International Journal of Industrial Engineering
http://ijie.gjpublications.com/
Vol. 1, No.1, 2017. Page 22-31.
ISSN: 2456-8449.

Research Article

Minimizing Power Loss in V2G Integration using PSO based Aggregator

K. Kalaiselvi*, P. Renuga

Department of Electrical & Electronics Engineering, Thiagarajar College of Engineering, Madurai – 625015. India.

Corresponding author e-mail: kkseee@tce.edu

Abstract

Vehicle to Grid (V2G) is absolutely part of the budding smart grid technology. If the charging and discharging between electric vehicles (EV) and grid are not coordinated, it will either increase peak demand and leads to grid problems or affect the load pattern of electric vehicle. Also uncoordinated charging/discharging will increase the losses in the electrical network. For a full exploitation of V2G potentialities, the role of the aggregator is essential to create value to customers by offering services to the distribution system operator. In this paper, the authors propose evolutionary algorithms such as particle swarm optimization (PSO) and evolutionary particle swarm optimization (EPSO) for optimizing the control strategy of the aggregator to minimize the joule loss in the network. IEEE 33 bus radial distribution system is modeled in MATLAB environment to implement the V2G integration concept. It is found that the loss in the distribution system is minimized with the proposed optimization methods. Also it is identified from the results that, the EPSO provides better solution with satisfactory execution time for the proposed problem.

Keywords: Particle swarm optimization, EPSO, electric vehicle, V2G, distribution system.

Introduction

Electric vehicle (EV) numbers are expected to significantly increase in the coming years reflecting their potential to reduce air pollutants and greenhouse gas emissions. Charging such vehicles will impose additional demands on the electricity network but at same time EV's battery can be used as distributed resource for power grid during peak hours. The Vehicle-to-Grid (V2G) is a relatively new concept in smart grid context where by the electric energy stored in the EV battery can also be fed back to the power grid. The V2G structure has bidirectional energy flow. That is, energy flows from electrical vehicles to grid and grid to electric vehicles. Utility grid operators can communicate with the plugged-in vehicles via communication link established. Utility can buy energy from the vehicle owners when it is required during peak hours and sell it back when demand is low during off peak hours. Therefore, if the charging or discharging pattern between EVs and grid is not coordinated, it will increase peak hour load and leads to local distribution grid problems such as extra power losses and voltage deviations. Intern, it will lead to overloading of distribution transformers and cables, increased power losses, and reduction in grid reliability and cost. An experiment has been conducted in the 1,200 node test system in Western Australia [1] to study into impacts of random uncoordinated EV charging on transformers. A significant load surging and voltage deviations even under low EV penetrations are observed from the test results. An increase of load on transformers for EV penetrations from 17% to 31% showed a significant rise in transformer currents [2].

Similarly, another work done at Belgium shows voltage deviations close to 10% were reported for a 30% EV penetration during peak hours in the evening due to uncoordinated charging of EVs [3]. An increase in peak load by 7% at 30% penetration of EVs, and household peak load by 54% are reported in a test grid in Netherlands [4]. Due to 10% penetration of EVs, the peak demand has been increased by 17.9% and 20% penetration leads to a 35.8% increase in peak load for uncontrolled charging in the distribution system in UK [5].

Utilization of EVs for frequency control has been discussed by developing an optimal aggregator [6]. A similar work is found in [7], where integration of V2G in a Danish farm has

Received: 01.03.2017; Received after Revision: 03.03.2017; Accepted: 03.03.2017; Published: 06.03.2017

been discussed; however, more importance has been given to energy storage rather than the V2G concept in these papers. Besides, the model has been developed for a transmission network. Impact of EVs on the distribution grid and its analysis using load flow techniques has been studied in [8]. These works, however, have not used any controlled techniques for charging or discharging of EVs energy to the grid.

Whereas coordinated charging and discharging of EVs can optimize charging profile [9] and power demand and reduce daily electricity costs, voltage deviations, line currents and transformer load surges [10] and also it can flatten the voltage profile of a distribution node. While researchers have successfully analysed and demonstrated the vehicle charging/discharging behaviour for some extent, the real time implementation of the individual EV and their coordination with other EVs present in the nearby area for grid support still needs more consideration. It is identified from literature survey that many researchers have focused their attention on electric vehicles and the optimization of the V2G management in some extends. One of the authors [10] has maximized the average state of charge (SOC) of the electric vehicles. Some others have applied the V2G for arbitrage, trying to maximize the revenue for the single vehicle’s owner [11]. But most of the cases, they try to optimize one vehicle at a time. Hence we propose a methodology to optimize the behaviour of an electric vehicles suitably coordinated by an aggregator.

