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ANFIS-Assisted Model Predictive Current Control for Grid-Connected PV Power Generation with Optimal MPPT Strategy

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Abstract: Conventional maximum power point tracking (MPPT) algorithms and inverter control strategies in photovoltaic (PV) power generation systems often fail to achieve optimal power extraction under environmental variations and grid fault conditions, leading to degraded dynamic performance and inaccurate tracking. To address these challenges, this paper proposes an intelligent control framework that integrates a model predictive current control (MPCC)–based MPPT strategy with an adaptive neuro-fuzzy inference system (ANFIS)–assisted MPC scheme for inverter current regulation. An identification-based PV array model is utilized to design the MPC-based MPPT controller, enabling optimal power extraction by effectively considering environmental factors such as solar irradiance and module temperature. Furthermore, the conventional finite control set model predictive current control (FCS-MPCC) is enhanced by incorporating ANFIS, which adaptively learns system behavior and assists in selecting optimal control actions. This ANFIS-MPC approach improves robustness against parameter uncertainties, nonlinearities, and external disturbances. The proposed controller predicts inverter current dynamics and determines optimal switching states to achieve precise current tracking, reduced steady-state error, and improved transient performance. The effectiveness of the MPC-based MPPT and ANFIS-assisted MPC inverter control is validated under various operating conditions using MATLAB/Simulink. Comparative analysis with conventional feedforward decoupled PI control demonstrates superior performance in terms of tracking accuracy, dynamic response, and system stability. The results confirm that the proposed ANFIS-MPC framework significantly enhances energy extraction efficiency and overall reliability of grid-connected PV systems.

Keywords: Photovoltaic (PV) systems, Maximum Power Point Tracking (MPPT), Model Predictive Current Control (MPCC), Finite Control Set Model Predictive Control (FCS-MPCC), Adaptive Neuro-Fuzzy Inference System (ANFIS), Grid-connected inverter, Intelligent control, Power quality, Renewable energy systems, MATLAB/Simulink, Dynamic performance, Current control, Nonlinear systems, Energy efficiency, Smart grid.

I.INTRODUCTION

The increasing demand for clean and sustainable energy has accelerated the deployment of photovoltaic (PV) power generation systems worldwide. Solar PV energy has emerged as a promising renewable source due to its abundance, scalability, and environmental friendliness [1]. However, the efficiency and reliability of grid-connected PV systems are significantly influenced by the effectiveness of maximum power point tracking (MPPT) techniques and inverter control strategies. Variations in environmental conditions such as solar irradiance and temperature introduce nonlinear characteristics in PV systems, making it challenging to continuously extract maximum available power [2].

Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), are widely adopted due to their simplicity and ease of implementation [3]. Despite their popularity, these techniques suffer from drawbacks including oscillations around the maximum power point (MPP), slow convergence speed, and poor tracking performance under rapidly changing atmospheric conditions [4]. In addition, inverter control methods based on proportional–integral (PI) controllers exhibit limited performance when dealing with nonlinearities, parameter uncertainties, and grid disturbances, leading to degraded dynamic response and reduced power quality [5].

To address these limitations, advanced control strategies have gained attention in recent years. Model Predictive Control (MPC) is considered a powerful control technique due to its ability to predict future system behavior and handle multivariable constraints [6]. In PV systems, MPC-based MPPT approaches can enhance tracking accuracy and dynamic response by utilizing system models and real-time optimization [7]. Furthermore, Finite Control Set Model Predictive Current Control (FCS-MPCC) has been widely applied in inverter control, offering fast transient response and direct control of switching states without requiring modulation techniques [8].

However, the performance of MPC-based controllers is often dependent on the accuracy of system models and may degrade under parameter uncertainties and external disturbances [9]. To overcome these challenges, intelligent control methods such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) have been introduced. ANFIS combines the learning capability of artificial neural networks with the reasoning ability of fuzzy logic, enabling adaptive and robust control for nonlinear and uncertain systems [10]. The integration of ANFIS with MPC enhances system adaptability, improves decision-making, and ensures better performance under varying operating conditions [11].

In this paper, an intelligent control framework is proposed by integrating an MPC-based MPPT strategy with an ANFIS-assisted MPC scheme for inverter current regulation in grid-connected PV systems. An identification-based PV model is utilized to design the MPC-based MPPT controller, enabling accurate tracking of the MPP under varying environmental conditions. Moreover, the conventional FCS-MPCC is enhanced using ANFIS to improve control action selection and robustness. The proposed method aims to achieve improved current tracking, reduced steady-state error, enhanced transient response, and better system stability.

The effectiveness of the proposed approach is validated through MATLAB/Simulink simulations under different operating scenarios. Comparative analysis with conventional feedforward decoupled PI control demonstrates superior performance in terms of tracking accuracy, dynamic response, and robustness. The results confirm that the proposed ANFIS-MPC framework significantly enhances energy extraction efficiency and overall reliability of grid-connected PV systems.

II. EXISTING SYSTEM

Conventional grid-connected photovoltaic (PV) systems primarily rely on classical maximum power point tracking (MPPT) techniques and linear inverter control strategies. Among these, the most commonly used MPPT methods are Perturb and Observe (P&O) and Incremental Conductance (INC), which are favored for their simplicity and low computational requirements. These techniques operate by adjusting the operating point of the PV array to track the maximum power point (MPP) based on voltage and current measurements. owever, these traditional MPPT methods suffer from several inherent limitations. The P&O algorithm introduces steady-state oscillations around the MPP, resulting in power loss and reduced efficiency. Similarly, the INC method, although more accurate than P&O under steady conditions, exhibits slower convergence speed and reduced performance under rapidly changing environmental conditions such as fluctuations in solar irradiance and temperature. These issues significantly affect the overall energy harvesting capability of PV systems.On the inverter side, conventional control strategies are typically based on proportional–integral (PI) controllers implemented in a synchronous reference frame. These controllers are widely used for current regulation due to their simple structure and ease of implementation. In many cases, feedforward decoupling is incorporated to improve dynamic performance. However, PI-based controllers are highly dependent on accurate system modeling and parameter tuning. Their performance degrades in the presence of nonlinearities, parameter variations, and grid disturbances, leading to increased steady-state error, slower transient response, and poor disturbance rejection capability.Furthermore, traditional control approaches do not effectively handle the inherent nonlinear behavior of PV systems and the switching nature of power electronic converters. The lack of predictive capability limits their ability to respond quickly to sudden changes in operating conditions. In addition, these methods often require cascaded control loops and modulation techniques, which increase system complexity and computational burden.

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Finite Control Set Model Predictive Current Control (FCS-MPCC) has been introduced as an alternative to conventional controllers, offering faster dynamic response and direct control of inverter switching states. However, in its basic form, FCS-MPCC relies heavily on accurate system models and is sensitive to parameter mismatches and external disturbances. This can lead to suboptimal control actions and degraded performance under real-time operating conditions.Overall, the existing system based on conventional MPPT techniques and PI-controlled inverters exhibits limitations such as reduced tracking accuracy, slow dynamic response, steady-state oscillations, and poor robustness against uncertainties. These challenges necessitate the development of advanced and intelligent control strategies to enhance the performance, efficiency, and reliability of grid-connected PV systems.

