

ABSTRACT

Nowadays solar energy has great importance. Because it is easily available resource for energy generation. But the only problem is efficiency of solar system. And to increase its efficiency many MPPT techniques are available for use. Incremental conductance (INC) method is one of those well known MPPT techniques. Development of INC method using two-step model predictive control by employing artificial neural network (ANN) is the main contribution of this paper. The multilevel inverter controller is based on fixed step current predictive control with small ripples and low total harmonic distortion (THD). The MPC method for the grid connected PV system speeds up the control loop by sampling and predicting the error two steps before the switching signal is applied. PI controller is used in the INC method and MPC-MPPT methods. If any disturbances are occurred in the system then PI controller does not give better dynamic response. It is less tolerable to the changes. To overcome these, PI controller is replaced with ANN in MPC-MPPT method. ANN is introduced to improve transient stability of the system and THD of the current. The proposed MPC-MPPT technique with ANN for a grid connected PV System was implemented using MATLAB and SIMULINK. Performance of the ANN in MPC-MPPT method is compared with the PI controller in INC method and MPC-MPPT method.

KEYWORDS: MPPT, Incremental Conductance, PV cell, Algorithm, Model predictive control, ANN

INTRODUCTION

The power demand is increasing day by day due to the depletion of conventional energy sources, hence now a days very high importance is given to the renewable energy sources like solar and wind where the energy is available seasonally. Renewable sources of energy acquire growing importance due to its enormous consumption and exhaustion of fossil fuel. Also, solar energy is the most readily available source of energy and it is free. Moreover, solar energy is the best among all the renewable energy sources since it is non-polluting.

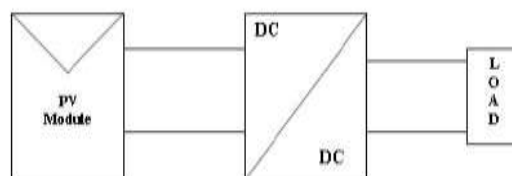


Fig.1. Block diagram of Typical MPPT system.

Energy supplied by the sun in one hour is equal to the amount of energy required by the human in one year. Photo voltaic arrays are used in many applications such as water pumping, street lighting in rural areas, battery charging and grid connected PV systems [1,3].

Solar energy can be harvested in two different fashions. One is the stand alone type where the energy obtained can be stored in the batteries and used for supplying the loads nearby. Second is the grid type where the harvested energy is directly fed to the grid. Here the PV array is a combination of series and parallel solar cells. This array

develops the power from the solar energy directly and it can be changes by depending on the temperature and solar irradiance.

MPPT:- Maximum Power Point Tracking, frequently referred to as MPPT, is an electronic system that operates the photovoltaic (PV) modules in a manner that allows the modules to produce all the power they are capable of. MPPT [4,6] is not a mechanical tracking system that “physically moves” the modules to make them point more directly at the sun.

MPPT is a fully electronic system that varies the electrical operating point of the modules so that the modules are able to deliver maximum available power. Additional power harvested from the modules is then made available as increased battery charge current. MPPT can be used in conjunction with a mechanical tracking system. Photovoltaic cell generates electricity from the sun. PV panel works under the phenomenon of photoelectric effect.

BLOCK DIAGRAM OF COMPLETE SYSTEM

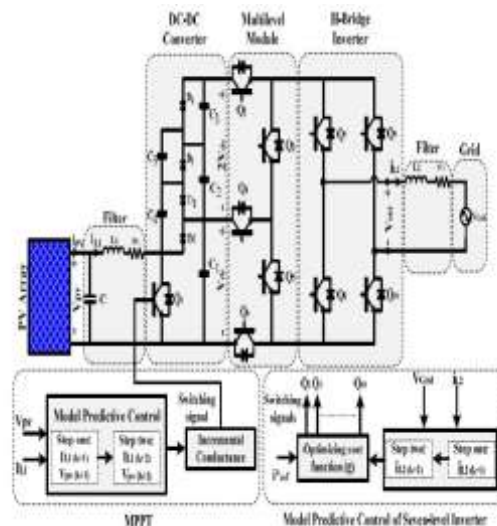


Fig.2. General Schematic of the system and model predictive control for grid connected PV system.

Fig.2 illustrates the general schematic of the complete grid connected photovoltaic system controlled by predictive methods. To extract the maximum power from the PV arrays and to feed it into the grid through a seven level inverter, a multilevel DC-DC boost converter [9] is used in the system. In the selected multi level boost DC-DC converter topology only one switch is used. Compared to other topologies such as the switched capacitor converter with a boost stage, this control procedure is simple. The output voltage of the DC-DC converter is proportional to the number of levels, which can be increased by adding two additional capacitors and diodes.

