i time interval, h_1 is the percentage amount of energy injected by EV battery, h_2 charging amount of energy by EV in percentage, price control factor preventing EV from dual operation simultaneously, b_{i-1} a control variable tracking battery SOC status at end of every 15 minute interval$(i-1)$, while b_i at the end of 15 minute period i. h_1 and h_2 maximum value should not exceed 5% of battery capacity. The constraint in (10) is to check the SOC does not fall within minimum to maximum of the setting.

The optimization procedure designated by (6) to (10) do not consider disconnected EV from the grid. But when deciding which battery will keep charging or discharging, the linear program start by finding optimal values for all variables assuming EV is connected to the grid, two input is needed at each step battery initial SOC and electricity price at a flexible price generally refer to as spot price in some cases. When executing the algorithm, the charging and discharging to the grid for the previous time interval is fixed to zero. Subsequently, the program calculates a new set of optimization values, at this stage an EV disconnected for the first time the price of electricity remained until next time interval. The program is repeated generating fresh optimizations values pending the final time an EV is disengaged from the grid, the algorithm is shown in Figure 3. The algorithm keeps tracking battery SOC throughout 24-hr charging period, at each time EV charge from the grid SOC increases and price determines the same case happen if EV discharge to the grid. For dynamic horizon of profit maximization to both grid and EV owner's a sub-routine algorithm is added take charge in predicting a driving pattern, and electricity prices for the next 24 hours, and compute the charging schedules for the following day in a related routine.