Here an aggregator [4] is used which will coordinate the transactions between the utility (grid) and the electric vehicles. Depending on the current scenario of grid conditions, the aggregator is capable for taking decisions of charging or discharging of EVs under its cluster. So in this scenario, a suitable optimization has to be done so that we can utilize the V2G topology efficiently. Hence, evolutionary algorithms such as particle swarm optimization (PSO) for optimizing the current in the distribution network during V2G integration is proposed in this paper. This work uses traditional PSO [12] and its one of the successful variants evolutionary particle swarm optimization (EPSO) [13] for optimizing the control strategy of the aggregator that reduces joule losses in the network by then reduces the energy cost. The state of charge (SOC) of the EVs battery, EV availability, grid voltage etc. is considered while optimizing the aggregator’s control strategy.

Problem environment

According to necessity of the distribution network and the electric vehicles energy is transported from vehicle to grid or vice versa. In general, the electric vehicles are considered as active loads and thus increase the demand on the electric grid during charging. Otherwise, it behaves like a generator when operating in regeneration mode. Hence it is important to study the impact of EVs when operating in both charging and discharging modes. The impact is expected to be significant in future due to the high energy capacity and mass deployment of electric vehicles. The resultant effects will definitely dictate the design of the electric vehicle interface devices and the way future power networks will be designed and controlled.

Intelligent recharge stations are needed in order to avoid massive capital expenditures for new infrastructures experienced by customer and utility. Smart recharge station is fully integrated within the emerging technology of smart grid and thus allows communicating with the EVs connected to public or private recharge points. The EV battery regeneration can be slowed down or postponed to less critical hours or boosted by implementing intelligently operated smart grid. For allowing EV owner to gather information on the EV charge level, hourly price of energy and to find the closest public charge service, an electric mobility manager (EMM) with web based graphic user interfaces are required. The EMM includes mobile communication devices such as smart phones, tablet computers, GPS navigation system etc. The complete integration of EMM within the smart grid will allow distribution system operator to compare the data from EVs with the current network status. And then, it helps to make the most effective actions to reduce losses and keep voltage within allowable boundaries. The actions includes charge limiting, power reduction, slowing down of the recharge process, and intelligent addressing of EV towards the less critical public charge stations.

To obtain the above, these charging and discharging rates have to be optimized. The input parameters to the parking lots are taken as the current state of charge (SOC) of each vehicle and the voltage profile at the node on which the parking lot is integrated with grid. A limited energy must be withdrawn from the electric vehicles batteries so that energy can be retrained in vehicles for the customer transportation usage. These limitations should not affect the benefits of vehicle to grid integration but it should enhance the performance of the electric vehicle. In other hand, the joule loss must be kept minimum by reducing the current flow. The proposed optimization scheme should be capable of producing a solution that has minimum charging/recharging necessity which intern reduces the burden of EVs by reducing joule loss.

Assumptions

A well-established smart grid infrastructure is assumed in the parking lot which is capable of communicating with electric vehicle and the demand side management system. Number of EVs is assumed to be 60 and capacity is 600 Ah and electric vehicles are connected between 5 P.M to 9 A.M, a period of 16 hours. The state of charge of batteries is considered randomly. A lot of things need to happen for V2G topology to be put into practice. It depends on the following assumptions for practical implementation.

- The population (market share) of electric vehicles will be very high.
- The vehicles will be EVs or PHEVs which normally have high capacity (20kWh to 50kWh) batteries, not HEVs which have much smaller (less than 2kWh) batteries.
- Commuters will arrive at work with sufficient charge left in their batteries to make the idea feasible; otherwise they must specify oversize batteries which are already very expensive.
- Users will need to specify suitably equipped vehicles and to install intelligent charging stations at home.
- Sufficient EV and PHEV owners will actually sign up to use the system.

PSO for V2G integration

Particle swarm optimization

Particle swarm optimization (PSO) algorithm is a kind of heuristic global optimization technology and comes under the division of swarm intelligence methods and also one of the nature intelligence based algorithm. PSO algorithm works by flying a population of co-operating potential solutions called particles in a problem's solution space. This method has been developed through a simulation of simplified social models like flocks of birds or schools of fish. The main advantage of PSO is its simplicity, while being capable of delivering accurate results consistently. It is fast and also very flexible, being applicable to a wide range of problems, with limited computational requirements. For these reasons, the present work focuses metaheuristics optimization approaches namely PSO and EPSO, applied to the V2G integration including charging and discharging of EVs to minimize energy loss through an aggregator which integrates EVs and grid.

