SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I8P122

Volume 12 Issue 8, 257-268, August 2025

Original Article

Moving Average-Based Artificial Neural Network Controller for Voltage Source Converter Transient Suppression

Viay Kumar Madasi[1], Jagan MohanRaju[2]

[1,2]*EEE Department, Kakatiya University, Telangana, India.*

[1]*Corresponding Author : vijji.715@gmail.com*

Received: 17 June 2025 Revised: 17 July 2025 Accepted: 16 August 2025 Published: 30 August 2025

Abstract - *Renewable energy sources are extensively incorporated into the conventional electric grid via Voltage Source Converters. Due to the sporadic nature of renewable sources, voltage fluctuations are developed at the input terminals of converters. However, these converters experience switching transients and inrush current issues during voltage fluctuations, degrading converter performance. With this, the electric grid experiences accelerated component aging, increased power loss, and frequent tripping. To mitigate these issues, a novel "Moving Average-based Artificial Neural Network (MA-ANN)" controller that fuses the Moving Average filter's smoothing feature with Artificial Neural Network adaptive learning capability has been suggested in this study for accurate current regulation in the system. The Input signal with transients is processed using the Moving Average Filter, where the Artificial Neural Network is trained to predict the appropriate switching to regulate the grid current. Analytical results are validated through the proposed controller, which is then simulated and tested in MATLAB/Simulink, where the DC source is modelled as a distributed energy resource (with its DC link connected to the grid through a voltage source converter). The proposed Moving Average-based Artificial Neural Network (MA-ANN) controller outperformed conventional Artificial Neural Network and Proportional–Integral (PI) controllers in suppressing switching transients, minimizing surge inrush current while maintaining accurate current tracking. This controller offers enhanced robustness, reduced converter stress, and improved power quality, making it a promising control strategy for next-generation renewable energy systems with high dynamic variability.*

Keywords - *ANN controller, Switching transients, Inrush current, Current regulation, Renewable energy integration.*

1. Introduction

Electrical energy plays a crucial role in meeting global energy demand. With ongoing technological advancements, renewable energy sources such as solar and wind are being rapidly integrated into the electric grid [1]. However, due to the intermittent nature of these sources and their variable and unpredictable output depending on environmental conditions, the conventional electric grid encounters several operational challenges. These include switching transient currents, inrush currents, and voltage sags [2]. Switching transients are short-duration, high-frequency disturbances that occur during the rapid connection or disconnection of renewable sources [3]. These are developed due to the frequent incoming and outgoing renewable energy sources concerning the electric grid, imposing voltage sags, and due to the adjusted switching pattern of voltage source converters for injecting required current into the system under voltage sag conditions [4, 5]. In contrast, this surge inrush currents are developed with large capacitance or inductance in the system, and frequent switching operation of Voltage source converters without a soft starting mechanism. These currents are large, sudden surges of current that occur when power converters are energized and can severely affect converter lifespan and reliability [6]. Addressing these challenges is important to protect the Voltage Source Converter (VSC) linking renewables to the electric grid. Voltage Source Converters change DC electricity from renewables into AC that follows the grid's requirements. The systems consist of semiconductor power devices designed to function within specific voltage, current, and power levels. To mitigate these issues of switching transients and surge inrush currents in the event of variable power generation, advanced control techniques and hardware-based solutions are explored in [7], including fast-acting voltage limiters and coordinated reactive power support. Fast-acting voltage limiters exhibit poor response, and coordinated reactive power support is restricted with Voltage source converter ratings, making these controllers ineffective in coordinating multiple energy sources during rapid grid changes.In contrast, Proportional Integral (PI) controllers are popular, easy to implement, and work efficiently in steady-state situations. Because of their fixed gain parameters, these controllers exhibit inadequate performance in dynamic system variations [8, 9]. Due to delayed response and poor damping, transient currents rise abruptly in the dynamic environment of the grid. This restricts the application of PI controllers to steady state over dynamic state [10].

However, Fuzzy logic controllers outperform PI controllers under dynamic conditions by adjusting their control actions based on the linguistic rules and membership functions, posing real-time challenges in implementation due to the complexity of the rule-based membership functions, which makes fuzzy systems inadequate in transient control [11]. Similarly, Model Predictive Control (MPC) is investigated for predictive voltage control but is restricted for real-time applications due to its dependency on accurate system models and high computational complexity [12]. Artificial neural networks have emerged as a promising solution for intermittent renewable energy resources by incorporating adaptive learning mechanisms [13]. Despite this advantage, Artificial Neural Networks-based controllers struggle to handle switching transients and Inrush currents during voltage fluctuations due to a lack of a smoothing mechanism [14], leaving a research gap. These limitations raise two key research questions: Can an intelligent control strategy be designed to enhance transient damping and surge current control during variable voltage input? Furthermore, how would such a strategy compare with conventional PI controllers in regulating current and suppressing voltage-related disturbances? To address these questions, this research aims to fill the gap of minimizing the switching transients and surge Inrush currents under variable input voltage conditions using the Artificial Intelligence-based techniques. A Novel Moving-Average-Based Artificial Neural Network (MA-ANN) augmented with a standard Artificial Neural Network Controller is designed to address these issues. This proposed controller demonstrated its superiority over the Proportional Integral controller through MATLAB-based simulations in damping out switching transients, Inrush currents, and regulating the current under dynamic input voltage conditions.

2. Research Methodology

This research employs a systematic methodology, as shown by the flowchart of Figure 2, to develop an effective control strategy for mitigating switching transients and inrush currents issues in grid-connected renewable energy systems. The approach begins with modelling the Voltage Source Converter (VSC) system in the rotating dq-reference frame, which simplifies the complex three-phase current control problem into a manageable form. Conventional Proportional-Integral (PI) controllers are first implemented as a baseline to highlight the limitations faced in dynamic operating conditions. To deal with these issues, the ANN-based controller is presented for adapting to the challenges caused by system nonlinearities. Recognizing the challenges posed by noise and transient spikes during switching, the ANN controller is augmented with a moving average filter, forming the Moving Average-Augmented ANN (MA-ANN) controller. The use of a hybrid design increases the system's ability to block noise and deal with sudden changes. The approach to design involves teaching the neural networks thoroughly, using powerful algorithms, and checking the performance with MATLAB simulations to guarantee proper control of the current and dampening of transients under all grid situations. Unlike voltage-mode control that computes active and reactive currents based on the phase and amplitude of the VSC's AC terminal voltage [15, 16], the current-mode approach directly regulates the VSC line current relative to the Point of Common Coupling (PCC). This technique delivers superior dynamic response, higher control accuracy, and stronger robustness to parameter variation in the voltage source converter and grid.

