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Power Quality Improvement in Utility Grid Integrated with Solar PV Plant by Employing an Adaptive Current Regulator

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Abstract

Introduction: Integrating renewable energy sources, particularly solar photovoltaic (PV) energy, into the utility-grid is crucial for the present-day power situation. The usage of various power processing units in this integration process produces harmonics which may lead to malfunction of the sensitive equipment that is connected to point of common-coupling.

Objectives: To lessen the harmonics that were produced in the system and also to achieve high voltage-levels at common bus.

Methods: Recurrent neural network (RNN)-based nonlinear intelligence approach is used. A novel adaptable (Hebbian least square mean based RNN) current-regulator is proposed in this work for enhancing the power quality and performance of grid-interfacing voltage source inverter. Also, for achieving high voltage-levels at a common bus, a high gain DC-DC converter along with PSO based MPPT algorithm is designed.

Results: The performance of this system using the novel current control-regulator is evaluated using MATLAB/Simulink. Using PSO MPPT and a high-gain boost converter with an RNN current controller, this project achieves better power quality and reduces THD below 5% under unbalanced voltage

Conclusion: Simulation results show superior performance and faster settling time compared to Kalman MPPT-based systems. Comparing to conventional PI controller, the proposed approach have several advantages, including a better ability to reduce harmonic distortions, greater adaptability, improved stability, and reduced settling time.

Keywords: Photovoltaic system, Hebbian least mean square, PSO maximum power point tracking, recurrent neural network.

1. Introduction

The modernization of society is causing a daily rise in the demand for power. The best way to meet this need is to use renewable energy sources. The outstanding performance features of solar PV plants have led to an increase in the amount of power they generated recently. [1] A PV plant provides a lot of benefits, but it also has some drawbacks, such as low generated voltage, difficulties locating the maximum power point, and also poor power quality. The PV low voltage is increased using DC to DC boost converter at bus terminals. The limitations of typical dc-dc converters include maximal diode reverse current, substantial power loss while the switching, and abrupt surge in the input side current. [2] As a result, dc micro grid connected to traditional converters experiences increased losses, excessive strain, and decreased efficiency.

In [3] The technical and economical analysis of renewable systems that included the power- quality which is used by FACTS devices was sourced by Ghiasi. Additionally, a method for providing differential power quality in grid-connected renewable energy systems have been provided that is based on optimization. For the purposes of quality power enhancing and managing in the PV powerplant and dc systems for industry applications, Liu et al.. presented a topology of transformer-based filtering in. [4], [5] For micro-grid systems, high-gain, highly efficient power processor units are used to outfight the challenges associated with conventional converters.

[6] presents a innovative design for a high-gain, more efficiency power-processing unit that combines a storage capacitor, a passive clamp circuit, coupled inductors connected in an interleaved way, and PSO MPPT. Even with a lesser duty ratio and smaller loss, the high- gain converter enhances the PV system's low voltage levels. In order to limit the rising impact of greenhouse gases, RES integrating with the utility

grid has become crucial. Therefore, improving power quality by regulation of voltage, and frequency deviations is necessary for the PV-power conversion. Therefore, to operate grid-connected converters, it requires a precise and quick controller. Additionally, a filtering circuit is necessary to eliminate the harmonics that which the power-electronic elements produce. [7], [8] However, the addition of the filtering circuits result in an instability issue. As a result, the voltage source inverter (VSI) is difficult to control. [9] While regulating the grid-connected VSI, the current controller functions in an unstable and also damping manner.

The traditional single-loop control approach on grid connected-systems have given way to a performance-driven approach, double- loop control which is current controlled and voltage controlled loops. The current control-loop was crucial to the grid-connected system's ability to maintain the quality of power supplied in the grid. [10] According to literature, [11] grid-connected inverters use a PI current- controller to set output current for a certain reference that is secured from the necessary power transferred to the grid. The main drawback of PI current controller is its inefficacy to work efficiently in unbalanced condition. This controller typically fails in following a referenced sinusoidal wave without steady-state-error. So, a non linear perceptive method using recurrent neural networks was used to both acquire better control over reactive power injected into the grid and lessen the harmonics created in the system. [12] RNN is more efficient way of control method than traditional control schemes since it can self-adjust to changes in system parameters and performs well in noisy environments. Additionally, it offers superior performance with significant load changes. [13] The implementation of an effective training algorithm has a crucial impact on the RNN current controller's performance.

