# Neural Network-Based PV Powered Electric Vehicle Charging Station

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***Abstract*— Global warming and some dangerous climate changes are becoming more prevalent as the demand for modern transportation systems grows for economic development and cultural comfort. To tackle this global warming issue due to transportation every country pushing for Electric Vehicles (EVs), As the number of electric vehicles on the road rises, Charging EVs with a fossil fuel-based infrastructure alone is not cost-effective or efficient. As a result, a charging station based on renewable energy has enormous potential and control for electric vehicle charging. In the current scenario, a solar-powered electric vehicle charging station and a Battery Energy Storage System (BESS) are required. Additional grid assistance is recommended to ensure that the charging station has uninterrupted power without putting additional burden on the grid, For effective power management in the charging station between solar, BESS, grid, and EVs an efficient charging station design with Adaptive Neuro-Fuzzy Inference System (ANFIS) voltage-controlled MPPT, PID controller, Grid with Neural Network technique is designed and evaluated in MATLAB/Simulink.**

***Keywords—Electric Vehicles, Battery energy storage system, Adaptive Neuro-Fuzzy Inference System, MPPT, PID controller, Neural Network, PV.***

## I. INTRODUCTION

Global warming and some dangerous climate changes are becoming more extensive as the demand for modern transportation systems grows. The toxic environmental pollutants emitted by internal combustion engine vehicles (ICEs) contribute to air pollution and greenhouse gas emissions. Internal Combustion (IC)-enabled automobiles are the primary cause of these negative environmental consequences. Electric vehicles (EVs) are one possible solution to the world's current reliance on gasoline-powered autos.

Electric vehicles are becoming more popular because EVs have more efficient electric motors than internal combustion engines, hence this mode of transportation saves energy compared to ICE vehicles and they reduce noise and pollution, they can also be used to lessen transportation's reliance on oil – as long as the electricity is supplied using non-oil fuels (1,2).

If electric grid electricity is used to charge the vehicles as more EVs are put on the road, charging the vehicles will become increasingly challenging. (3) when a large number of electric cars (EVs) are linked to the grid, the operation and control of the grid will necessarily suffer. Furthermore, charging EVs with traditional energy sources on the electric grid provides no benefits. As a result, efficient charging infrastructure for electric vehicles that use renewable energy sources is required. A battery energy storage system (BESS) that can operate as a buffer between the EV charging station (EVCS) and the utility is another preferable approach (4–7). Nonetheless, while the usage of BESS will relieve some of the strain on the utility grid, the vast number of EVCSs predicted in the future remains an issue.

In a charging station, an efficient battery energy storage system (BESS) which is integrated with solar PV is discussed in (8). The implementation and control of power flow in renewable energy-based (WECS) wind energy conversion system and photovoltaic (PV) array for charging electric vehicles (EVs) is talked about in (9). Using environmental data, creating an efficient, adaptable, and PV-based EV charging station that is a cost-effective model is discussed in (10). Charging of Electrical Vehicles using solar and battery in the workspace is discussed in (11). Maximum power point tracking of a stand 4-alone PV array using an adaptive neuro-fuzzy inference method is discussed in (12).

In this proposed work, a Neural network-based approach used for the power management of a solar-powered electric vehicle charging station and a battery energy storage system connected to the AC grid is discussed. An ANFIS voltage-controlled technique is utilized to get the most electricity out of solar panels under variable irradiance and temperature.

A neural network uses solar power output and state of charge (SOC) of BESS parameters to control the power output of the AC grid. Solar PV is the primary energy source. During maximum irradiance, PV supplies power to charge the EV, and excess power is given to the AC grid as well as used to charge BESS. When PV electricity is not available at night, a battery can be used as an energy storage device to charge the EV. Solar or BESS power generation is necessary to charge electric vehicles. Sometimes the power will be drawn from the AC grid to charge EV and BESS to ensure an uninterruptible power supply, The proposed system has been simulated in MATLAB/Simulink.