2.1. System Configuration and Modelling

As shown in Figure 1, a DC energy source, representing Distributed Energy Resources (DERs), connects to an ideal AC grid via a Voltage Source Converter (VSC) operating at grid-imposed frequency. The VSC controls both active and reactive current injection, while the AC grid is modelled as an ideal, balanced three-phase voltage source Vsabc with constant frequency and sinusoidal waveform. To simplify control design, the three-phase system is transformed using a space vector representation, as defined by

$$\vec{f}(t) = f e^{-j(\omega t+\theta_0)} \tag{1}$$

This is mapped into the stationary αβ frame:

$$f_\alpha + j f_\beta = \hat{f} e^{j\theta_0} \tag{2}$$

Finally, it is projected into the rotating dq-frame:

$$\vec{f}(t) = (f_d + j f_q) e^{j\rho(t)} \tag{3}$$

The dq transformation reduces the three-phase sinusoidal current tracking problem into a decoupled DC control problem, which is ideal for PI-based regulators.

2.2. Current Control Equations

In the dq reference frame, the dynamic behavior of the converter is captured by :

$$L\frac{di_d}{dt} = \left(L\frac{d\rho}{dt}\right) i_q - (R + r_{on}) i_d + V_{td} - \hat{V}_s \cos(\omega_0 t + \theta_0 - \rho) \tag{4}$$

$$L\frac{di_q}{dt} = \left(L\frac{d\rho}{dt}\right) i_d - (R + r_{on}) i_q + V_{tq} - \hat{V}_s \sin(\omega_0 t + \theta_0 - \rho) \tag{5}$$

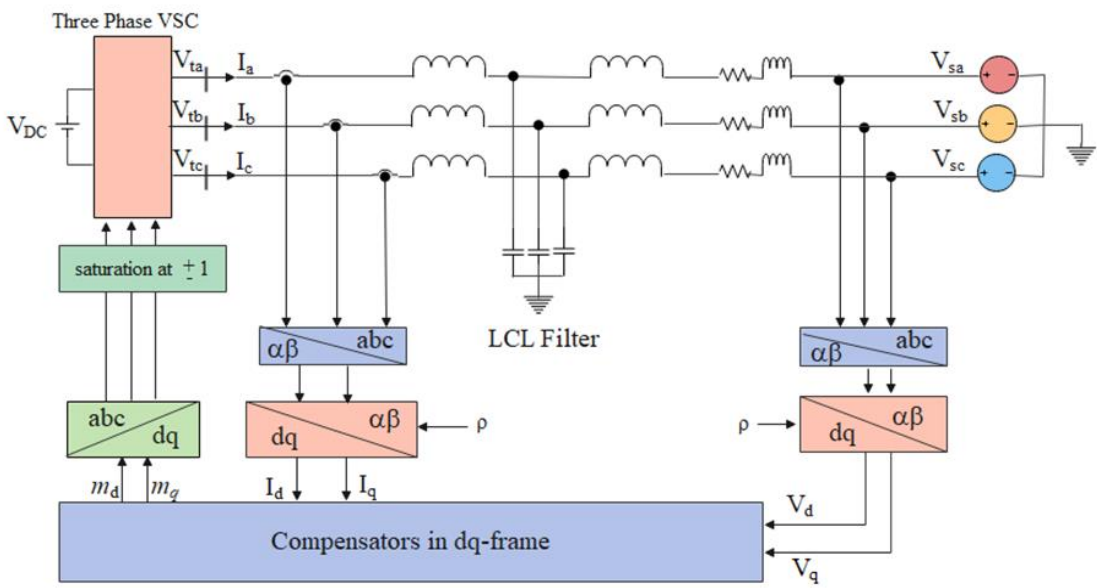

Fig. 1 dq-axis frame-based VSC control

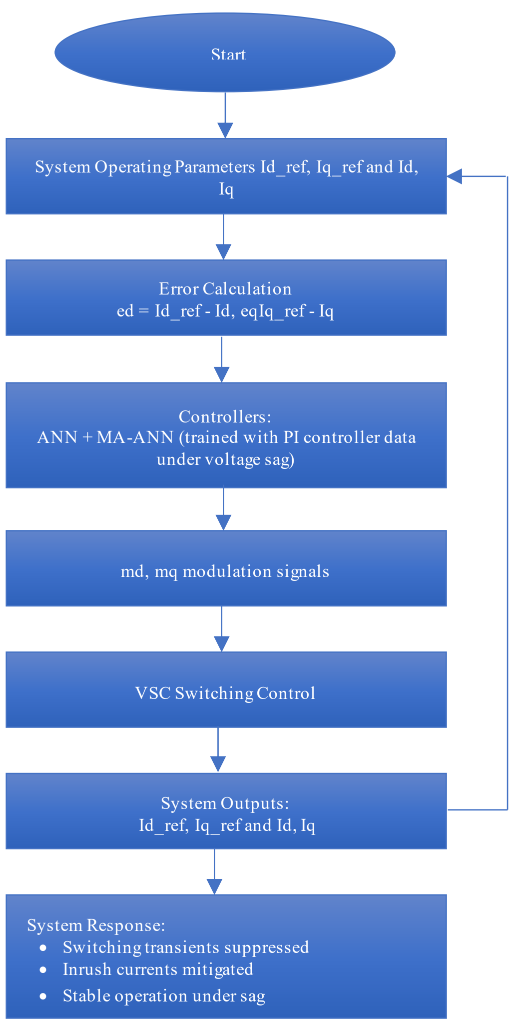

Fig. 2 Control strategy

The system angular frequency is:

$$\frac{d\rho}{dt} = \omega(t) \tag{6}$$

The VSC modulation signals in the dq-frame are derived as:

$$m_d(t) = \frac{2}{V_{dc}}\left(u_d - L\omega_0 i_q + V_{sd}\right) \tag{7}$$

$$m_q(t) = \frac{2}{V_{dc}}\left(u_q + L\omega_0 i_d + V_{sq}\right) \tag{8}$$

Here i_d, i_q are state variables V_{td}, V_{tq} are control inputs, and V_{sd}, V_{sq} Are disturbance inputs [17, 18]. The control loop uses PI compensators that transform the sinusoidal tracking into a DC tracking task with modest steady-state error, as shown in Figure 3.

2.3. Artificial Neural Network (ANN) Based Controller

The active and reactive current control of the Voltage Source Converter (VSC) system, as shown in Figures 1 and 3, is implemented using an Artificial Neural Network (ANN)-based controller in place of conventional Proportional-Integral (PI) controllers. These intelligent controllers are trained to inject the required currents into the grid to achieve effective current regulation. The control strategy is developed using simulated data generated from the voltage source converter model under the PI-based current control loops of Figure 3. This data is used to train the artificial neural network controller, with the input features being the control loop errors ed and eq, and the corresponding output variables being the modulated indices md and mq. For mapping the nonlinearity between the input errors and the desired modulating indices, a three-layer feedforward neural network architecture is used [19].