For improving a grid-connected VSI's performance over different operating scenarios, a new adaptable to establish enhanced grid current power quality and a outer loop with voltage control to maintain/keep constant-voltage levels at VSI's input. The inside loop is controlled by an LMS-trained-RNN controller that current regulator [using RNN based on the Hebbian-least-mean-square (LMS) method] is offered in this study. The Hebbian LMS algorithm is adopted to train the neurons that make up the RNN current controller. The RNN network uses a new unsupervised learning method to automatically adapt to different operating circumstances. [14][15] The primary system components, control method, stability analysis are covered in this article.

2. Objectives

Objectives of this work are:

1) An adaptable recurrent network trained by using Hebbian- LMS weight update algorithms is being used to determine the 3phase reference currents, that which are then used to produce the required pulsewidth modulation signals for the grid interface inverter, enhancing the power-quality of PV system.

2) For the sake to achieve the appropriate voltage level out at dc-link bus terminals, a high- gain dc- dc boost converter through the usage of a PSO MPPT-algorithm is used and then it's compared with Kalman MPPT based system.

3. Methods

Figure.1 shows the electricity which is produced and transmitted with the means of a grid-connected solar-PV plant with RNN control strategy. The work in [16] is referred for the modelling and also the design requirements of the solar PV array. A very effective high-gain dc to dc converter is used while developing this proposed system for coupling the solar PV plant to a common dc-bus. When comparing to existing topologies, this DC-DC converter enhances efficiency, increases voltage, and decreases switching losses and stress. The PSO MPPT controlling method was used to better controlling of the higher-gain and more-efficient converter. Similarly, the voltage-source-inverter is controlled using a double-loop(inner and outer) power flow technology. This control technology typically consisting of an inner loop along with current control uses Hebbian learning. Additionally, VSI is linked to the electric grid using step-up transformers and LC filters.

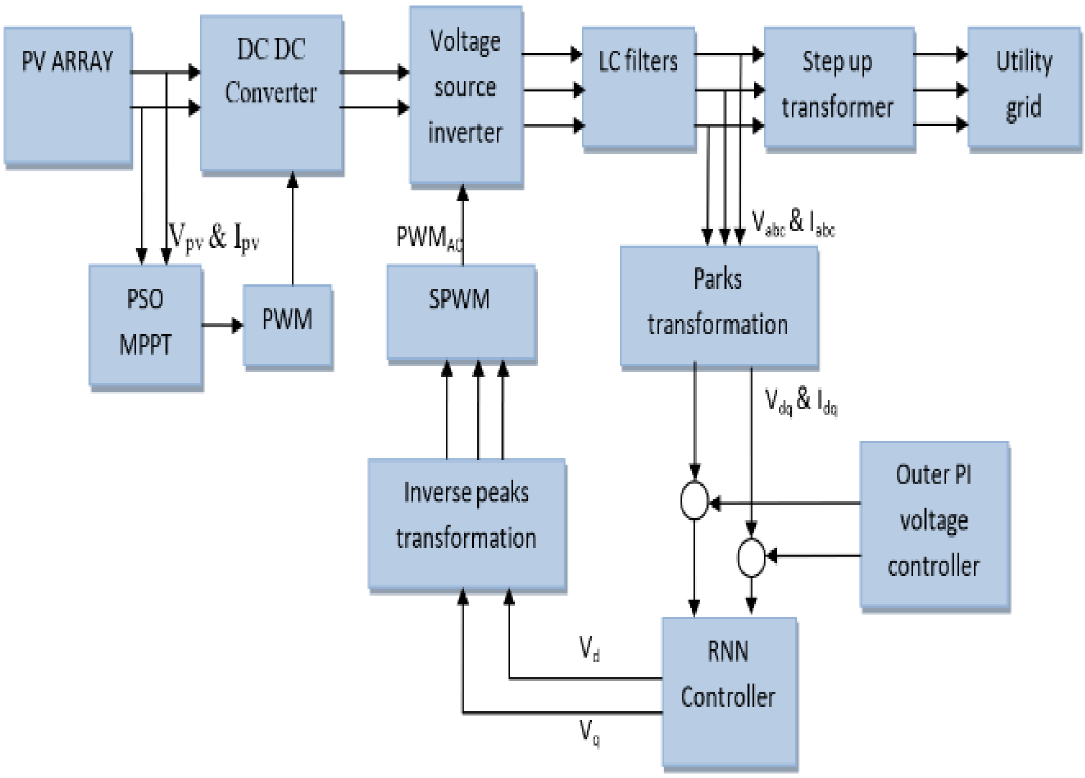

Fig. 1 PV System connected to utility grid

3.1. PSO MPPT Algorithm

The PSO algorithm has been generated and implemented as the PV system's controller so as to accurately track the MPP. PSO is reliable optimization method thats based upon swarm behaviour and intelligence. Each particle maintains a record of the coordinates in the solution space that correspond to the best solution (fitness) the particle has so far attained. This is called personal best(P_{best}). Another best value that the PSO monitors is best value so far acquired by any particle in that particle's immediate neighbourhood. This value is known as G_{best}. [17]

Step1: Randomise the positions of each one particle Di using Equation

$$D_i = \propto , \quad 1 \leq \text{i} \leq N_p \qquad (1)$$

where α, the random number [D_{inf}...D_{sup}]

Step2: Every particle sets its local best(optimal) position (D_{Pbesti}).

