ELM-ANFIS BASED CONTROLLER FOR PLUG-IN ELECTRIC VEHICLE TO GRID INTEGRATION

Kalaiselvi KANDASAMY[1], Renuga PERUMAL[2], Suresh Kumar VELU[3]

[1]Research Scholar and [2,3]Associate Professor
Department of Electrical and Electronics Engineering,
Thiagarajar College of Engineering, Madurai – 625 015, Anna University, Tamil Nadu, India
Email: kkseee@tce.edu, preee@tce.edu, vskeee@tce.edu

Abstract: *In this paper, the authors propose adaptive neuro fuzzy inference system (ANFIS) algorithm, based on extreme learning machine (ELM) concepts for designing a controller for electric vehicle to grid (V2G) integration. First, learning speed and accuracy of the proposed algorithm is checked and second the transient response of the ELM-ANFIS (e-ANFIS) based controller is analyzed. The proposed new learning technique overcomes the slow learning speed of the conventional ANFIS algorithm without sacrificing the generalization capability. Thus, even with an involvement of a large number of plug-in hybrid electric vehicles (PHEV), a control technique for their charge and discharge pattern can be easily designed. To study the computational performance and transient response of the e-ANFIS based controller, it is compared with conventional ANFIS based controller. To implement the vehicle to grid integration concept, IEEE 33 bus radial distribution system is modelled in MATLAB environment.*

Keywords: *Grid integration, electric vehicle, distribution system, extreme learning machine, ANFIS.*

1. Introduction

Depletion of fossil fuel resource, climate change, and air pollution etc are all key public issues of the recent years. Particularly, the power generation and transportation sector raises these concerns as they are among the major consumers of conventional fossil fuels. A battery electric vehicle (BEV)/plug-in hybrid electric vehicles (PHEV) may seem to solve the problems on the transportation end [1]. However, the potential introduction of electric vehicles is seen by electricity utilities as an added load and EVs operating in the grid-to-vehicle (G2V) mode of operation can aggravate the peak hour demand issue. At the same time, the EVs can be operated in vehicle-to-grid (V2G) mode which may potentially contribute to backup power generation to meet out peak demand [2].

The V2G is a relatively new concept 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. Here an aggregator [3] is used which will coordinate the transactions between the utility 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 [4].

If the charging or discharging 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 [5]. An experiment has been conducted in the 1,200 node test system in Western Australia [6] 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 [5].

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 [7]. 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 [8]. 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 [9]. Another work presented in [10,11] also discussed the ill effects of uncontrolled charging and discharging.

Whereas coordinated charging and discharging of EVs can optimize charging profile and power demand and reduce daily electricity costs, voltage deviations, line currents and transformer load surges [5, 7] and also it can flatten the voltage profile of a distribution node [12]. Based on the above study, it is found that optimized charging and discharging pattern can reduce charging cost by about 51% for a single isolated EV and almost 40% for multiple coordinated vehicles when penetration is higher.

It is identified from literature survey that only modest work has been done on control aspect of electric grid and electric vehicles in the past. Utilization of EVs for frequency control has been discussed by developing an optimal aggregator [13]. A similar work is found in [14], where integration of V2G in a Danish farm has been discussed; however, more importance has been given to energy storage rather than the V2G concept. 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 [13,15]. These works, however, have not used any controlled techniques for charging or discharging of EVs energy to the grid. 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 [16,17]. Therefore a novel method for load management is proposed in this paper for coordinating the charging of multiple plug-in electric vehicles.

In this paper, the authors have proposed the concept of a charging station to support the grid in terms of valley filling and peak shaving through an aggregation of EVs. A novel e-ANFIS [18] based controller has been developed in this work to control the energy flow between EVs and grid for voltage compensation and peak shaving. Based on the concept of extreme learning machine (ELM) [19, 20], the new e-ANFIS learning algorithm is developed. The proposed new learning technique overcomes the slow learning speed of the conventional learning techniques [21] like neural networks and support vector machines without sacrificing the generalization capability. Thus, even with an involvement of a large number of EVs, a control technique for their charge and discharge rates can be easily designed.

Two controllers, namely charging station controller and V2G controller are designed here. The main purpose of the V2G controller is to control the power flow between the concerned nodes and the charging station and charging station controller will decide on the individual participation of the EVs for charging or discharging.