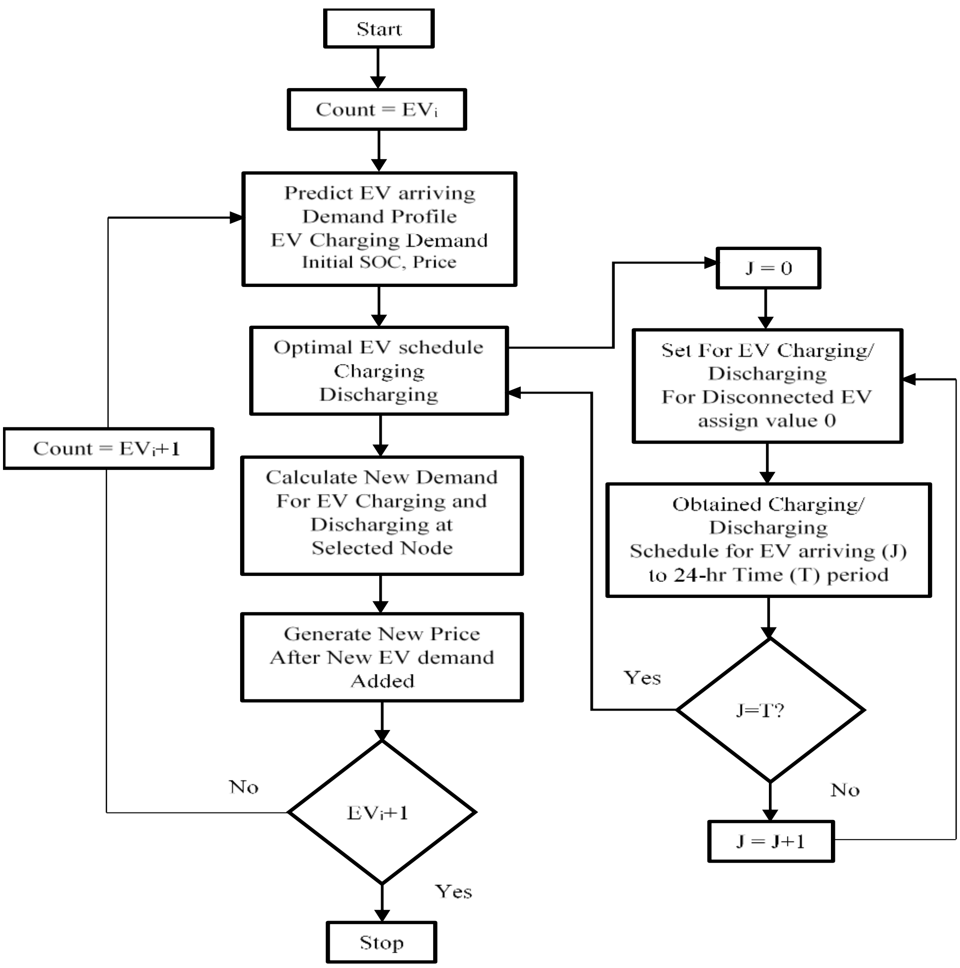

Figure 3: Flowchart for optimal smart price charging schedule in price control

4. RESULTS AND DISCUSSIONS

Two different cases steady-state load flow analysis are examined; uncontrolled charging and smart price control scenarios for avoiding peak load and overloading. In all the cases, the same number of EVs are integrated including a lump sum of residential loads demand. Since EV connected at any node contribute to voltage variation in another node point, node 12 is selected for all the analysis due to sensitivities and voltage variation. A total number of 464 EVs are considered for all the charging scenarios, with the total power demand of 1.856 MW representing 49.9% of the grid total demand. The distribution of EVs arriving after the final trip for charging/discharging depending upon the scenario, it is expected charging to commence from 11:00 hr and terminate 21:00 hr approximately. The actual residential demand for node 12 without EV charging for the 24-hr period is shown in Figure 4, with peak power demand of 1.3684 MW, it's assumed that all the connected grid nodes are having the same load demand pattern, but may differ in peak values. The impact of uncontrolled (Dumb) charging scenario is witnessed in Figure 5, normally with arrival of EVs it's expected that a sudden charging will commence since no control mechanism is applied, load pick is observed between 11:00 hr to 21:00 hr periods, these periods coincided with residential peak load demand, with period 18:00 hr to 21:00 hr exhibit much higher penetration of EVs. A new peak power load demand of 2.002 MW is observed due to EVs charging, representing an increase of 31.59% base demand with EV connected. This will definitely overload the grid, causing the network congestion during the period under consideration.