Step3: All particles must adhere to the globally best position (D_{Gbest}).

Step4: Adjust positions of the each particle using Equations

$$D_i^{k+1} = w \times D_i^k + \left(D_{Pbesti} - x_i^k\right) r_1 c_1 + \left(D_{Gbest} - x_i^k\right) r_2 c_2 \qquad (2)$$

$$D_i^{k+1} = D_i^k + D_i^{k+1} \qquad (3)$$

Where r_1 , r_2 are random numbers, c_1 , c_2 are acceleration constants, w is inertia. D_i^{K+1} is the newest particle position; D_i^k is the particle's actual position, ΔD_i^{K+1} is the perturbation to be applied at actual position; and ΔD_i^k is perturbation from the previous iteration.

Step5: Repeat 2nd,3rd, and 4th Steps up until every particle position converges to the DGbest.

For PSO technique to be adapted in MPPT field, Di which was the particle position, is considered to be dutycycle and also the duty-cycle step which was based on the three criteria weighted sum. This statistic is shown as following:

$$\Delta D_i^{k+1} = \omega \times \Delta D_i^k + \left(D_{Pbesti} - x_i^k\right)\alpha + \left(D_{Gbest} - x_i^k\right)\beta \qquad (4)$$

Where $\alpha + \beta + \omega = 1$

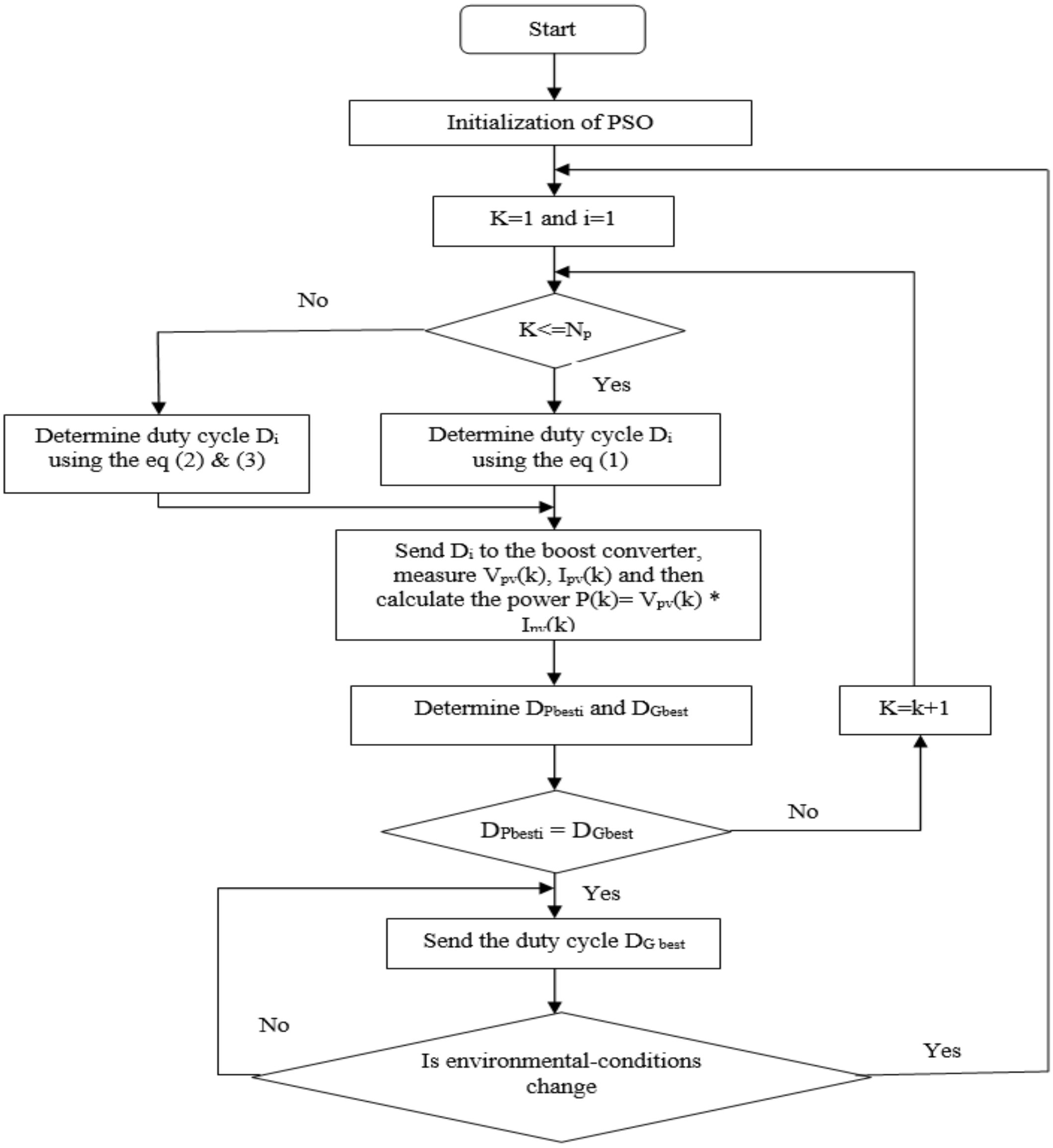

Fig. 2 Flowchart of PSO MPPT Algorithm

D_{Gbest},the duty cycle that which is corresponding to globally best power, whereas D_{Pbesti} is to design the dutycycle value of i^{th} particle, corresponding to the locally best power that is generated during k^{th} teration. The three weighting coefficients(α, β,ω) can be tuned to provide various static and dynamic behaviors from controller.

3.2. Controlling voltage source inverter

The grid-interfacing VSI(voltage-source inverter) should be controlled with dual- loop control techniques of power flow. This control technique consists of voltage controller at outer-loop and current controllers at inner-loop. The PI controller will be used as voltage controller in the given study and the controller gains are chose by trial-and-error method. The RNN controller trained by Hebbian-LMS algorithm is being used as the innerloop current controller. RNN network topology outperforms conventional neural networks because it provides greater precision by feeding output signals back to input. As a result of the RNN current control's short response time and Hebbian LMS algorithm training, system stability may be attained more quickly, improving power quality. In turn, when it compared to feed forward network, it is more stable and dynamic. Thus, it is appropriate for closed-loop control applications. [18][19] The utility grid continues to receive currents of higher quality because of the implementation of RNN inner current-loop control function. The active power and the reactive power are governed by d-axis and q-axis control loops.

