Real-Time Simulation of an Islanded Mode Solar PV System with New Elman NN-Based MPPT

Bappa Roy, Shuma Adhikari, Aribam Deleena Devi, and Kharibam Jilenkumari Devi

1 Introduction

Solar power is one of the most important and easily available renewable energies in most parts of the world. By converting the sunlight and ultraviolet radiation of solar energy, a solar cell generates electrical power [1]. The generation of power from the PV cell depends completely on solar irradiance and the temperature of the PV panel, and it gives a steady output. To achieve maximum power (MP) in this power extraction process, the maximum power point tracking (MPPT) system is necessary. The MPPT helps to increase the productivity of the PV module [2].

Various techniques are applied around the world to generate MP from solar irradiation by researchers. P&O and INC methods are mostly used to track the peak power because of their simplicity and low maintenance [3–6]. Artificial neural network algorithm-based MPPT system has more advantages compared to conventional MPPT techniques [7]. Conventional methods have some disadvantages likes as they are slow in tracking the peak point of power when there is a sudden change in irradiation [8]. Different fuzzy logic techniques [9–13] and different optimization techniques such as particle swarm optimization and optimization of the colony were

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applied to get a fast response in tracking. Machine learning [14] and deep learning-based [15] MPPT techniques have also been applied for tracking the peak power by predicting the reference voltage.

This paper proposes an MPPT system based on the new Elman neural network to extract MP from irradiation and improve the operation of the solar-battery system. The studied model consists of a PV panel along with an energy-storing system linked to a three-phase load through a DC/AC inverter. Both the PV and the battery are linked to two different boost converters to manage power flow. For the real-time verification of the studied model, real-time design and simulation are performed in RT-LAB with a real-time simulator OP4510.

2 System Configuration and Modeling

An islanded mode solar PV model is given in Fig. 1. A solar PV panel and battery energy storage are included in the studied model to feed the load.

The components of the studied model are described below.

2.1 Solar PV and Boost Converter

The solar system's output is linked to a converter (boost) as shown in Fig. 1 to rise the voltage level for controlling the output. A solar cell equivalent circuit is given in Fig. 2. It consists of a source of current, diodes, resistance in series, and resistance in parallel.

The mathematical formulation for the current output of a cell of the PV panel is expressed in Eq. (1).

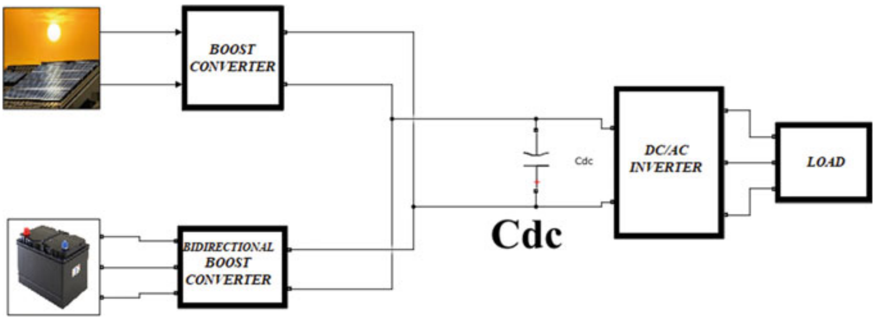

Fig. 1 Typical islanded solar PV battery system

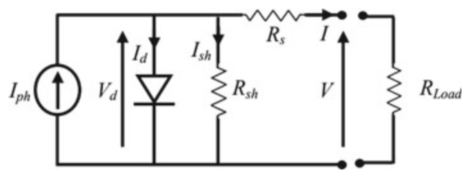

Fig. 2 Solar cell equivalent circuit

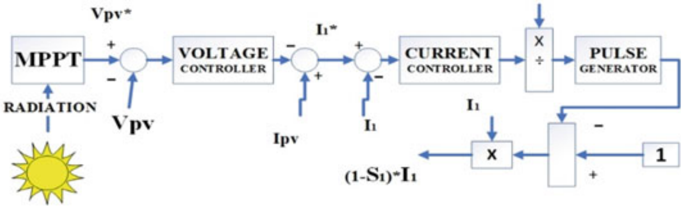

Fig. 3 DC-DC boost converter of solar

$$I = I_{\text{ph}} - I_d.\left[\exp\left(\frac{q.(V + R_s.I)}{nKT}\right) - 1\right] - \frac{V + R_s.I}{R_{\text{sh}}}, \tag{1}$$