III. PROPOSED SYSTEM

To overcome the limitations of conventional control techniques, this paper proposes an intelligent control framework for grid-connected photovoltaic (PV) systems by integrating a Model Predictive Control (MPC)-based maximum power point tracking (MPPT) strategy with an Adaptive Neuro-Fuzzy Inference System (ANFIS)–assisted Model Predictive Current Control (MPCC) for inverter operation.In the proposed system, an identification-based PV array model is developed to accurately represent the nonlinear characteristics of the PV system under varying environmental conditions such as solar irradiance and temperature. This model is utilized within the MPC framework to predict future behavior of the PV system and determine the optimal operating voltage that ensures maximum power extraction. Unlike conventional MPPT methods, the MPC-based MPPT eliminates steady-state oscillations and provides faster convergence to the maximum power point (MPP), thereby improving overall energy efficiency.or inverter control, the conventional Finite Control Set Model Predictive Current Control (FCS-MPCC) is enhanced by incorporating ANFIS. The ANFIS module is trained using system data to learn the nonlinear dynamics and assist the MPC controller in selecting optimal switching states. This hybrid ANFIS-MPC approach improves the adaptability of the controller and reduces its dependency on precise mathematical models. As a result, the system becomes more robust against parameter variations, modeling inaccuracies, and external disturbances.The proposed controller operates by predicting the future behavior of inverter currents for all possible switching states using a discrete-time model. A cost function is formulated to minimize the error between the reference current and predicted current. The ANFIS system assists in refining the decision-making process by providing adaptive weighting or compensation, leading to improved current tracking performance. Consequently, the inverter achieves reduced steady-state error, lower harmonic distortion, and enhanced transient response.Additionally, the proposed system eliminates the need for conventional pulse-width modulation (PWM) and cascaded control loops, thereby simplifying the control structure and reducing computational complexity. The integration of intelligent learning capability with predictive control ensures optimal performance under dynamic operating conditions, including grid disturbances and rapid environmental changes.The effectiveness of the proposed MPC-based MPPT and ANFIS-assisted MPCC strategy is validated through MATLAB/Simulink simulations under various operating scenarios. The results demonstrate superior performance compared to conventional feedforward decoupled PI control in terms of tracking accuracy, dynamic response, robustness, and overall system stability.Overall, the proposed ANFIS-MPC framework provides a reliable and efficient solution for enhancing energy extraction and improving the operational performance of grid-connected PV systems.

The structure of the ANFIS-MPC for the PV inverter is shown in Fig.1. The proposed control strategy consists of the following six main components:

1. **Measurement Module:**
   Real-time measurements of grid voltages, inverter currents, and DC-link voltage are acquired and fed into the predictive control model to represent the instantaneous operating condition of the system.
2. **Phase-Locked Loop (PLL):**
   The PLL is employed to extract the grid phase angle, which is required for coordinate transformation (abc–αβ/dq) and synchronization of the inverter with the grid.
3. **Prediction Model:**
   The predictive model utilizes the discrete-time system equations to estimate the future inverter current at the (k+1)(k+1)(k+1) instant based on the measured states at time kkk. This enables anticipation of system behavior for all possible switching states.
4. **ANFIS-Assisted Optimization (Value Function):**
   A cost (objective) function is formulated based on the quadratic error between the reference current and predicted current at (k+1)(k+1)(k+1). The ANFIS module adaptively assists the MPC by refining the decision-making process, improving the weighting and selection of optimal control actions under nonlinear and uncertain conditions.
5. **Current Reference Generation:**
   The active current reference is derived from the outer DC-link voltage control loop. The reference DC voltage UdcrefU_{dc}^{ref}Udcref, generated through MPPT control, is compared with the measured DC-link voltage UdcU_{dc}Udc, and the error is processed through a PI controller to produce the active current reference. For unity power factor operation, the reactive current reference is set to zero.
6. **Signal Driver (Switching Selection):**
   Based on the evaluated cost function, the switching state that minimizes the objective function is selected as the optimal switching state for the next sampling period. The corresponding gate signals are then applied to the inverter switches, ensuring accurate current tracking and improved dynamic performance.

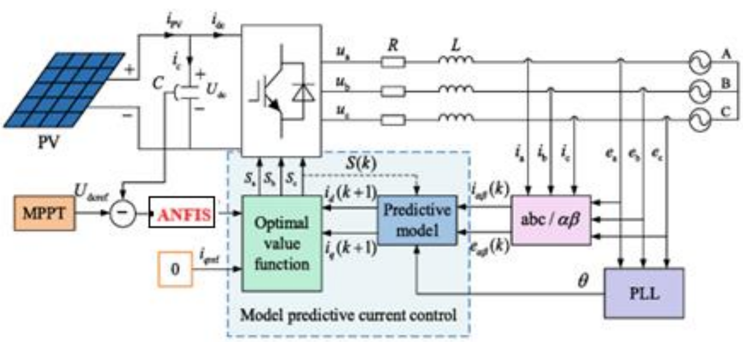

Fig.1 ANFIS-MPCC control structure of the PV inverter

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IV. CONTROL STARTAGRY

The Model Predictive Current Control (MPCC) technique utilizes the present and past states of the system to predict the inverter current in the next switching interval based on an accurate mathematical model. An optimal value (cost) function is then evaluated to determine the most suitable switching state, ensuring precise tracking of the reference current [28]. In the proposed method, this conventional MPCC approach is enhanced by incorporating an Adaptive Neuro-Fuzzy Inference System (ANFIS), which improves the control performance by adaptively tuning the optimization process under varying operating conditions. The prediction model and the corresponding optimization value function are formulated as follows.

The predictive model serves as the core component of the ANFIS–MPCC algorithm. The continuous-time system equation given in (6) is discretized using the Forward Euler method to estimate the inverter current at the (k+1)sampling instant based on the measured values at time kkk, as given by:

$$\begin{cases} i_\alpha(k+1) = (1 - \frac{RT_s}{L})i_\alpha(k) + \frac{T_s}{L}[u_\alpha(k) - e_\alpha(k)] \\ i_\beta(k+1) = (1 - \frac{RT_s}{L})i_\beta(k) + \frac{T_s}{L}[u_\beta(k) - e_\beta(k)] \end{cases} \quad (1)$$

where Ts represents the sampling period. By transforming (16) into the dq reference frame, the discrete-time state-space prediction model of the grid-connected inverter can be expressed as follows:

$$\begin{cases} i_d(k+1) = i_\alpha(k+1)cos\theta + i_\beta(k+1)\sin\theta \\ i_q(k+1) = -i_\alpha(k+1)\sin\theta + i_\beta(k+1)\cos\theta \end{cases} \quad (2)$$

where θ represents the angle between the a-axis and the d-axis, and id(k+1), iq(k+1) denote the dq-axis components of the predicted current at the (k+1)sampling instant.