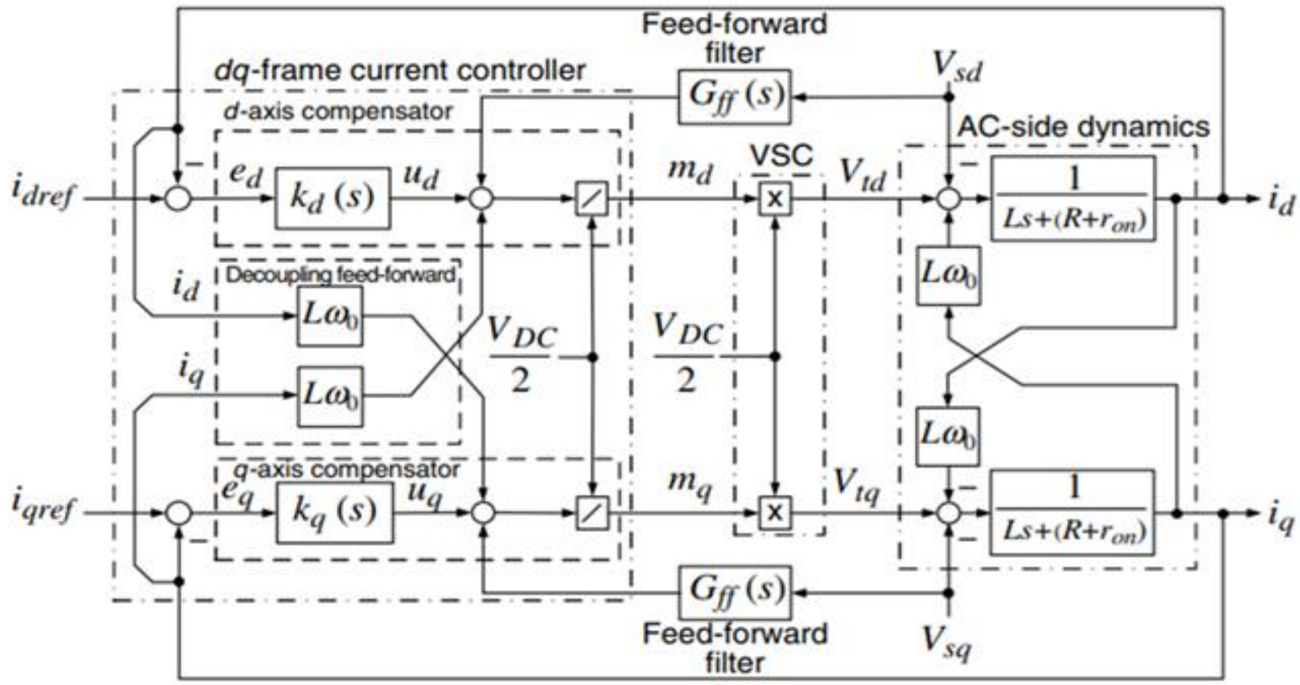

Fig. 3 dq axis frame based VSC control

The neural network is designed with an input layer, a hidden layer with 50 neurons of sigmoid activation functions, and an output neuron with a pure linear transfer function. The Levenberg-Marquardt (LM) learning algorithm is used for training the model due to its fast convergence property and suitability for function approximation problems. This LM algorithm is the most efficient training method, requiring large memory compared to other optimization techniques, irrespective of the large memory requirement. The Mean Squared Error is decreased by penalizing larger errors than smaller ones to match network predictions closely with the target values [20, 21]. Once trained, the ANN successfully mimics the behaviour of the dq-frame closed-loop current control strategy. The trained ANN model will map active currents (e_d to v_d) and reactive currents (e_q to v_qUpon successful training, depicting the process of conventional controllers.

The effectiveness of the ANN is validated through performance plots shown in Figures 4(a) through 4(f). While Figures 4(a) and 4(b) display the regression plots of the d-axis and q-axis controllers, comparing the ANN outputs with the actual target values. The regression coefficients of these controllers are 0.9, which indicates a perfect fit. Figures 4(c) and 4(d) represent the error histograms of the trained neural network with the distribution of prediction errors. After validation, error values are within the range of ±0.1, and the presence of only a few outliers suggests the network's high accuracy and generalization capability. Figures 4(e) and 4(f) show the ANN's training, validation, and testing performance. The final MSE is small, and the error curves for the validation and testing phases exhibit similar trends. This performance implies that the network is generalized well to unseen data and does not overfit the training set. Overall, the ANN-based current controller demonstrates its effectiveness in capturing the nonlinear behaviour of the VSC system and serves as a robust alternative to conventional PI controllers.

2.4. Moving Average-Augmented ANN (MA-ANN) Controller

The proposed Moving Average-based ANN controller integrates a Moving Average Artificial Neural Network filter with an Artificial Neural Network (ANN) controller to address the limitations of conventional PI and ANN-based controllers. These conventional controllers often struggle with transient spikes during the switching operations of Renewable sources. In contrast, the Moving Average-based ANN filter and ANN controller suppress transients and inrush currents, resulting in enhanced performance and reliability of Voltage Source Converters (VSCs). The design procedure of the controller filter follows a systematic procedure as illustrated in Figure 5. A noisy signal is developed to simulate real-time transient conditions by combining a clean sine wave with Gaussian noise, as shown in Figure 6. This noisy signal is then processed using a proposed controller to produce a smoother signal that serves as the input to the voltage source controller. The formula for the moving average filter model is presented below.

- Noisy_signal=Clean_signal+Noise
- Clean_signal=Idealsinewave
- MA_signal=movmean(Noisy_signal,Window_size)