This RNN control approach have two input ports, two hidden layers, and two output ports. Current errors Id error and Iq error serve as the input signals for RNN network, these are stated as follows

$$\hat{I}_{d\ error} = \hat{I}_d - \hat{I}_{d\ ref} \quad (5)$$

$$\hat{I}_{q\ error} = \hat{I}_q - \hat{I}_{q\ ref} \quad (6)$$

To get the required responses six neurons are sufficient. So, RNN current controller has six weights in both hidden layers. By using this two hidden layers, error could be reduced efficiently. In the RNN current control, the structure's output feeds back to the input to produce a more accurate result. This controller's architecture is simpler and more effective because it just requires current errors as inputs. Trial-and-error is used to calculate the neurons initial weights. The pulses for grid-side converter (VSI) are produced by the output layer using d and q voltage control signals. The RNN current controller could be referred to as R(Îdq(k), V̂dq(k), Ŵ), where it is the function of V̂dq, Îdq, and network-weights Ŵ and Ŵ- indicates all those weights that corresponding at each of the hidden layer. In greater detail, (Îdq(k), V̂dq(k), Ŵ) is shown as $R\left(\hat{I}_{dq}(k), \hat{V}_{dq}(k), \widehat{W}\right) = (\widehat{W}_2(\widehat{W}_1 \times V_{dq}(k)))$

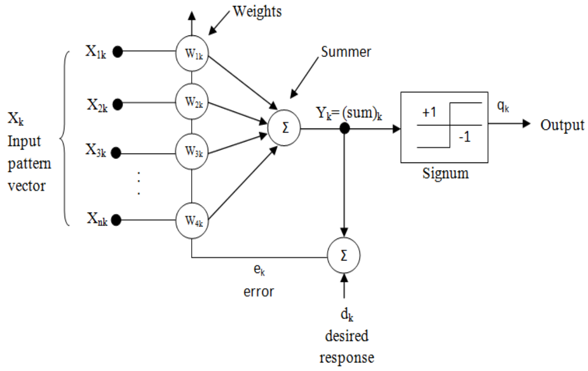

Fig. 3 LMS algorithm

To obtain the necessary response, the weights must be adjusted once they are finalised at every iteration in accordance with the error. The LMS algorithm by Hebbian is implemented to update or train RNNs so as to get greater performance compared to other algorithms. This was given to neurons to obtain the necessary error signal. The total sum of all the weights at each of the hidden layer is the error signal that is obtained, The learning algorithm is expressed as

$$w_{k+1} = w_k + 2\mu e_k X_k \quad (7)$$

$$e_k = f(sum_k) = f(X_k^T, w_k) \quad (8)$$

The neuron output is given as

$$Out_k = \begin{Bmatrix} SGM(sum_k) = SGM(X_k^T, w_k), & for\ (sum_k) > 0 \\ Otherwise\ 0, & for(sum_k) < 0 \end{Bmatrix}$$