## II. EV CHARGING STATION MODEL

A suggested solar-powered charging station with energy storage in the form of a battery and AC grid is depicted schematically in Fig.1. A 400V DC bus with one EV battery is considered at a time for proposed work. All the component's technical specifications are shown in Table I.

### A. *PV array with a Boost converter*

In MATLAB/Simulink, a 2000W PV panel with a 298.4V open circuit voltage is investigated for the charging station design. To acquire the needed DC bus voltage of 400V, a boost converter is employed to step up the PV array voltage and an

ANFIS voltage controller with Proportional-Integral (PI) controller is utilized to get the most power out of the PV array.

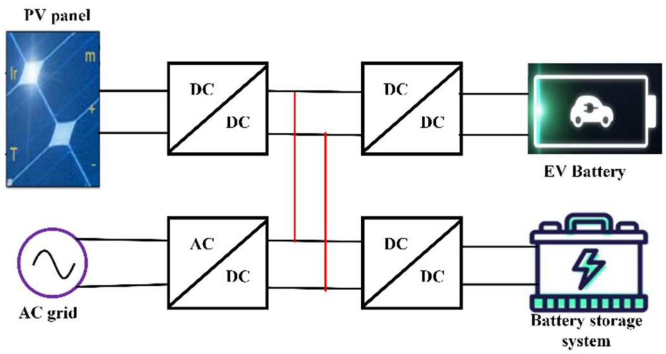



Fig. 1. Representation of EV charging station

TABLE I. Charging station data

| | |
|---|---|
| **Module Data** | |
| Number of cells | 60 |
| Open circuit voltage | 37.3 V |
| Short-circuit current | 8.66 A |
| Voltage at MPPT | 30.7 V |
| Current at MPPT | 8.15 A |
| **Array Data** | |
| Parallel cells | 1 |
| Series connected modules per string | 8 |
| **BESS Data** | |
| Nominal voltage | 240 V |
| Rated capacity | 40 Ah |
| Battery type | Lithium-ion |
| **EV Battery Data** | |
| Nominal voltage | 240 V |
| Rated capacity | 7 Ah |
| The initial state of charge | 9 % |
| Battery type | Lithium-ion |
| **Boost Converter Data** | |
| Switching frequency | 10 kHz |
| Capacitance | 4.0704 µF |
| Inductance | 0.0153 H |

### B. (BESS) Battery Energy Storage System with Bidirectional Boost DC-DC converter

Extrasolar electricity is collected and stored in a battery energy storage system, which is then used to charge electric vehicles at night. The charging and discharging of the BESS are controlled by a bidirectional boost DC-DC converter. A 240V 40Ah BESS is utilized for the charging station. BESS is anticipated to discharge at a rate of at least 20% SOC.

### C. Grid with Inverter

The 230V, 50Hz AC grid is being explored for the charging station's additional power requirements. A 230V AC source is used as the grid in MATLAB/Simulink. The AC grid is connected to a 400V DC bus using an inverter. To generate pulses for inverter switches neural network Simulink model is developed by taking PV array output power and %SOC of the BESS as input data to a neural network.

### D. EV Battery

A 240V, 7Ah Battery is considered for the charging station, The EV battery is charged from a 400V DV bus using a PI controller for a DC-DC boost converter. The incoming EV's battery is expected to have a minimum of 10% SOC for simulation purposes. The energy required ( $E_{ev}$) for charging of the EV battery can be calculated from the nominal voltage ( $V_n$), remaining % state of charge ( $SOC_r$) and Ampere-hour rating (Ah) of the battery.

$$E_{ev}=\frac{V_n * SOC_r * Ah}{100} \tag{1}$$

## III. CONTROL METHODOLOGY

### A. An adaptive neuro-fuzzy inference system

An adaptive neural fuzzy logic network, or ANFIS, is a network that mimics the behavior of neural and fuzzy inference systems. The adaptable neural network does not have synaptic weights, but it does have non-adaptive and adaptive nodes. It's simply converted into a typical feedforward neural network structure, hence the name adaptable network (13).