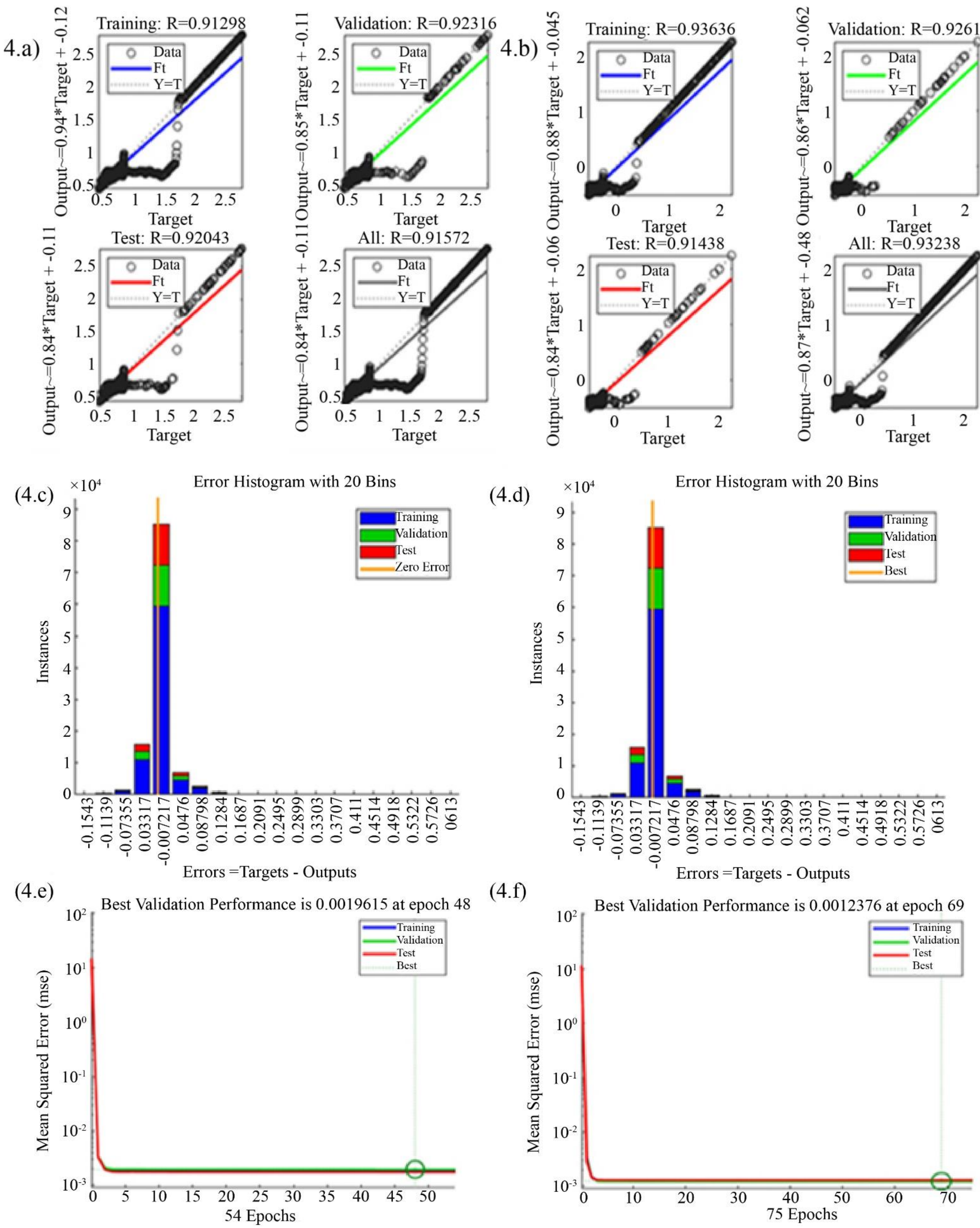

Fig. 4 Performance metrics of ANN controller

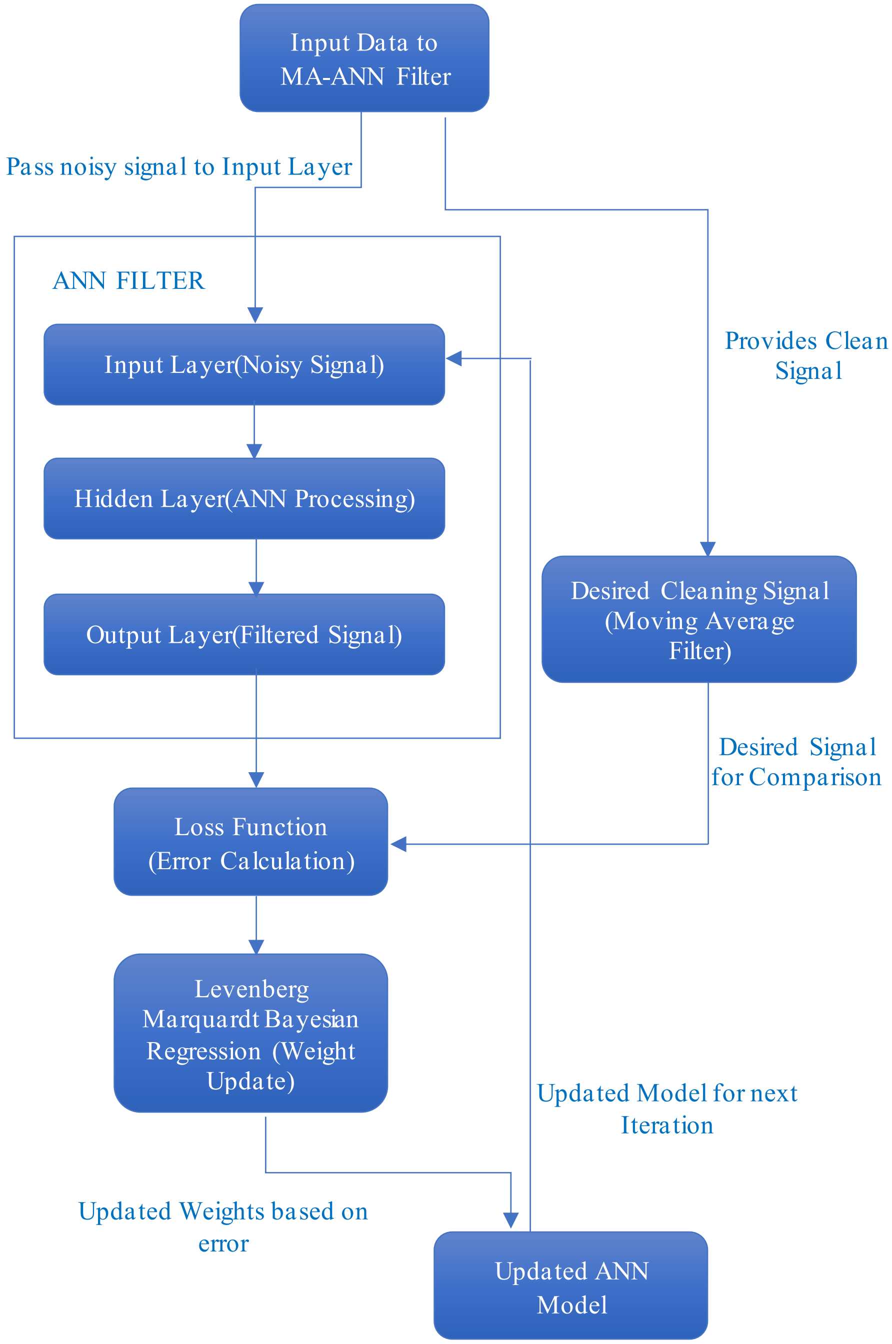

Fig. 5 Flow chart to design MA-ANN filter

The movmean function calculates the local mean of the noisy signal over a sliding window. Specifically, M = movmean(A, k) computes the k-point moving average of array A, where k is the window size. If k is odd, the window centers on the Current element. If k is even, it centers between the current and the previous elements. The formula for the mean is

$$\mu = \frac{1}{N}\sum_{i=0}^{N} A_i \quad (9)$$

The MA signal goes into the ANN; the target output is the clean signal. The structure of the MA-ANN filter uses a feedforward type of three-layer neural network. During the training, the controller aims to continuously change the MA signal into a clean signal by filtering the information it receives. Adjusting the weights during training reduces the error between the network output and the clean signal. A noisy signal is generalized with the Bayesian regularization algorithm. This approach combines the Levenberg-Marquardt optimization algorithm with Bayesian regularization to prevent overfitting and ensure robust learning.

Although this method increases training time, it produces a network that performs well even on small or noisy datasets. Training continues iteratively until the network achieves validated performance. Performance validation metrics confirm the effectiveness of the MA-ANN filter. The regression value reaches 0.97, indicating a strong correlation between the predicted and actual clean signals. Furthermore, the error remains bounded between -0.5 and +0.5, as illustrated in Figure 7.