In this paper DC-DC converter has three levels. At the dc-link stage of the system, V_{dc} is the average voltage across the capacitor C_1 , then $2V_{dc}$ is the average voltage across capacitors C_2 and C_3 together. The seven level inverter topology is used to feed power to the grid. It can be divided into two parts: multilevel module and H-bridge inverter. The multilevel module is cascaded with an H-Bridge inverter. To reduce switching losses it is operating at low frequency.

The summary of the output voltage levels as a function of switching states is demonstrated in Table 1. 1 and 0 are representing the states of the switches. Where state 1 means the switch is ON, state 0 means the switch is OFF.

PRINCIPLE OF MODEL PREDICTIVE CONTROL

For high power applications, application of model predictive control (MPC) in power electronics with low switching frequency is used. Because high switching frequencies for the MPC algorithm requires large calculation time. Now by improvement of high speed microprocessors, interest in the application of MPC in power electronics with high switching frequency has been increased considerably.

Output Voltage (V _{out})	Multilevel Inverter Switches States								
	Q ₂	Q ₃	Q ₄	Q ₅	Q ₆	Q ₇	Q ₈	Q ₉	Q ₁₀
+3V _{dc}	1	0	0	0	1	1	0	0	1
+2V _{dc}	1	0	1	1	0	1	0	0	1
+V _{dc}	0	1	1	0	1	1	0	0	1
0	0	1	0	1	0	1	0	0	1
-V _{dc}	0	1	1	0	1	0	1	1	0
-2V _{dc}	1	0	1	1	0	0	1	1	0
-3V _{dc}	1	0	0	0	1	0	1	1	0

Table I. Output voltage levels as function of switching states.

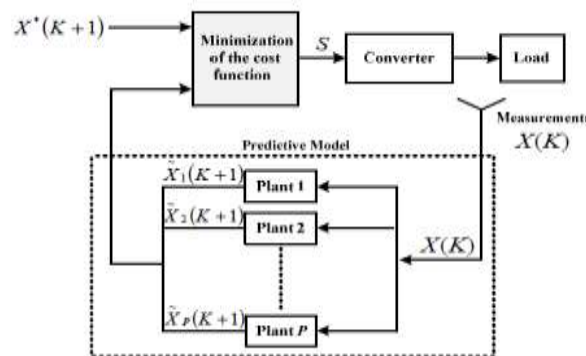


Fig.3. MPC general schematic for power electronic converters.

Predicting the future behavior of the desired control variables until a specific time in horizon is the main characteristic of MPC. The optimal switching state was obtained by minimizing a cost function. For this, the predicted control variables are used. For prediction, the discrete time model of the control variables is used which can be presented as state space model as follow:

$$x(k+1) = Ax(k) + Bu(k) \tag{1}$$

$$y(k+1) = Cx(k) + Du(k) \tag{2}$$

The future states, references and future actuations are considered in the cost function. It can be defined as:

$$g = f(x(k), u(k), \dots, u(k+N)) \tag{3}$$

For a predefined horizon in time N , the defined cost function g should be minimized. A sequence of N optimal actuations can be determined. Where the only first element of sequence is applied by the controller:

$$u(k) = [1 \ 0 \ \dots \ 0] \arg \min g \tag{4}$$

The optimization problem is solved again by using new set of measured data at each sampling time to obtain a new sequence of optimal actuation. The MPC for power electronics converters can be designed using the following steps. Determination of power converter model which specifies the input-output relation of the voltages and currents. Determination of discrete-time model of the control variables for predicting their future behavior. Designing the cost function, subject to minimization, which demonstrates the preferred behavior of the power converter. The general scheme of MPC for power electronics converters is illustrated in Fig.3.

In this block diagram, measured variables $X(k)$ are used in the model to estimate predictions $\tilde{X}(k+1)$ of the controlled variables for all of the p possible switching states (plants), where $p \in \{1 \dots P\}$ for P possible resulting circuit configurations (plants). These predictions are then evaluated using a cost function which compares them to the reference values $X^*(k+1)$ by considering the design constraints. Finally the optimal actuation S is selected and applied in the converter. The general form of the cost function g subject to minimization can be formulated as

$$g = |X_I^*(K+1) - \widehat{X}_1(K+1)| + \lambda_p |X_2^*(K+1) - \widehat{X}_2(K+1)| + \dots + \lambda_p |X_P^*(K+1) - \widehat{X}_P(K+1)| \quad (5)$$

Weight factor for each objective is λ . The schematic of Fig.3 is comprehensive and can be applied to any power converter topology and number of phases as well as the generic load illustrated in Fig. 3 which can represent the power grid or any other active or passive load. In this paper the multilevel boost DC-DC converter and multilevel grid connected inverter have been used as power conversion stage.