The ANFIS adaptive network has a structure that is similar to the adaptive Takagi-Sugeno fuzzy controller's adaptive network emulator. This adaptive network works in the same way that a fuzzy inference system does(FIS). The techniques employed are back-propagation gradient descent and least-squares to adapt the ANFIS network's input and output parameters for the given input/output data set. The ANFIS network's input and output parameters are referred to as linear and nonlinear parameters. The antecedent and succeeding parts of the ANFIS network are the two primary sections. A fuzzy inference system with a rule-based system connects these components. Figure 2 depicts the five-layer ANFIS structure.

Layer 1: Node 1 in this layer is known as an adaptive node, and nonlinear parameters of the ANFIS network are the parameters in this layer. Eq. (2) expresses the function of each node as,

$$L_{1,i} = \mu A_i(e) \qquad \text{for i=1, 2…j}$$

$$L_{1,i} = \mu B_i(\Delta e) \qquad \text{for i= 1,2..j} \tag{2}$$

where e and Δe are the layer 1 node i's inputs. The membership functions of each node are $A_i$ and $B_i$. Normally, each node's membership function is assigned by the input variables are distributed using a Gaussian membership function. The function of Gaussian membership is formulated as follows: as a result of Eq. (3).

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{3}$$

where $\sigma$ and c are the gaussian membership function's width and center, respectively. Nonlinear parameters are the center and width parameters, which are modified during the learning process.

Layer 2: A fixed node that is denoted by the symbol "Π" with the node's output coming from the product of Layer 1 node signals. Eq. (4) expresses the node function as,

$$L_{2,k} = W_i = \mu A_i(e)\mu B_i(\Delta e) \text{ for i= 1, 2…j}^2 \tag{4}$$

The output of each layer 2 node determines the rule base's firing strength.

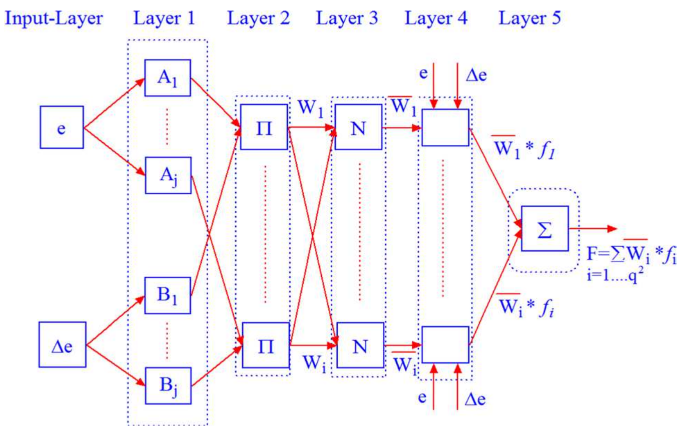



Fig. 2. Five-layer adaptive neuro-fuzzy inference system structure

Layer 3: This layer node is referred to as a fixed node and is denoted by the letter "N." Its output is calculated by dividing each node's value by the sum of all node's values.. Eq. (5) expresses the node function as,

$$L_{3,i} = \overline{W}_i = \frac{W_i}{\sum_{i=1}^{j^2} W_i} \tag{5}$$

Layer 4: This node is fexible. Eq. (6) expresses the functionality of this node as,

$$L_{4,i} = \overline{W}_i f_i = \overline{W}_i \left( p_i e + q_i \Delta e + r_i \right) \tag{6}$$

Where $W_i$ is the normalized layer 3 firing strength and $\left( p_i, q_i, r_i \right)$ are the ANFIS network's linear parameters, also known as network consequent parameters. These parameters are modified using the least-square approach during the learning phase.

5th layer: This layer, which is signified by the symbol "Σ" is and has a fixed node known as the output layer. The output from this layer is calculated using the weighted average technique, and it is given by Eq. (7) as,

$$L_{5,i} = \sum_{i=1}^{j^2} \overline{W}_i f_i = \frac{\sum_{i=1}^{j^2} W_i f_i}{\sum_{i=1}^{j^2} W_i} \tag{7}$$

A hybrid technique is used to update the nonlinear and linear parameters of Layer 2 and Layer 4. The ANFIS parameters hybrid algorithm is a structure that combines the steepest descent and least-square methods.