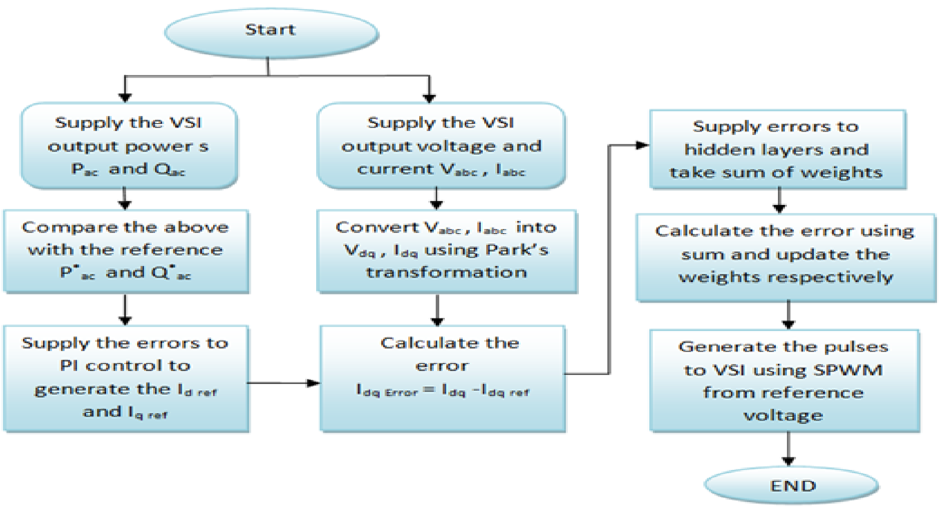

Fig. 4 Flowchart of power flow chart

In this manner, the error was minimised fastly and accurately with this RNN controller. The flowchart gives the power flow for controlling VSI.

Table 1. System Parameters

Parameters	Value
Grid frequency	50HZ
Nominal power	30KW
PV array voltage	300V
PV array current	100A
Grid inverter current	500V
Grid inverter current	40A
Grid side transformer(Δ-Y)	30KVA, 230V/33KV
Grid side capacitor	22pF
Grid side inductor	150mH
Grid side local load(R-L)	20KW

4. Results and Discussion

The solar PVarray connected to utility-grid is modelled by using MATLAB simulink. The PV system was connected to highly efficient DC to DC converter to get stable output voltage,then it is connected to voltage-source-inverter which is connected to RLC load through transformer and LC filters. Table. 1 contains the system's specifications. To demonstrate how much better the PSO MPPT algorithm performs in the terms of output and settling time, it is compared to the Kalman MPPT method,. The controller using RNN is examined in two scenarios, such as solar irradiance and unbalanced grid voltage, to ensure its performance under various system situations.

The overall simulation block model of the proposed system is shown in Figure 5. The dual loop power flow control technology using PI as outer loop and RNN as inner loop, the simulation blocks of this is shown in Figure 6.

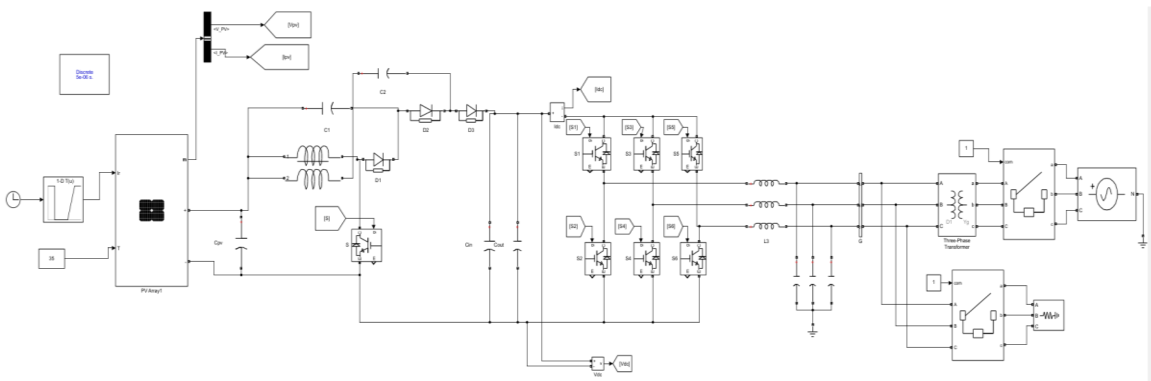

Fig. 5 Complete simulation block of PV plant integrated with grid.