MODEL PREDICTIVE CONTROL OF THE SYSTEM

A. Predictive Maximum Power Point Tracking

Predicted control variables can be determined by using the discrete time model of the DC-DC converter [12]:

$$I_{L1}(K+n+1) = I_{L1}(K+n) [1 - r_{L1} \times \frac{T_s}{L_1}] + V_{PV}(K) \frac{T_s}{L_1} - (1-S) \times V_C(K+n) \quad (6)$$

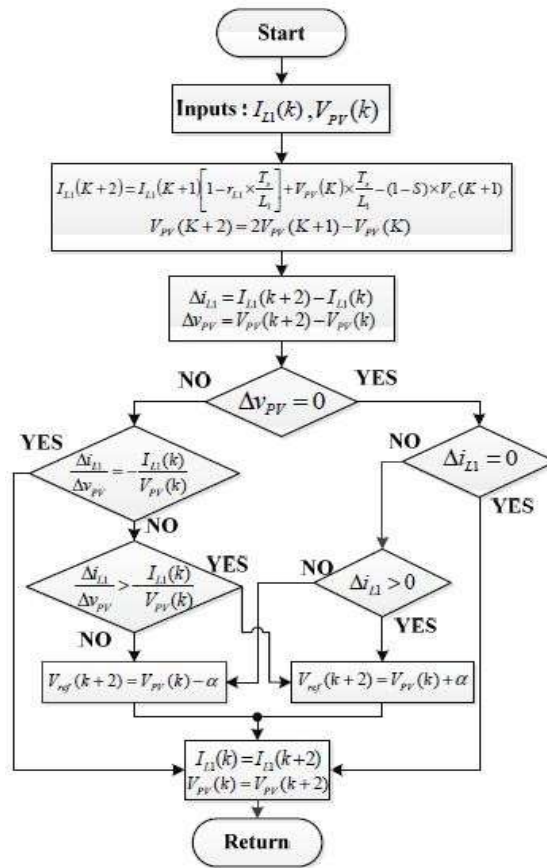


Fig.4. MPC maximum power point tracking procedure.

$$V_{PV}(K+n+1) = V_{PV}(K) + [I_{PV}(K+n) - I_{L1}(K+n)] X \frac{T_s}{C} \quad (7)$$

At the current K^{th} step the number of steps in the future being predicted is $n+1$, S is 1 when the switch is ON and 0 when the switch is OFF, T_s is the sampling time. In this the control variables are predicted two steps in horizon. Four inputs I_{L1} , V_{pv} , I_{pv} , and V_C are there in Equations (6) and (7). These equations can be rearranged by decreasing the number of input variables to reduce the number of sensors. Thus equation (7) can be represented as

$$V_{PV}(K+2) = 2V_{PV}(K+1) - V_{PV}(K) \quad (8)$$

The estimated value of the current of the inductor, $L1$, and PV voltage at time $K+1$ are used to calculate the value of control variables at time $K+2$. Therefore four values for control variables are predicted and the optimum value will be selected at sampling time $K+2$.

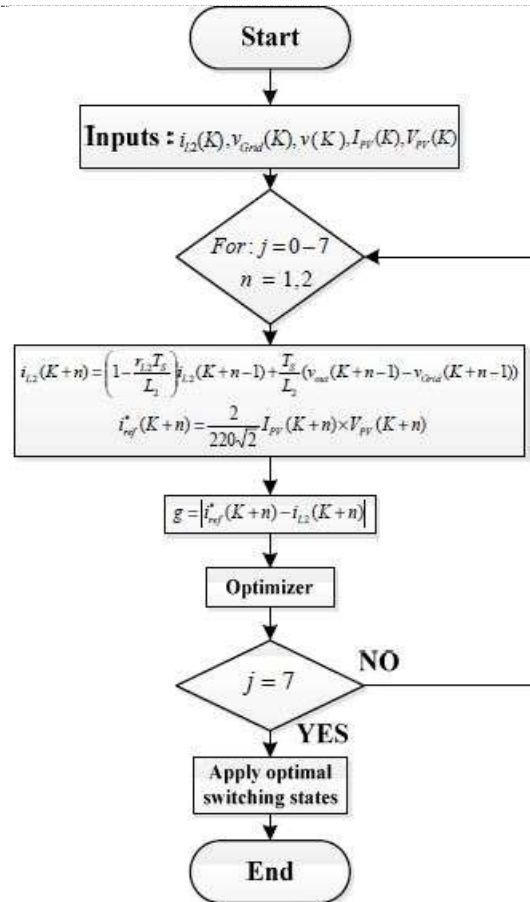


Fig.5. Model predictive control of the multilevel inverter.