Forward and backward propagation is the two types of propagation used by the hybrid method. The output of the nodes is forwarded up to Layer 4 during forwarding propagation of the hybrid algorithm, and linear parameters are changed using the least-square approach.

During backward propagation of the hybrid approach, the erroneous signals flowed backward and the nonlinear parameters were altered by gradient descent. Because the search space dimensions are substantially reduced during training, this hybrid approach converges significantly quicker than conventional back-propagation algorithms (14, 15).

### B. *Maximum power point tracking with an adaptive neuro-fuzzy inference system-PI controller.*

ANFIS voltage-controlled MPPT is shown in figure 3.

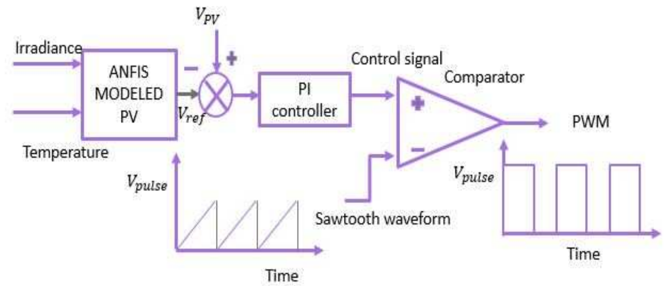



Fig. 3. ANFIS voltage-controlled MPPT

ANFIS is used to create a model of a solar PV system that is identical to the original in this MPPT structure. Under diverse irradiance and temperature conditions, ANFIS is trained with two inputs (irradiance and temperature) and a single output (voltage). The voltage reference is collected from the ANFIS system's output, which is compared to the real PV voltage to produce error voltage. The proportional-integral controller processes the error voltage and produces a duty cycle for the PWM generator.

A PWM generator generates the pulse for a DC-DC boost converter to extract the most power from a solar PV array.

### C. *Neural network-based AC grid*

Figure 4 shows the trained neural network model for the AC grid.

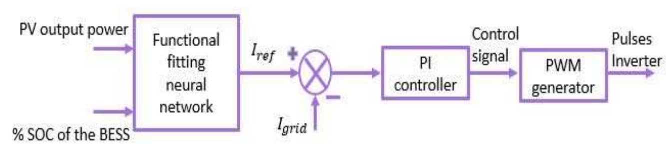



Fig. 4. Block diagram of neural network

The data of PV array output power with a variation of irradiance and SOC of the BESS are taken to build the functional fitting neural network model in MATLAB/Simulink. The current reference is collected from the neural network Simulink model, which is compared to AC grid input current to produce error currently. The proportional-integral controller processes the error current and produces a duty cycle for the inverter.

## IV. Operation of Charging Station

### A. *Operational modes*

- 1st mode: PV array alone charging EV battery. During this mode, The Temperature is kept constant, the PV panel's irradiance is changed and the PV array's maximum power is taken using ANFIS voltage-controlled method.
- 2nd mode: EV battery and BESS are charged using solar power only when BESS is connected to a DC bus. Operating PV panel at MPPT by ANFIS.

- 3rd mode: EV battery is charged using both solar power and BESS with a variation of irradiance. ANFIS ensures the highest amount of power that can be extracted from the PV array.
- 4th mode: During the night when irradiance of the PV array is zero, the EV battery is charged using AC grid and BESS. A functional fitting neural network controls the power flow of the AC grid.
- 5th mode: Irradiance and Temperature of PV array is varied. Charging of EV battery when solar PV array, BESS, and AC grid are connected. Excess electricity is fed into the AC grid.

## V. Simulation Results

The constructed Simulink model is evaluated for varying sun irradiation levels and temperature levels. The Simulink model of a neural network-based PV-powered EV charging station is displayed in Figure 5.

