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ANN Based MPPT for Electric Vehicle Charging Station

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Abstract: *Power is the crucial key for the commercial growth of any developing country. In recent years, environmental concerns and rising oil prices have contributed to the development and commercialization of Electric Vehicle (EV) and Hybrid Electric Vehicles (HEV). Electric Vehicle is emerging in the market with rapid pace and their supporting equipment has become inevitable. The charging station is one such module, were this work has been attempted. In this proposed work, Artificial Neural Network (ANN) based MPPT is applied to track the maximum power from the solar panel which is employed in the EV charging station. In ANN, Levenberg-Marquardt algorithm is used for tracking maximum power. This algorithm trains the neural network which is used for controlling the duty cycle of the DC-DC converter. Here electric vehicle charging station integrates solar photovoltaic (PV), energy storage system. The output and efficiency is compared between the Bayesian Regularization and Levenberg-Marquardt algorithm. Based on the results obtained, the performance of the proposed method is evaluated using MATLAB/ Simulink software and the advantage of this type of method is that it has greater accuracy.*

Keywords: Electric Vehicles, Solar PV Generation, Battery Energy Storage System, Grid EV Charge..

I. INTRODUCTION

Nowadays, the need for energy is increasing in our day-to-day life. It has contributed to the concept of Electric Vehicles (EVs) are completely pollution-free. Growing population in the world, an additional more number of EVs is required. An electric vehicle has acquired a most important role in electrification transport. So, in a true sense, the EVs can be a green and clean alternative to the present transport system when the electrical energy required for the charging of EV, comes from the renewable energy sources correspondent as solar, wind, etc. An efficient energy management approach for the photovoltaic systems to power the electric vehicle battery charging facility while utilizing the electric vehicle battery as an energy storage system that can mitigate the photovoltaic impacts and allow the growth of photovoltaic systems in power grids. In energy management of the electric vehicle battery-photovoltaic system can reduce the impacts of the high penetration of electric vehicles and photovoltaic on power distribution grids and can effectively improve the self-consumption of the photovoltaic systems [1]. Then charger is supported with the synchronization and seamless mode switching control so that the charger automatically connects/disconnects from the grid without disturbing the EV charging and household supply. The charger is also enabled with the vehicle-to-grid (V2G) active/ reactive power support to the grid and vehicle-to-house (V2H) power transfer for supporting the local loads in an islanded condition [2]. The implementation of the solar-based EV charging station. However, the dc-dc converter (mostly boost converter) is used to connect the PV array to the dc link. In this paper, the solar PV array is directly connected to the dc link. The major advantages of this topology, include the reduction in one power stage through the elimination of the dc-dc converter stage, circuit complexity, and the cost of the converter, without compromising the performance of the PV array. Moreover, this topology is a kind of retrofit solution wherein the PV array can be augmented to the existing charging infrastructure with the fewest change in the software (maximum power point tracking control algorithm) alone [3].

II. ARTIFICIAL NEURAL NETWORK BASED MPPT TECHNIQUE

A number of maximum power point tracking algorithms were developed to track the maximum power point in renewable system efficiently. Most present MPPT algorithms suffer from slow tracking, erroneous tracking, and oscillations during quickly changing weather conditions, decreasing utilisation efficiency.To overcome these drawbacks, an ANN based MPPT Control technique is introduced in this paper as it improves the performance of the system and efficiency with much better than any other conventional methods. In this technique a multi layered neural network is used and a multi layered trained artificial neural network based MPPT is added to estimate the temperature & irradiance levels from the PV array voltage and current signals. A multi layered feed-back neural networks with back propagation trained network is used to give better performance even under rapidly changing environmental conditions for both steady and transient instants. To reduce the training set usually multilayer is adopted for implementing the MPPT to irradiance levels, which increases in tracking efficiency. MPP may be tracked without time increment through PV characteristics changes since it is independent of time dependency and trade property. To overcome the problem of nonlinear characteristics of PV array with rapidly changing irradiation and temperature using conventional MPPT to track the maximum power point, an ANN based MPPT is introduced. This method solves the time dependence and trade off as tracking time is very fast compared to conventional incremental conductance and P&O methods even in sudden change of the weather conditions. The mean square error is introduced to give better performance and accuracy of the network. This multi layered neural network algorithm is also used to estimate battery power influencing factors like light intensity, temperature, battery junction and temperature. It estimates the temperature and irradiance levels from array voltage and current signals in order to determine the optimum peak operating point, by approximating the maximum power point locus. It is of high speed, low-complexity MPPT technique, which always controls the PV panel output voltage in the order to give the good response due to sudden changes of irradiance levels, which increases in tracking efficiency. This network is tested for series and parallel connected solar panels to produce the load required power with overcoming the drawbacks of slow, wrong tracking and to operate it at maximum power point and to reduce the oscillations during rapidly changing weather conditions.