The derived equations can be expressed in matrix form by (9) and (10) when the switch is ON and OFF respectively.

$$\begin{bmatrix} I_{L1}(K+2) \\ V_{PV}(K+2) \end{bmatrix} = \begin{bmatrix} 1 - r_{L1} \frac{T_s}{L_1} & \frac{T_s}{L_1} \\ 0 & 2 \end{bmatrix} \times \begin{bmatrix} I_{L1}(K+1) \\ V_{PV}(K+1) \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \times V_{PV}(K) \tag{9}$$

$$\begin{bmatrix} I_{L1}(K+2) \\ V_{PV}(K+2) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \times \begin{bmatrix} I_{L1}(K+1) \\ V_{PV}(K+1) \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \times V_{PV}(K) \tag{10}$$

The summary of the proposed

MPPT algorithm is illustrated in Fig.4.

Predictive Current Control

The next step is the current predictive control of the multilevel inverter [13]. In continuous form load current can be determined by using the following expression

$$v_{OUT} = L_2 \frac{di_{L2}}{dt} + r_{L2} i_{L2} + v_{Grid} \tag{11}$$

Discretized form of the derivative in (11), can be written as approximately by using the Euler forward method

$$L_2 \frac{di_{L2}}{dt} = L_2 \frac{i_{L2}(K+1) - i_{L2}(K)}{T_s} \tag{12}$$

The load side current can be predicted for n steps in horizon of time based on (11) and (12) by using below eq. where T_s is the sampling period

$$i_{L2}(K+n) = \left[1 - \frac{r_{L2} T_s}{L_2} \right]^n i_{L2}(K) + \frac{T_s}{L_2} (v_{OUT}(K+n-1) - v_{Grid}(K+n-1)) \tag{13}$$

Predicted value of the grid side current at time K+n is i_{L2}(K+n). i_{L2} is predicted in two steps, in this paper. n=2, into the horizon of time. The reference current to be tracked and the cost function, g, is given by

$$i_{ref}^*(K+n) = \frac{2}{220\sqrt{2}} I_{PV}(K+n) X_{VPV}(K+n) \quad (14)$$

$$g = |i_{ref}^*(K+n) - i_{L2}(K+n)| \quad (15)$$

By evaluating all of the possible switching states presented in Table 1 for each step, the cost function needs to be minimized. In Fig.5 the summary of optimal switching state selection procedure is illustrated.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like peoples, learning by examples. An ANN [14] is configured for a specific application, such as pattern recognition or data classification through a learning process. Learning in biological systems involves adjustment to the synaptic connections that exist between the neurons. This is true ANN as well. It offers very large capabilities concerning complex system modeling, prediction, control and performance

Artificial Neural Networks (ANN) are neural network models in artificial intelligence. Models are associated with a particular learning algorithm or learning rule. ANN model is a class of such functions, where members of the class are obtained by varying parameters, connection weights, or specifics of the architecture such as the number of neurons or their connectivity. A neural network model can be understood as the representation of the current understanding of how neurons operate and interoperate. Among those such models perceptron model is used in MPC-MPPT method.

The Perceptron is one of the oldest and simplest learning algorithms. It has a linear decision boundary. It can learn iteratively, sample by sample. It uses a threshold function. Learning algorithm can actually be summarized by 4 simple steps:

1. Initializing the weights to 0 or small random numbers.
2. For each training sample:
 - a. Calculating the output value.
 - b. Updating the weights.

The first step in the algorithm is to compute the net output Z as the linear combination of our feature variables x and the model weights w .

$$Z = w_1x_1 + w_2x_2 + \dots + w_mx_m = \sum_{j=1}^m x_j w_j$$

Then, define a threshold function to make a prediction. i.e. If z is greater than a threshold θ , we predict class 1, and 0 otherwise.

$$g(z) = \begin{cases} 1 & \text{if } z \geq \theta \\ -1 & \text{o.w} \end{cases}$$

In the perceptron model the predicted class labels are used to update the weights. Weight update in each iteration can be written as:

$$w_j := w_j + \Delta w_j$$

$$\Delta w_j = \eta (\text{target}^{(l)} - \text{output}^{(l)}) x_j^{(l)}, \text{ eta is the learning rate.}$$

So, in the learning phase the weights are adjusted according to the weighted sum of the inputs (net output). In the standard perceptron the net output is passed to the activation function and the function's output is used for adjusting the weights.

