

Power Quality Improvement of PV Interfaced Distribution System by Using Adaptive Back Propagated Based Control Strategy

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ABSTRACT— A serious concern regarding degradation in power quality, has originate with the increasing in combination of solar photovoltaic energy (PVE) sources to the utility primarily in the synopsis of weak distribution grid. So, power quality improvement of the grid connected solar energy conversion system is essential by implementation of a robust control technique. This work handle with a Delta-Bar-Delta neural network (DBD-NN) control for operating optimally by delivering active power to the loads and remaining power to the grid as a function of distribution static compensator (DSTATCOM) capabilities such as reducing harmonics, balancing of load and improving power factor (PF). The control algorithm provides the ability to adjust weightsappropriately in an independent manner and hence it offers remission in model complexity predominant during abnormal grid conditions along with reduction in computational time. Furthermore, the neural network (NN) based control technique offers improved accuracy due to the combinational neural network structure in the estimation process. The solar PV array efficient utilization is achieved through an Incremental conductance (INC)based Adaptive back propagated (ABP) control approach for Power quality improvement of interfaced distribution system with based on maximum power point tracking (MPPT) technique. For validating the behaviour of proposed system, its performance is studied in MATLAB Simulink with obtained results.

Key words: adaptive back propagation (ABP), incremental conductance (INC), delta-bar-delta (DBD), MPPT, voltage source converter (VSC)

I. INTRODUCTION

The energy has emerged as the backbone of the economic and technological development of the world during the past few years. In accordance with the reports, the population of the world is estimated to grow by 1% in the coming years. However, the gross domestic product (GDP) rise is estimated to be around 3%. Further, considering GDP per capita as the global energy demand index, the rising requirement of energy sources, is prevalent [1]. So, with an increase in the energy requirement of the world and the dissipate of fossil fuels (like coal, natural gas and petroleum etc.), the significance of renewable energy sources is Predominant [2]. In addition to, the increasing pollution levels due to an increase in the carbon emissions, is one of the main factors for the leaning towards utilization of renewable energy sources. In order to achieve a large energy base, there is a need to full fill the available renewable energy resources. Currently, the contribution by the renewable energy sources, is around 18% of the world energy demand (WED). However, according to an estimate by the International Energy Agency (IEA), the overall energy requirement of the world, is expected to increase by 50% in the near future [3]. With the controlling pollution and an increase in grid parity as the major benefits using solar energy which is gaining popularity due to the encouragement given by the government, with an

government subsidies for providing the easy installation and operation

The contribution of solar power in terms of meeting the global energy demand is increasing rapidly. During recent times, the major factors include a sudden fall in the cost of silicon, which is the significant resource in the solar power production [5] and an escalation in technical skill thereby leading to a decrease in cost of the overall solar photovoltaic (PV). Villalva et al. [6] have presented the modelling of PV array, where it is simple, fast and accurate method is given for accomplishing the solar PV array. However, the solar PV array characteristics represent the nonlinear behaviour between its voltage and current. As a result, it is needed to essence maximum power from the solar PV array by using the maximum power point tracking (MPPT) technique in order to ensure that the combined power converter is capable of self-adjusting its parameters during run time based on the varying current or voltage levels of the PV array source. The awareness of MPPT controllers [7] can be based on different methods and algorithms.

However, the frequent techniques include perturb and observe (P&O) [8] and incremental conductance (INC) techniques. Due to the reduced oscillations in INC method while deceiving the maximum power point (MPP), it is chosen here and it is also desirable for commercial purposes. The usage of solar photovoltaic systems, can be merged into single stage or double stage topologies. At the same time, the benefits of single stage topology, include reduction in cost as the required number of components are less, decrease in losses of the system. The reduction in the overall complexity of the system thereby improving the utilization of solar PV array, which makes it a preferable choice over double stage topology as presented by Wu et al. in [9]. The grid cannot be supplied directly with power controlled from the PV array thus, a power converter like voltage source converter (VSC) is essential for the DC-AC conversion process. Therefore, the combination of solar PV array and VSC at the point of intersection (POI) with utility grid, can be used in standalone and grid-connected system.