III. CONTROL METHODOLOGY

The proposed simulated model of the ANN-based solar PV for tracking maximum power point is designed by MATLAB/Simulink as shown in Fig 2. Temperature (T) and irradiance (Ir) are two input variables and voltage of MPP (Vmpp) is the output variable of ANN. It's necessary to get some data as input and output variables to train the neural network. Accordingly, weights of neurons in different layers are acquired. PV model programming in MATLAB is used to get data. There are Bayesian Regularization algorithm methods to train ANN. The Electricity generation from solar panels depends on solar irradiance and solar panel temperature; therefore, the input data set of irradiance and temperature for ANN are calculated by (1) and (2), respectively.

Irradiance Ir(W/m^2):

$$Ir = [(Ir_{Max} - Ir_{Min})\ x\ Rand]+Ir_{Min} \quad (1)$$

Temperature T (C):

$$T = [(T_{Max} - T_{Min})\ x\ Rand]+T_{Min} \quad (2)$$

Maximum Voltage, VMP(V):

$$T = [(T_{Max} - T_{Min})\ x\ Rand]+T_{Min} \quad (3)$$

Maximum Current, IMP (A):

$$T = [(T_{Max} - T_{Min})\ x\ Rand]+T_{Min} \quad (4)$$

After training the ANN and specification of neuron weights, for any T and Ir as inputs of ANN, the output of ANN is the Vmpp. Now, the current of the maximum power point (Impp) can be acquired by using the V-I characteristic of the modeled PV. accordingly, maximum power (Pmax) is reached by multiplying Vmpp and Impp. PV and maximum power point tracker system, which is composed of a dc-dc boost converter and neural network-based Proportional Integral control unit to the duty cycle of the chopper is obtained by the following equation(5).

$$D = 1 - \sqrt{\frac{Vmpp}{Impp} \times \frac{Iout}{Vout}} \quad (5)$$

IV. RESULTS AND DISCUSSIONS

The proposed system simulation diagram is shown figure 1.1. Solar PV acts as the primary source to charge the battery. Solar panel is connected to the boost converter. In the boost converter neural network is used for generating gate pulse. Levenberg– Marquardt algorithm is used for training the neural network. The source side output is connected to the

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common 48V DC bus. The power from source side is stored in the battery. In cloudy weather condition or power from PV at night is not available, the stored energy from the battery is provided to load.