As compared to other models of ANN, this perceptron model is giving output with higher accuracy. Regarding complexity it is easy to design and understand.

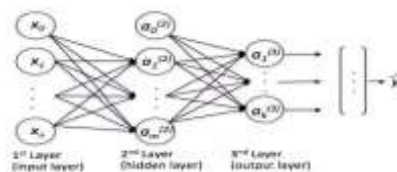


Fig.6. General structure of multilayer perceptron model.

In PV system with MPC-MPPT technique, proportional integral controller is replaced with ANN to improve dynamic performance of the grid connected system.

SIMULATION RESULTS

In this paper the ANN based MPC-MPPT method is compared to the commonly used incremental conductance method. Let us consider photovoltaic cell with Irradiance is 1250 W/m^2 . PV systems by INC-MPPT technique, by MPC-MPPT technique and by MPC-MPPT Technique with ANN circuits are simulated and the results are shown below.

The proposed controller for the PV system is modeled in MATLAB-Simulink. The SUNPOWER SPR-305-WHT is used as PV module type. Under standard test condition ,the PV module characteristics are (STC: solar irradiance = 1 kW/m^2 , cell temperature = $25 \text{ }^\circ\text{C}$) are:

- Open circuit voltage (V_{oc}) = 64.2 V
- Short circuit current (I_{sc}) = 5.96 A
- Voltage at MPP (V_{MP}) = 54.7 V
- Current at MPP (I_{MP}) = 5.58 A

The sampling time, T_s , is $10\mu\text{s}$. Below figures illustrate the simulation results of the INC-MPPT and MPC-MPPT methods.

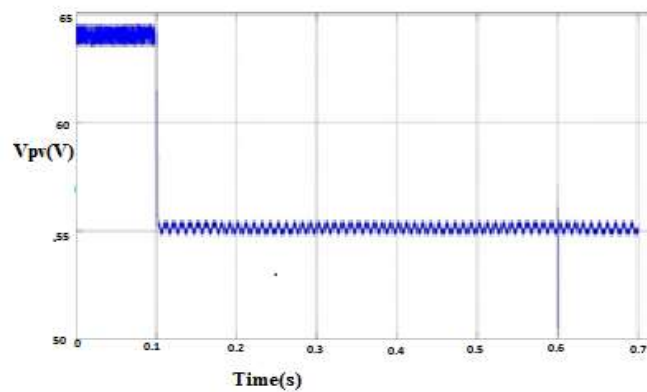


Fig.7. PV voltage by INC-MPPT

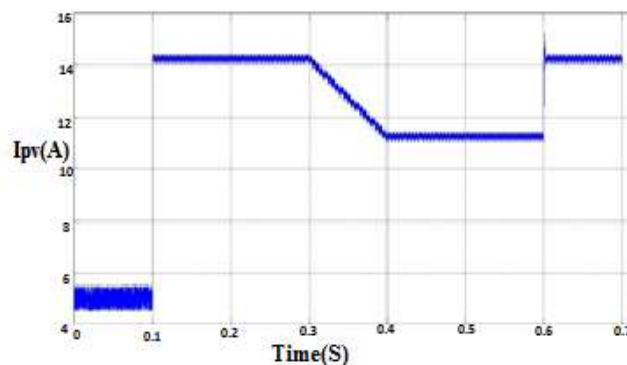


Fig.8. PV current by INC- MPPT

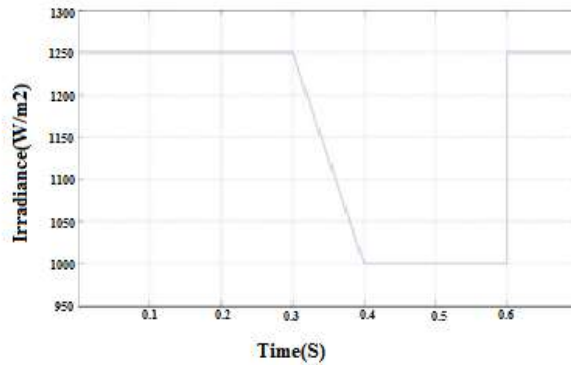


Fig.9. Irradiance level

Fig.7 and 8 are simulation results of the INC-MPPT. In Fig.9 MPPT is enabled at time 0.1s, the irradiance decreases gradually at time 0.3s from 1250 W/m² to 1000 W/m², and finally there is a step change in irradiance level at time 0.6s from 1000 W/m² to 1250 W/m².