II. PROPOSED SYSTEM:

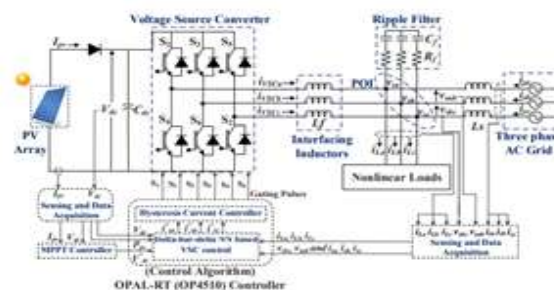


Fig.1. The system configuration is representing It consists of a solar PV (PV) array, which is utilized under standard test conditions. Further, in order to utilize the PV array at maximum power. A maximum power point tracking technique (MPPT) is used based on incremental conductance (INC) method. A Voltage Source Converter (VSC) is used for combine the single stage solar PV energy conversion system with 3 phase utility grid connected and non-linear loads at the point of intersection (POI). It is connected through an inductor (L_f) in order to reduce the current harmonics, present in the proposed system. Then a ripple filter consisting of R_f , C_f is connected in shunt at the POI for softening

the switching ripples. The VSC consists of Insulated Gate Bipolar Transistors (IGBT) based Gate Bipolar Transistors (IGBT) based switches (S_1 - S_6), where the switching pulses are monitored by the generated reference currents (i^*_{Sa} , i^*_{Sb} , i^*_{Sc}) with the proper application of Delta-Bar-Delta NN based control with the help of the adaptive back propagation control method. An efficient eradication of the load current active power component is obtained, which is employed in estimation of the active power component in the grid currents. After that, it is used for the generation of switching pulses for VSC. In order to enhance the efficiency of VSC, it is imperative to utilize an adaptive back propagation control algorithm.

$$I_{ph} = [I_{scr} + K_i(T - T_r)] \frac{S}{100}$$

III. SOLAR CELL

Sun based cells are intended to change over (something like a part of) accessible light into electrical energy, as their name recommends. They achieve this without depending on synthetic cycles or moving parts.

1. CHARACTERISTICS OF SOLAR CELLS

The sun-based cell, which is for the most part built of PV wafers, changes over sun-oriented illumination's light energy straightforwardly into voltage and flow for load, and conveys power without the utilization of an electrolytic impact. The electric energy is acquired from the PN interface of semiconductor straightforwardly; accordingly, the sun-based cell is otherwise called PV cell. The same circuit of sun-based cell as displayed in Figure2 below.

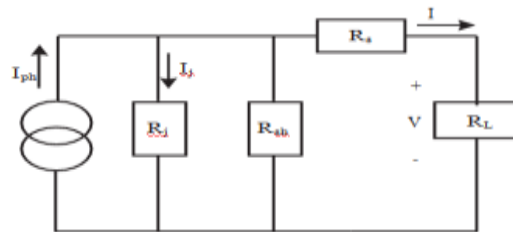


Fig2: Equivalent circuit of pv array

The latest source the cell photovoltaic current is addressed by I_{ph} , the nonlinear obstruction of the p-n intersection is addressed by R_j , and the natural shunt and series protections are addressed by R_{sh} and R_s , separately. Typically, the worth of R_{sh} is very high, though the worth of R_s is somewhat low. Therefore, the two of them may be disregarded to improve on the investigation. PV modules are comprised of PV cells that are assembled in bigger groupings. They are additionally interconnected in series-equal mix to shape PV clusters. The numerical model used to work on the PV exhibit is addressed by the condition

$$I = n_p I_{ph} - n_p I_{rs} \left[e^{\left(\frac{q}{kTA} \cdot \frac{V}{n_s} \right)} - 1 \right]$$

Where I addresses the PV cluster yield current, V addresses the PV exhibit yield voltage, n_s addresses the quantity of series cells, n_p addresses the quantity of equal cells, q addresses the charge of an electron, k addresses the Boltzman steady, A addresses the p-n intersection ideality factor, T addresses the cell temperature, and I_{rs} addresses the cell invert immersion current. The sun powered cell's uniqueness from the best p-n intersection character is dictated by factor A chooses the deviation of sun-oriented cell from the

best p-n intersection attributes. It's worth reaches from one to five. The photograph current I_{ph} relies upon the sunlight-based irradiance and cell temperature as below.

Where I_{scr} is the PV cell short circuit current at reference temperature and radiation, K_i is the temperature co-efficient and S is the solar irradiance in mW/cm^2 . The MATLAB Simulink model of PV array is shown in Fig. 1. This model consists of three sub-systems. APV model for one sub-system and two more sub-systems for modelling I_{ph} and I_{rs} .