The organization of the paper is as follows. Following the introduction, modelling of the distribution system is provided in Section II. Section III presents the problem definition for the voltage imbalance as well as for the grid support. Section IV and V presents the ANFIS and e-ANFIS used for the V2G control technology respectively. In Section VI, computer simulation is performed to prove the effectiveness of the suggested method and results are analyzed. Finally, conclusions are drawn in Section VII.

2. System model

The components and power flow of a proposed V2G system are represented in Figure 1. There are two controllers namely charging station controller (CSC) and vehicle to grid (V2G) controller. The V2G controller is connected to a particular node of the distribution system. IEEE 33 bus radial distribution system is considered in this work. In general, EVs with V2G interfaces can charge or inject energy into the grid when parked and connected. In general, power flow and communications are bidirectional to report battery status and node voltage level.

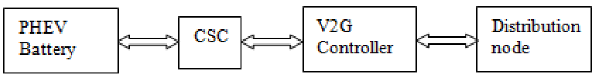

Figure1 Block diagram of V2G system

2.1 IEEE bus system

To implement the vehicle to grid integration concept, IEEE 33 bus system is modelled in this work. This is an IEEE recommended balanced distribution systems, it includes 32 section branches, nominal voltage of 12.66kV, total real and reactive power losses are 3.72MW and 2.3 MVAr respectively and corresponding losses are

5.95% and 6.53%. The system is assumed to be a balanced three phase system.

The network diagram is shown in Figure 2 and distribution system voltage profile is given in Table 1. From the table, it is clear that the last three nodes (nodes 16, 17, 18) of the radial sub feeder are more susceptible to voltage instability as compared to other nodes. Hence it is decided to provide compensation in the last node of the radial sub feeder (node 18).

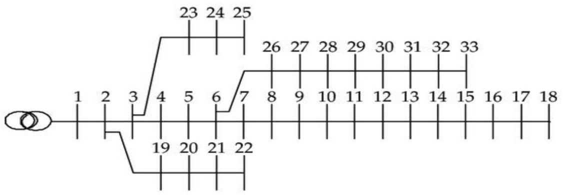

Figure 2 IEEE 33 bus radial distribution system

Table 1
IEEE 33 bus radial distribution system voltage profile

Bus No.	Voltage (pu)	Bus No.	Voltage (pu)	Bus No.	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

2.2 Charging station controller

Here two controllers are used namely charging station controller and V2G controller as shown in Figure 3. Individual participation of EVs charging and discharging is decided by charging station controller (CSC) and the V2G controller will be at distribution node level. The present node voltage of the grid and individual vehicle battery's SOC are input parameters to the CSC. State of charge (SOC) is the percentage of charge remaining in the vehicle's battery when they arrive.

The SOC of the electric vehicle can be determined based on km driven and the all-electric range (AER) of the EV [4]. The SOC is expressed as a percentage of the total charge available. For example, the SOC of a vehicle driven by x km is calculated using (1) when the fully charged PHEV-y drives 'y' km on electricity.

$$SOC = \begin{cases} 100\left(\dfrac{y-x}{y}\right); x \le y \\ 0; x > y \end{cases} \tag{1}$$

Where y is AER of the EV and x is the total distance driven by the vehicle. CSC will output the total energy available for grid support from charging station based on each and every vehicle's SOC and the present grid conditions. In this case, the energy will flow from EV to grid for positive energy output and energy will flow from grid to EV in other case. This positive or negative sign energy output is needed depends on whether the node voltage requires to be increased or decreased.

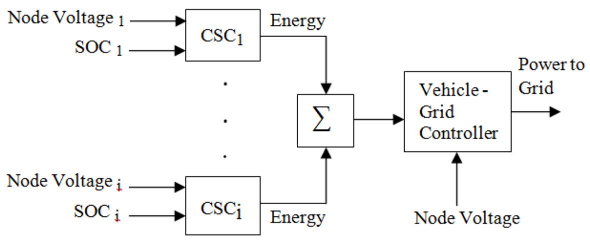

Figure 3 CSC and V2G controller

2.3 Vehicle to grid (V2G) controller

Depending on the energy output information from the CSC, the V2G controller decides the amount of power flow to and from the node on which the charging station has been placed. The output of the V2G controller, as shown in Figure 3 is connected to node for controlling the power flow between EVs and the grid. This node is the ultimate node of interest for voltage support and peak load management. It is assumed that the output power notation is positive when the EV's discharges power to grid and it is negative when EV's charges energy from grid.