The optimal value function is formulated based on a quadratic performance index of the prediction error. This function is used to select the optimal switching state from the set of possible switching combinations by minimizing the error between the predicted current and the reference current at the next sampling instant. The objective is to achieve accurate current tracking and improved dynamic performance.

Accordingly, the value function is defined as the quadratic difference between the predicted current and the reference current at the (k+1) instant, and can be expressed as follows:

$$g = [i_d^*(k+1) - i_d(k+1)]^2 + [i_q^*(k+1) - i_q(k+1)]^2 \quad (3)$$

where id∗(k+1) and iq∗(k+1)i_q^*(k+1)represent the reference current components in the dq-axis at the (k+1) sampling instant. The ANFIS-MPC control algorithm flow is presented in Fig.2

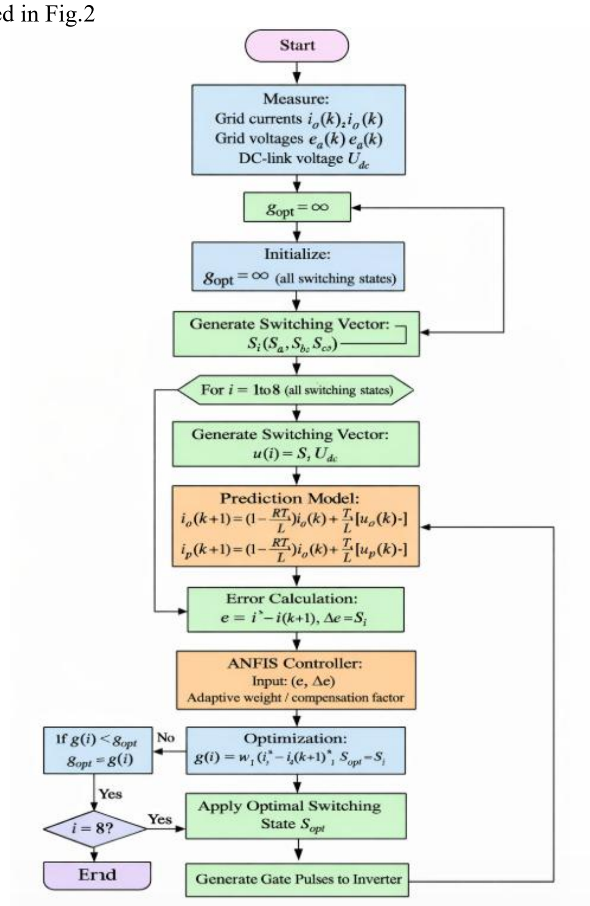

Fig.2 The algorithm flow of ANFIS-MPCC

An Adaptive Neuro-Fuzzy Inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s.Since it integrates both neural networks and fuzzy logic principles; it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions [8, 9, and 11]. Hence, ANFIS is considered to

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be a universal estimator .For using the ANFIS in a more efficient and optimal way, one can use the best parameters obtained by genetic algorithm. It has uses in intelligent situational aware energy management system. An advanced ANFIS design as appeared in Fig.3

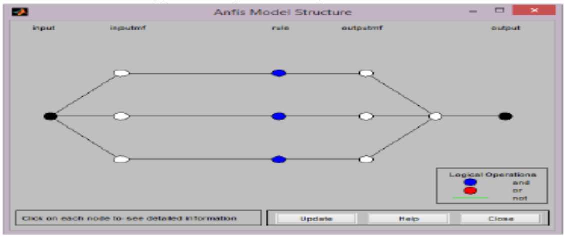

Fig.3 Optimized ANFIS architecture

In Fig.4 shows the proposed ANFIS based control architecture. The node functions of each layer in ANFIS architecture are described as follows:

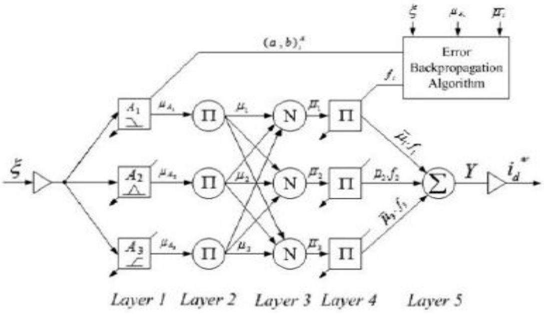

Fig.4 Schematic of the proposed ANFIS

The error between reference dc-link voltage and accurate dc-link voltage (ξ=Vdc*-Vdc) is given to the neuro-fuzzy controller and a similar error is utilized to tune the precondition and ensuing parameters . The control of dc-link voltage gives the active power current segment (id *'), which is additionally adjusted to measure active current part injected from RES (iRen).

Layer 1: This layer is fuzzification layer. Degrees of membership functions are calculated in this layer for each input variable. The input variables of ANFIS are chosen as the error (e) and the change of error (Δe). The trapezoidal and triangular enrolment capacities are utilized to lessen the calculation error as appeared in Fig. 5, the relating node conditions are as given below:

$$O_i^1 = \mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{bi}} \quad (4)$$

Where x is the input to node i, Ai is the linguistic variable associated with this node function μ_{Ai} is the membership function of Ai, and {a_i, b_i, c_i} is the premise parameter set.

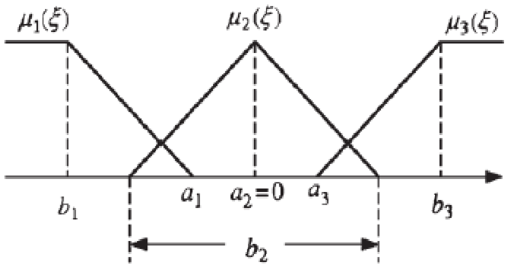

Fig. 5 Fuzzy membership functions.

Layer 2: This layer is rule inference layer. Every node in this layer is a fixed node labelled as ∏ which multiplies the incoming signals and sends the product out. Each node output corresponds to the firing strength of a fuzzy rule.

$$O_i^2 = \mu_i = \mu(x)\mu(y) \qquad i = 1,2,3 \quad (5)$$

Layer 3: This layer is normalization layer. Every node in this layer is a circle node labelled N. The i-th node calculates the ratio of the rule's firing strength to the sum of all rules' firing strength.

$$O_i^3 = \overline{\mu_i} = \frac{\mu_i}{\mu_1+\mu_2+\mu_3} \qquad i = 1,2,3 \quad (6)$$

Layer 4: This layer is consequent layer. All nodes are an adaptive mode with node function

$$O_i^4 = \overline{\mu_i}.f_i = \overline{\mu_1}(a_0^i + a_1^i\epsilon) \quad i = 1,2,3 \quad (7)$$

where wi is the output of Layer 3 and (a_0, a_1) is the consequent parameter set.