A. MPPT of Solar PV Array by implementing Incremental Conductance (INC) Technique

A maximum power point tracking (MPPT) algorithm at a particular level of panel heating based on incremental conductance (INC) method, is realized in the system. The absolute operating point is obtained through INC algorithm as it terminates perturbation on achieving the MPPT. An INC method is used due to its better steady state performance, easy implementation and quick dynamic responses as well as good convergence rate. The operation of INC based MPPT, is regulated according to the following equations,

$$\frac{dP_{PV}}{dV_{PV}} = -\frac{I_{PV}}{V_{PV}}, \frac{dP_{PV}}{dV_{PV}} = 0 \text{ therefore, } V_{MPPnew} = V_{MPPold} \quad (1)$$

$$\frac{dP_{PV}}{dV_{PV}} > -\frac{I_{PV}}{V_{PV}}, \frac{dP_{PV}}{dV_{PV}} > 0 \text{ therefore, } V_{MPPnew} = V_{MPPold} + \Delta V_{MPP} \quad (2)$$

$$\frac{dP_{PV}}{dV_{PV}} < -\frac{I_{PV}}{V_{PV}}, \frac{dP_{PV}}{dV_{PV}} < 0 \text{ therefore, } V_{MPPnew} = V_{MPPold} - \Delta V_{MPP} \quad (3)$$

where, the new and old reference DC-link voltages are represented as VMPPnew, VMPPold and the old sample values are used for upcoming iterations, which are stored as Vpv and Ipv.

B. Calculation of Active Component of Load Current

The current components of load active power (ϕ_{as} , ϕ_{bs} , ϕ_{cs}), are determined with the usage of Delta-Bar-Delta NN technique from the unbalanced load currents using governed and feedforward principle. Here, the input layer is expressed for the three phase.

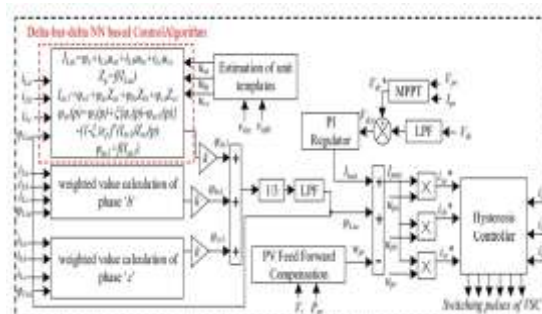


Figure 3: block diagram of DBD-NN

IV. NEURAL NETWORK:

Neural networks are indeed a new technology that is becoming popular today era. The different layers of neurons combine to create NN. These layers transform input once they are able to label the optimized solution. Each neuron multiplies its measured value by a weight, then combines with other results coming into that neuron, modifies the inverting input by bias value, and emits the value using the activation function. In relation to fuzzy logic networks, neural networks

have characteristics such as increased noisy tolerance and the ability to identify data or trends to which they have not been trained.

Layers of ANN:

An input layer, hidden layers, and output layers make up the network's many "layers" of neurons. The data is given to the hidden layers using input layers (so-called hidden because the user cannot see the inputs or outputs for those layers). The output layer receives the results from these hidden layers, and do required computation.

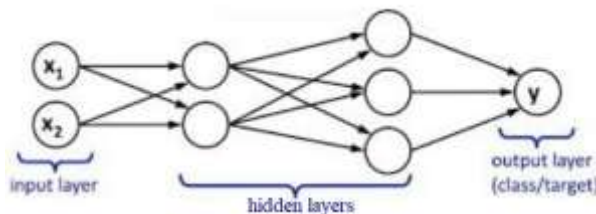


Figure 4 Neural network

The architecture of an artificial neural network is depicted in the diagram (ANN). The input layer, the hidden layer, and the output layer are the three neuron layers that make up the ANN controller. The input signal is sent from the input

layer to the concealed layer. The output layer continues the learning process and delivers outputs, whereas the input layer starts the learning process. The ANN controller is made up of three layers: two input layers, two hidden levels, and one output

layer. It has a two-input layer that is derived from the difference in reference voltage and output plant model error. The PWM generator uses the ANN controller's output as a reference variable. As a result, the output of an ANN with altering amplitude and phase is compared to a carrier signal using a comparator. The PWM circuit creates high output when the ANN output's magnitude is more than the carrier signal's magnitude, and low output when the ANN output's magnitude is less than the carrier signal's magnitude.