2.4 EV's battery model

The objective of this work is to establish coordination of charging and discharging between electric vehicles and electric grid. Hence loss of the battery and cyclic efficiency due charging and discharging is not considered here. It is assumed that the SOC level of the battery is constant when it is ready to discharge into the grid or vice versa. That is, the voltage deviation with respect to SOC of the batteries is not considered.

3. Problem description

Load of the distribution system varies according to the time. There are different loading patterns like peak load, off peak load and base load. Base load is characterized by industrial load which is 'on' most of the day so consumption is constant but domestic loads are variable according to time, so load profile also varies. These variations in the load affect the voltage profile. The impact of EVs on voltage profile can be evaluated by comparing changes in power grid characteristics with or without extra load due to the EVs charging demand. For radial distribution system shown in Figure 2, a simple feeder line power flow is formulated as given in equation (2-4).

$$P_i = P_{i+1} + P_{Li+1} + R_{i,i+1}\left[\frac{P_i^2 + Q_i^2}{|V|_i^2}\right] \tag{2}$$

$$Q_i = Q_{i+1} + Q_{Li+1} + X_{i,i+1}\left[\frac{P_i^2 + Q_i^2}{|V|_i^2}\right] \tag{3}$$

$$|V|_{i+1}^2 = |V|_i^2 - 2(R_{i,i+1}P_i + X_{i,i+1}Q_i) + (R_{i,i+1}^2 + X_{i,i+1}^2)\left[\frac{P_i^2+Q_i^2}{|V|_i^2}\right] \tag{4}$$

Where Qi and Pi are reactive and active power flowing in the line from bus i. QLi and PLi are the reactive and real power loads at bus i. The reactance and resistance of the line between i and i+1 are expressed as Xi, Xi+1. These load flow is executed for IEEE 33 bus distribution test system for the 18th node where the real power is 90MW and the reactive power is 40 MVAr, voltage is 0.9038 pu and the voltage drop is about 0.0962 pu. Hence 18th node has highest voltage drop when compared all other branches. Electric vehicle is integrated with the grid and the change in voltage is formulated as given in equation (5) [5].

$$\nabla V_{EV} = \frac{P_{EV} r_i + Q_{EV} x_i}{V_i} \tag{5}$$

It is identified from above equations that bus voltage can be improved when EVs' battery is integrated with the grid. In this work, voltage profile at 18th node is analyzed since its voltage level is obviously worse than other nodes.

3.1 Assumptions

The ANFIS based V2G realization is designed at a system level. Power converters connected for charging and discharging the EVs is not modeled due to the large dynamics involved in the distribution system. EV battery efficiency, charging system, design of communication infrastructure and converters, economics, tariff rates have not been considered since the objective of this work is only to focus on the design of controller based on E-ANFIS algorithm for the implementation of grid support by EVs.

4. ANFIS for V2G integration

The advantages of ANFIS architecture and its approximating capabilities with great accuracy have been proved already by Jang [21] and others. ANFIS is an adaptation and robustness method since it combines the advantages of ANN and FLC. Since both fuzzy logic and artificial neural network (ANN) have their relative advantages, a powerful processing tool with both advantages can be obtained by combining them together. This ANFIS incorporated the self-learning ability of artificial neural network with the linguistic expression function of fuzzy inference. By using a hybrid learning procedure, i.e., least square estimation and back-propagation, the ANFIS can construct an input-output mapping based on both human knowledge and stipulated input-output data pairs. ANFIS can be considered as an effective method for tuning the membership functions to minimize the measured output errors. Here, ANFIS architecture and its learning algorithm for the Sugeno fuzzy model are used. It is assumed that the FIS under consideration has two inputs *m* and *n* and one output *f*. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if / then rules can be expressed as:

Rule 1: If (m is A_1) and (n is B_1) then $f_1 = p_1 m + q_1 n + r_1$

Rule 2: If (m is A_2) and (n is B_2) then $f_2 = p_2 m + q_2 n + r_2$

-where x and y are crisp inputs and A_1, A_2, B_1 and B_2 are linguistic variables.