The cascaded ANN controller and MA-ANN filter, depicted in Figure 8, implements a closed-loop current control strategy. It enables the VSC to inject clean, distortion-free current into the grid, even under varying operating conditions. The integration of the MA-ANN filter into this framework significantly reduces the impact of switching transients. Compared to standalone PI and ANN controllers, the proposed system provides a safer, reliable, and cost-effective solution with extended operational life. To evaluate the effectiveness of the proposed control strategies, a simulation-based experimental setup was developed using MATLAB/Simulink for a grid-connected Voltage Source Converter (VSC) system integrated with a Distributed Energy Resource (DER). The model includes a DC energy source, an LCL filter [22], and the VSC operating under various current control schemes: a conventional Proportional-Integral (PI) controller, a standalone Artificial Neural Network (ANN) controller, and the proposed Moving Average-Augmented ANN (MA-ANN) controller.

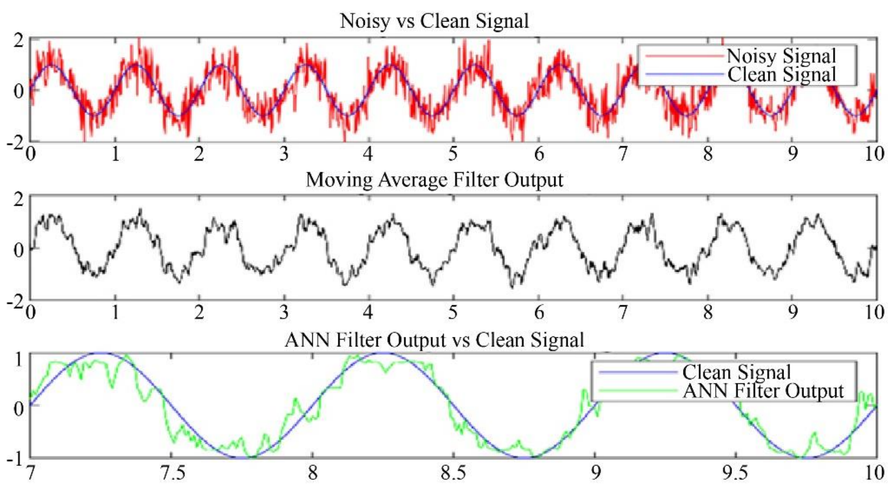

Fig. 6 Performance of MA-ANN filter

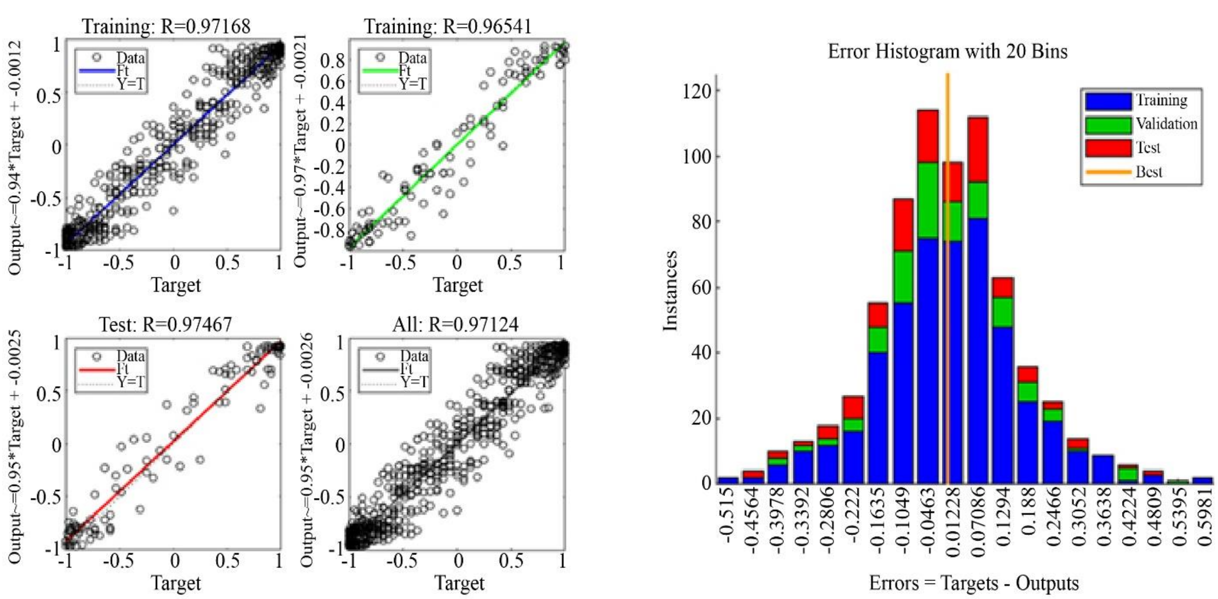

Fig. 7 Regression and error plots of MA-ANN filter

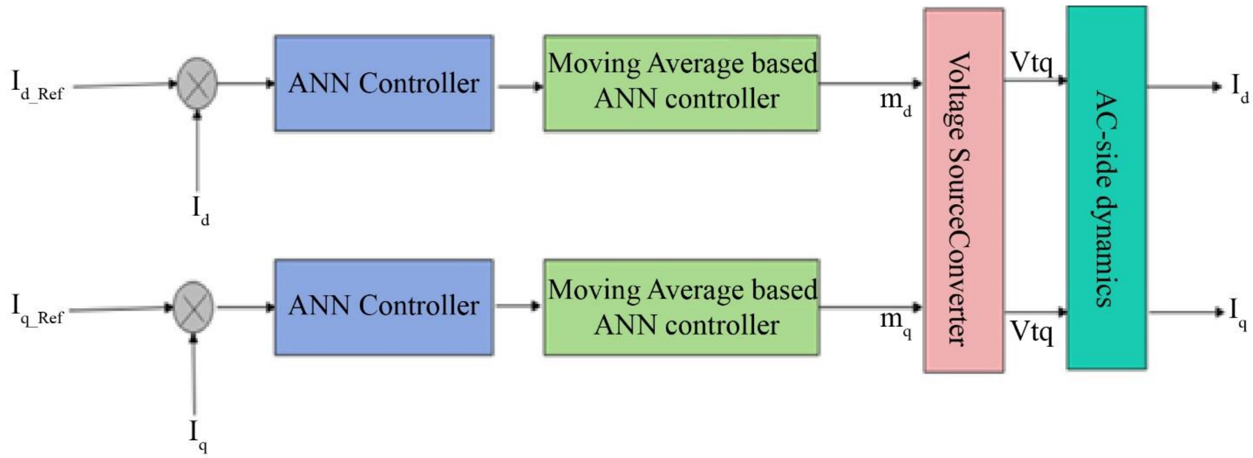

Fig. 8 Proposed MA-ANN controller

The system parameters, such as grid voltage, switching frequency, and filter elements, were chosen to ensure stable operation and accurate current tracking [16] as shown in Table 1. Three voltage dips were introduced at 0.1s, 0.3s, and 0.5s to simulate real-world disturbances, reflecting transient events commonly observed in renewable energy systems.