Neural Network Training:

The basic goal of ANN training is to identify appropriate weight values that will result in the desired output. The back propagation technique is utilized for rapid convergence. Choose an ANN topology with the desired number of layers, nodes, and random weights. The error voltage at the load and reference voltage are the neural network's inputs. Calculate the difference between the expected and actual outputs, which is an error. A part of the mistake is transmitted backward via the network when it is determined.

Proposed methodology:

The principle of an artificial neural network (ANN) was first presented in the field of biology, where neural networks play a crucial role in the human body. The neural network is used to do tasks in the human body. A neural network is just a web of millions and millions of interconnected neurons. All parallel processing in the human body is done by the help of these linked neurons, and the human body is the finest example of Parallel Processing. In recent years, the Artificial Neural Network (ANN) has been effectively used to a wide range of control system applications. Artificial neural networks have strong learning and nonlinear mapping essences, and their parallel and distributed structure may offer a nonlinear mapping between inputs and outputs buck converter without any prior knowledge of a model. An artificial neural network (ANN) is a structure made up of closely linked neurons that can adapt basic

processing units (also known as artificial neurons or nodes) capable of massively parallel computations for data processing and knowledge representation. Although ANN is one of the primary abstractions of biological equivalents, the objective of ANN is to leverage what is known as the functioning of biological networks to solve complicated issues rather than to duplicate the operation of biological systems. The voltage at the load is then compared to the reference voltage, which serves as the ANN's input layer. The ANN controller is made up of three layers: two input layers, two hidden levels, and one output layer. The output produced when the training is complete is genuine and reactive. Under spontaneously, the control scheme's goal is to maintain a constant voltage magnitude at the point where a sensitive load is attached. We implemented a current topology termed backpropagation based NN in this situation.

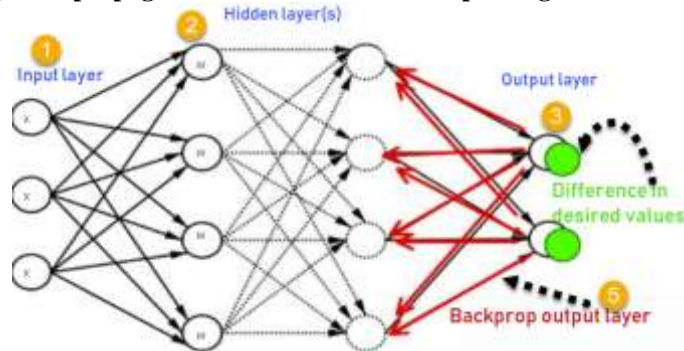
Back propagation:

The core of neural network training is backpropagation. It's a technique for fine-tuning the weights of a neural network using the error rate gained in the training phase following period (i.e., iteration). By fine-tuning the weights, you may decrease error needs and increase the model's generalization, making it more trustworthy. Backpropagation is a short form for "backward propagation of errors" in a neural network. It's a common way to train artificial neural networks. This approach is useful for calculating the gradient of a loss function with respect to all of the network's weights.

How Backpropagation Algorithm Works

The chain rule is used by the back propagation method in neural networks to determine the gradient of the loss function for a single weight. Unlike native direct processing, it efficiently computes one layer at a time. It computes the gradient but doesn't specify how it'll be used. It makes assumptions the delta rule's calculation.

Consider the following Back propagation neural network example diagram to understand:



How Backpropagation Algorithm Works

1. X inputs enter via a pre-connected route.
2. Real weights W are used to model the input. The weights are generally chosen at random.
3. From the input layer to the hidden layers to the output layer, calculate the output for each neuron. Calculate the error in the outputs
4. Error= Actual Output – Desired Output
5. Return from the output layer to the hidden layer to modify the weights in order to reduce the error. Keep repeating the process until the desired output is achieved

Why We Need Backpropagation?

- Backpropagation is fast, simple and easy to program
- It has no tuning factors other than the number of inputs.
- It's a flexible technique because it doesn't require any prior network expertise.
- It's a tried-and-true approach that usually works.
- The characteristics of the function to be understood do not require any specific remark.