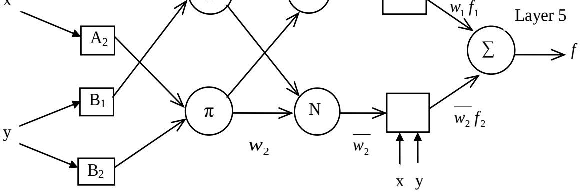

Figure 4 ANFIS architecture

There are five layers as shown in Figure 4, namely a fuzzy layer, a product layer, a normalized layer, a defuzzy layer and a total output layer in the

FIS architecture [21]. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt. The function of each five layer is given below.

Layer 1

Each node i in the layer 1 represents fuzzy membership function. The output of each node is given in (6) and (7).

$$O_j^1 = \mu_{A_i}(x); i = 1,2 \tag{6}$$

$$O_j^1 = \mu_{B_{i-2}}(y); i = 3,4 \tag{7}$$

So, the $O_j^1(x)$ is essentially the membership grade for x and y.

The membership functions could be anything but for illustration purposes bell shaped function is used as given in (8).

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{8}$$

where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2

Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades. For example, the product is shown in (9).

$$O_j^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y); \quad i = 1,2 \tag{9}$$

Layer 3

Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules as shown in (10).

$$O_j^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{10}$$

Layer 4

The nodes in this layer are adaptive and perform the consequent of the rules and it is performed based on (11).

$$O_j^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{11}$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5

There is a single node here that computes the overall output as shown in (12).

$$O_j^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{12}$$

ANFIS uses a two pass learning algorithm namely forward pass and backward pass. The ANFIS parameters are trained using the forward pass and backward pass alternatively. Forward pass is computed using LSE algorithm and backward pass is computed using gradient descent algorithm such as back propagation. So, the hybrid learning algorithm (HLA) uses a combination of steepest descent and least squares to adapt the parameters in the adaptive network. The gradient method has some disadvantages as explained in next section and hence new computation algorithm called E-ANFIS [18] is proposed in this paper for the effective implementation of V2G integration.

5. E-ANFIS

A novel extreme-ANFIS (e-ANFIS) learning algorithm is proposed based on the concept of extreme learning machine (ELM) [19,20]. The proposed algorithm helps to minimize learning time of ANFIS architecture. Conventional ANFIS introduced in [21] uses forward and backward pass, which is a combination of LSE and back propagation based on gradient descent method. In gradient method, the calculation of gradient is possible with differentiable membership functions only, over fitting, and an iterative method. Therefore it is time consuming. The proposed extreme-ANFIS learning algorithm [18] is simple and derivative-less algorithm which eliminates drawbacks of gradient based hybrid learning algorithm. The input weights and hidden biases are randomly generated instead of tuned in the case of ELM. Therefore determination of the output weights is as simple as finding the least square solution to any linear system. The proposed algorithm [18] is explained in section 5.1.

5.1 Algorithm

Let us assume training data scattered over the possible input range are presented for a particular problem as: [I_1 I_2 I_3 ….. I_n; f], where I_i, i=1, 2 … n are inputs and f is the corresponding output.

Step 1: Determine the range of every input to get the universe of discourse for input membership function as, $range_i = \max\{I_i\} - \min\{I_i\}$, where i=1, 2 … n is number of input and decide shape of membership function. And then, find the number of membership functions which represent linguistic partitions of universe of discourse. Bell shaped membership function is used here. The mathematical representation of bell shape membership function is given in (13) as,

$$\mu_{ij=}\frac{1}{1+\left|\frac{I_i - z_j}{x_j}\right|^{2y_j}} \qquad (13)$$

where μ_{ij} represents membership grade of i^{th} input and j^{th} membership function, x_j,y_j,z_j are position and shape deciding parameters. The z_j represents the center of j^{th} membership function, x_j decides half width of membership function, $y_j/2x_j$ represents slope at membership grade $\mu_{ij}= 0.5$.

Step 2: The premise parameters (x_j,y_j,z_j) values are generated randomly with some constraints on ranges of those parameters. These ranges depend on the number of membership functions used and size of universe of discourse. Assume there are m uniformly distributed membership functions with parameters (x_j^*,y_j^*,z_j^*) in universe of discourse. The random parameter selection formulae are as follows.