Objective function

The purpose of aggregator is to coordinate the charge and discharging needs of all the vehicle's batteries in order to minimize the losses and also to meet customer needs. Mathematically the problem is expressed by (1).

$$\text{Min } L=\sum_{h=1}^{N_h}[\, I_{load}(h) \sum_{j=1}^{N_{EV}} I_{EV,j}(h)]^2 \qquad (1)$$

Subjected to,

$$E_{min,j} \le E_{j,h} \le E_{max,j} \quad h= 1,\dots, N_h \text{ and } j= 1,\dots N_{EV} \qquad (2)$$

$$[E_{j,h} - E_{j,h+1}] \le \Delta\, E_{max,j} \quad h= 1,\dots, N_h \text{ and } j= 1,\dots N_{EV} \qquad (3)$$

$$E_{j,h_d} \ge E_j^{requested} \quad h= 1,\dots, N_h \text{ and } j= 1,\dots N_{EV} \qquad (4)$$

Where,

$I_{load}(h)$ is expected current demand,

$I_{EV,j}(h)$ is charging or discharging current of j^{th} electric vehicle at h^{th} hour,

$E_{min,j}$ and $E_{max,j}$ are the minimum and maximum state of charge admitted,

$\Delta\, E_{max,j}$ is the maximum charge or discharge rate,

$E_j^{requested}$ is the minimum state of charge retained in the battery.

Penalty factor method

The violations of the constraints are to be incorporated into the objective function using penalty factor method. The penalty factor method can be explained as (5),

Min f(*x*) (5)

Subject to,

$c_i(x) \geq 0 \ \forall_i \in I$ (6)

This problem can be solved as a series of unconstrained minimization problem.

Min $\phi_k(x)$ = f(x) + $\sigma_k \sum_{i \in I} g(c_i(x))$Where, $g(c_i(x)) = \min(0, c_i(x))^2$ (7)

In the above equations, $g(c_i(x))$ is the penalty function while σ_k are the penalty coefficients. In each iteration *k* of the method, we increase the penalty coefficient σ_k (e.g. by a factor of 10), solve the unconstrained problem and use the solution as the initial guess for the next iteration. Solutions of the successive unconstrained problems will eventually converge to the solution of the original constrained problem.

Case study

Distribution system model

In this work, to implement the vehicle to grid integration concept, IEEE 33 bus system is modeled using MATLAB. This is an IEEE recommended balanced distribution systems, it includes 32 section branches. Figure 1 shows the IEEE 33 bus radial distribution system.

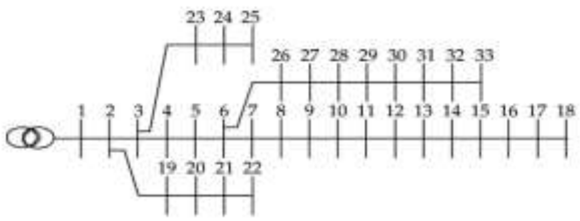

Figure 1. IEEE 33 bus radial distribution system

The current at the nodes of the above network can be computed using the main sweep algorithm. The approach begins with the assumption of flat voltage start at all nodes. The node current injections, line-charging current and main branch currents are evaluated using (8) to (10). The node voltages are evaluated using (11). The node voltages evaluated are compared with the previous values of node voltages. If the differences in the node voltages between successive iterations are not within the specified tolerance then the above procedure is repeated until convergence in node voltages. The step by step procedure of main sweep algorithm as follows,

Current injection at any node n can be written as,

Ln=S_n^*/V_n^* (8)

Where n = 1, 2, ….n

Line charging current at any branch b can be written as,

$I_{cb} = 1/2 y_b V_b + y_b V_{b+1}$ (9)

Where b = 1,2,….. V_b, V_{b+1} are the node voltages at node b and b+1 respectively. y_b = line charging admittance of branch b.

Branch current in any branch b in the main line can be written as,

$I_b = I_{b+1} + I_{L(b+1)} + I_{cb} + \sum_{l=1}^{N_l} I_{bl,l}$ (10)

Where b = 1, 2, ….(en_M-1) and l = 1, 2, ….N_l

Voltage of any node n is given by,

V= $V_{n-1} - I_b Z_b$ (11)

Where V_{n-1} = Voltage at (n-1)th node I_b = Current in the branch b and Z_b = Impedance of the branch b

Voltage profile of the distribution system

By using the main sweep algorithm, the node voltages and main line currents are obtained and tabulated. Table 1 shows the node voltage for all 33 nodes present in the network. It is observed that the voltage at 18th, 17th, 16th nodes are 0.9038 pu, 0.9044 pu and 0.9064 pu respectively and which are less comparatively to the other nodes in the network. So it is decided to place the electric vehicles in these nodes as a source of power.

Table 1. Node voltages for 33 bus radial distribution system

Bus No.	Bus Voltage (pu)	Bus No.	Bus Voltage (pu)	Bus No.	Bus Voltage (pu)
1	1.000	12	0.9177	23	0.9793
2	0.9970	13	0.9115	24	0.9726
3	0.9829	14	0.9093	25	0.9693
4	0.9754	15	0.9078	26	0.9475
5	0.9679	16	0.9064	27	0.9450
6	0.9495	17	0.9044	28	0.9335
7	0.9459	18	0.9038	29	0.9253
8	0.9323	19	0.9965	30	0.9218
9	0.9260	20	0.9929	31	0.9176
10	0.9201	21	0.9922	32	0.9167
11	0.9192	22	0.9916	33	0.9164