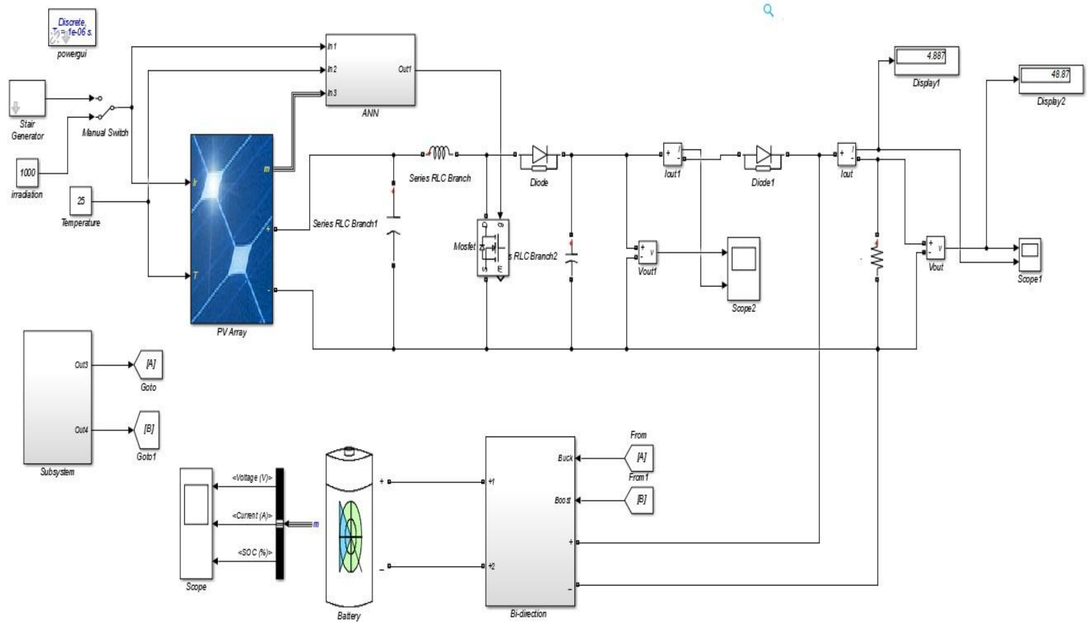

Figure 1.1 Simulation diagram

The discrete simulation is used instead of continuous simulation for optimal analysis. The perfect prediction of ANN depends on the volume of the trained dataset and the training Levenberg–Marquardt algorithm. Generally, the ANN predicts negligible error for the large volume of the trained dataset. The input data (solar irradiance and array temperature) are fed to the solar panel from the lookup table, synchronized by a clock.

The parameters like regression, mean square error, gradient, momentum parameter, and validation check are commonly used for identifying the performance and accuracy of the Levenberg–Marquardt algorithm for the trained dataset. The regression represents the predictive quality where output is a function of inputs, whereas error is calculated by subtracting output from the target. Three types of samples are used for the neural network: training, validation, and testing. The training is used to train the dataset, and the network is adjusted according to its error. The validation is used for the generalization of the network, which halts training during error handling. In contrast, testing provides an independent measure of network performance during and after training which causes no effect on the training of the dataset shown in figure 1.2.

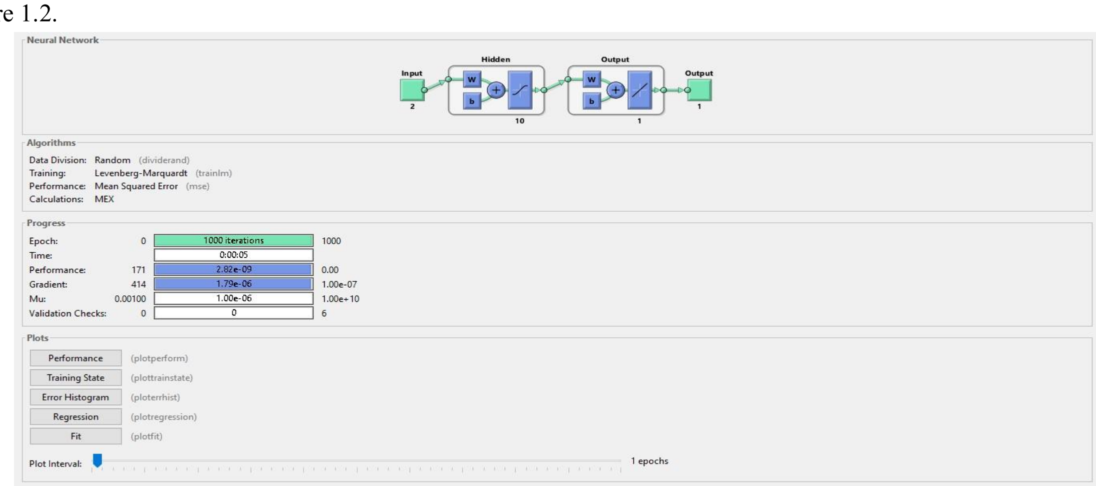

Figure 1.2 ANN Training Toolbox

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The regression plot for the ANN of figure 1.3 regression, R = 1, represents the perfect prediction of output according to input and correlation between output generated voltage and target generated voltage of the selected solar panel. In most cases, an error is determined by subtracting the output from the target. The regression plot of Fig. 1.3 shows that the data is perfectly trained using the Levenberg-Marquardt algorithm with negligible error where the output follows the target value.