V. SIMULATION RESULTS

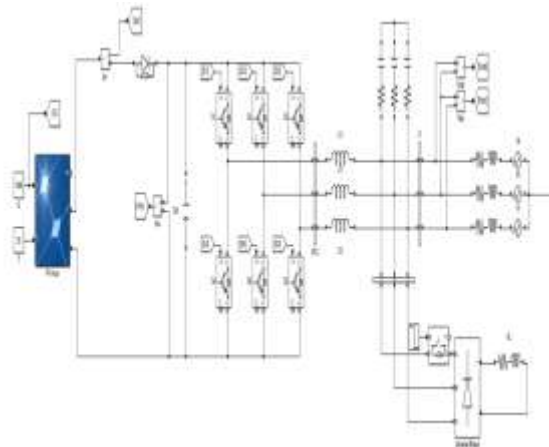


Figure5: Simulink model

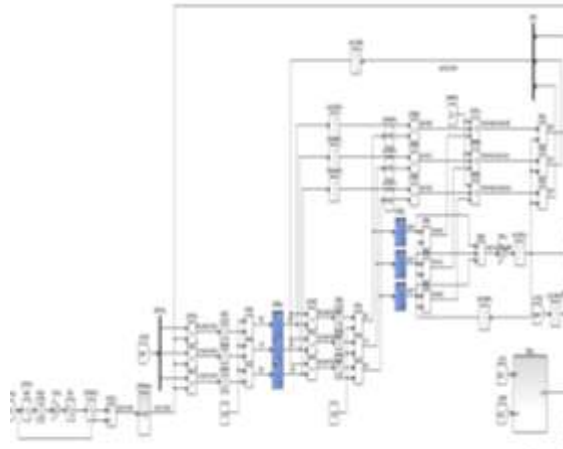


Figure6: Simulink model for ABP

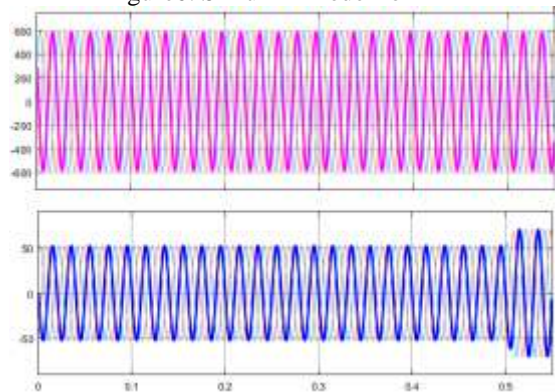


Figure7: source voltage and current

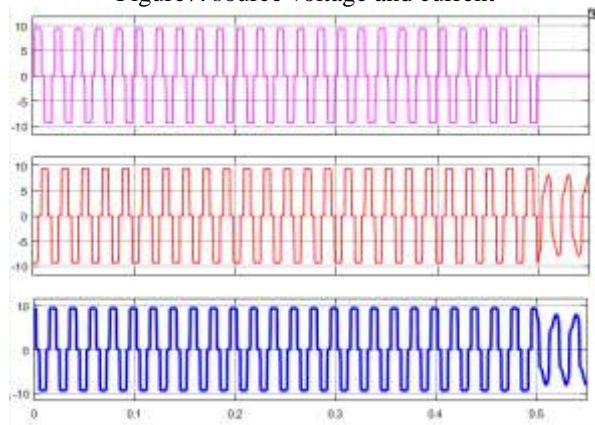


Figure8: shows line currents

By using the DBD-NN based system focused on voltage sags, swells & THD they will be modified but due to the load variations regarding non-linear unbalanced loads and non-linear

loads. by sudden change in loads the problems regarding in power quality issues is raised. so, we challenged to mitigate the problems in the source & load