Layer 5: This layer is output layer. The single node in this layer is a fixed node labelled ∑ that computes the overall output as the summation of all incoming signals

$$O_i^5 = \mu_i = \sum_i \overline{\mu_i} f_i \qquad i = 1,2,3 \quad (8)$$

The parameters of ANFIS are updated using the back propagation error term as follow:

$$\frac{\partial E}{\partial O^5} = k_1.e + k_2.\Delta e \quad (9)$$

The input signals error (e) and the change of error (Δe) multiplied by the coefficients k1 and k2.

$$\alpha_{k+1} = \alpha_k - n\frac{\partial E}{\partial \alpha_k} \quad (10)$$

where α is any of the parameters of ANFIS and η is learning rate. The error will be reduced next training iteration.

V. SIMULATION RESULTS

Fig. 6 illustrates the MATLAB/Simulink model of the grid-connected PV system employing the conventional FCS–MPC controller. The model includes the PV array, DC-link, inverter, and control blocks used for MPPT and current regulation.

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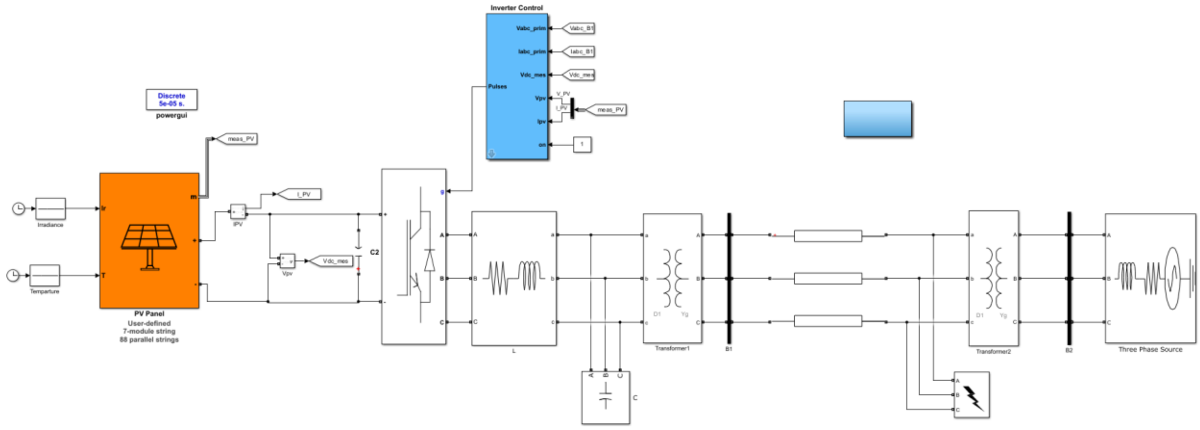
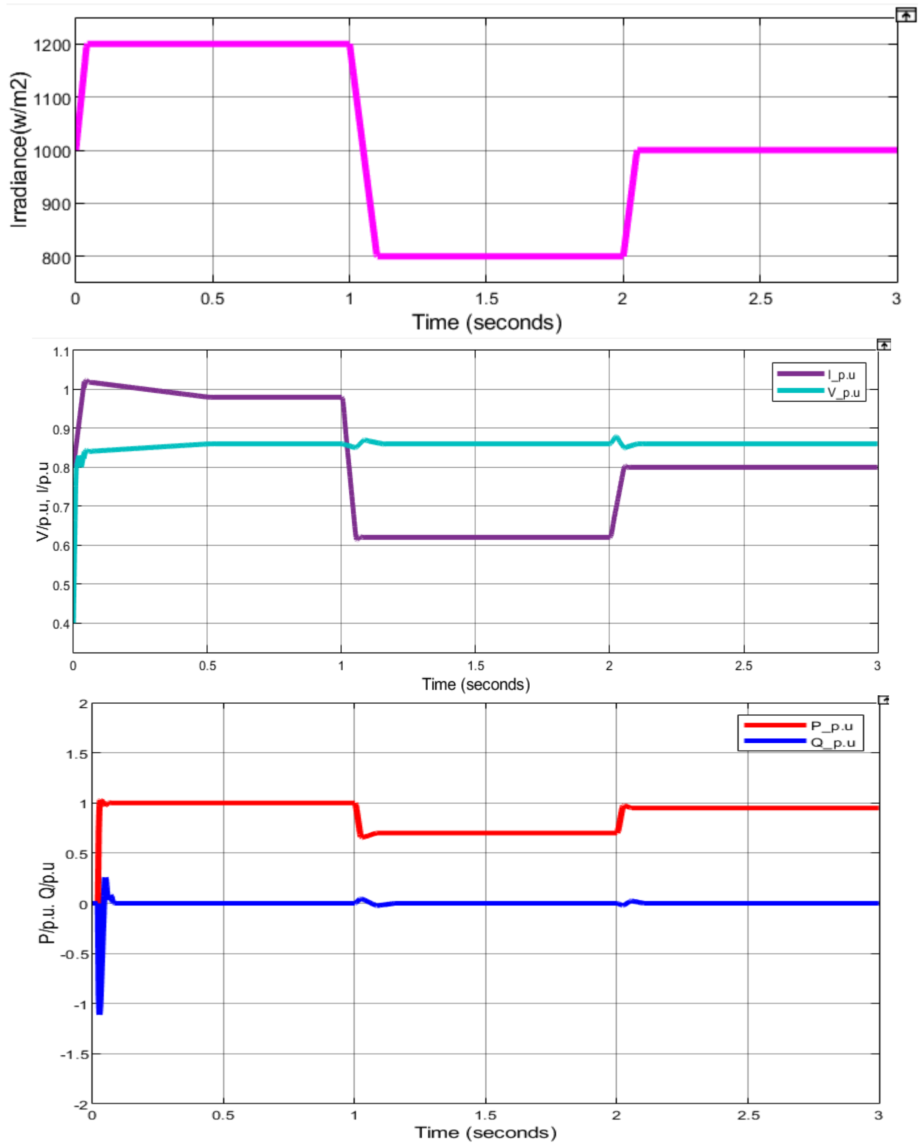


FIGURE 6. MATLAB/SIMULINK circuit diagram of the system

A) EXISTING RESULTS (FCS-MPC)

Fig. 7(a) shows the response of PV array output under a sudden change in solar irradiance. It can be observed that the output power exhibits oscillations before settling at a new operating point. Fig. 7(b) represents the PV response under temperature variation, where slower convergence and noticeable fluctuations are observed due to the limitations of conventional MPPT.