where the current of a solar array is denoted by I, the output voltage is denoted by V, the light-generated current is represented by I_{ph}, I_d denotes a diode reverse saturation current, the electronic charge is denoted by q, n is the deviation factor of an ideal diode, K is the constant (Boltzmann's), the cell temperature is denoted by T, R_s is the resistance connected in series, and R_{sh} is the resistance connected in parallel. Figure 3 shows the working strategy for the regulation of the PV boost converter.

The input, solar irradiance led through the maximum power point tracker to calculate the PV reference voltage ($V_{\text{pv}}{}^*$) along with its maximum power. The actual voltage signal is compared with the calculated voltage (reference) and goes through a voltage PI controller for finding the current reference. Then the error in current goes through a current controller to produce the controlled voltage for monitoring the unidirectional converter of the solar unit as shown in Fig. 3.

2.2 Solar PV MPPT and New Elman Neural Network

MPPT allows the PV panel to track the MP point by computing the reference voltage. The maximum voltage at which PV panels can extract optimum power is called the peak power point. In this study, a new Elman neural network-based algorithm is used to find the MP point. The components for building the network are given in Table 1, and a training performance plot is given in Fig. 4.

For the training of the network, three layers of activation function along with one output function are applied. The first layer is the Tansig (activation) function with 100 hidden neurons, the second layer is the Logsig (activation) function with

Table 1 New Elman neural network components

Number of layers	Training algorithm	Max epochs	Training rate
4	Scaled conjugate gradient	5000	0.05

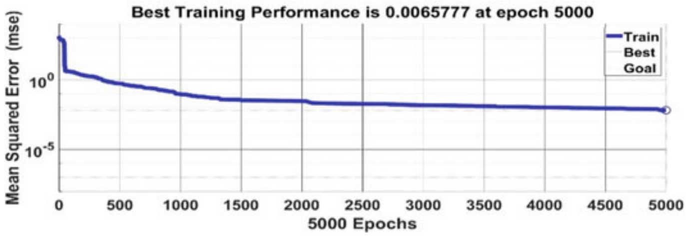

Fig. 4 Network training performance

50 hidden layers, the third layer is the Tansig (activation) function with 25 hidden layers, and the fourth layer or the output layer is the Purelin linear activation function with one hidden layer. A total of 10,000 historical data is been considered for the training of the network, where 15% of data is considered for testing and 15% of data is considered for validation.

2.3 Battery Energy Storage System and Bidirectional Boost Converter

Depending upon the weather condition, the solar unit gives its output, and because of that, the supply of power can become unstable. To overcome this problem of solar PV, an energy storage system is installed with the solar unit in the studied model. A bidirectional converter is connected to the battery to regulate the power flow depending on the surplus energy and load demand. The bidirectional boost converter control scheme is shown in Fig. 5.

The energy storage system stores energy when the generation of power is more than the demand, and it starts discharging when the solar power generation is lower

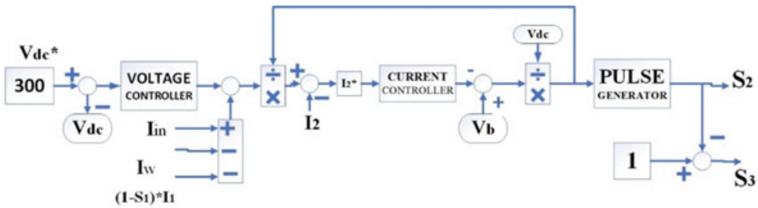

Fig. 5 Bidirectional DC/DC boost converter control

than the load. In control of the DC/DC boost converter, the actual DC voltage is equated with the reference DC voltage to get the mismatch value and it goes over the DC-link controller (voltage) to generate the current reference value of the DC-link. By comparing the actual current and reference current, an error in battery current is obtained, and then for generating the controllable battery voltage, the current error goes through the current PI controller.