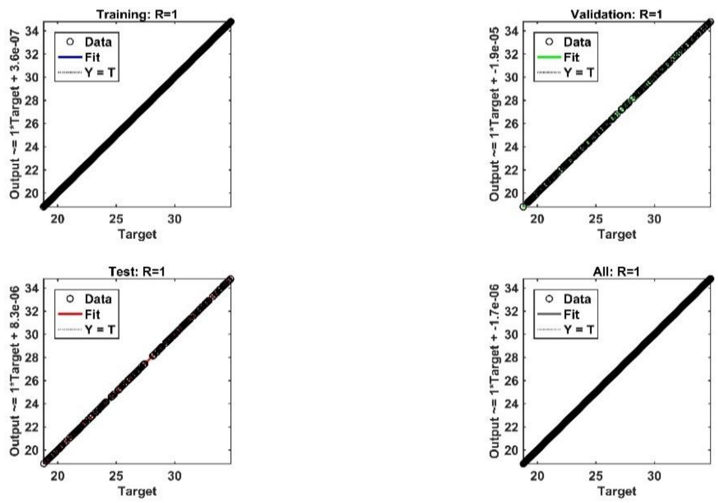

Figure 1.3 Regression plot

In figure 1.4 the mean squared error is represented for different epochs where the samples of the trained data set are converged with the best training result at 1000 epochs. Therefore, the best validation performance of the trained dataset is attained at 1000 epochs. According to the simulation result, the best validation performance is 3.4531e-09 which is attained at 1000 epoch. The Levenberg Marquardt algorithm's near-zero validation performance reflects low error for MPPT prediction.