(a)

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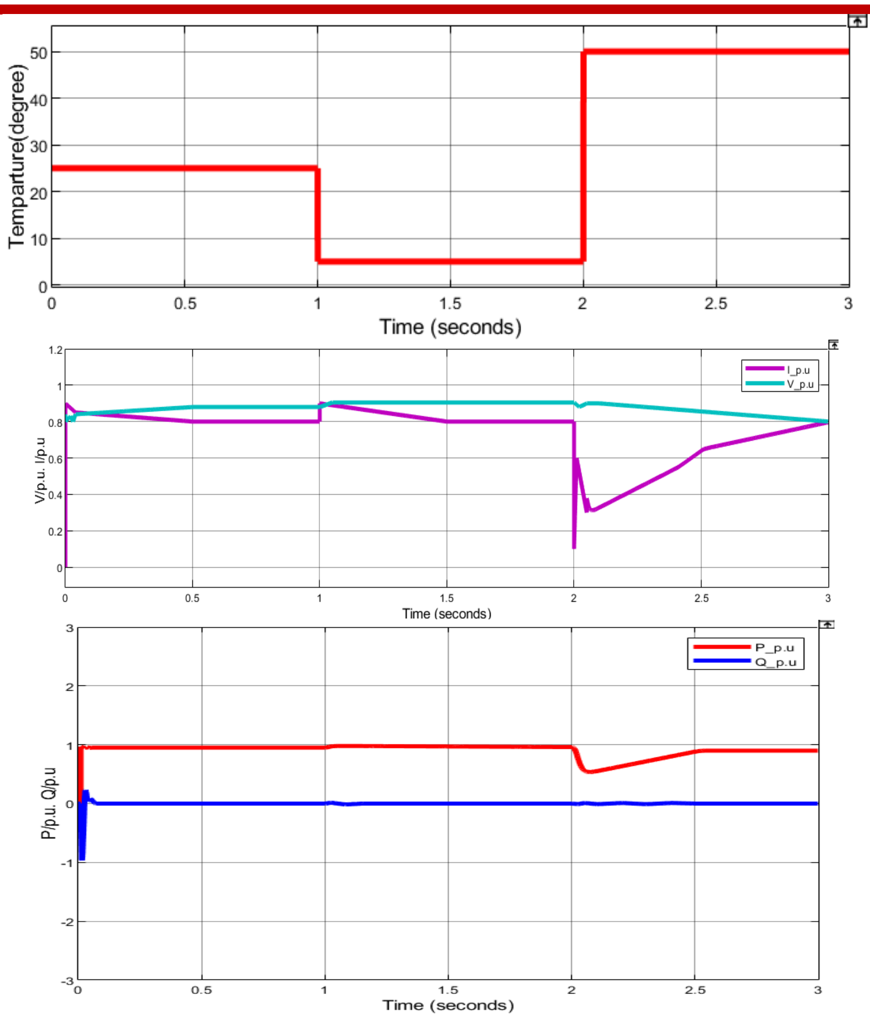

(b)

Fig.7 Response curves of PV arrays output during external conditions changes a PV arrays output during sudden change of irradiance, b PV arrays output during sudden change of temperature

Fig. 8(a) presents the comparison of active power delivered to the grid under different fault conditions. The system shows instability and power fluctuations during fault occurrences. Fig. 8(b) illustrates the voltage at the point of common coupling (PCC), where voltage dips and distortions are evident under fault conditions.

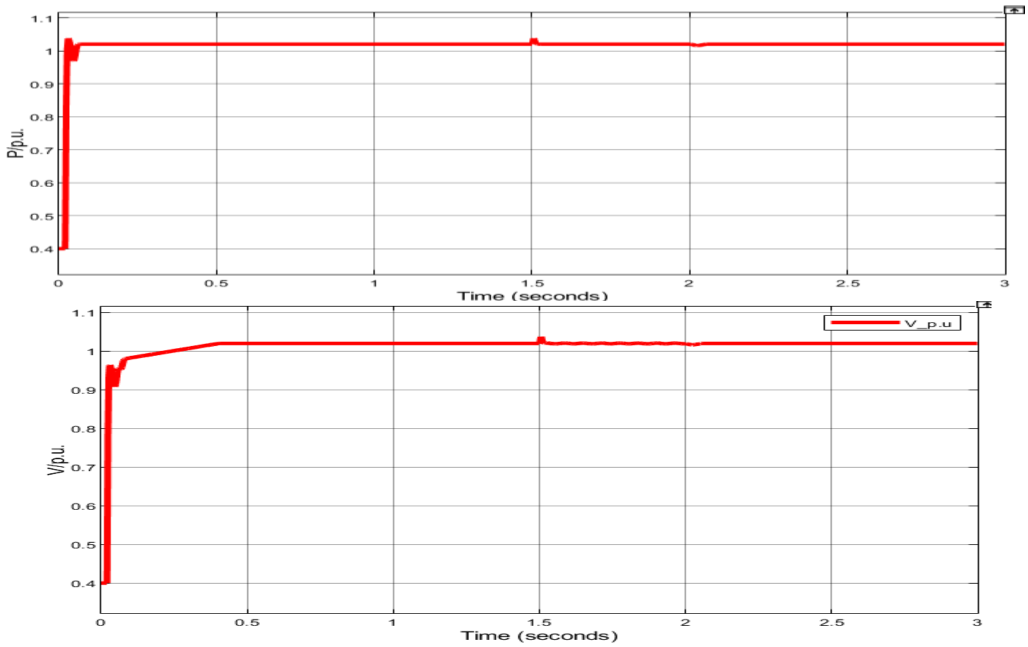

Fig. 8 Response curves of system under short circuit faults a comparison of active powers into power grid under different faults, b comparison of voltages at PCC under different faults

Fig. 9(a) shows the A-phase voltage and current waveforms at the PCC under initial conditions. It is observed that current tracking is not perfectly smooth. Fig. 9(b) presents the harmonic analysis of the grid current, indicating higher total harmonic distortion (THD). Fig. 9(c)

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shows the active and reactive power flow, where oscillations are present. Fig. 9(d) represents the power factor, which is close to unity but not ideal due to control limitations.