Step 3: Select x_j. The parameter x_j selects the width of membership function. The default value of parameter in uniformly distributed membership function is expressed as in (14).

$$x_j^* = \frac{range_i}{2m-2} \qquad (14)$$

The range of selection of random value x_j is given in (15) as,

$$\frac{x_j^*}{2} \le x_j \le \frac{3x_j^*}{2} \qquad (15)$$

Step 4: Select y_j. The parameter y_j with the help of x_j gives slop as $y_j/2x_j$. The default value of y_j in uniformly distributed membership functions is 2. The slight change in this value significantly changes the slop hence its range is limited within 1.9 to 2.1.

Step 5: Selection of z_j. The range for random value for center (z_j) of membership function is decided such that one center should not cross the center of consecutive membership function. The range of z_j selection is as given in (16).

$$\left(z_j^* - \frac{d_{cc}}{2}\right) < z_j < \left(z_j^* - \frac{d_{cc}}{2}\right) \qquad (16)$$

where z_j^* is center of uniformly distributed membership function, d_{cc} is distance between two consecutive centers of uniformly distributed membership.

Step 6: Determine final output f. The final output f becomes a simple linear combination of consequent parameters as shown in (17).

$$f = \sum_{k=1}^{m^n} \overline{W}_k \left(\sum_{i=1}^{n} R_{ki} I_i + Q_k \right) \qquad (17)$$

where k represents number of rule, m is number of membership function, n is number of inputs, m^n are the maximum number of rules, i represents number of input, I_i is a value of i^{th} input, R_{ki} and Q_k are consequent parameters corresponding to k^{th} rule and i^{th} input. Assume there are p number of training data pairs and then linear matrix of p equations are represented in (18) as,

$$F_{p\times 1} = \beta_{p\times m^n(n+1)} U_{m^n(n+1)\times 1} \qquad (18)$$

Where, F is output matrix of β weighted input parameter matrix and U is unknown consequent parameter matrix. This can be solved using LSE method (forward pass of hybrid learning algorithm).

Step 7: Run the algorithm for several times. Then find out the root mean square error (RMSE) in each iteration.

Step 8: Generate the FIS model. The flow chart is given in Figure 5.

5.2 E-ANFIS based CSC

Here two controllers are used namely charging station controller and V2G controller. Individual participation of EVs charging and discharging is decided by charging station controller (CSC) and the V2G controller will be at distribution node level as discussed in chapter 2. In this work, Sugeno type FIS is generated. First phase is to collect and load the data for each input and output pairs. It is considered that the distribution system node voltage and state of charge (SOC) as inputs and energy as output for the charging station controller (CSC). For vehicle to grid (V2G) controller, it is considered that the node voltage and energy which represents SOC of the battery as the inputs and power as the output.

As in the case of conventional ANFIS, training and testing of network is done here. Small portion of the extracted data is used for testing (10%) and remaining portion is used for training (90%). The training and testing data should match in a linear order so that the formed network will be correct. Then, these data are trained of the specified epochs (iterations). The proposed algorithm is run for several times and root mean square error in each epoch is determined and finally sugeno type FIS model is generated. The e-ANFIS algorithm is implemented in MATLAB and tested for time efficiency and accuracy. Similar to CSC, FIS structure is obtained for V2G controller as well. The membership functions are formed by proposed ANFIS itself and output is found to be accurate.

6. Results and discussion

The vehicle to grid interfacing system is modelled using MATLAB. It consists of a battery, power converter and other integrating devices. Converter is connected to distribution network and electric vehicles motor. The node voltage from distribution system and SOC of the electric vehicle's battery is given to charging station controller. The CSC will decide the output energy. The output of CSC and grid voltage is given as the input for vehicle to grid controller and it will decide the available or required power from the particular station. The transmission voltage is reduced to 11 KV from 120 KV and in distribution side the voltage is stepped down to 440V. From this 440V three phase line, a single phase 440V is taken for coordination of electric vehicle.

