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Electric Grid and Vehicle Integration using ANFIS Controller in Smart Grid Context

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Abstract: *In this paper, implementation of adaptive neuro fuzzy inference system (ANFIS) based controller for vehicle to grid (V2G) and grid to vehicle integration (G2V) in smart grid context is analyzed. In the case of plug in hybrid electric vehicles, if the charging/discharging between vehicle and grid is 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 network. Therefore ANFIS based controller is designed and better control is achieved for the different conditions of electric vehicle's battery and the distribution network. It is proved that the proposed ANFIS based controller improves the grid stability by flattening the load profile and reduces power losses. It is also found that the transient response of the ANFIS based controller is better than fuzzy and PI controller. IEEE 33 bus radial distribution system is modeled in this work using MATLAB/SIMULINK to implement the V2G concept.*

Keyword: *Electric vehicle; Artificial intelligence; Fuzzy logic; ANFIS; Smart grid, Vehicle to grid;*

1. INTRODUCTION

Climate change, air pollution, and depletion of fossil fuel resource are all key public issues of the recent years. Both power and transport industries raises these concerns since they are the major consumers of conventional fossil fuels. To minimize the power consumption and to co-ordinate these two sectors, vehicle to grid (V2G) and grid-to-vehicle (G2V) concept are suggested [1-2] as part of smart grid. Power can be sent grid from the electric vehicle when there is a requirement during peak hours. Similarly, power can be sent back to vehicle during off peak hours/ as per vehicle's owner urgency. Therefore, aggregator [3] is necessary to coordinate electric grid and vehicles.

Sometimes it can lead to overloading of distribution transformers and cables, increased power losses, and reduction in grid reliability and cost, if there is no coordination between these two. A study [4] shows the impacts of random uncoordinated electric vehicle (EV) charging on transformers. Another paper 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. Netherlands [5] test system shows, an increase in peak load by 7% at 30% penetration of EVs, and household peak load by 54%. Similarly UK [6] system shows that, 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. Another work presented in [7] also discussed the ill effects of uncontrolled charging and discharging.

But, co-ordinated 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 . Also it can flatten the voltage profile of a distribution node [8]. It is identified 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 [9]. A similar work is found in [10], 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 [11]. These works, however, have not used any controlled techniques for charging or

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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 [12]. Therefore a novel method for load management is proposed in this paper for coordinating the charging of multiple plug-in electric vehicles.

Ferreira et al. 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. Fuzzy logic controller (FLC) and ANFIS based controller has been developed to control the energy flow between EVs and grid for voltage compensation and peak shaving. Fuzzy [13, 14] and Adaptive Neuro fuzzy system [15-17] control techniques have been used due to its linguistic representation of rules without having to develop a mathematical model of the system. 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.

2. PROBLEM FORMULATION

The proposed study model of V2G/G2V system which is one of the parts of smart grid is shown Fig. 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. EVs with V2G interfaces can charge or inject energy into the grid when parked and connected.

Figure1 Block diagram of V2G/G2V system

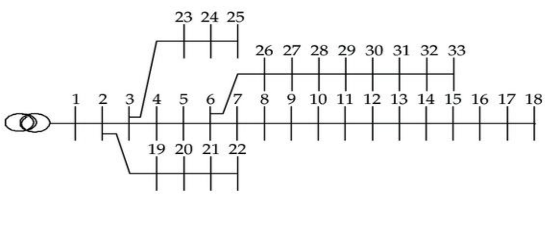

Figure 2 IEEE 33 bus system

IEEE 33 bus system is modeled in this work to implement the vehicle to grid integration concept. The bus diagram is shown in Fig. 2. Table I gives the distribution system voltage profile. 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. Therefore, voltage compensation is provided in the last node of the radial sub feeder.

TABLE I IEEE 33 BUS SYSTEM VOLTAGE PROFILE

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

2.1 Charging Station and V2G/G2V Controller

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. One case the energy will flow from EV to grid for positive energy output and energy will flow from grid to EV in other case. The V2G controller decides the amount of power flow to and from the node on which the charging station has been placed based on the energy output information from the CSC. The output of the V2G controller is connected to the distribution grid. This is the ultimate node of interest for voltage support and peak load management. Here, 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.