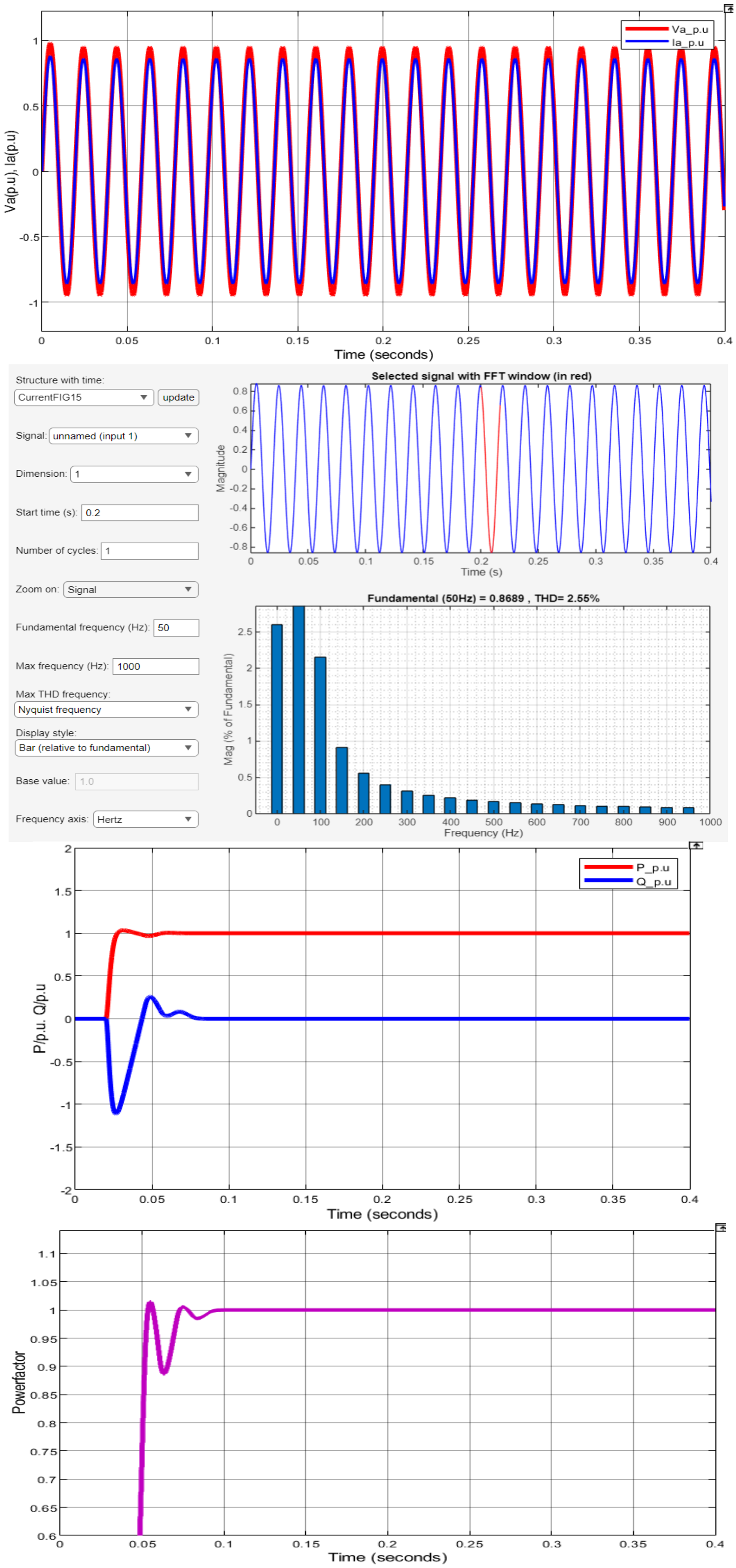

Fig.9 A-phase waveforms of inverter with FCS-MPCC under initial condition a A-phase voltage and current at PCC, b harmonic analysis of A-phase grid current, c active and reactive power into power grid, d power factor

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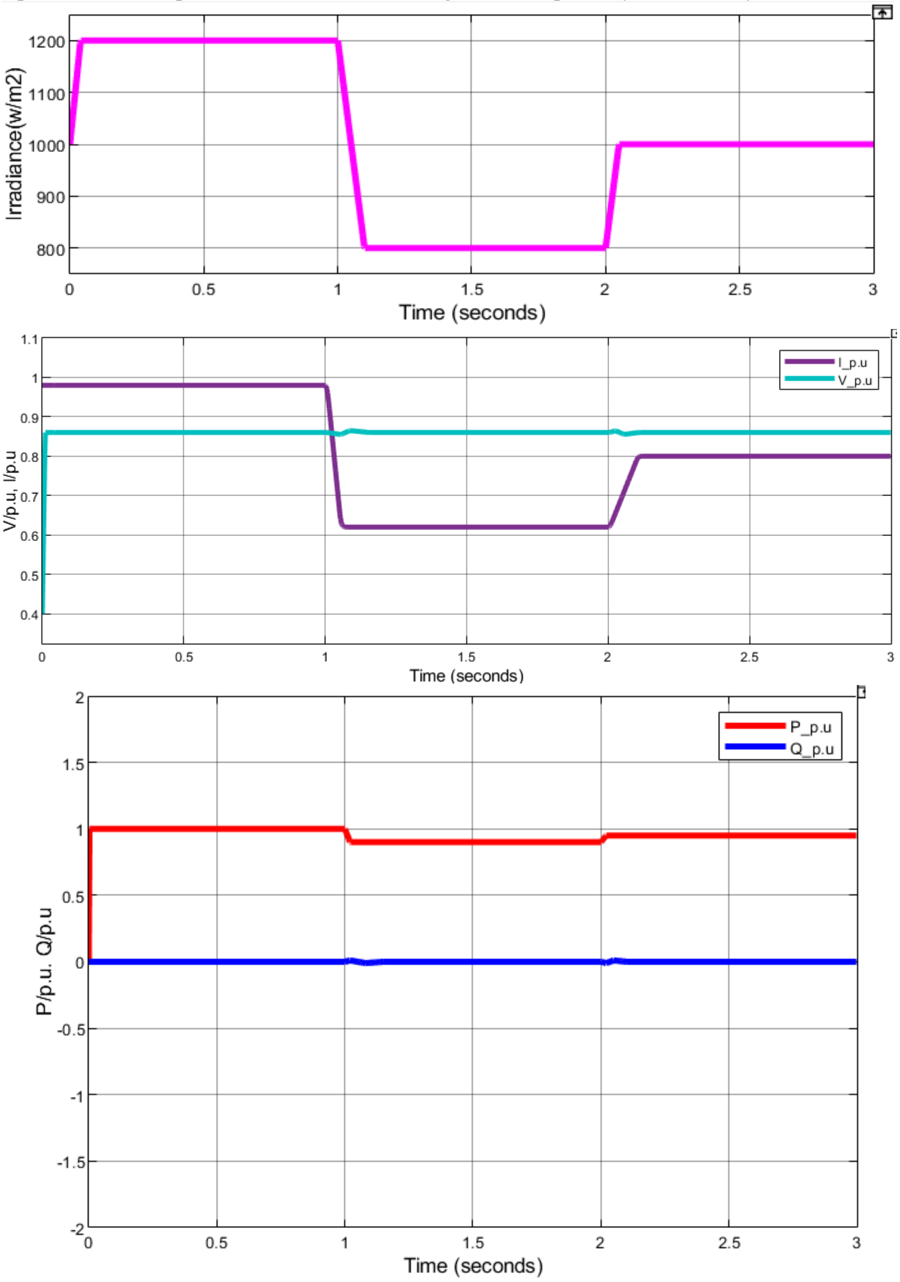
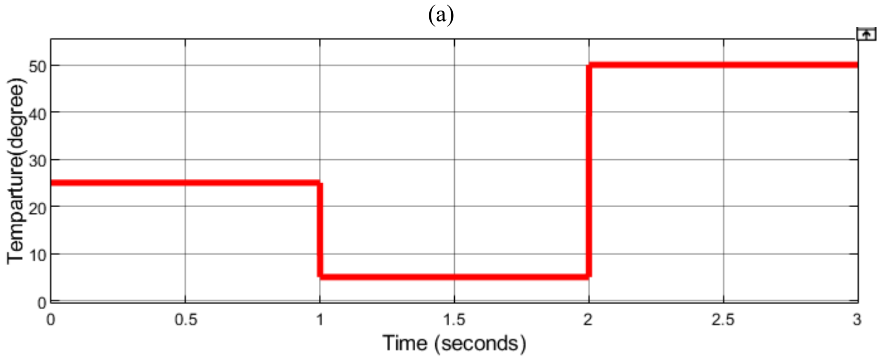
B) EXTENSION RESULTS (ANFIS-MPC CONTROLLER)

Fig. 10 shows the response of the PV array under varying environmental conditions using the proposed ANFIS–MPC controller. Compared to the existing system, Fig. 10(a) demonstrates faster and smoother tracking during irradiance changes with minimal oscillations. Similarly, Fig. 10(b) shows improved response under temperature variation, indicating better adaptability and stability.