6.1 Simulation results

First, the performance of e-ANFIS algorithm is checked in off-line on the basis of time required to learn parameters from training data, training error and testing error. In the case of proposed algorithm, the time required for finding gradient and to upload premise parameters iteratively reduced which resulted in significant reduction in overall learning time since backward pass of hybrid learning algorithm (HLA) is completely eliminated in proposed algorithm. The learning speed is further improved due to perceptive assumption of random premise parameters in the form of membership functions which are spread throughout the universe of discourse of input variable and local mapping ability of FIS in the form of rule base.

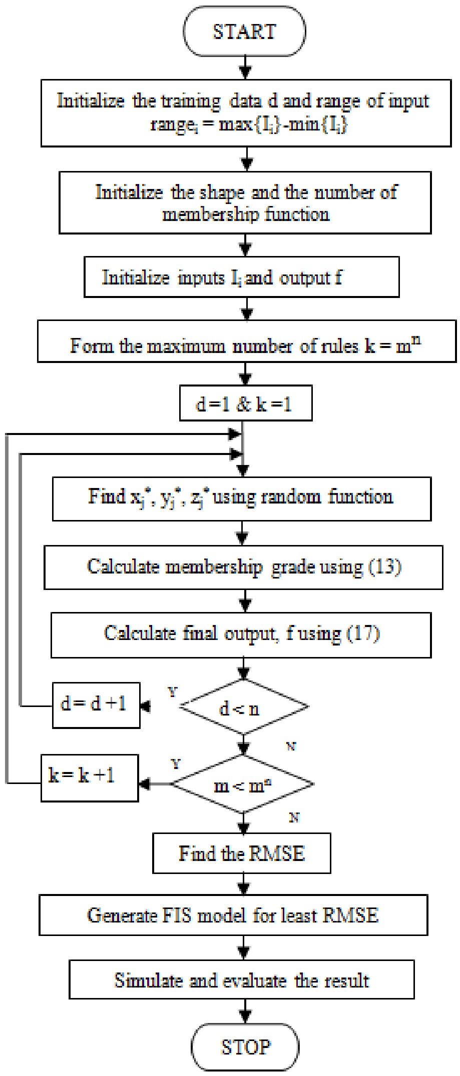

Figure 5 Flowchart

Also by eliminating differentiability constraint on membership function, the e-ANFIS algorithm improves the flexibility of ANFIS architecture. For modelling complex nonlinear system such as V2G integration, the reduction in step of learning algorithm allows ANFIS architecture to increase number of inputs and number of membership functions within required time constraints to improve accuracy. It is identified that the e-ANFIS algorithm is much simpler, faster and provides better generalization than conventional HLA. The performance results are given in Table 2. By taking average of nearly 50 trails, the learning time, training and testing error are presented in Table 2 for different membership function (MF) values.

Table 2
Performance analysis

Algorithm	No. of MF	Time (s)	RMSE in training	RMSE in testing
ANFIS	5	0.921	0.0443	0.056
	7	4.332	0.0041	0.053
	12	31.42	0.814×10^{-7}	0.058
e-ANFIS	5	0.672	0.0418	0.051
	7	1.088	0.0056	0.051
	12	2.230	0.45×10^{-12}	0.044

It is well known that accuracy increases with increase in membership function. Whereas, time to learn parameter increases with increase in membership function with conventional algorithm. But in the case of e- ANFIS, this negative feature is completely eliminated without disturbing generalization of conventional method and accuracy.

Second, simulation has been performed to check the coordination between PHEV and grid using e-ANFIS based controller. To study the performance of proposed controller, it is compared with conventional ANFIS based controller. These controllers are designed such that the EV will inject power to the grid during peak hours and accept the power during off peak hours when SOC of the battery is less than 50%. For grid charging, it is fixed that battery SOC level should be ≥ 50%. To check the transient performance of the controllers, the simulation study is carried out for 0.05 seconds. Since reactive power compensation is not considered in this work, the power factor is assumed to be constant during the study period. The grid voltage at 18th node in the distribution system is measured before discharging the EV's energy into the grid as shown in Figure 6.

It is observed that the node voltage is improved from 0.90 pu to 0.98 pu after discharging the EV's energy into the grid as shown in Figure 7. Next, power factor of 0.97 and 0.99 is considered and real power injection into the grid is analyzed. The node voltage is improved to 0.94 and 0.96 when power factor is 0.97 and 0.99 respectively as shown in Fig. 8 with e-ANFIS controller. The results clearly indicate that high power factor increases the amount of real power flow.