2.4 Real-Time Modeling of the Studied Simulink Model

For the real-time justification of the studied Simulink model, MATLAB/Simulink environment along with OPALRT-LAB is used to design the studied model. The simulator OP4510 is applied for the simulation. A diagram of the real-time setup for real operation is given in Fig. 6. Where a real-time target simulator, OP4510, is connected to the host system via an Ethernet cable, which includes MATLAB and RT-LAB.

For the real-time design of any MATLAB/Simulink model, models need to be divided into subsystems as shown in Fig. 7. There are a minimum of two subsystems: one for the computational parts of the model and another for the input-output components of the model. Depending upon the difficulty of the Simulink model and depending on the number of cores of the real-time simulator, the number of subsystems in the model can be more than two but, in a model, only one input–output subsystem can be made. Every input signal coming to any subsystem of the model should go through an 'OpComm' block, and here naming of the subsystems has an important role. Without giving the proper and particular names of the subsystems, the OpComm block cannot be added inside any subsystems. The name of the input–output subsystem must be the 'SC_subsystem,' the nearest subsystem (computational subsystem) name of the input–output subsystem must be 'SM-subsystem,' and the rest of the subsystems can be named as 'SS-subsystem.'

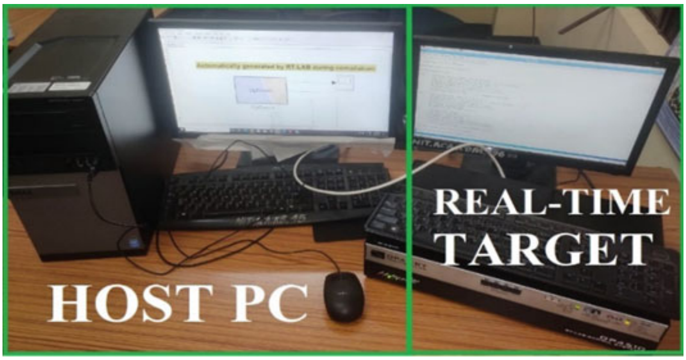

Fig. 6 Real-time simulation setup

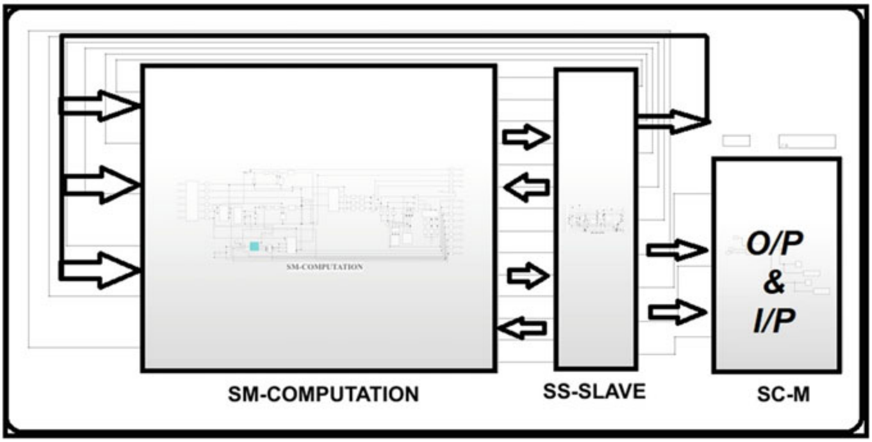

Fig. 7 Real-time modeling

3 Results and Discussion

The studied model is tested in dual simulation platforms, online mode, and offline mode. The online environment for the simulation included MATLAB/Simulink, and in the offline mode simulation, MATLAB/RT-LAB environment is considered. In the online mode, real-time simulation is carried out with the help of a real-time simulator, OP4510 as shown in Fig. 6.

3.1 Offline Mode

Offline mode responses are given in Fig. 8.