The main objective of this study is to assess each controller's performance in terms of current regulation, suppression of switching transients, and mitigation of inrush currents during startup or source reconnection. The MA-ANN controller was specifically designed to enhance transient stability and current smoothness by combining real-time adaptability with noise suppression, thus demonstrating its superiority over conventional methods in dynamic and noisy grid conditions.

Table 1. Grid and VSC parameters

Parameter Name	Acronym	Value	Unit
Nominal AC voltage	V_{nom}	230	V
Nominal frequency	f_{nom}	50	Hz
Nominal Angular Frequency	ω_{nom}	$2\pi * f_{nom}$	$rad/_s$
DC-link voltage	V_{DC}	800	V
LCL filter Inductance	L_f	500	Mh
LCL filter Capacitance	C_f	100	Mf
Line Resistance	R	0.5	Ω
Line Inductance	L	1	µF

3. Results and Discussion

This study analyzes the performance of three current control strategies for a grid-connected Voltage Source Converter (VSC): the conventional Proportional-Integral (PI) controller, a standalone Artificial Neural Network (ANN) controller, and the proposed Moving Average-based Artificial Neural Network (MA-ANN) controller. The comparison focuses on current regulation, transient suppression, and inrush current mitigation under sudden voltage fluctuations, reflecting the conditions typical of renewable energy systems.

Simulation results confirm that the MA-ANN controller outperforms both the PI and ANN controllers. It consistently tracks the reference current with precision, suppresses transient disturbances, and mitigates inrush surges. Under all tested scenarios, it maintains a settling time below 10 milliseconds, ensuring rapid dynamic response and operational reliability in volatile grid conditions. Figure 9 shows that the PI controller responds to voltage dips by reducing current proportionally but lacks damping capability.

The current waveform exhibits large oscillations, and after voltage recovery, it overshoots sharply, often exceeding twice the rated current. This behavior prolongs settling time and places thermal and electrical stress on converter components. Although the PI controller reacts to disturbances, it cannot stabilize the system against high-frequency events.

Figure 10 presents the performance of the MA-ANN controller under the same disturbance. Unlike the PI strategy, it maintains smooth and stable current tracking. During a voltage dip, the controller follows the reference without significant oscillation. After voltage recovery, the current returns to its target value without overshoot.

This behavior results from its two-stage architecture: the moving average filter attenuates fast voltage fluctuations before the signal enters the ANN. With this preconditioning, the ANN produces precise and stable control responses. Together, these stages prevent overreactions to high-frequency noise and enhance the robustness of the system.