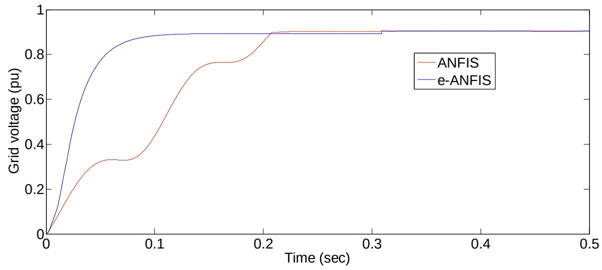

Figure 6 Grid voltage without EV's support

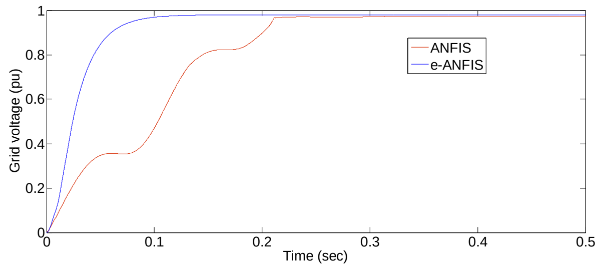

Figure 7 Grid voltage with EV's support

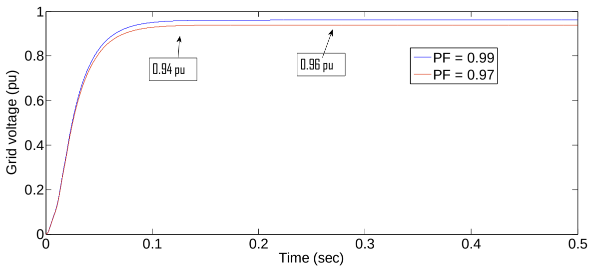

Figure 8 Grid voltage for different PF with e-ANFIS controller

Similarly charging pattern of EVs is analyzed e-ANFIS controller. Here the controller restricts the real power flow according to the distribution node voltage. The node voltage before and after charging of electric vehicle is shown in Figure 9. It clearly shows that distribution node voltage is reduced to 0.92 from 0.96 pu after charging the vehicles.

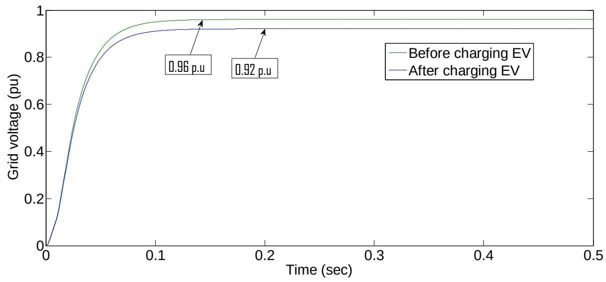

Figure 9 Grid voltage before and after discharging to EV

7. Conclusion

A coordinated charging and discharging between electric vehicle and grid is studied in this paper. e-ANFIS based controller is proposed in this paper to overcome the drawbacks of existing controllers in V2G integration. The controller is used to control the flow of energy between electric vehicles and grid to improve the stability. First, computational performance in term of accuracy and time efficiency of e-ANFIS algorithm is checked with conventional ANFIS algorithm and second, the transient response of the proposed e-ANFIS based controller is compared with conventional ANFIS based controller. It is identified that both the controllers can improve the grid stability by flattening the load profile but the transient response of e-ANFIS based controller is superior to conventional ANFIS controller. It is also found that learning speed of proposed e-ANFIS algorithm is greatly improved than conventional ANFIS algorithm without affecting accuracy and hence it is well suitable for modeling any nonlinear system.

Acknowledgement

The authors' thank University Grants Commission (UGC), New Delhi, India for supporting to carry out this research work under the grant: F1-17.1/2011-12/3157/SA-III.

References

[1] Shahidinejad, S. Filizadeh, and E. Bibeau : "Profile of charging load on the grid due to plug-in vehicles", IEEE Trans. on Smart Grid, Vol. 3, No. 1, (2012), pp. 135–141.