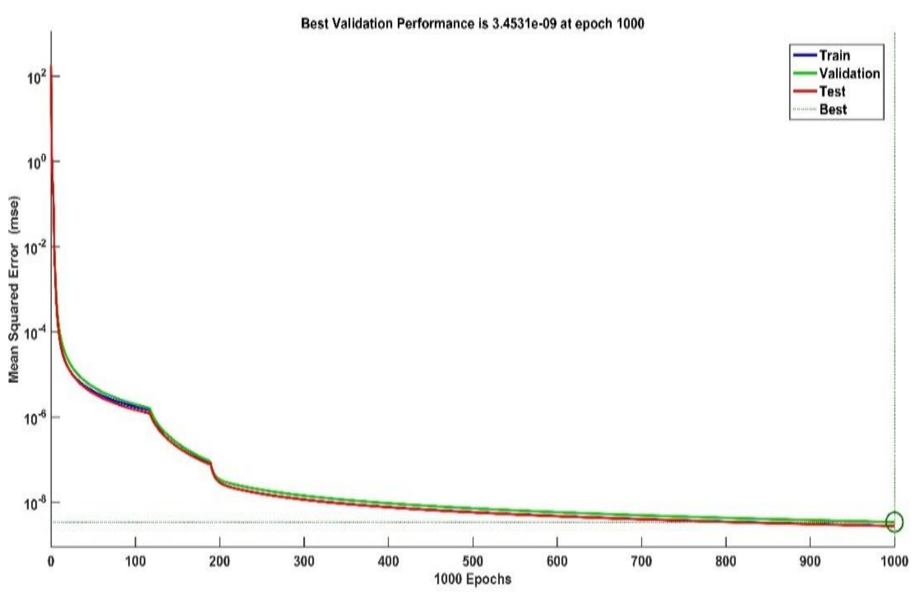

Figure 1.4 Performance Validation

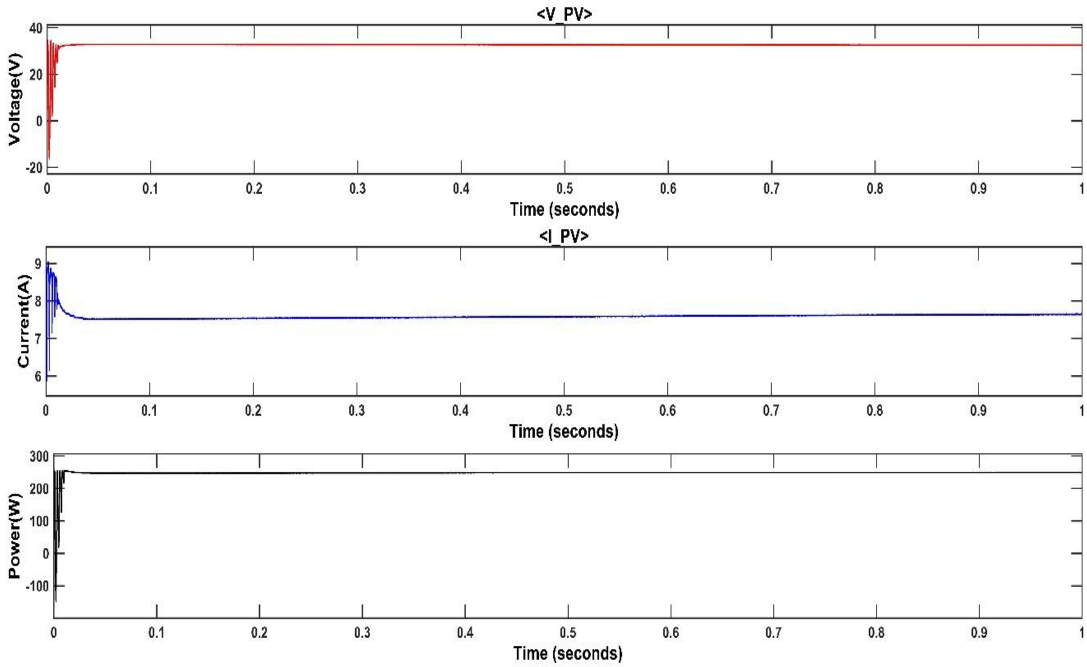

Figure 1.5 Solar Panel Output

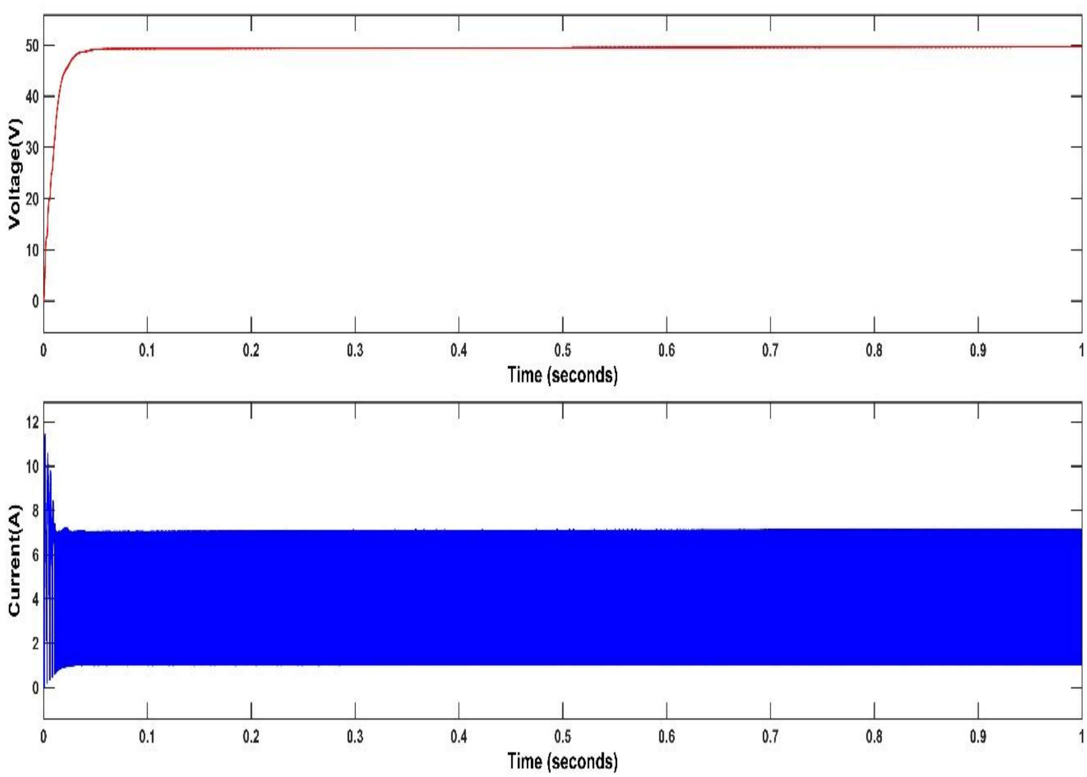

Figure 1.6 Boost Converter Output

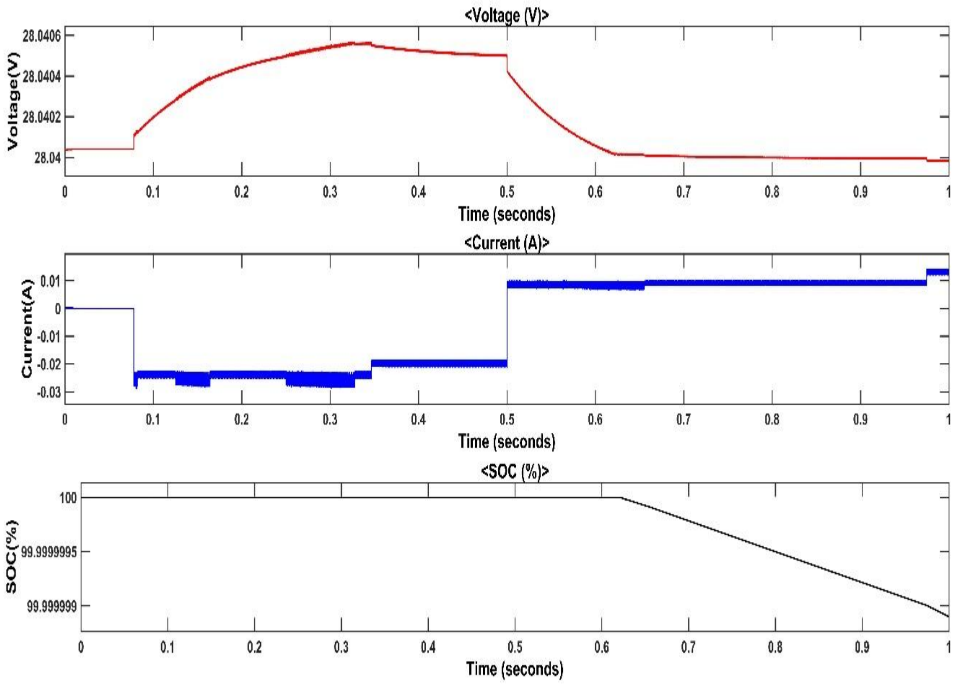

Figure 1.7 Battery Storage Output

The above simulation result conveys the battery performance where it displays the three parameters such as voltage, current, and SOC(%). If there is no power in the solar, the energy stored in the battery is utilized to charge the EV vehicle for the shown in figure 1.7.