Table 2. Current at low voltage nodes

Time	18^{th} Node	17^{th} Node	16^{th} Node
1	78.79	21.7594	36.769
2	102.52	22.0081	39.2937
3	111.427	26.68	64.031
4	131.103	31.622	56.32
5	122.1965	29.12	50
6	111.427	26.68	64.031
7	96.66	20.8806	36.055
8	74.3236	14.6379	22.803
9	60.926	10.853	15.14248
10	52	8.5465	10.81
11	52	8.5465	10.81
12	64.62	12.01886	17.3307
13	96.66	20.8806	36.055
14	111.427	26.68	64.031
15	122.1965	29.12	50
16	102.52	22.0081	39.2937

Current profile of the distribution network

Load patterns are assumed between the hours 5 PM to 9 AM and the corresponding current during these intervals is calculated and given in Table 2. Using main sweep algorithm, current values are obtained as 78.79A, 21.7594A and 36.769A at 18^{th}, 17^{th}, 16^{th} nodes respectively.

Results and discussion

The grid current pattern of distribution network before optimization is shown in Figure 2. This current is to be optimized such a way that the grid current variation is minimized and reduce the net current so that the joule losses are reduced. Optimization is to be done with an addition of 60 numbers of EV's with 600 Ah capacity.

SOC profile with PSO

The different SOC profiles obtained after optimization by particle swarm optimization of the aggregator (Agg) is given in Table 3. Where, the initial SOC is 0.2 and the final SOC is 1.0 and it is inferred from Table that constrains of minimum and maximum SOC level to be maintained and change of SOC between two intervals (that is 0.2) is satisfied.

The Figure 3 shows the SOC pattern of the Electric vehicle for the three aggregators and for the 16 intervals by using PSO. It shows the variable SOC according to the demand of the grid and time of integration.

Table 3. SOC Profile obtained as a result of PSO

Interval	Agg1	Agg 2	Agg 3
1	0.2	0.2	0.2
2	0.214	1	0.856
3	0.219	0.914	0.937
4	0.22	0.828	0.991
5	0.221	0.927	0.936
6	0.337	0.976	0.964
7	0.448	0.999	0.999
8	0.611	1	0.999
9	0.93	0.803	1
10	0.968	0.93	1
11	0.977	0.867	1
12	0.993	0.893	0.896
13	0.999	0.786	0.926
14	0.999	0.973	0.954
15	1	0.839	0.975
16	1	1	1