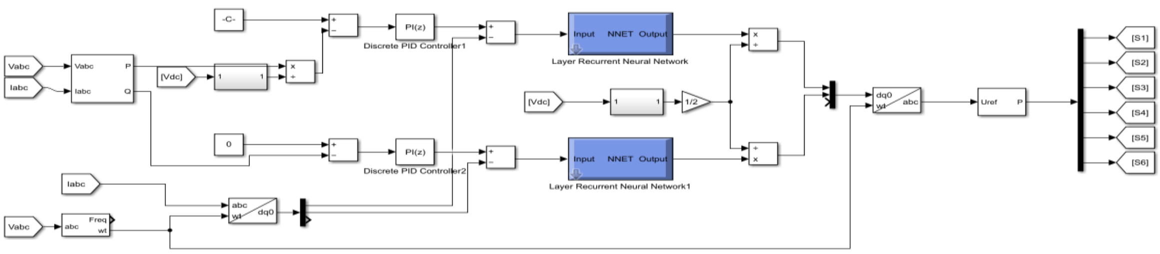

Fig. 6 Dual loop control with PI outer loop and RNN inner loop

The simulation results are given in two test cases.

Test Case 1:

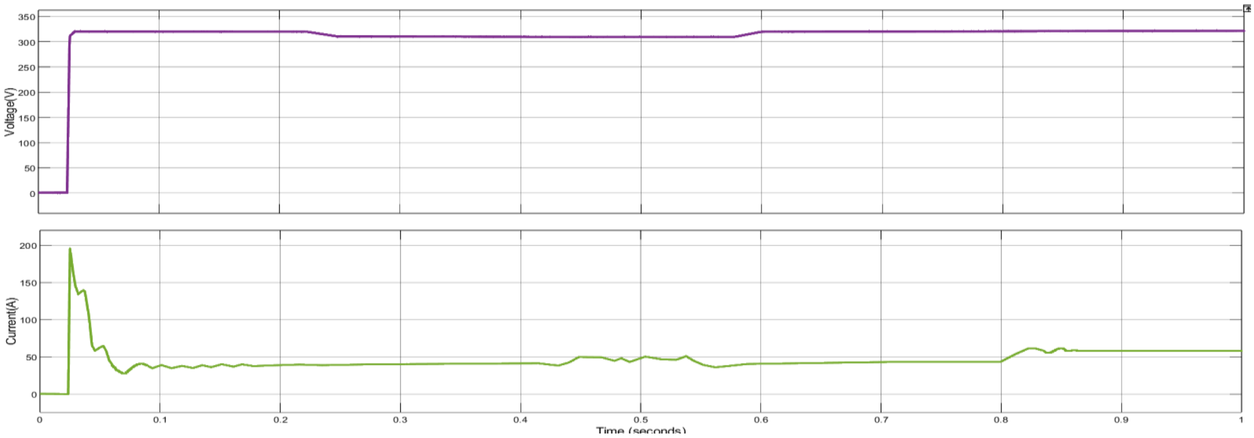

Fig. 7(a) Voltage and Current at common-coupling point in Kalman MPPT based system

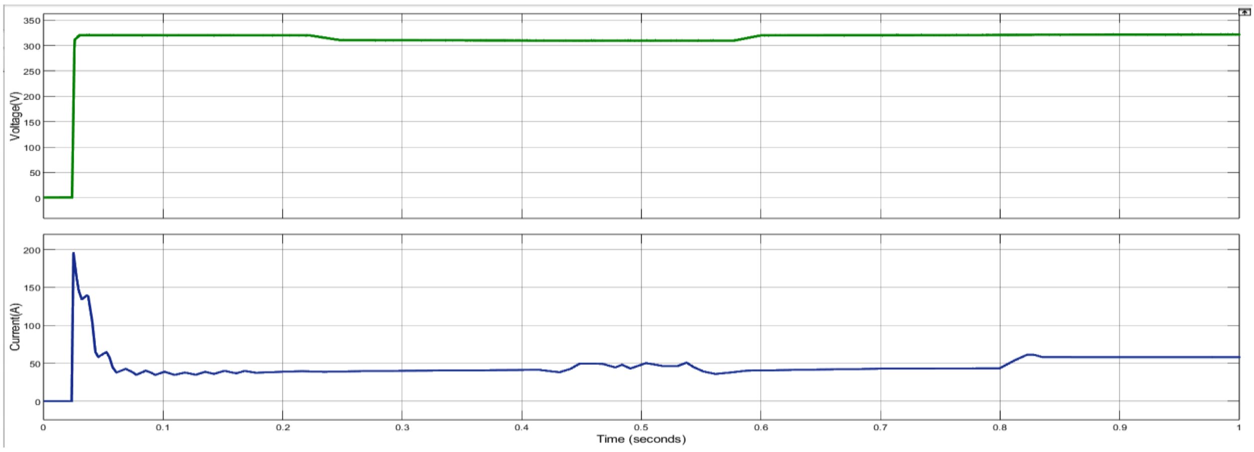

Fig. 7(b) Voltage and Current at common-coupling point in PSO based system.