### A. *ANFIS controller training with a PV array model*

The data from the PV array is used to train the ANFIS voltage controller. The voltage at the maximum power point is measured as a function of temperature and irradiance. After importing this data, the grid partition method of subtractive clustering is used to define the membership function for the inputs. The ANFIS controller is trained using a hybrid learning approach, with 100 iterations being evaluated. The ANFIS controller will then be tested with test data. After it has been properly tested, the ANFIS controller is converted into a reference PV model. Table II illustrates the ANFIS controller's MATLAB training.

### B. *1st mode*

Temperature is maintained constant at $25^0$ C and Irradiance of PV array is varied in steps, PV power is 2000W at maximum irradiance of 1000 W/m$^2$. PV voltage is constant and PV power varies with the variation of irradiance which ensures the maximum power extraction from the PV array as shown in Fig. 5. Initially, 9% SOC of EV is considered for simulation purposes. The negative EV battery current indicates that it is charging as shown in Fig. 6.

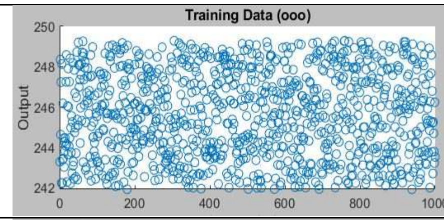
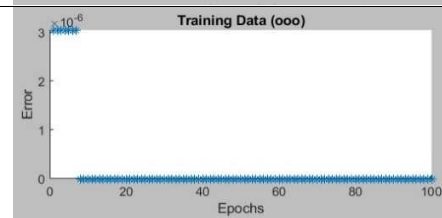
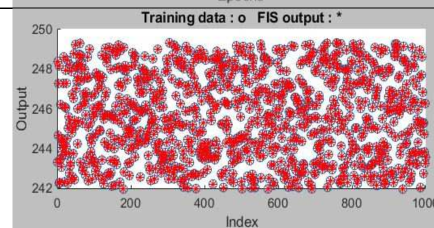
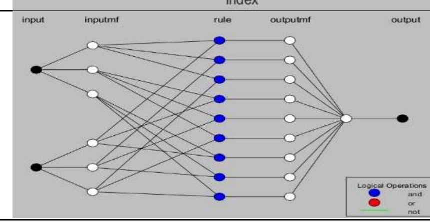
### C. *2nd mode*

Both the BESS and EV battery is charged as shown in Fig. 7. With the extraction of maximum power available from PV array at different irradiance and temperature which is shown in Fig. 8.

### D. *3rd mode*

The DC bus connects the PV array, BESS, and EV battery, DC bus voltage of 400V is maintained and power is transferred from the PV array to the DC bus with the variation of irradiance and temperature of the PV array as shown in Fig. 9. EV battery is charged by taking power from DC bus and BESS, Fig. 10. Shows that energy is transferred from BESS which is represented by decreasing of %SOC of BESS and charging of EV battery which is represented by increasing of %SOC of EV battery.

TABLE II. Training of ANFIS controller

| S.No | Training phases | Representation of training phases in MATLAB |
|---|---|---|
| 1 | ANFIS controller output data |  |
| 2 | Training error plot for 100 epochs |  |
| 3 | Trained data testing |  |
| 4 | ANFIS trained structure |  |

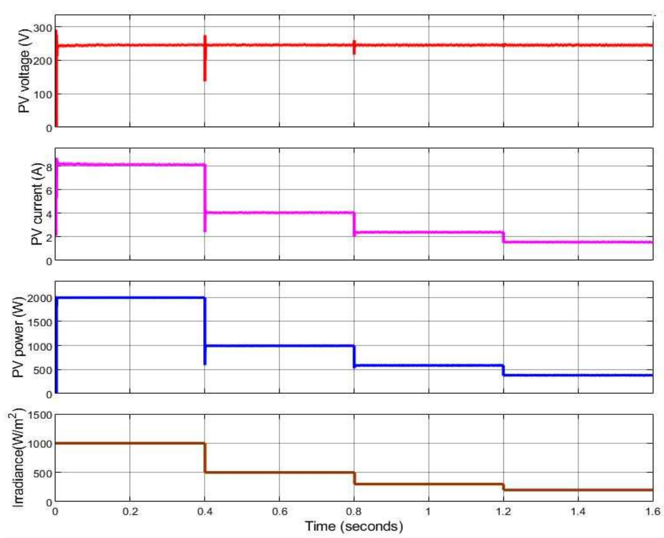



Fig. 5. PV Voltage, current, and power with a variation of irradiance.