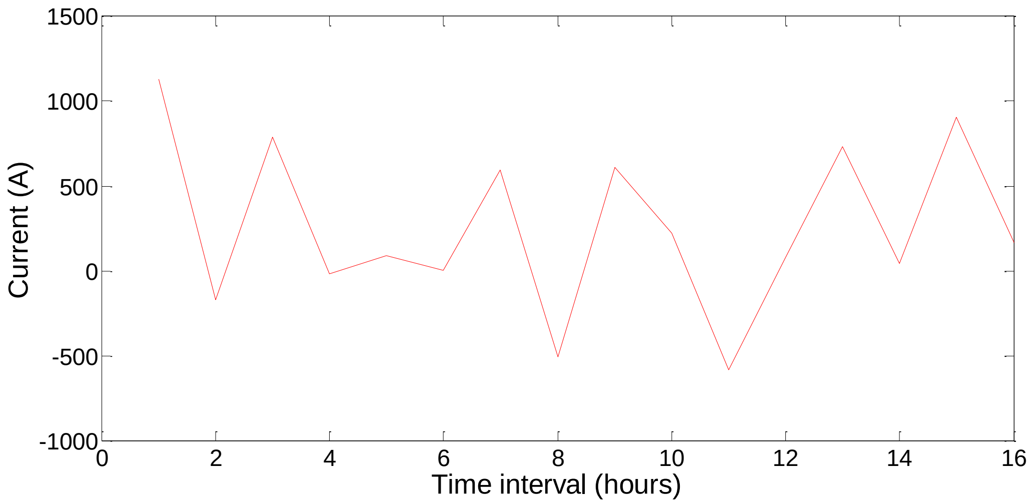

Figure 2. Grid current pattern before optimization

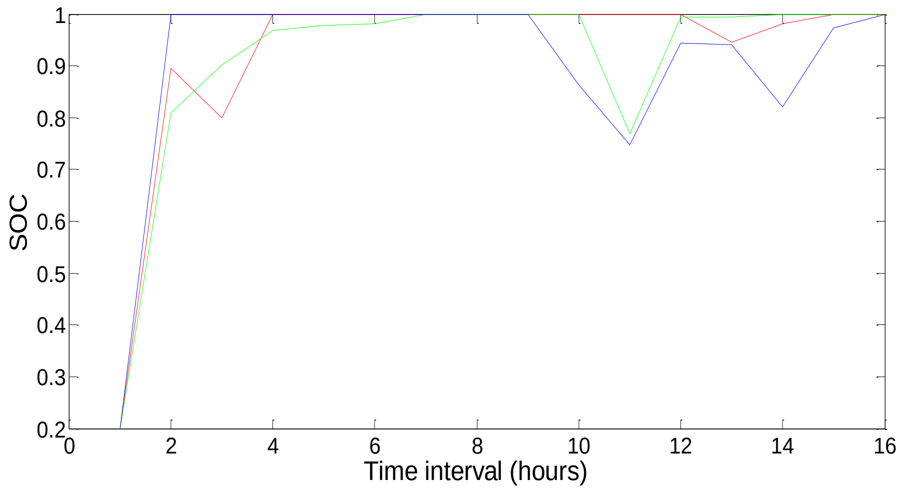

Figure 3. SOC Pattern of EV's obtained using PSO

Current pattern of aggregators with PSO

The Figure 4 shows the current pattern obtained as a result of PSO for the aggregator 1. Positive sign indicates charging and negative sign indicates the discharging currents to and from the electric vehicle to the distribution network. Similarly, the Figure 5 and 6 shows the current pattern obtained as a result of PSO for the aggregator 2 and aggregator 3 respectively. The Figure 7 shows the current profile after optimization. It is inferred that the current profile of the grid is optimized as compared to Figure 2.

SOC profile with EPSO

As explained earlier, the different SOC profiles obtained after optimization using EPSO of the aggregator is given in Table 4. The Figure 8 shows the SOC pattern of the EV for the three aggregators and for the 16 intervals obtained using EPSO. It shows the variable SOC according to the demand of the grid and time of integration.

Table 4. SOC profile as a result of EPSO

Interval	Agg 1	Agg 2	Agg 3
1	0.2	0.2	0.2
2	0.44	0.58	0.67
3	0.35	0.43	0.85
4	0.32	0.35	0.76
5	0.49	0.32	0.2
6	0.2	0.58	0.43
7	0.41	0.999	0.27
8	0.89	0.54	0.5
9	0.81	0.23	0.46
10	0.34	0.35	0.49
11	0.63	0.28	0.34
12	0.55	0.2	0.78
13	0.62	0.52	0.87
14	0.98	0.79	0.68
15	0.64	0.54	0.4
16	1	1	1