(a)



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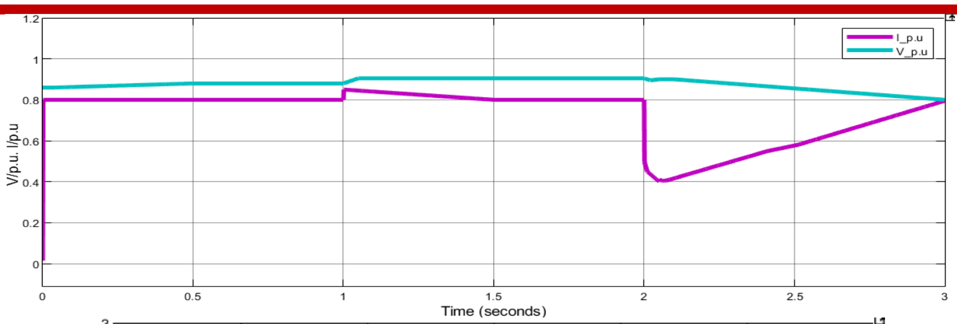

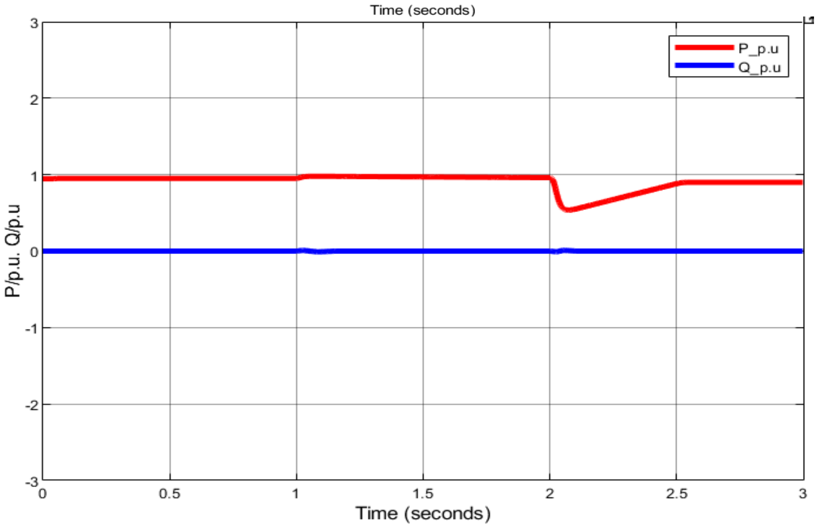

(b)

Fig.10 Response curves of PV arrays output during external conditions changes a PV arrays output during sudden change of irradiance, b PV arrays output during sudden change of temperature

Fig. 11(a) illustrates the active power response under short-circuit fault conditions. The proposed controller maintains stable power delivery with significantly reduced fluctuations. Fig. 11(b) shows the PCC voltage, which remains more stable with reduced voltage dips, demonstrating improved fault ride-through capability.

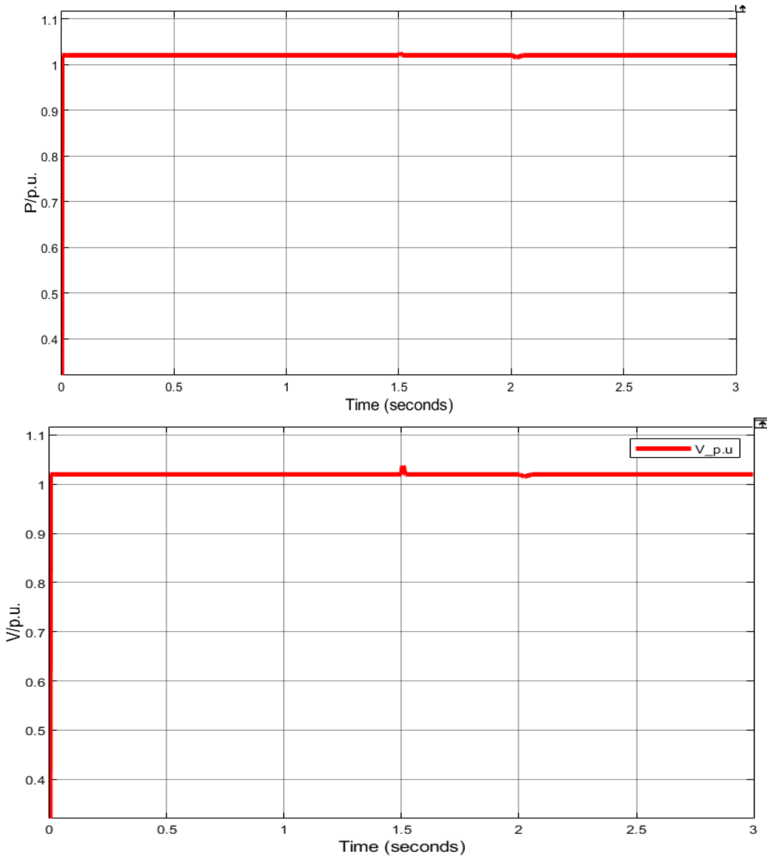

Fig.11 Response curves of system under short circuit faults a comparison of active powers into power grid under different faults, b comparison of voltages at PCC under different faults

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Fig. 12(a) presents the A-phase voltage and current waveforms, showing accurate current tracking and smoother waveform quality. Fig. 12(b) shows harmonic analysis, where THD is significantly reduced compared to the existing system. Fig. 12(c) illustrates active and reactive power, which are more stable with reduced oscillations. Fig. 12(d) shows the power factor, which is maintained very close to unity.