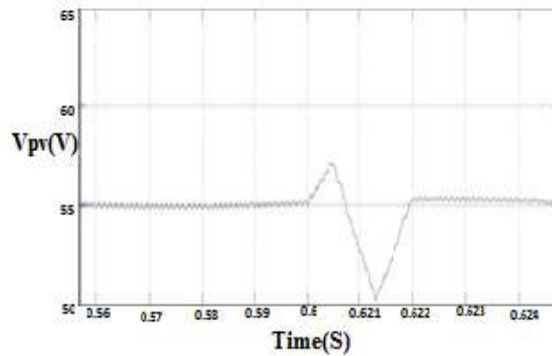


Fig.10. Zoomed in plot of PV voltage by INC-MPPT at time 0.6s

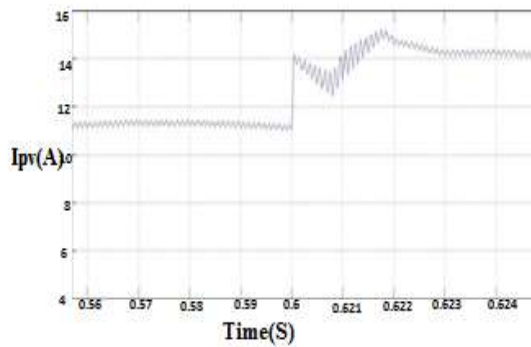


Fig.11. Zoomed in plot of PV Current by INC-MPPT at time 0.6s

Fig.10 and 11 are zoomed plots of PV current and PV voltage of INC-MPPT at time 0.6s. The maximum power point when using conventional INC- MPPT is achieved 4 ms after the step change in solar irradiance occurred. Step change in solar irradiance occurred at 0.6 sec.