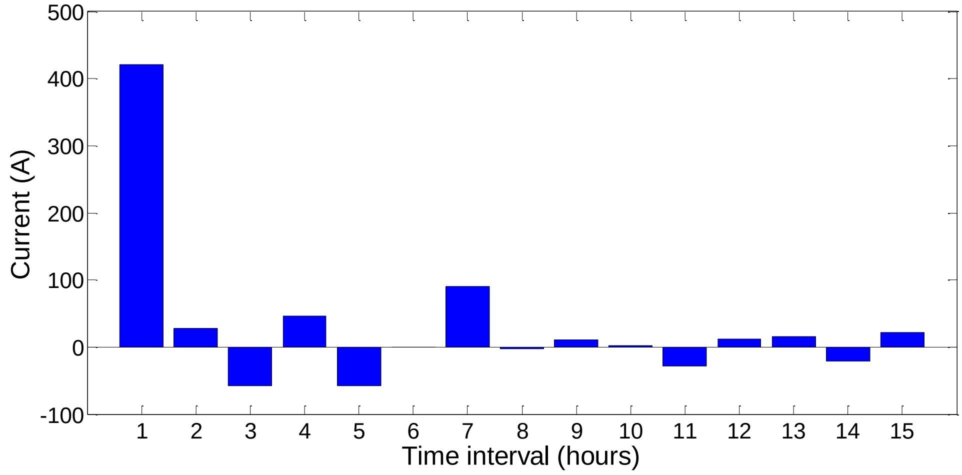

Figure 4. Current pattern of aggregator 1

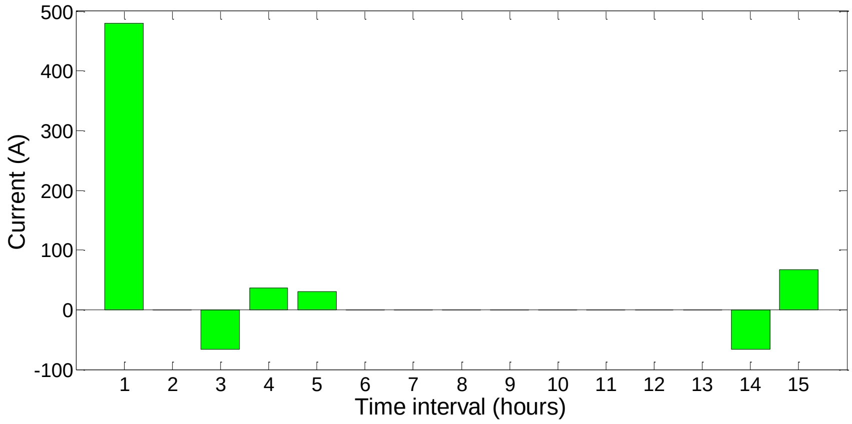

Figure 5. Current pattern of aggregator 2

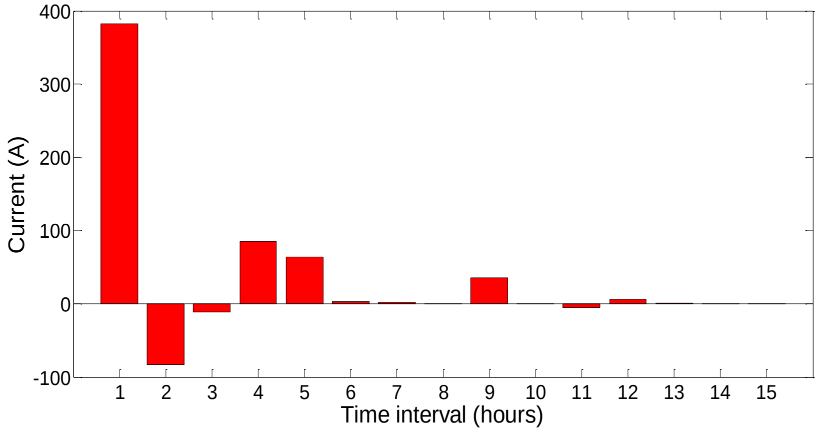

Figure 6. Current pattern of aggregator 3

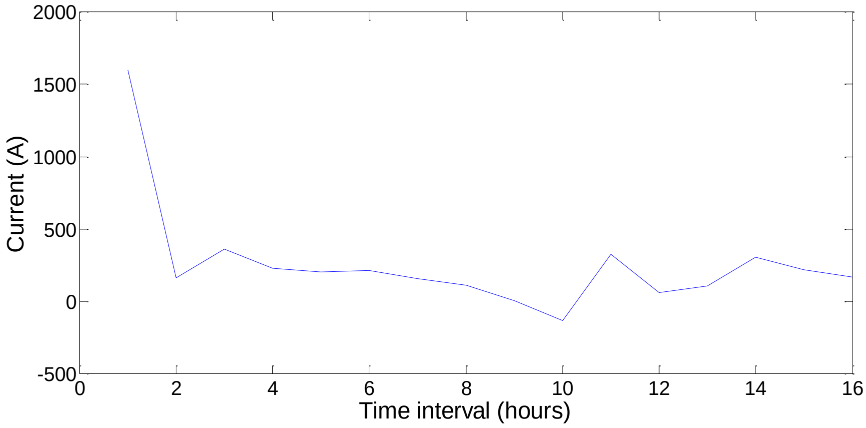

Figure 7. Current profile of the grid obtained using PSO

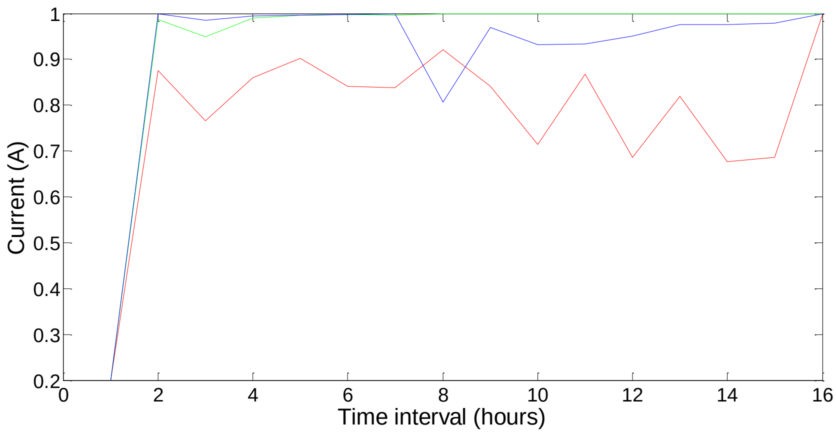

Figure 8. SOC pattern of EVs with EPSO

Current pattern of aggregators with EPSO

The Figure 9 shows the optimized current pattern obtained as a result of EPSO for the Aggregator 1. Positive sign indicates is charging and negative sign indicates the discharging currents to and from the electric vehicle to the distribution network. The Figure 10 and Figure 11 shows the optimized current pattern obtained as a result of EPSO for the aggregator 2 and 3 respectively. The Figure 12 shows the current profile after implementing EPSO. Current profile obtained with PSO and without optimization adopted also compared as shown in Figure 12. The conventional PSO stops at 300 iterations whereas EPSO stopped at 97 iterations.