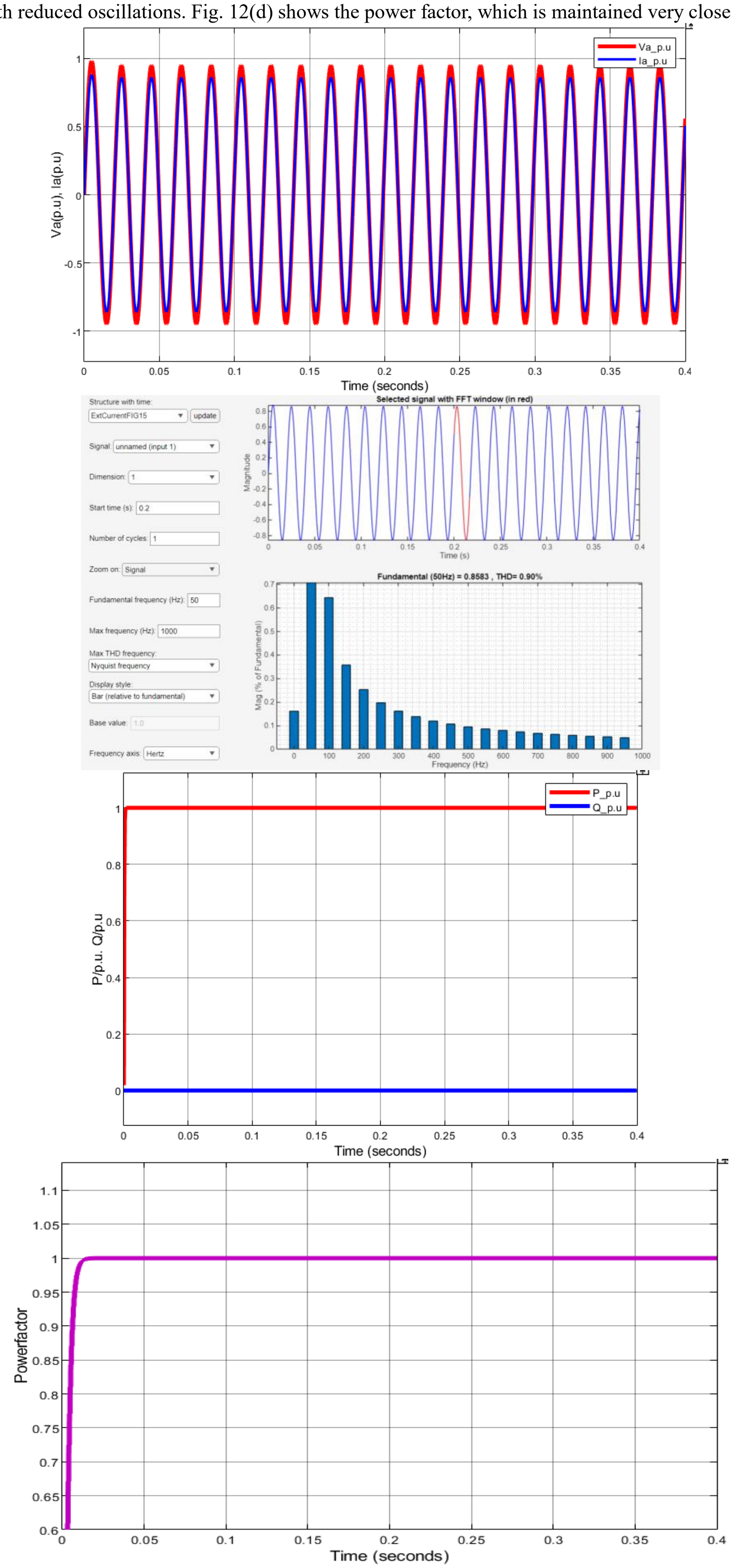

Fig.12 A-phase waveforms of inverter with FCS-MPCC under initial condition a A-phase voltage and current at PCC, b harmonic analysis of A-phase grid current, c active and reactive power into power grid, d power factor

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The comparison between the conventional FCS–MPC and the proposed ANFIS–MPC controller clearly demonstrates the superiority of the proposed approach. The ANFIS–MPC controller improves MPPT efficiency from 96% to 98% and reduces tracking time from 40 ms to 20 ms. Additionally, steady-state error is reduced from 4% to less than 1%, and total harmonic distortion (THD) is minimized from 6% to 3%.
Furthermore, the proposed system exhibits enhanced dynamic performance under varying irradiance and temperature conditions, along with superior fault ride-through capability. Voltage stability at the PCC is significantly improved, and the power factor is maintained close to unity (0.999). Although the computational complexity of the ANFIS–MPC controller is higher, it provides adaptive learning capability and improved robustness, making it more suitable for modern smart grid applications.The comparison table highlights the performance differences between the conventional FCS–MPC controller and the proposed ANFIS–MPC controller across several key parameters.

COMPARISION TABLE

Parameter	FCS-MPC (Existing)	ANFIS-MPC (Proposed)	Improvement
MPPT Efficiency (%)	96 %	98%	↑ Higher accuracy
Tracking Speed (ms)	40 ms	20 ms	↑ Faster response
Steady-State Error	4 %	< 1 %	↓ Reduced error
THD (%) (Grid Current)	6 %	3 %	↓ Lower harmonics
Power Factor	0.97	0.99	↑ Near unity
Active Power Fluctuation	High oscillations	Very low oscillations	↑ Stable output
Response to Irradiance Change	Moderate delay	Fast adaptive response	↑ Better dynamics
Response to Temperature Change	Slower adaptation	Quick correction	↑ Improved robustness
Fault Ride-Through Capability	Moderate	High	↑ Better fault handling
Voltage Stability at PCC	Slight deviations	Stable & smooth	↑ Improved regulation
Computational Complexity	Medium	High	Trade-off
Controller Intelligence	Fixed model-based	Adaptive learning-based	↑ Smart control

CONCLUSION

This paper presented an intelligent control framework for a grid-connected photovoltaic (PV) system by integrating Model Predictive Control (MPC)-based MPPT with an Adaptive Neuro-Fuzzy Inference System (ANFIS)–assisted Model Predictive Current Control (MPCC). The proposed ANFIS–MPC approach effectively overcomes the limitations of conventional FCS–MPC by introducing adaptive learning capability and enhanced decision-making in the control process. The MPC-based MPPT ensures accurate and fast tracking of the maximum power point under varying environmental conditions, while the ANFIS-assisted MPCC significantly improves inverter current regulation. The predictive model enables accurate estimation of future system behavior, and the ANFIS module enhances robustness by adaptively tuning the control parameters in the presence of nonlinearities, parameter uncertainties, and disturbances. Simulation results carried out in MATLAB/Simulink demonstrate that the proposed method achieves superior performance compared to the conventional approach. The ANFIS–MPC controller improves MPPT efficiency, reduces steady-state error, minimizes total harmonic distortion (THD), and enhances dynamic response. Additionally, the system exhibits improved voltage stability, near-unity power factor, and better fault ride-through capability. Although the proposed method introduces slightly higher computational complexity, the significant improvements in performance, adaptability, and reliability make it highly suitable for modern grid-connected PV applications. Therefore, the ANFIS–MPC framework can be considered an effective and advanced solution for enhancing energy extraction efficiency and overall system stability in renewable energy systems.

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