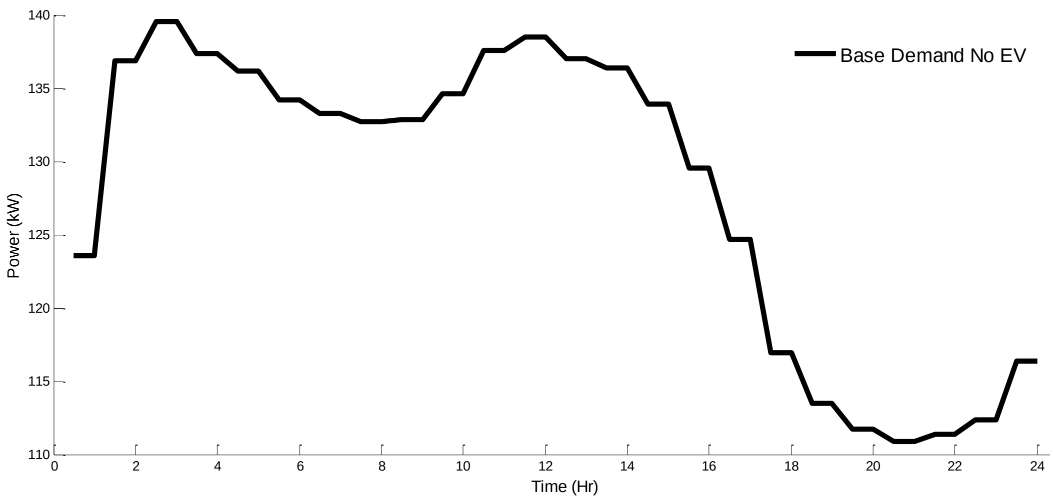

Figure 4: Base demand at node 12 for 24-hr period

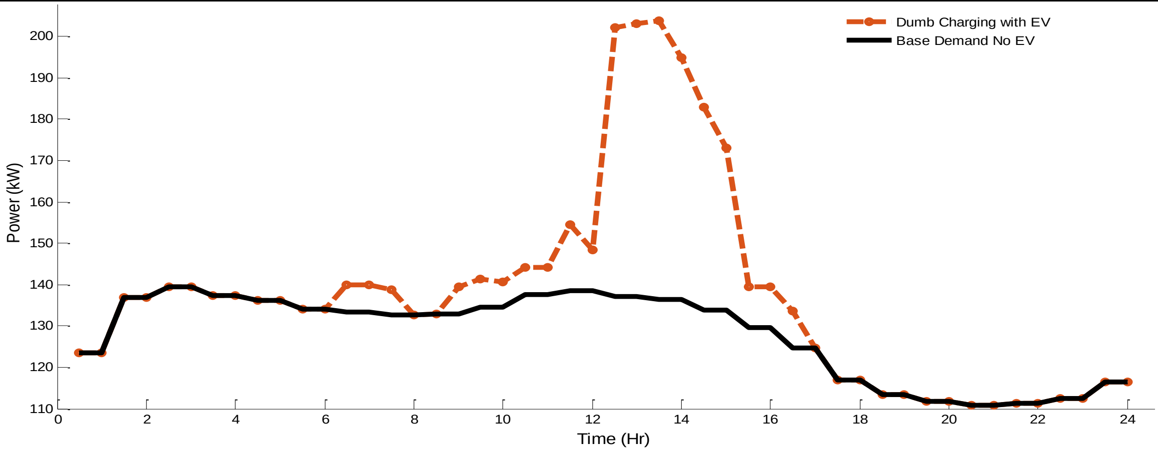

Figure 5: Uncontrolled charging effect load profile for EV power demand without any strategy