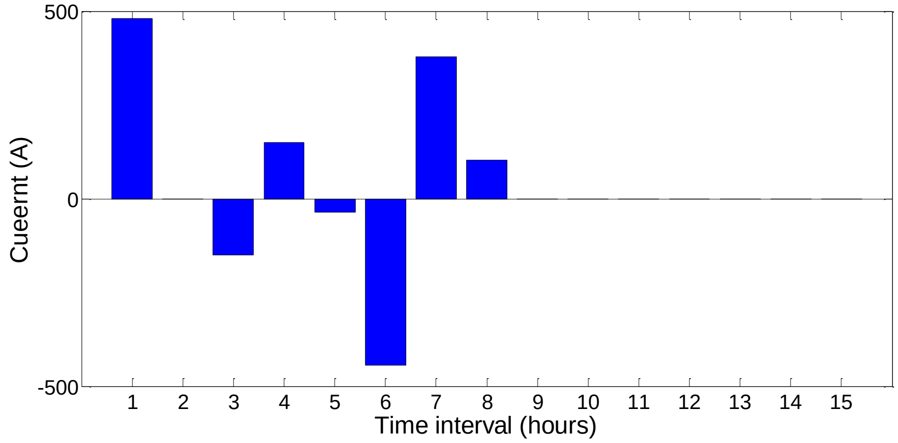

Figure 9. Current pattern of aggregator 1

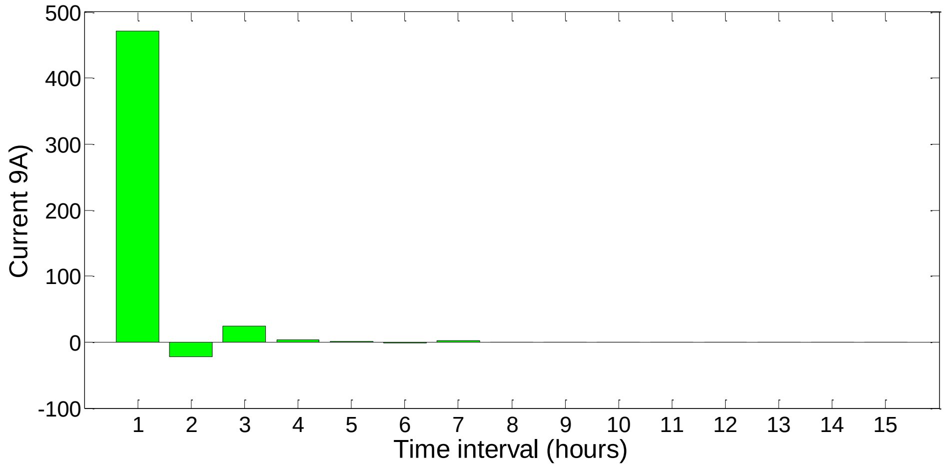

Figure 10. Current pattern of aggregator 2

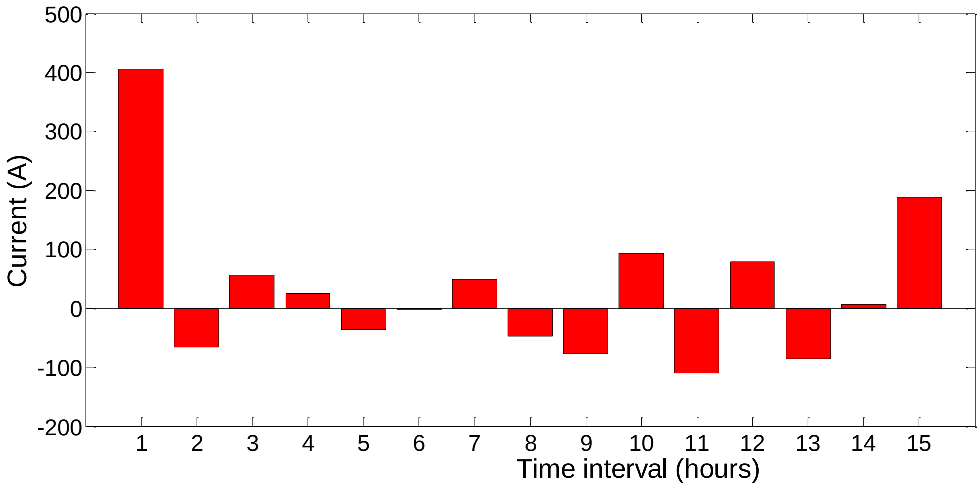

Figure 11. Current pattern of aggregator 3

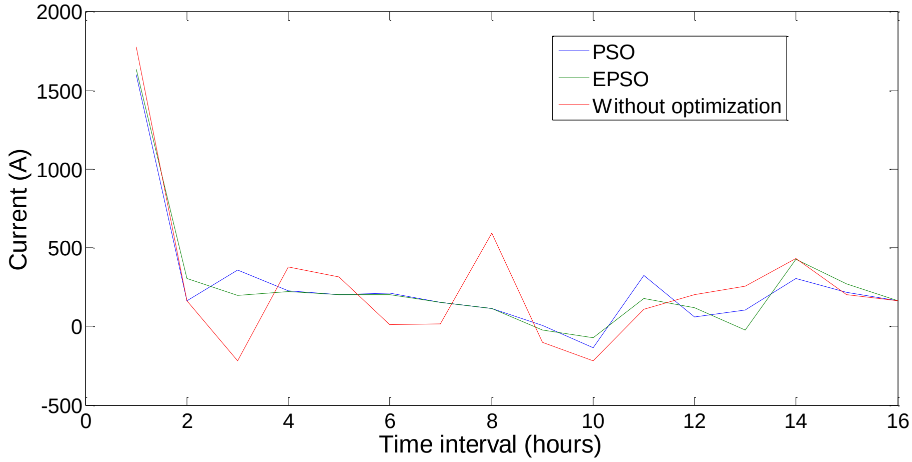

Figure 12. Current profile of the grid

Conclusions

In the paper, PSO based approaches were implemented to minimize the joule loss in V2G integration. The approaches are specifically evolutionary particle swarm optimization (EPSO) and the traditional PSO. The load current in the distribution network is normalized optimally by filling the valley and shaving the peak with the help of aggregators which is controlled by means of artificial intelligence methods. It can be inferred from the results that the losses in the distribution system is minimized with the proposed optimization methods. It is identified from the results that EPSO provides better solution with satisfactory execution time for the proposed problem.

Conflict of interest

Authors declare there are no conflicts of interest.

References

[1] Celli G, Ghiani E, Pilo F, Pisano G, Soma G G. Particle Swarm Optimization for Minimizing the Burden of Electric Vehicles in Active Distribution Networks. Proc. of IEEE Power and Energy Society General Meeting. 2012, pp. 1-7.

[2] Clement-Nyns K, Haesen E, Driesen J. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Trans Power Syst. 2010;25:371–380.

[3] Chenrui J, Jian T, Prasanta G. Optimizing Electric Vehicle Charging With Energy Storage in the Electricity Market. IEEE Transactions on Smart Grid. 2013;4:311-320.

[4] Deilami S, Masoum AS, Moses PS, Masoum MAS. Real time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. IEEE Trans. Smart Grid. 2011;2:456–467.

[5] Han S, Han S, Sezaki K. Development of an optimal vehicle-to-grid aggregator for frequency regulation. IEEE Trans Smart Grid. 2010;1:65–72.

[6] João S, Hugo M, Zita. Particle Swarm Optimization Based Approaches to Vehicle-to-Grid Scheduling. Proc. of IEEE Power and Energy Society General Meeting. 2012. pp. 1-8.