### E. *4th mode*

During night power supplied by PV array is zero, at simulation time of 0.1sec functional fitting neural network start controlling the power flow from the grid as shown in Fig. 11. AC grid is connected to the DC bus through the inverter. Fig. 12. shows the grid voltage and current through the inverter when the grid is supplying power to the DC bus. Charging of EV battery from DC bus is shown in Fig. 13.

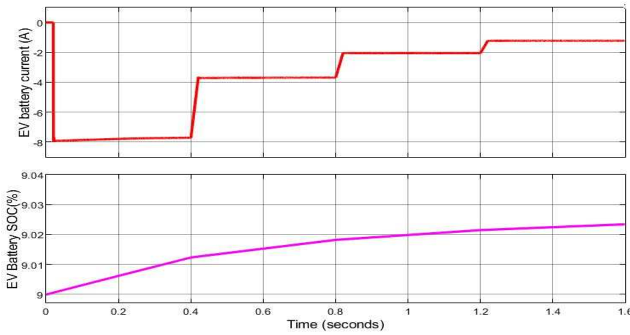



Fig. 6. EV battery charging current and % SOC.

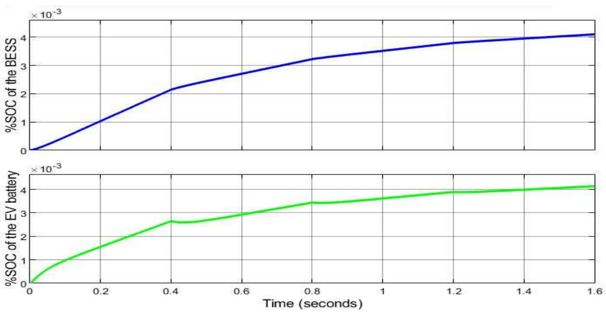



Fig. 7. % SOC of BESS and EV battery

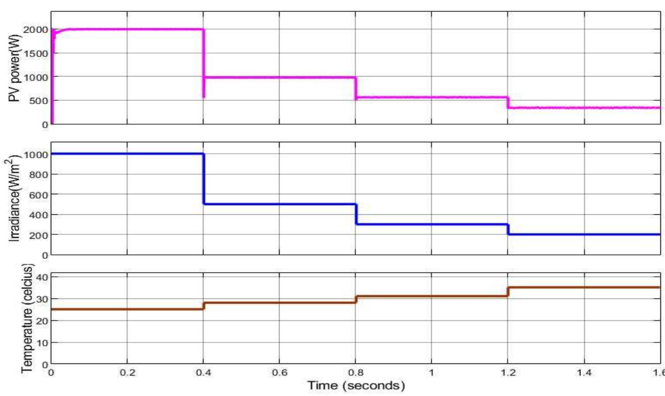



Fig. 8. Output power, Irradiance, and temperature of PV array.