Simulation Time, $t = 0$ to 0.2 s: At starting 0.2 s of the simulation time, load is 1 kw and the solar is supplying nearly 2.2 kw of power. So, some surplus energy is available because the amount of generated solar power is more than the load. With that remaining energy, the battery starts charging itself. Figure 8a shows the PV, battery, and load power curves with simulation time.

Simulation Time, t = 0.2–0.4 s: At 0.2 s of simulation time, the load starts increasing and it reaches up to 2.2 kw. From 0.2 s to 0.4 s of simulation time, the load is around 2.2 kw, and at the same time, power from the solar PV is also 2.2 kw as shown in Fig. 8a. So, because of the lack of surplus power supply from the generation, the battery begins to discharge. Battery voltage and current response are shown in Fig. 8c, d.

Simulation Time, t = 0.4–0.6 s: At this time duration, the demand is at its peak, nearly 3 kw, and the solar PV output is only at around 2.2 kw. The energy storage system stops charging at this time duration and continuously discharges

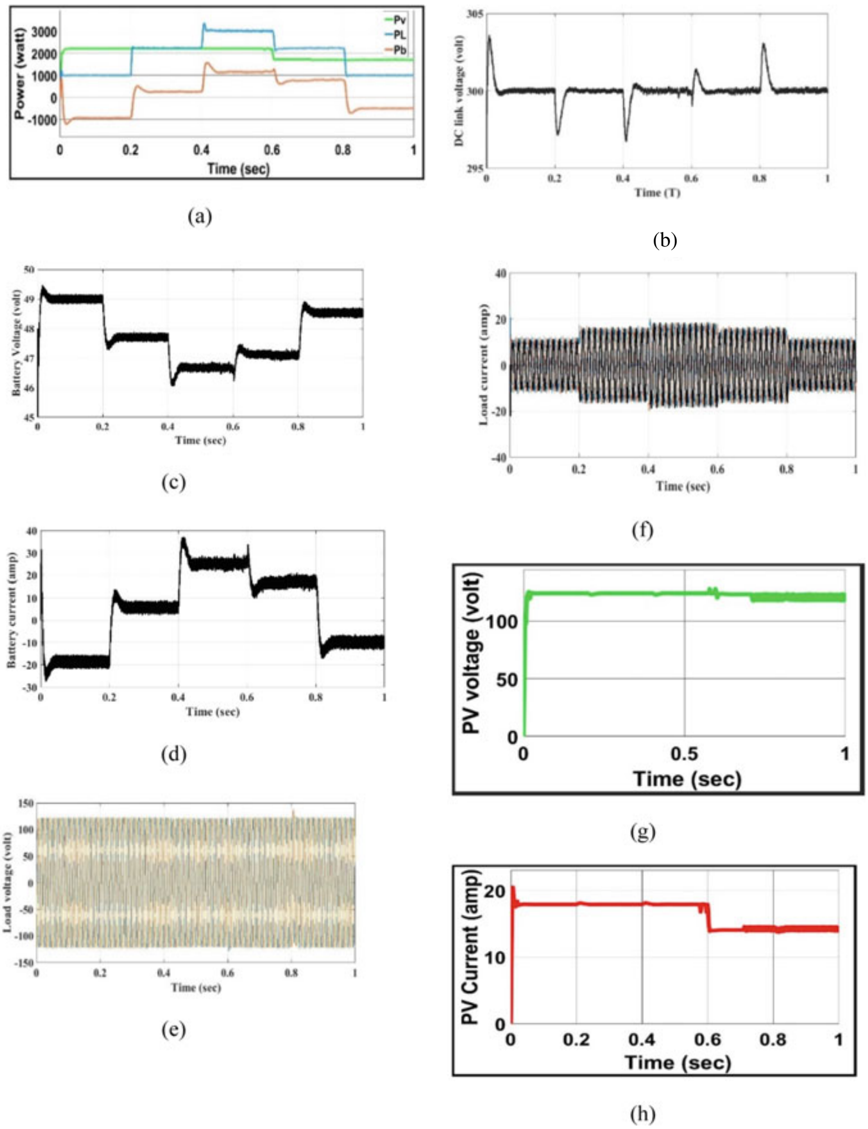

Fig. 8 **a** Power, **b** voltage (DC-link), **c** voltage (battery), **d** current (battery), **e** load voltage, **f** load current, **g** PV voltage, and **h** PV current

power because the generated power from the PV is less compared to the load. The DC-link voltage is maintained at 300 V as shown in Fig. 8b.