At a system level, the fuzzy based V2G/G2V controller is realized. Due to the large dynamics involved in the distribution system, power electronics associated with charging and discharging the EVs is not modeled. Similarly, other factors associated with vehicle's battery such as efficiency of vehicle's battery, charging/discharging system electronics, communication infrastructure, economics, tariff rates are not considered since the objective of this work is implementation of grid support.

3. FLC FOR V2G INTEGRATION

The objective of the work is to design fuzzy as well as ANFIS based controller for the better coordination between electric vehicle and grid to ensure voltage

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stability of the grid. Fuzzy logic theory is seen as one of the most successful of today's technologies for developing sophisticated control systems. The reason for which is very simple as it resembles human decision making with an ability to generate precise solutions from approximate information. Fuzzy design can accommodate the ambiguities of real-world human language and logic where as other approaches require exact equations to model real-world behaviors of the system. The fuzzy logic fills vital gap in engineering design methods left vacant by purely mathematical approaches and purely logic-based approaches.

TABLE II RULE BASE FOR CSC

V/SOC	EL	VL	L	M	H	VH	EH
EL	VPL	PL	PL	PH	VPM	PH	VPH
VL	VNL	PL	PH	VPM	PH	PH	VPH
L	NL	PL	PL	PL	PM	PM	VPM
M	NM	VPL	VPL	PL	PL	PM	PM
H	VNM	VNM	NM	NM	NL	NL	NL
VH	NH	NH	VNM	NM	NM	NL	VNL
EH	VNH	VNH	NH	VNM	NM	VNL	VNL

The CSC output (energy) is fuzzified into 12 fuzzy regions represented by linguistic variables and its membership function is shown in Fig. 4. Table II gives rule base for charging station controller. The charging station controller is used to determine the amount of energy available for grid support.

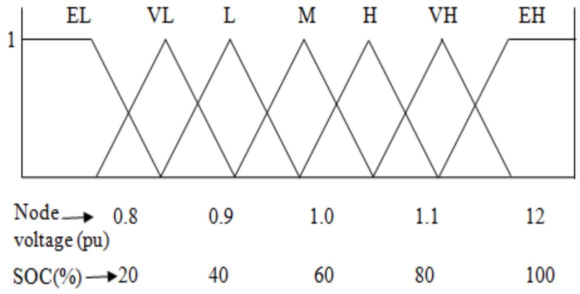

Figure 3 Member ship functions for node voltage and SOC

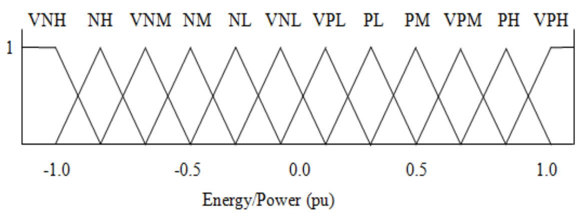

Figure 4 Membership function for energy and power output

This fuzzy logic based CSC takes two inputs as grid voltage and state of charge of battery (SOC). Depending on every vehicle's SOC and the present grid conditions, the CSC will output the total energy available for grid support from that charging station. Triangular membership function is used in this case to represent both input and output membership functions. The maxmin inference method is used for fuzzification and center of gravity method is used for defuzzification. Seven linguistic variables are used to describe node voltage and SOC and its membership function is shown in Fig. 3.

Energy available in charging station and grid voltage is the two inputs for vehicle to grid controller. Vehicle to grid controller tells about how much power we want to charge or discharge from each vehicle. Twelve linguistic variables are used to describe EV's output power and its membership function is shown in Fig. 4. The rule base for vehicle to grid controller is given in Table III.