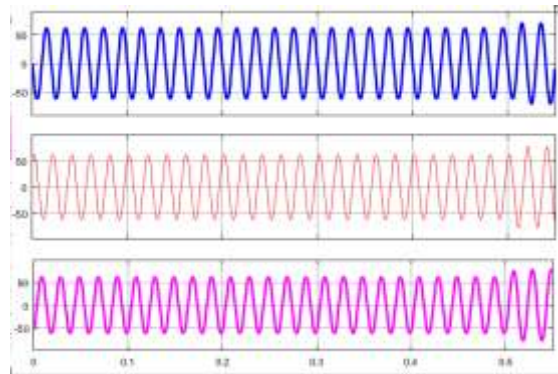


Figure9: shows phase voltages

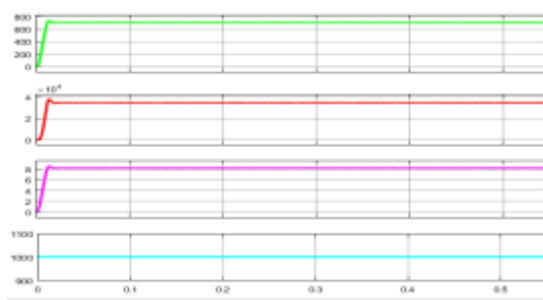


Figure10: shows sola power & insolation conditions

Response of under unbalanced non-linear loads with grid connected pv system

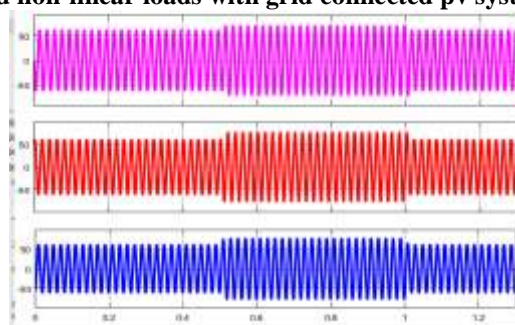


Figure11: shows line currents

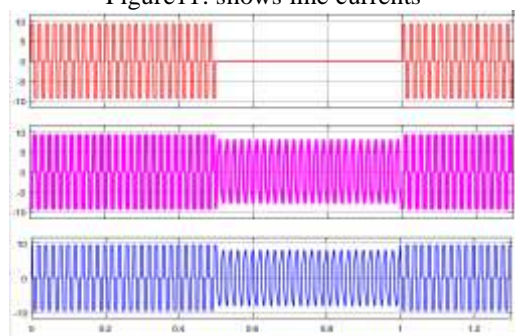


Figure12: shows phase voltages

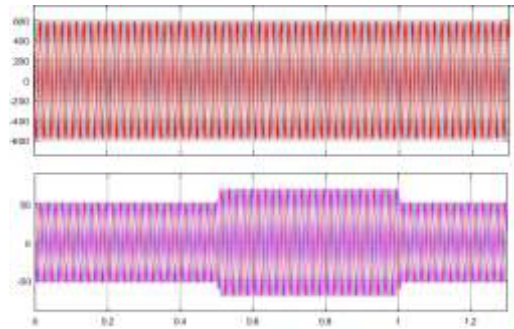


Figure 13: shows source voltages & currents

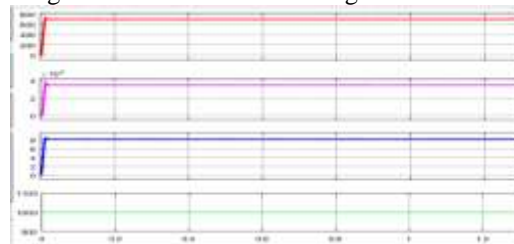


Figure 14: shows power & solar insolation

Response under nonlinear loads of grid connected solar PV system

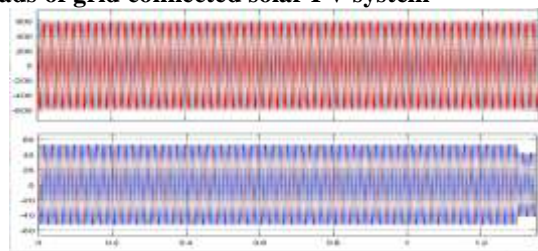


Figure 15: shows voltage & current

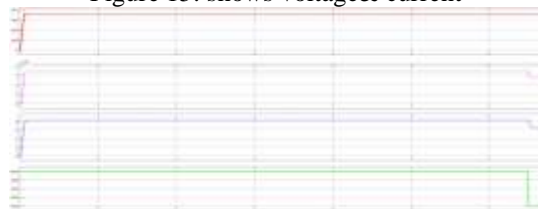


Figure 16: shows power & solar insolation

Response under the non-linear loads and non-linear unbalanced loads by using adaptive back propagation:

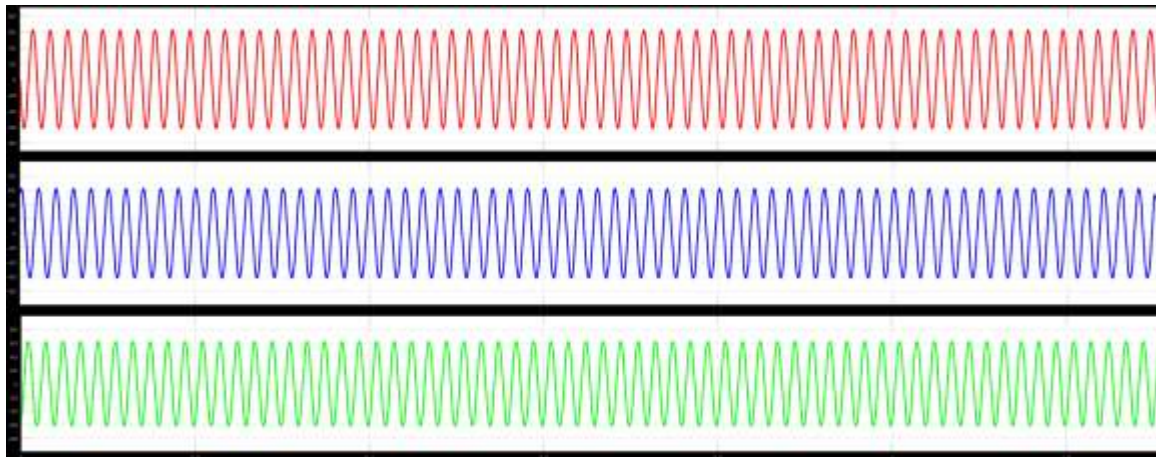


Figure17: Modified load voltages

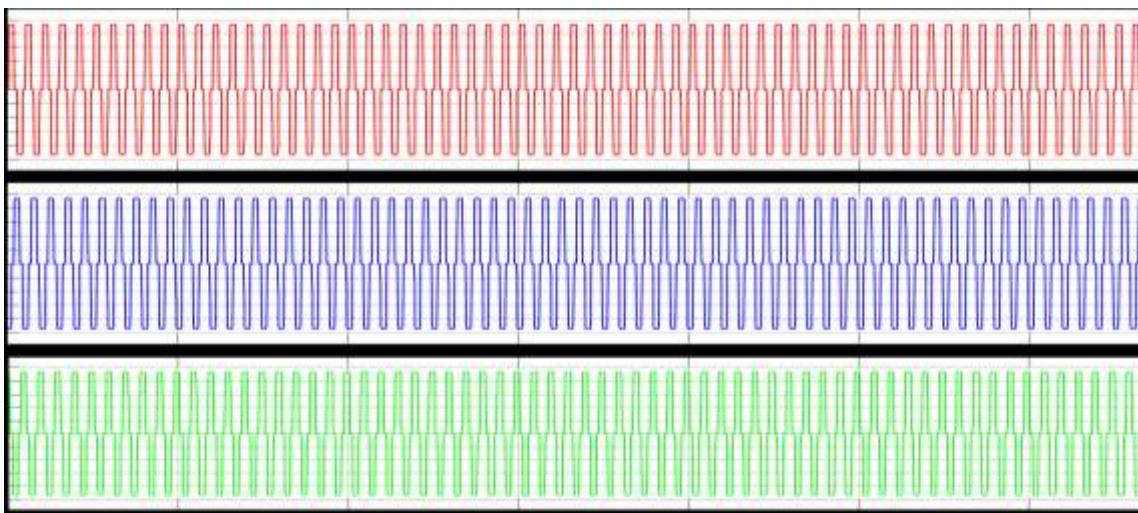


Figure18. Modified phase currents

VI. CONCLUSION

For solar PV connected to a three-phase grid system, an adaptive back propagated (ABP) neural network-based control approach is presented. In order to get the most power out of the solar PV array, the incremental conductance based MPPT was implemented. Multiple functions of load balance and harmonics reduction are performed by the control method.

voltage sag, voltage swell, and load current balancing the grid-tied PV system's performance under nonlinear load has been tested under unexpected grid situations such as load unbalancing, decreasing solar insolation, and voltage sag. Using reference currents collected by the control structure, VSC switching pulses are generated. The proposed control technique reduces

system complexity and is simple to implement in the system. Backpropagation is a quick, basic, and straight forward method. Apart from the input numbers, there are no parameters to modify.

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