Simulation Time, $t = 0.6–0.8$ s: The load as well as the PV generation of power drops at this time duration. The load power is 2.2 kw, and the solar power generation is nearly 1.7 kw. The generation of power is less than the load, and the required

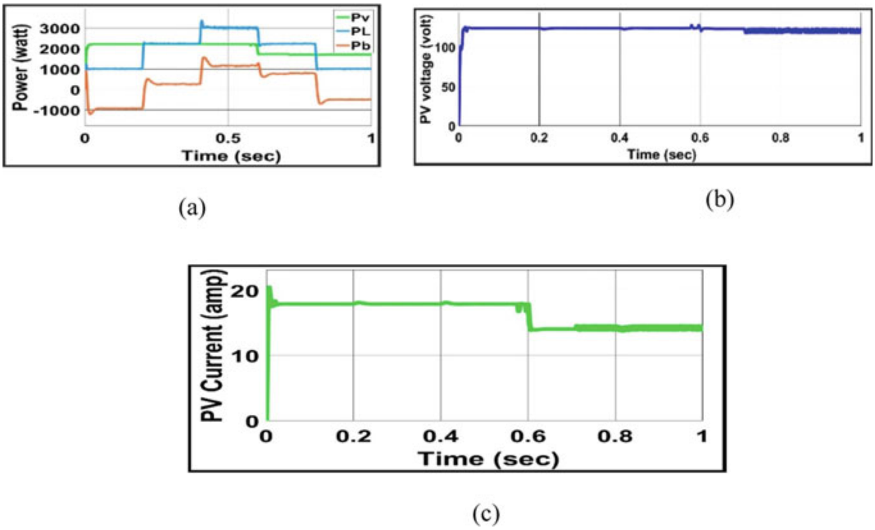

Fig. 9 **a** Power, **b** PV voltage, and **c** PV current

amount of power is provided by the battery storage system. The solar PV voltage and current curve with time are shown in Fig. 8g, h.

Simulation Time, $t = 0.8$–1 s: The load falls to 1 kw, but the generation of power from the PV stays at 1.7 kw. So, the energy storage starts charging by the surplus energy. Figure 8e, f show the load voltage and load current curve, respectively.

3.2 *Online Mode*

In this section, real-time simulation outcomes are discussed and given in Fig. 9 for the output power of the studied model, PV voltage, and PV current.

3.3 *Comparison Between the Offline Mode and Online Mode Results*

In this section, a comparison between the real-time (online mode) and MATLAB (offline mode) simulation results for the studied model is discussed in Table 2.

Table 2 Comparison of online and offline simulation

Sl. No.	Parameter	Offline mode	Online mode
1	Change in output response	Response of the studied model is taken after MATLAB/Simulink simulation and shown in Fig. 8. From Fig. 8a, it can be realized that the power flow is managed suitably depending on the load demand. So, the system worked as it was designed	For the online mode or real-time simulation of the studied model, OPALRT simulator along with MATLAB is used and shown in Fig. 9. It is visible by comparing Fig. 9a with Fig. 8a that both the power output curves are almost the same

4 Conclusion

A solar PV system including a battery energy storage system is built in MATLAB/Simulink environment with its coordination control to manage power flow. A vector control technique is implemented to achieve the control of the load-side converter. A new Elman neural network-based MPPT system is considered for the PV to track maximum power. Simulation results show that the studied system is working accurately, and the flow of power is managed accurately to fulfill the load demand. The studied model is also implemented in OPALRT-LAB with the help of a real-time simulator, OP4510, to validate the simulation results. It is observed from the comparison between the offline and online mode results that the PV source and battery system can feed the load according to its control technique in real time.

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