[2] J. Tomic and W. Kempton : "Using fleets of electric-drive vehicles for grid support", Journal. Power Sources, Vol. 168,(2007), pp. 459–468.

[3] David P. Tuttle, Ross Baldick : "The evolution of plug-in electric vehicle-grid interactions", IEEE Trans. on Smart Grid, 3:1,(2012), pp. 500–505.

[4] Ali Keyhani and Muhammad Marwali : "Smart Power Grids", Springer-Verlag Berlin Heidelberg, 2011.

[5] M. A. S. Masoum, P. S. Moses, and S. Hajforoosh : "Distribution transformer stress in smart grid with coordinated charging of plug-in electric vehicles", in Proc. Rec. IEEE Power Energy Syst. Innovative Smart Grid Technology Conf.,(2012), pp. 1-8.

[6] P. S. Moses, M. A. S. Masoum, and S. Hajforoosh : "Overloading of distribution transformers in smart grid due to uncoordinated charging of plug-in electric vehicles", in Proc. Rec. IEEE Power Energy System Innovative Smart Grid Technology Conf., (2012), pp. 1-6.

[7] K. Clement-Nyns, E. Haesen, and J. Driesen : "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid", IEEE Trans. Power System, Vol. 25, No. 1, (2010), pp. 371–380.

[8] O. Van Vliet, A. S. Brouwerb, T. Kuramochi, M. van den Broek, and A. Faaij : "Energy use, cost and CO2 emissions of electric cars", Journal of Power Sources, Vol. 196, (2011), pp. 2298–2310.

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

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

[11] S.Deilami, A. S. Masoum, P. S.Moses, and M. A. S. Masoum : "Real time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile", IEEE Trans. Smart Grid, Vol. 2, No. 3, (2011), pp. 456–467.

[12] D. Crabtree, T. Faney, K. Koudigkelis, A. Papavasiliou, I. Sidhu, P. Kaminsky, and B. Tenderich : "Optimal charging of electric vehicles," Centre for Entrepreneurship & Technology Technical Brief No. 2009.6.V.1.1(2009).

[13] S. Han, S. Han, and K. Sezaki : "Development of an optimal vehicle-to-grid aggregator for frequency regulation", IEEE Trans. Smart Grid, Vol. 1, No. 1, (2010), pp. 65–72.

[14] Jayakrishnan Radhakrishna Pillai, and Birgitte Bak-Jensen : "Integration of vehicle-to-grid in the western Danish power system", IEEE Trans. Sustainable Energy, Vol. 2, No. 1, (2011), pp. 12-19.

[15] M. Singh, I. Kar, and P. Kumar : "Influence of EV on grid power quality and optimizing the charging schedule to mitigate voltage imbalance and reduce power loss", in Proc. 14th Int. Power Electronics & Motion Control Conf. (EPE/PEMC), (2010), pp. T2-196–T2-203.
[16] Mukesh Singh, Praveen Kumar, and Indrani Kar : "Implementation of vehicle to grid infrastructure using fuzzy logic controller", IEEE Trans. Smart Grid, Vol. 3, No. 1, (2012), pp. 565-577.
[17] J. C. Ferreira, V. Monteiro, and J. L. Afonso : "Smart electric vehicle charging system", in Proc. IEEE Intelligent Vehicle Symposium (IV), (2009), pp. 758–763.
[18] P.Jagtap, G.N. Pillai : "Comparison of extreme-ANFIS and ANFIS networks for regression problems", Proc. IEEE International Advance Computing Conference (IACC), (2014), pp. 1190 – 1194.
[19] G.B.Huang, Q.Y.Zhu, C.K.Siew : "Extreme learning machine: theory and applications", Elsevier Journal on Neurocomputing, Vol.70, (2006), pp.489-501.
[20] Zhan-Li Sun, Kin-Fan Au, and Tsan-Ming Choi : "A neuro-fuzzy inference system through integration of fuzzy logic and extreme learning machines", IEEE Trans. on Systems, Man, and Cybernetics—Part B: Cybernetics, Vol. 37, No. 5, (2007), pp. 1321-1331.
[21] J.S.R. Jang : "ANFIS: Adaptive-Network-Based Fuzzy Inference System", IEEE Trans. Systems, Man, Cybernetics, Vol.23, No.(5/6), (1993), pp.665-685.