TABLE III RULES FOR V2G CONTROLLER

E/V	EL	VL	L	M	H	VH	EH
VNH	VPL	PL	PM	VPM	PH	VPH	VPH
NH	VPL	PL	VPM	PH	VPH	VPH	VPH
VNM	VPL	PL	VPM	VPM	PH	VPH	VPH
NM	VPL	PL	PM	VPM	PH	VPH	VPH
NL	VPL	PL	PL	PM	PH	PH	VPH
VNL	VNL	PL	PL	PM	VPM	PH	PH
VPL	VNL	NL	NL	NM	VNM	PM	VPM
PL	VNL	NL	NL	NM	VNM	PM	VPM
PM	NH	NH	VNM	NM	VNL	VPM	VPM
VPM	VNH	VNH	NH	NM	PM	VPM	PH
PH	VNH	VNH	VNM	NM	VPL	VPL	VPL
VPH	VNH	VNH	NH	NL	VNL	VPL	VPL

4. ANFIS BASED CONTROLLER FOR V2G INTEGRATION

ANFIS is an adaptation and robustness method since it combines the advantages of ANN and FLC [16, 17]. 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 proposed ANFIS can construct an input-output mapping based on both human knowledge and stipulated input-output data pairs. In which, human knowledge can be transformed by using "If—then" rules since no standard methods for transforming human knowledge exist. 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 as-

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sumed 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 is expressed as:

Rule 1:If (m is A1) and (n is B1) then f1= p1 m+ q1 n +r1
Rule 2:If (m is A2) and (n is B2) then f2= p2 m+ q2 n +r2

Where p1, p2, q1, q2, r1 and r2 are linear parameters, and A1, A2, B1 and B2 non linear parameters (linguistic variables).

There are five layers, namely, a fuzzy layer, a product layer, a normalized layer, a defuzzy layer and a total output layer in the FIS architecture. Layer 1 is the fuzzy layer, in which m and n are the input of nodes A1, A2, B1 and B2 respectively. Where A1, A2, B1 and B2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. Layer 2 is the product layer that consists of two nodes and performs AND functions. The third layer is the normalized layer which function is to normalize the weight function. The nodes in the fourth layer are adaptive and perform the consequent of the rules. In fifth layer, there is a single node that computes overall output.

ANFIS uses forward pass and backward pass learning algorithm and its parameters are trained using the forward pass and backward pass alternatively. Forward pass and backward pass is computed using LSE algorithm and gradient descent algorithm, respectively. The hybrid learning algorithm uses a combination of steepest descent and least squares to adapt the parameters in the adaptive network.

Here two controllers are used namely charging station controller and V2G controller. Individual participation of EVs charging and discharging is decided by CSC and V2G controller.

4.1 ANFIS based CSC and V2G Controller

First-order sugeno inference system is used in this paper. Here, the distribution system node voltage and SOC are given as inputs. The energy is the output of the CSC. The data can be obtained from the formula or from the fuzzy logic rule viewer. The datum for loading ANFIS based CSC controller is obtained from fuzzy logic rule viewer. Next, 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), so that the back propagation neural network is generated. The ANFIS learning algorithm is composed of a forward pass and backward pass. In the forward pass, with fixed premise parameters, the least squared error estimate approach is employed to update the consequent parameters. In the backward pass, the gradient descent method is applied to fix the consequent parameters and to update the premise parameters. Premise and consequent parameters will be identified for MF and FIS by repeating the forward and backward passes. When input and output data are given, ANFIS creates a fuzzy inference system to which parameters of the membership functions are adjusted. Grid partition type is used for generating FIS and a back propagation type optimization method is used for training the data.

Finally, the ANFIS structure for CSC controller is obtained. It consists of seven membership functions and has an ability to produce output for highly nonlinear systems. The node voltage and energy which represents SOC of the battery are the two inputs to V2G controller and power is the output. V2G controller decides the required power level to charge or discharge from vehicles. FIS structure is obtained for V2G controller as well similar to CSC. The membership functions are formed by ANFIS itself and output is found to be accurate.

5. RESULTS AND DISCUSSION

MATLAB /SIMULINK model is used model the vehicle to grid interfacing system. All the components associated with the V2G/G2V integration system are also modeled. As explained in section 3.2, voltage from distribution system and SOC of the electric vehicle's battery is given to CSC. The level of output energy is calculated by ANFIS based CSC. Then, the outputs of CSC and grid voltage are given as the input to V2G controller.