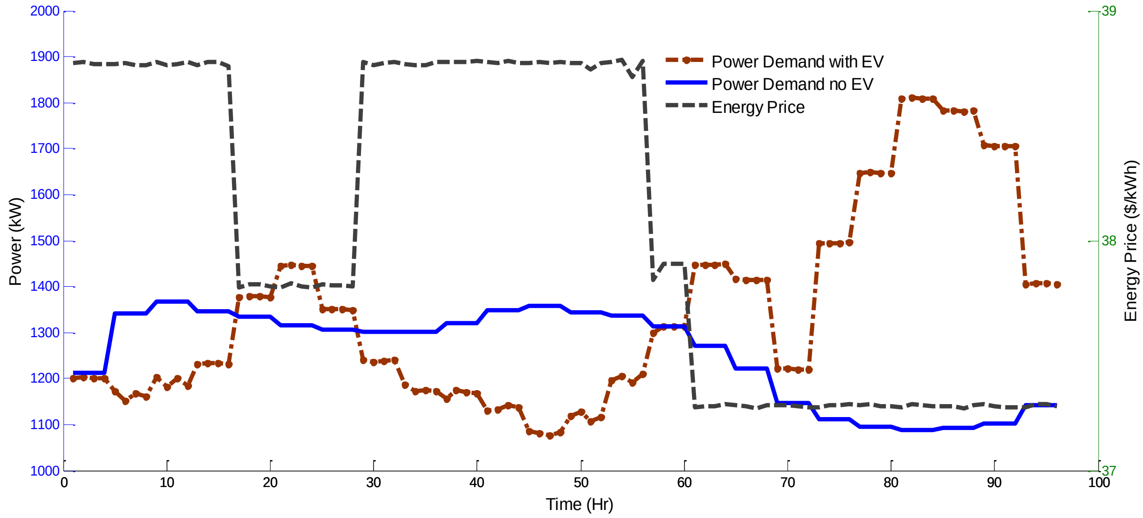

Figure 6: Flexible price control effect of EV charging

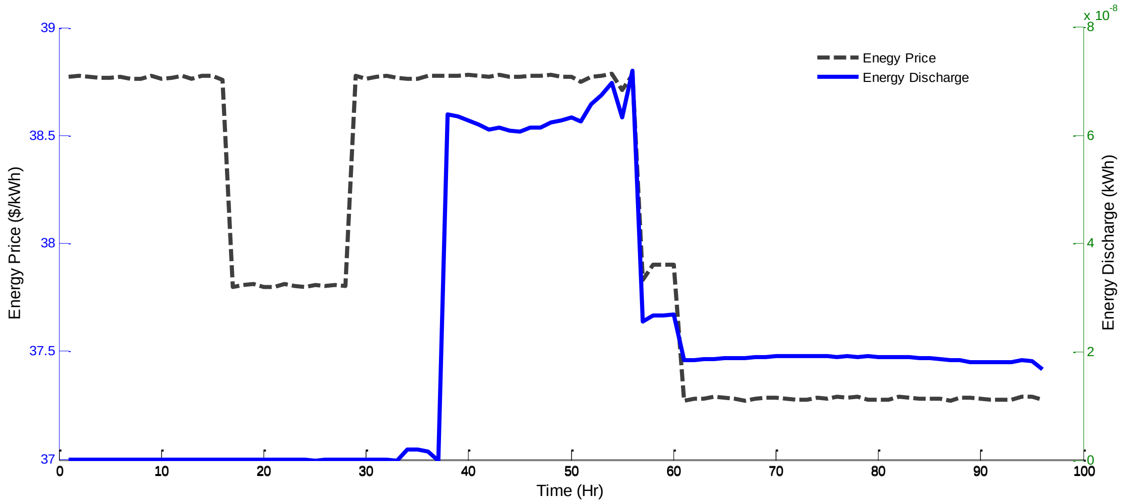

Figure 7: Energy Discharge and price respond

For smart price control scenario, the 15-minute time interval representing 96 slots is plotted together with price in Figure 6, with optimized control its expected battery charge at low price and discharge at a high price, unlike a normal situation price of electricity, follow load demand in a respective manner. This optimal control scenario makes it possible for load profile to avoid concentrated grid overload. A new load profile with shifted to off-peak period is observed, with a peak demand of 1.8107 MW representing 9.47% reduction.

The most important aspect of this scenario is grid load demand balancing, overload shift demand and avoiding grid congestion. Because highest peak demand due to EV charging corresponds to off-peak residential loads demand at low electricity price. Relationship between energy discharge to the grid and electricity price is shown in Figure 7, in the early hour of the day electricity price are high, but EV is unable to participate due to limited battery SOC limit, in the middle hour of the day the price is high for 60 to 85% SOC a number of EVs participate creating somehow valley filling effect.

5. CONCLUSIONS

With a smart control strategy, a kind of grid overloading will be reduced to the minimum. Two control strategies are applied uncontrolled charging with no incentive and an optimal flexible smart price control for EV to participate in grid service at all time. The results indicated that uncontrolled can increase peak load profile and voltage profile beyond limit not all EVs can participate in grid services at this stage and each EV must have a certain level of battery SOC as a cardinal condition. On the other hand, an optimal flexible price-based control algorithm proved to be effective in reducing peak load demand, reduced congestion and shift peak demand to off-peak periods for EV charging.

Flexibility and incentive make it friendly and attractive for more EV owner to participate, the algorithm can be alternative to expanding grid infrastructures accommodating more EV with existing facilities. From the foregoing, it is clearly demonstrated that an EV charging in low voltage grid is practically possible with existing grid components without a possible component upgrade, but with efficient strategies is achievable to accommodate 50% of EVs penetration. The new approach will enable electric vehicles and loads to goes beyond exchanging power with the grid, but also allow efficient exploitation of the current grid capacity, thus facilitating higher penetration of electric vehicles charging station at a reduced cost and carbon emission.

REFERENCES

Bessa, R. J., Matos, M. A., Soares, F. J. and Lopes, J. A. P. (2012). Optimized Bidding of an EV Aggregation Agent in the Electricity Market. IEEE Transactions on Smart Grid, Vol. 3, No. 1, pp. 443-452.

Bessa, R. J., and Mato, M. A. (2011). Economic and technical management of an aggregation agent for electric vehicles: a literature survey. Euro. Trans. Electr. Power, Vol. 22, No. 3, pp. 334–350.

Fan, Z. (2012). A Distributed Demand Response Algorithm and Its Application to PHEV Charging in Smart Grids. IEEE Transactions on Smart Grid, Vol. 3, No. 3, pp. 1280-1290.

Galus, M. D., Zima, M. and Andersson, G. (2010). On integration of plug-in hybrid electric vehicles into existing power system structures," Energy Policy, Vol. 38, No. 11, pp. 6736–6745.