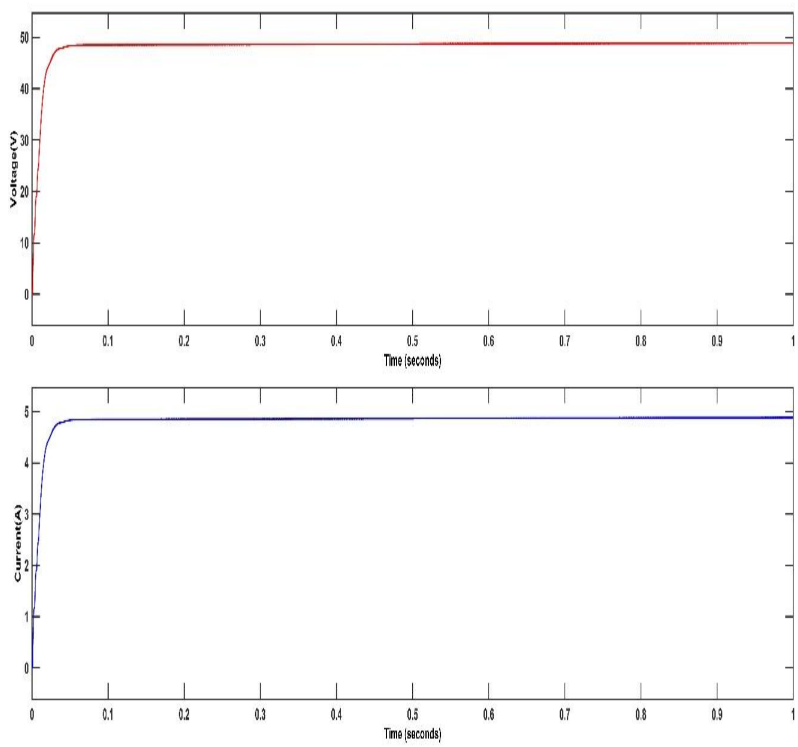

Figure 1.8 EV charging output

TABLE 1.1 Solar Panel Detail

Describes	Ratings
Model	1Soltech 1STH-FRL-4H-255-M60-BLK
Maximum power(W)	255
Open circuit voltage Voc(V)	38.46
Short circuit current Isc(A)	8.89
Voltage at maximum power point Vmp(V)	31.24
Current at Maximum power point Imp(A)	8.16
Temperature Coefficient of Voc (%deg.C)	-0.35601
Temperature Coefficient of Isc (%deg.C)	0.07

TABLE 1.2 Comparative analysis of ANN and Different MPPT Techniques

	P &O MPPT		**Bayesian Regularization Algorithm**		**Levenberg-Marquardt Algorithm**	
Irradiation (W/m^2)	800	1000	800	1000	800	1000
Voltage(V)	34.83	43.31	44.42	49.23	44.60	49.65
Current(A)	3.48	4.31	4.44	4.87	4.46	4.96
Power(W)	121	187	197	245	198	246

V. CONCLUSION

The world's energy need is ever increasing. The techno-economic growth of the developing countries and the growing population are the two factors that stimulate the energy demand. Tracking the maximum power point of a solar panel is the most important factor in almost all photovoltaic applications. This project applies artificial neural network (ANN)-based (MPPT) under the varying atmospheric conditions. Therefore, one of the advantages of artificial neural network (ANN) in the photovoltaic (PV) system with the maximum power point tracking (MPPT) is that it has better dynamic performance in comparison with the other methods. A comparative performance analysis of ANN algorithms namely Levenberg-Marquardt, Bayesian Regularization and other Different MPPT Techniques for the MPPT energy harvesting in a solar PV system. Two-layer feedforward neural network in the ANN toolbox is trained with real-time input datasets of solar irradiance, panel temperature and output dataset of Vmpp. The ANN algorithms are trained with 1460 datasets to identify the appropriate algorithm. The Levenberg-Marquardt algorithm shows better performance in overall data processing with near-zero error at the middle epoch. The near to zero value of momentum parameter, gradient and validation checks at 1000 epochs justify the improved performance of the Levenberg-Marquardt algorithm for the proposed MPPT energy harvesting. Also, the maximum power point is tracked by using the dc-dc boost converter. So the maximum power and better efficiency is obtained from the solar energy. The artificial Neural Network (ANN) technique can track the sudden irradiance changes, which yields a better tracking efficiency and increases the generated energy, making it a reliable MPPT technique for any EV with integrated PV generation.

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