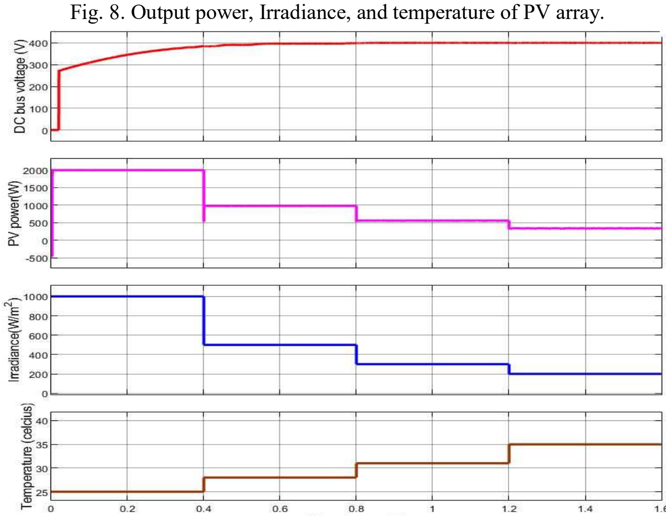



Fig. 9. DC bus voltage, PV output power, Irradiance, and temperature of PV array.

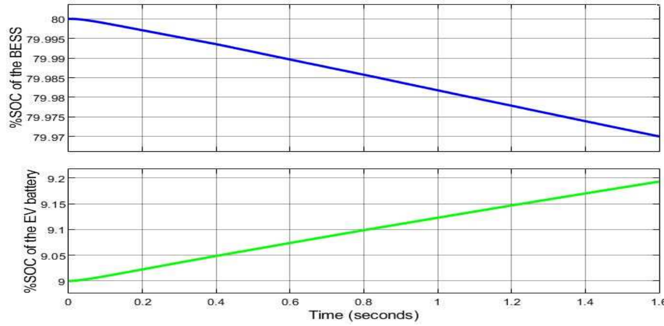



Fig. 10. %SOC of BESS and EV battery

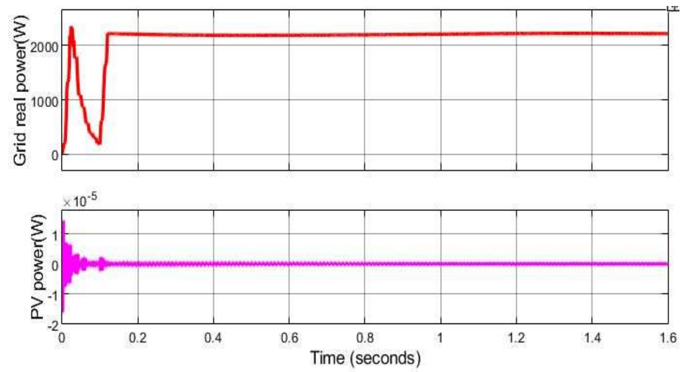



Fig. 11. Grid supplied power when PV output power is zero

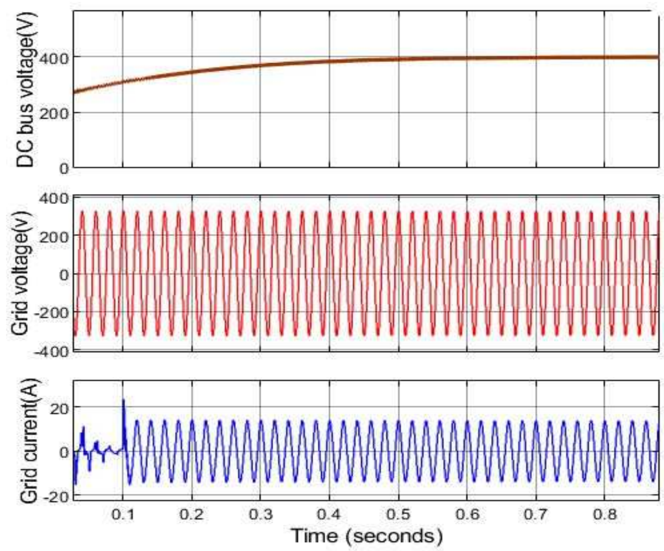



Fig. 12. DC bus voltage, Grid voltage, and grid current

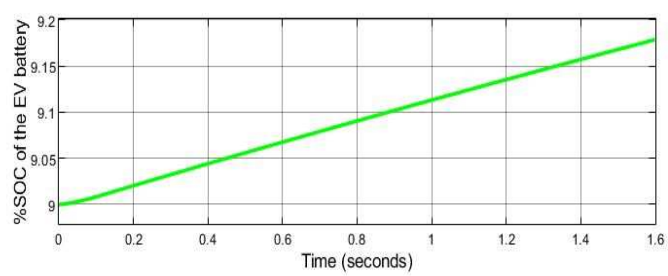



Fig. 13. Charging of EV battery represented by increasing %SOC

### F. $5^{th}$ mode

At simulation time 0.1sec functional fitting neural network starts controlling the AC grid power, during simulation time 0.1sec – 0.4sec grid real power is negative which shows that power is fed to AC grid from DC bus as shown in Fig. 14. BESS supplies power to DC bus and EV battery is charged from DC bus as shown in Fig. 15.

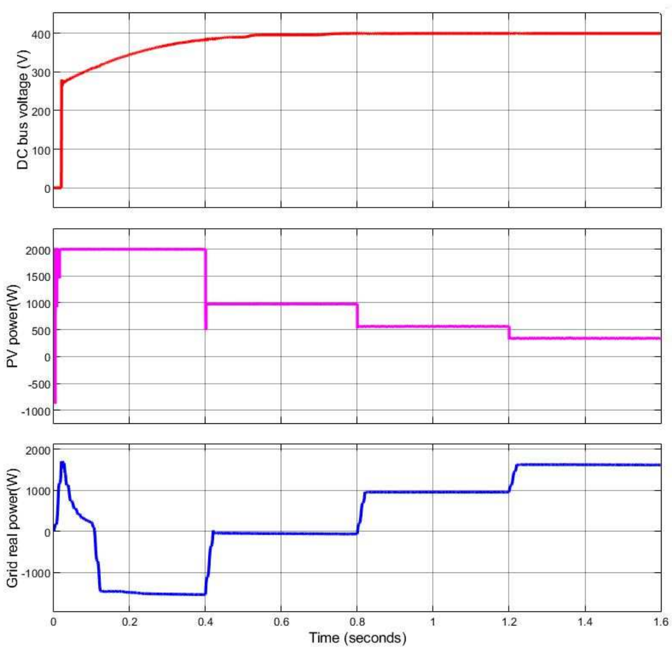



Fig. 14. DC bus voltage, Power supplied by PV array, and Grid real power

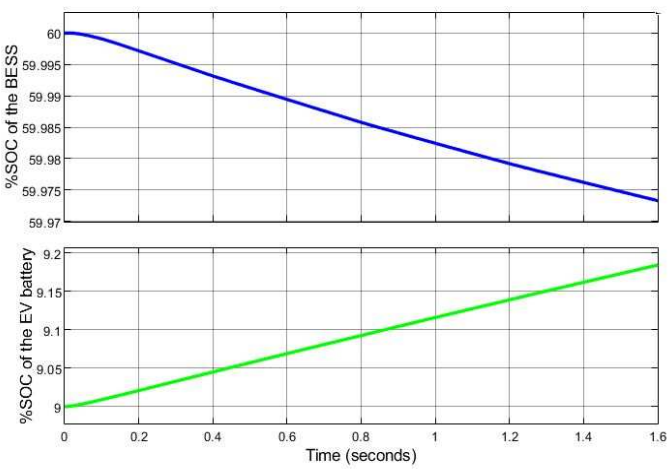



Fig. 15. BESS supplying energy to DC bus and Charging of EV battery

## VI. Acknowledgment

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## VII. Conclusion

With the growing number of electric vehicles on the road, EV charging has become a major issue. A charging station powered by a PV array combined with a (BESS) battery energy storage system and a promising approach is enhanced by grid support. To meet the charging needs of all linked electric vehicles ANFIS voltage control, PI controller, and neural network is used. By maintaining a steady DC bus voltage, the desired power can be obtained. The station's bus voltage remains constant. The proposed station's power management is discussed and validated using MATLAB/Simulink in five distinct modes. With further exploring the proposed model for more number of electrical vehicles This can be implemented, with a significant power rating and capacity for power supply EV charging station at work or in the parking lot.

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