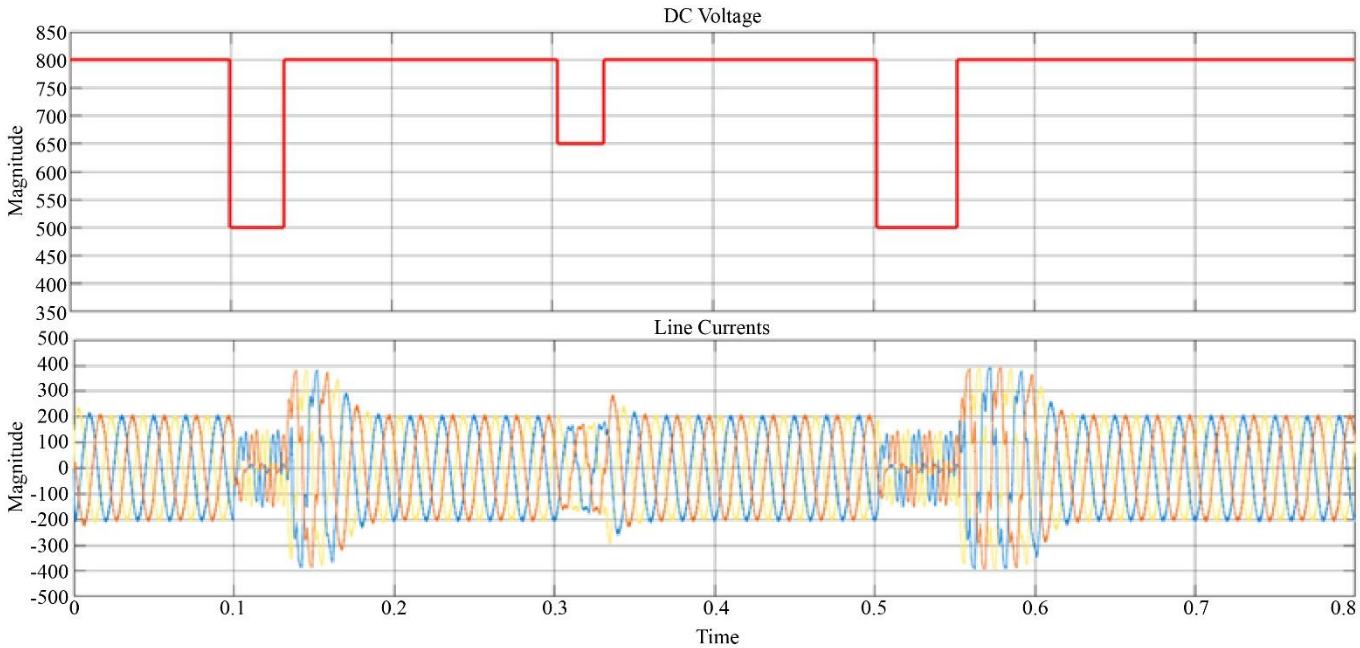

Fig. 9 Line currents PI-based current controller

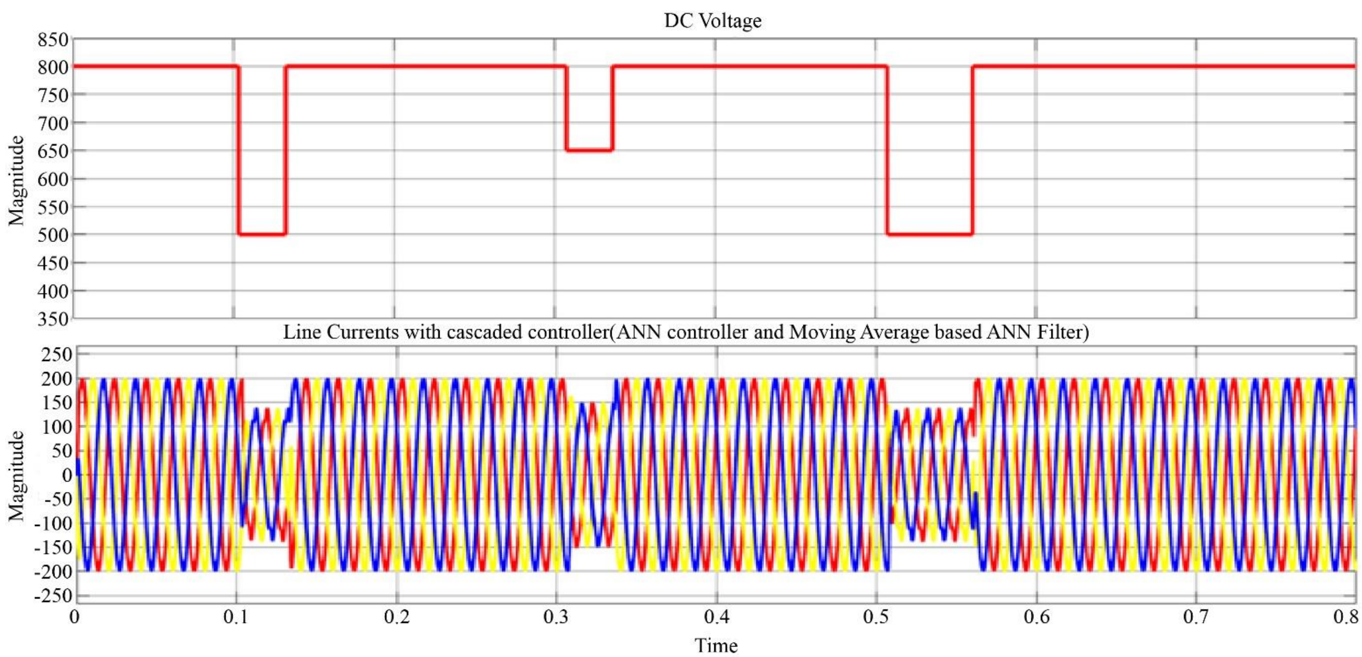

Fig. 10 Line currents with cascaded controller (ANN and Moving Average)

As shown in Figure 11, the MA-ANN controller maintains control accuracy under both leading and lagging power factor conditions. It injects high-quality current into the grid without waveform distortion, regardless of the reactive power demand. This adaptability supports real-time grid interaction, a critical requirement for modern renewable systems with dynamic active and reactive power flows. Inrush current behavior, illustrated in Figure 12, highlights another clear advantage. The PI controller produces high surge currents during converter startup, and the standalone ANN reduces this surge only partially. In contrast, the MA-ANN controller introduces a gradual current ramp-up.

This soft-start behavior avoids excessive stress on components, minimizes the risk of triggering protection mechanisms, and ensures safer and reliable energization. Throughout all test cases, the MA-ANN controller rapidly restores the converter current to its reference value, always within 10 milliseconds. This quick stabilization helps suppress high-frequency transients and reduces inrush currents.