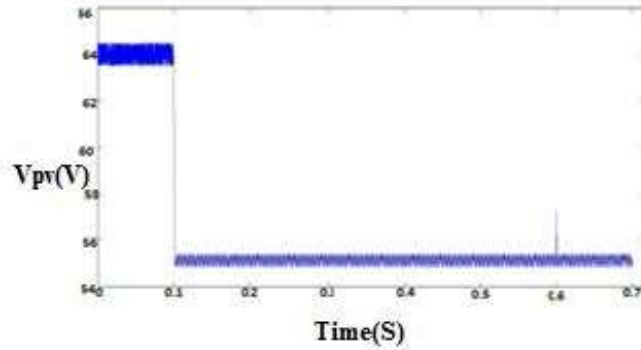


Fig.12. PV voltage by MPC-MPPT

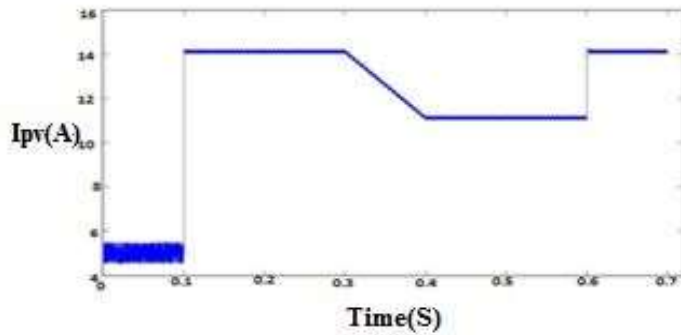


Fig.13. PV current by MPC- MPPT

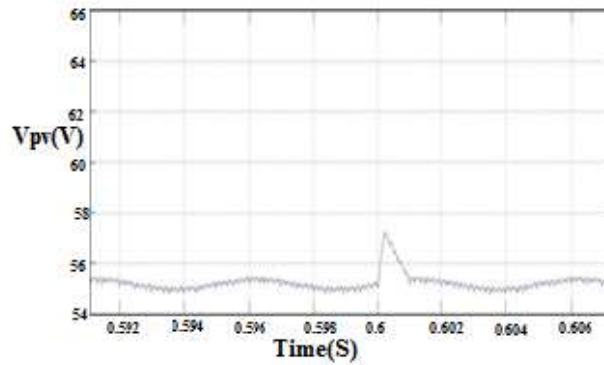


Fig.14. Zoomed in plot of PV voltage by MPC-MPPT at time 0.6s

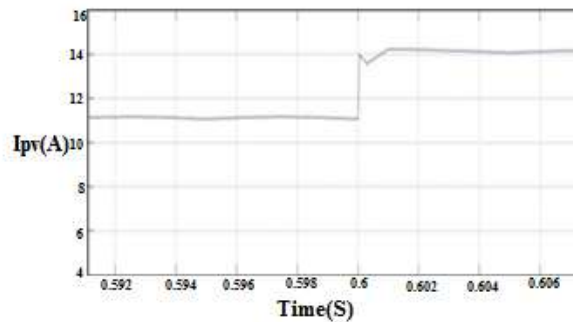


Fig.15. Zoomed in plot of PV current by MPC-MPPT at time 0.6s

Fig.12 to Fig.15 are simulation results of PV system with MPC-MPPT. The maximum power point when using two steps MPC-MPPT is achieved 1 ms after the step change in solar irradiance occurred. Step change in solar irradiance occurred at 0.6 sec.

It can be noticed that the maximum power is tracked much faster when using two steps in MPC-MPPT than the conventional INC-MPPT method.

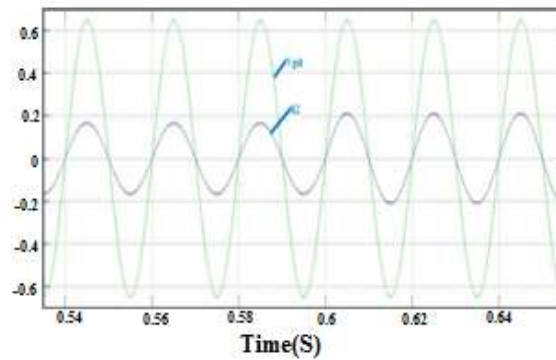


Fig.16. Grid side voltage and injected current

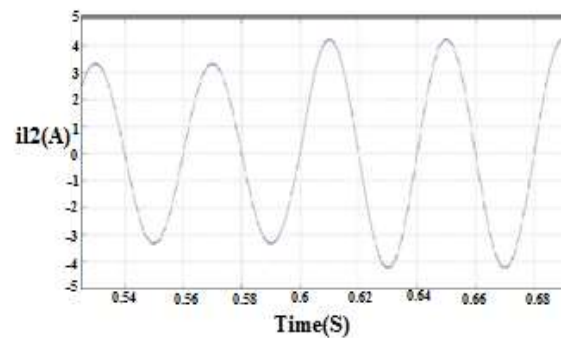


Fig.17. Zoomed in plot of injected current to the grid by using MPC-MPPT and predictive control of seven level inverter at time 0.6s

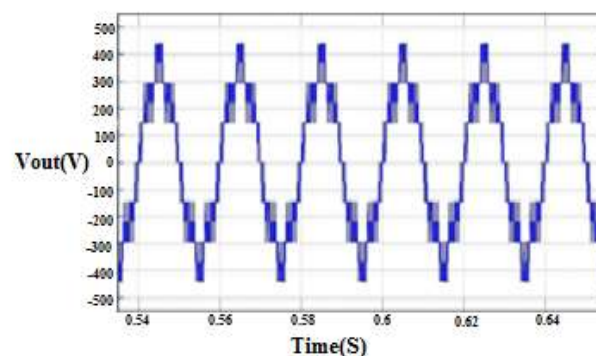


Fig.18. Output voltage of the seven level grid connected inverter

The simulation results of the grid side voltage and current using MPC for the multilevel inverter is illustrated in Fig.16 to Fig.18. The output voltage of the 7 level grid connected inverter is demonstrated in Fig.18. When the step change occurs in solar irradiance at time 0.6s the injected current to the grid has fast dynamic response shown in Fig.17.

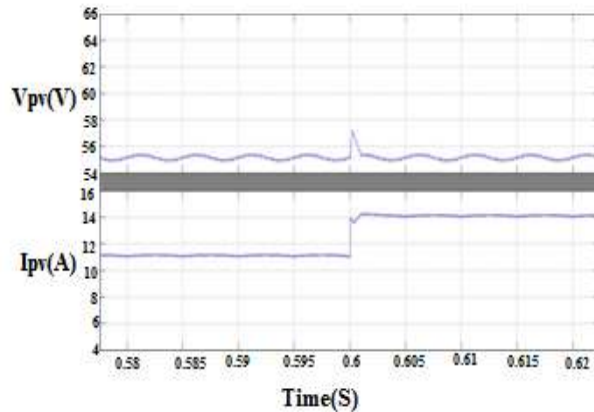


Fig.19. PV voltage and PV current by MPC- MPPT employing artificial neural network

By using the Artificial neural network in the place of PI controller in PV system using MPC-MPPT technique, transient stability of system is improved. Fig.19 demonstrates PV voltage and PV current at $t=0.6s$ using ANN.