Test case-1: In this case, the solar-irradiance was varied stepwise from 1000 to 600 W/m2 at t = 0.2 s, then increased again linearly over a period of 0.6-0.8 s. The performance traits of the system with the Kalman MPPT and RNN are shown in Figure 7(a) whereas the performance traits of implied system with Hebbian-LMS-based RNN-based current controller and PSO MPPT algorithm are shown in Figure 7(b). The voltage and currents of PV terminal are shown in Figure 7(a) and 7(b) at input side of boost-converters, and changes in PV current are correlated with changes in irradiance, respectively. Similar to this, the grid current's %THD content when the solar irradiance changes with the Kalman MPPT and PSO MPPT, respectively, is 1.50% and 0.36%.

Test Case 2:

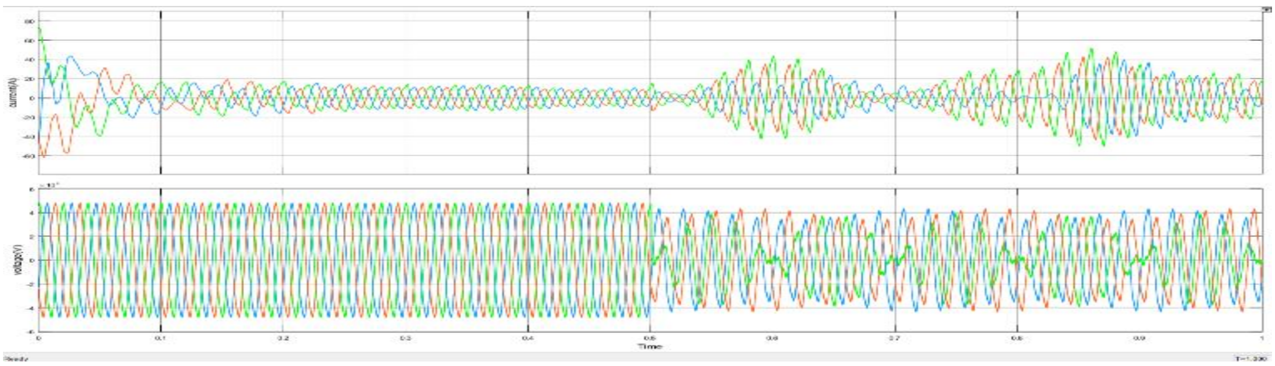

Fig. 8(a) Unbalanced grid voltage and current in Kalman MPPT based system

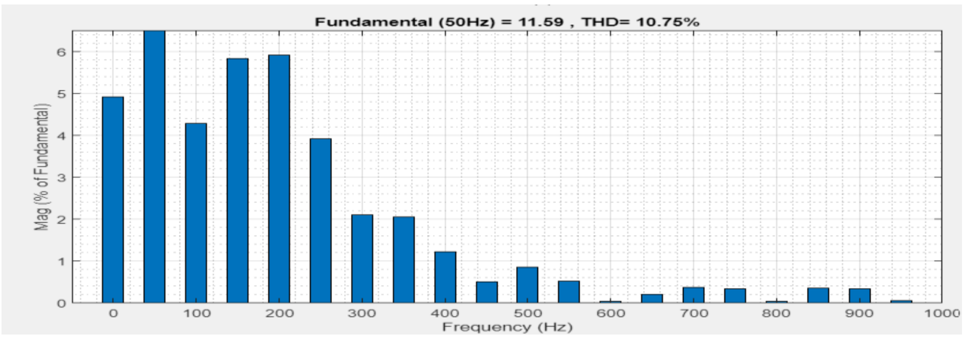

Fig. 8(b) %THD of grid side current

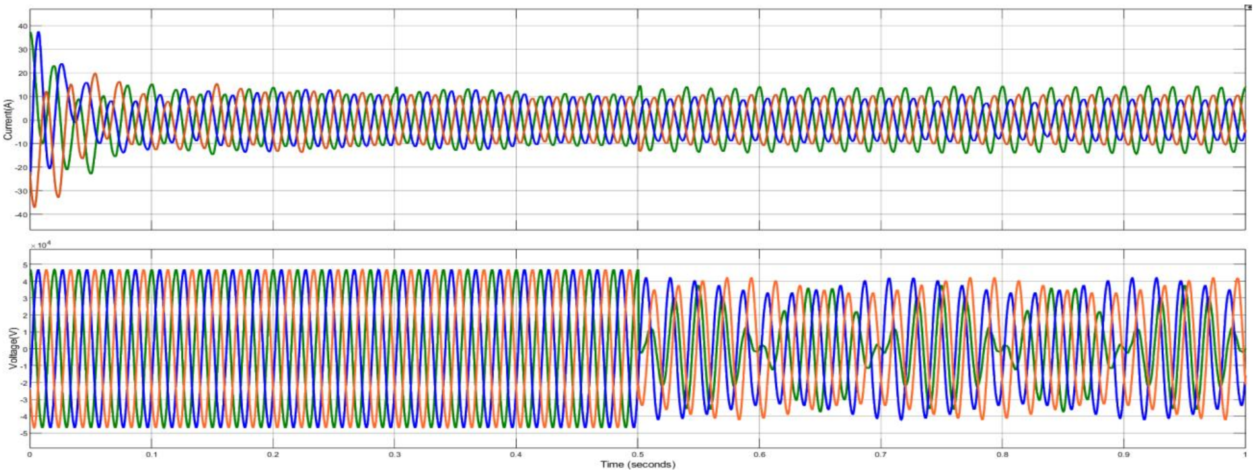

Fig. 8(c) Unbalanced grid voltage and current in PSO MPPT system

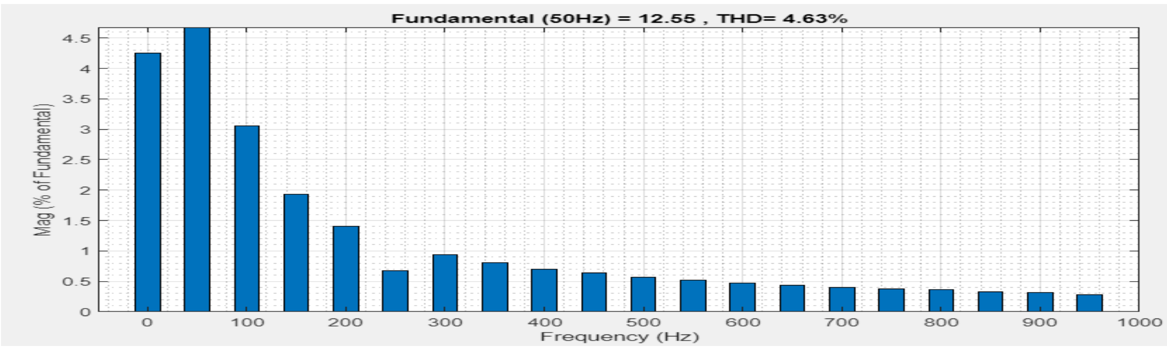

Fig. 8(d) %THD of grid side current

Test Case 2: This case, taking unbalanced voltage at grid side(i.e, unequal phase and magnitude) into consideration, at t = 0.5–1 s. The 3phase voltages and currents at balanced condition and unbalanced grid voltage conditions are depicted in. Figure 8(a) and Figure 8(c), respectively. The results are shown through Figure 8(b) and Figure 8(d), which shows that THD content percent for this grid current under imbalanced grid voltage scenario using the PI controller and proposed RNN controller is, respectively, 10.75% and 4.63%. Finally, it is demonstrated that the suggested PSO MPPT-based system with an RNN current controller exhibits enhanced power quality, better stability, and reduced damping response. Additionally, even with dynamic changes, the system's stability has remained strong with the proposed controller. The high-gain converter, which can increase the generated-PV voltage by up to 500 Volt while achieving greater efficiency, has also been selected in this article.

Conclusion

Generating power by using renewable sources specially solar is getting high attention in recent times. Integrating solar plant to this existing grid is limited with few demerits which includes low voltages as well as low power quality when operating by different load-conditions and during faults. To overcome all these drawbacks, in this project, PSO MPPT was used along with a boost-converter with high gain and also a current controller with a recurrent neural network trained by the Hebbian-LMS technique was used to get better power -quality with lesser harmonic distortion(THD). Simulation results shows that, performance of the proposed system is better than Kalman MPPT based system with regarding to settling time. The exceptional performance of RNN current controller using the proficient Hebbian-LMS makes the THD of system less than 5% under unbalanced voltage. This demonstrates the potential of using such a controller in applications of realtime .

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