Green II, R. C., Wang, L. and Alam, M. (2011). The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook. Renew. Sustain. Energy Rev., Vol. 15, No. 1, pp. 544–553.

Hota, A. R., Juvvanapudi, M. and Bajpai, P. (2014). Issues and solution approaches in PHEV integration to smart grid. Renew. Sustain. Energy Rev., Vol. 30, pp. 217-229.

Hu, J., Si, C., Lind, M. and Yu, R. (2016). Preventing distribution grid congestion by integrating indirect control in a hierarchical electric vehicles' management system. IEEE Transactions on Transportation Electrification, Vol. 2, No. 3, pp. 290-299.

Kang, Q., Wang, J., Zhou, M. and Ammari, A. C. (2016). Centralized charging strategy and scheduling algorithm for electric vehicles under a battery swapping scenario. IEEE Transactions on Intelligent Transportation Systems, Vol. 17, No. 3, pp. 659-669.

Kempton, W., and Tomic, J. (2005). Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. Journal of Power Sources, Vol. 144, No. 1, pp. 280–294.

Liu, Z., Wu, Q., Huang, S., Wang, L., Shahidehpour, M. and Xue, Y. (2017). Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," IEEE Transactions on Smart Grid, vol. PP, no. 99, pp. 1-1.

MATLAB R2014a, MathWorks, Inc.

Pillai, J. R., Paul, T., Jan, M. and Bak-Jensen, B. (2012). Integration of Electric Vehicles in low voltage Danish distribution grids. In: Proceeding of Power and Energy Society General Meeting, 2012 IEEE, San Diego, CA, USA, 22-26.

Rahbari-Asr, N., Chow, M., Yang, Z. and Chen, J. (2013). Network cooperative distributed pricing control system for large-scale optimal charging of PHEVs/PEVs," presented at 39th Annual Conference of the IEEE on Industrial Electronics Society, Vienna, Austria, pp. 6148 – 6153.

Richardson, D. B. (2013). Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. Renew. Sustain. Energy. Rev., Nol. 19, pp. 247–254.

Rotering, N. and Ilic, M. (2011). Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets. IEEE Trans. Power Syst., Vol. 26, No. 3, pp. 1021-1029.

Rahbari-Asr, N. and Chow, M. (2014). Cooperative distributed demand management for community charging of PHEV/PEVs based on KKT conditions and consensus networks. IEEE Transactions on Industrial Informatics, Vol. 10, No. 3, pp. 1907 – 1916.

Richardson, P., Flynn, D. and Keane, A. (2012a). Local versus centralized charging strategies for electric vehicles in low voltage distribution systems. IEEE Transactions on Smart Grid, Vol. 3, No. 2, pp. 1020-1028, 2012.

Richardson, P., Flynn, D. and Keane, A. (2012b). Optimal charging of electric vehicles in low-voltage distribution systems. IEEE Trans. Power Syst., Vol. 27, No. 1, pp. 268-279.

Sundstrom, O. and Binding, C. (2012). Flexible charging optimization for electric vehicles considering distribution grid constraints. IEEE Transactions on Smart Grid, Vol. 3, No. 1, pp. 26-37.

Tushar, M. H. K., A. Zeineddine, W. and Assi, C. (2017). Demand-side management by regulating charging and discharging of the EV, ESS, and utilizing renewable energy. IEEE Transactions on Industrial Informatics, Vol. PP, No. 99, pp. 1-1.

Urkmez, A. and Nurettin, C. (2010). Determining spot price and economic dispatch in deregulated power systems," Mathematical and Computational Applications, Vol. 15, No. 1, pp. 25-33.

Zhang, X., Wang, Q., Xu, G., and Wu Z. (2014). A review of plug-in electric vehicles as distributed energy storages in smart grid. In: Proceeding of IEEE-ISGT Europe, Istanbul, Turkey, pp.1-6.

Zulpo, R. S., Leborgne, R. C. and Bretas, A. S. (2014). Optimal siting and sizing of distributed generation through power losses and voltage deviation. In: Proceeding of 16th International Conference on Harmonics and Quality of Power (ICHQP), Bucharest, Romania, pp. 871-875.