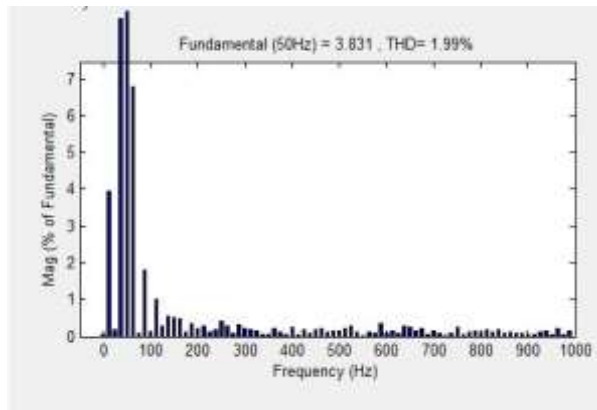


Fig.20. Spectrum analysis of grid side current (i_{L2}) when using INC-MPPT

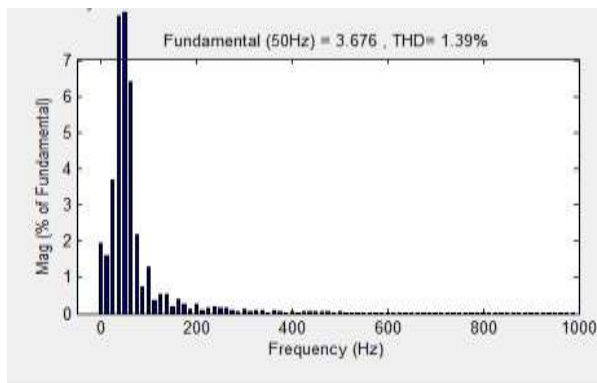


Fig.21. Spectrum analysis of grid side current (i_{L2}) when using MPC-MPPT

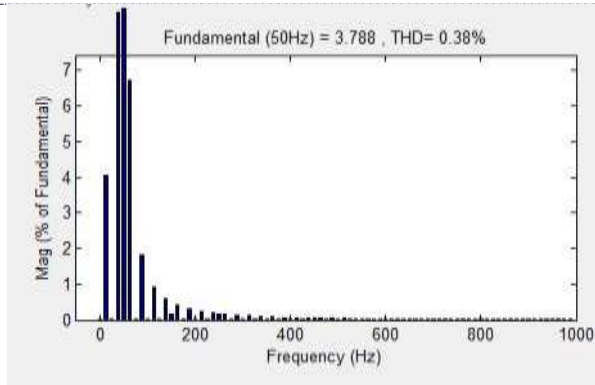


Fig.22. Spectrum analysis of grid side current (i_{L2}) when using MPC-MPPT with ANN

By comparing Fig.20 to Fig.22, the THD of the grid side current when using MPC-MPPT is about 1.39% which is less than when using conventional INC Method which is 1.99%. The THD of the grid side current is improved to 0.38% by using ANN with MPC-MPPT.

S.no	Control strategy	Settling time (ms)	Peak overshoot (%)
1	INC-MPPT	604	12.72
2	MPC-MPPT	601	4.54
3	MPC-MPPT with ANN	601	3.63

Table 2. Performance of PV voltage under different methods.

S.no	Control strategy	Settling time (ms)	Peak overshoot (%)
1	INC-MPPT	604	7.14
2	MPC-MPPT	601	3.57
3	MPC-MPPT with ANN	601	1.42

Table 3. Performance of PV current under different methods.

CONCLUSION

This paper presented an ANN based model predictive control (MPC) for a single phase grid connected photo voltaic system using MPPT technique which could be competitive to the well known controls. By predicting the future behavior of the PV system, the MPC method has faster response than the conventional INC technique.

This paper provided a comparison of the ANN in MPC-MPPT method with the PI controller in INC method and MPC-MPPT methods, in which significant improvement in dynamic performance is observed in ANN based method. It has been shown that the developed MPC based controllers are ANN and PI controller, in which ANN gave high transient stability and low harmonic distorted grid current.



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