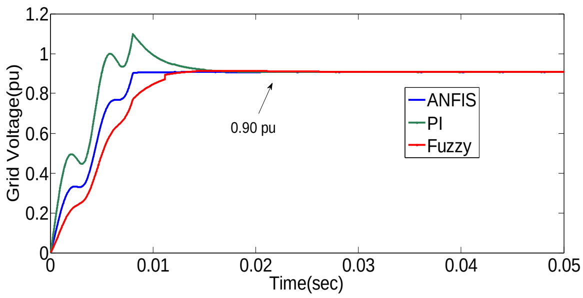

Figure 5 Grid voltage without EV's support

Again, the ANFIS controller will decide the available or required power from the particular station. Simulation has been performed to check the coordination between PHEV and grid. It is assumed that the battery SOC level should be ≥ 50% during grid charging. The FLC and ANFIS based controller is 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%. To check the transient performance of FLC and ANFIS based controller, the simulation study is carried out for 0.05 seconds.

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The grid voltage at 18th node in the distribution system is measured without EV's support as shown in Fig. 5. It is found that the transient response of the ANFIS based controller is better than other controllers including PI controller. 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 Fig. 6. Next, power factor of 0.93, 0.96 and 0.99 is considered and real power injection into the grid is analyzed.

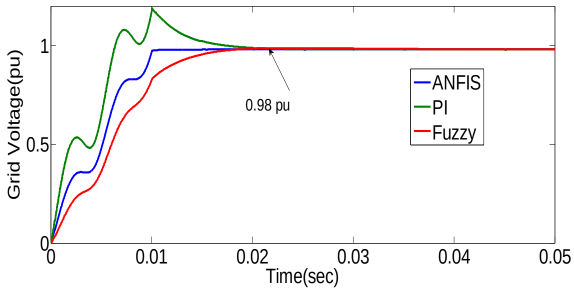

Figure 6 Grid voltage with EV's support

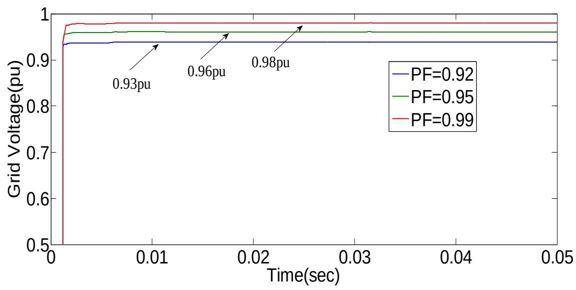

Figure 7 Grid voltage for different PF with ANFIS controller

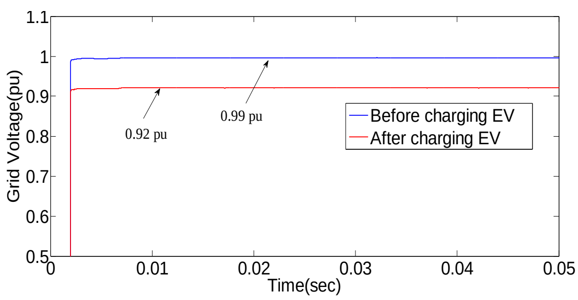

Figure 8 Grid voltage before and after discharging to EV

The node voltage is improved to 0.93, 0.96 and 0.98 when power factor is 0.92, 0.95 and 0.99 respectively as shown in Fig. 7 with ANFIS controller. The results clearly indicate that high power factor increases the amount of real power flow. Similar way charging of electric vehicle is studied. The node voltage before and after charging of electric vehicle is shown in Fig. 8. The distribution node voltage is reduced to 0.92 from 0.99 pu after charging the vehicles. That is, it confirms the charging of the vehicle.

6. CONCLUSION

This paper analyzed V2G/G2V concept in smart grid environment. The coordination between grid and vehicle is achieved by using PI, fuzzy logic and ANFIS based charging station controller and V2G controller. The controllers are used to control the flow of energy between electric vehicles and grid to improve the stability. MATLAB/SIMULINK model was developed considering IEEE 33 bus radial distribution system to realize the V2G/G2V concept. It is verified that all the types of controller can improve the grid stability by flattening the load profile and as the same time, it is identified that the transient response of ANFIS based controller is better than other two controllers.

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