[7] Jinghong Z, Xiaoyu W, Kun M, Chun Z, Shouzhen Z. Aggregation Model-Based Optimization for Electric Vehicle Charging Strategy. IEEE Transactions on Smart Grid. 2013;4:1058–1066.

[8] Masoum MAS, Moses PS, Hajforoosh S. Distribution transformer stress in smart grid with coordinated charging of plug-in electric vehicles. Proc. Rec. IEEE Power Energy Syst. Innovative Smart Grid Tech. Conf. 2012. pp. 1-8,

[9] Moses PS, Masoum MAS, Hajforoosh S. Overloading of distribution transformers in smart grid due to uncoordinated charging of plug-in electric vehicles. Proc. Rec. IEEE Power Energy Syst. Innovative Smart Grid Tech. Conf. 2012. pp. 1-6.

[10] Pillai JR, Jensen BB. Integration of vehicle-to-grid in the western Danish power system. IEEE Trans. on Sustainable Energy. 2011;2:12-19.

[11] Singh M, Kar I, Kumar P. Influence of EV on grid power quality and optimizing the charging schedule to mitigate voltage imbalance and reduce power loss', Proc.

14th Int. Proc. Power Electron. Motion Control Conf. 2010. pp. T2-196–T2-203.

[12] Vinoth Kumar M, Selvan MP. A Simplified Approach for Load Flow Analysis of Radial Distribution Network', International Journal of Computer and Information Engineering. 2010;2:416–427.

[13] Vliet OV, Brouwerb AS, Kuramochi T, Broek M, Faaij A. Energy use, cost and CO2 emissions of electric cars. Journal of Power Sources. 2011;196:2298–2310.

[14] Wenbo S, Wong VWS. Real time vehicle-to-grid control algorithm under price uncertainty. Proc. IEEE Smart grid communication. 2011. pp.261-266.

[15] Wencong S, Mo-Yuen C. Performance Evaluation of A PHEV Parking Station Using Particle Swarm Optimization. Proc. of IEEE Power and Energy Society General Meeting. 2011. pp.1-6.

[16] Zhou X, Wang G, Lukic S, Bhattacharya S, Huang A. Multifunction bi-directional battery charger for plug-in hybrid electric vehicle application. Proc. IEEE Energy Conversion Congress Expo. 2009. pp. 3930–3936.

****