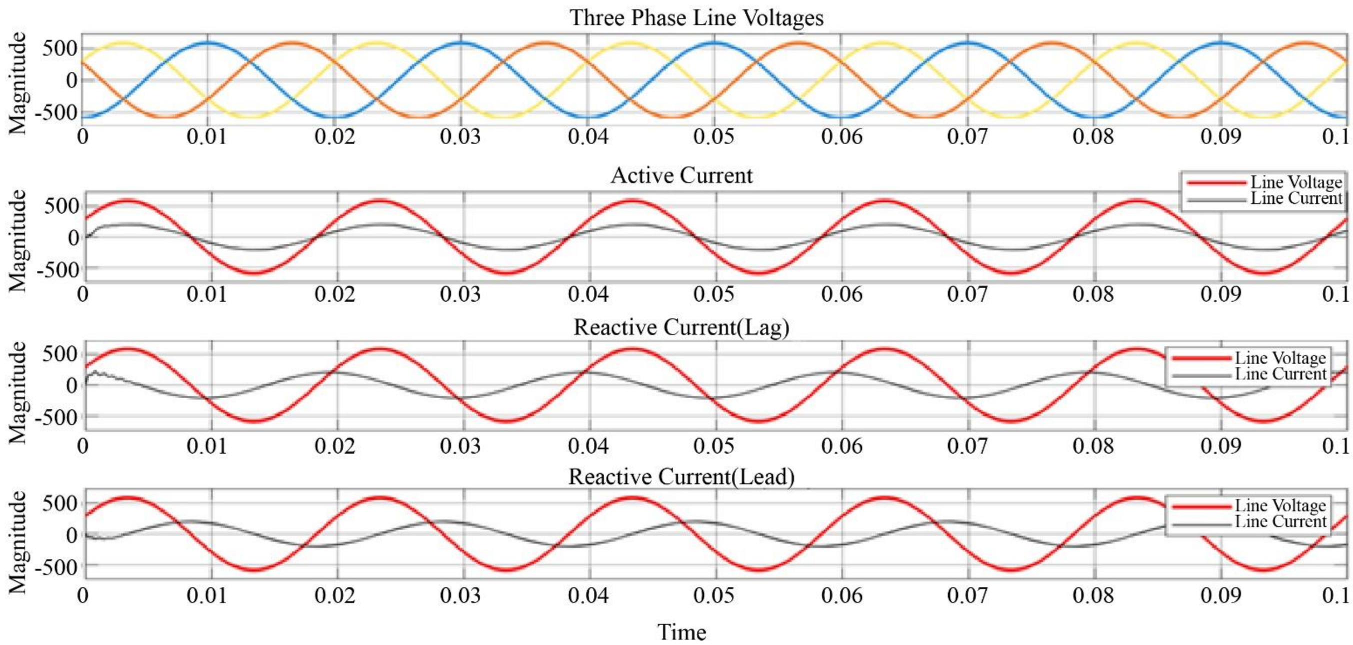

Fig. 11 Line currents under unity, lag, and lead cases

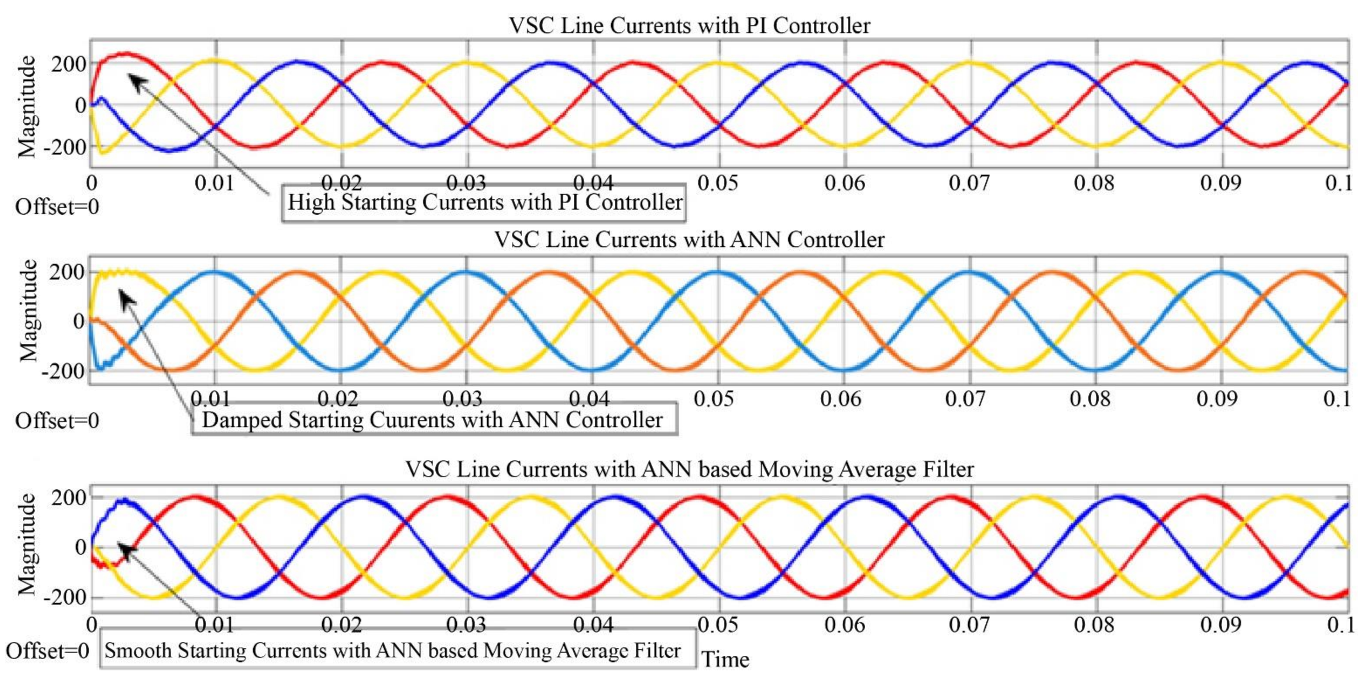

Fig. 12 Surge inrush currents with PI, ANN, and cascaded ANN-controller

It also protects sensitive loads downstream, which is crucial in distributed energy systems where switching events occur frequently. The research aimed to determine whether a cascaded MA-ANN controller could improve current regulation, suppress switching transients, and reduce inrush currents under renewable-induced voltage disturbances. The simulation outcomes confirm this objective. Compared to both the PI and ANN controllers, the MA-ANN controller consistently delivers superior performance in every key metric. Quantitative results further validate this conclusion. During fault recovery, the PI controller exhibits overshoot close to 200 percent of the nominal current, while the MA-ANN controller eliminates this overshoot. At startup, the inrush current under PI control exceeds rated limits, whereas the MA-ANN controller maintains a controlled ramp. Figures 9 through 11 substantiate these improvements with clear visual and numerical evidence.

These results underscore the MA-ANN controller's practical value for renewable energy integration. PI controllers are too slow and rigid for real-time response, while ANN controllers, although adaptive, suffer from sensitivity to noisy inputs. Sensitive loads downstream are also protected, which is necessary for distributed energy, as switches are activated regularly. The study focused on understanding whether using a cascaded MA-ANN controller can improve the current regulation methods, control switching transient oscillations, and decrease the amplitude of inrush currents due to voltage faults from renewable sources. The simulation results confirm this objective. The MA-ANN controller outperforms the PI and ANN controllers in addressing these issues. During faults, the PI controller overshoots the nominal current by nearly 200 percent, but the MA-ANN controller stops the overshoot from occurring. During startup, the PI controller causes the current to rise above rated values, but the MA-ANN controller maintains a slow increase. The findings demonstrate that using an MA-ANN is practical for integrating renewable energy. Although PI controllers are slow, they still respond in real time, but ANN controllers that can learn from inputs are sensitive to noisy data.

4. Conclusion

The paper presented an MA-ANN controller as a method to achieve dynamic behavior when VSCs are used to interface renewable energy sources to the grid. To address two continuous issues during converter switching in variable renewable energy systems, the controller takes care of switching transients and inrush currents. An MA-ANN controller takes advantage of the way moving average filters have the capacity to reject noise and how artificial neural networks can update their learning. The MA filter removes noise present in the signals, allowing the ANN to find the connection between the filtered output and a neat surface.

Together, they inject a steady and undistorted current into the grid under all running conditions. Results from the simulation confirm that the proposed MA-ANN controller is superior to traditional PI and standalone ANN approaches. It allows for less overshoot, shorter settling times, and a nicer response at the start of switching actions. These benefits are useful for converter protection, power consistency, and system stability against sudden voltage swings due to renewable sources. By limiting distortion, removing sharp transient peaks, and allowing instant recovery, the MA-ANN controller keeps the converter hardware intact and increases the system's operational lifetime. Smooth active and reactive current management and successful operation under various load conditions benefit grid matching. Adding an MA-ANN controller to VSC systems connected to the grid increases their dependability and stability. Because as renewables are on the rise, this controller helps create a flexible and intelligent setup that ensures stable and secure grid operation.

References

[1] Kanchan Jha, and Abdul Gafoor Shaik, "A Comprehensive Review of Power Quality Mitigation in the Scenario of Solar PV Integration into Utility Grid," *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, vol. 3, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Debin Zhang et al., "A Closed-Loop Soft Startup Strategy to Suppress Inrush Current for Full-Bridge Modular Multilevel Converters," *IEEE Transactions on Power Electronics*, vol. 39, no. 11, pp. 14787-14799, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Muhammad Khalid, "Energy 4.0: AI-Enabled Digital Transformation for Sustainable Power Networks," *Computers & Industrial Engineering*, vol. 193, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[4] Peixuan Yu, and Shiliang Wu, "Analysis of the Impact of Grid Voltage Fluctuations on Photovoltaic Inverters," *Proceedings of 2024 International Conference on Energy Engineering*, Singapore, pp. 39-54, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Negin Shahidi, and Ebrahim Salary, "Enhancing Grid-Connected Photovoltaic Systems' Power Quality Through a Dynamic Voltage Restorer Equipped with an Innovative Sliding Mode and PR Control System," *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, vol. 11, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Lucian PÎSLARU-DĂNESCU et al., "Surge Protection Methods Used for Electrical Equipment," *Electrotehnica, Electronica, Automatica*, vol. 72, no. 4, pp. 3-18, 2024. [Google Scholar]

[7] Rouzbeh Haghighi et al., "Survey of Reliability Challenges and Assessment in Power Grids with High Penetration of Inverter-Based Resources," *Energies*, vol. 17, no. 21, pp. 1-26, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Javier Gutiérrez-Escalona et al., "Artificial Intelligence in the Hierarchical Control of AC, DC, and Hybrid AC/DC Microgrids: A Review," *IEEE Access*, vol. 12, pp. 157227-157246, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ming Li et al., "Stability Studies on PV Grid-Connected Inverters under Weak Grid: A Review," *Chinese Journal of Electrical Engineering*, vol. 10, no. 4, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] A. Ravi, P.S. Manoharan, and J. Vijay Anand, "Modeling and Simulation of Three Phase Multilevel Inverter for Grid Connected Photovoltaic Systems," *Solar Energy*, vol. 85, no. 11, pp. 2811-2818, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[11] Lorena Castro, Sandra Peréz-Londoño, and Juan Mora-Flórez, "Application of Fuzzy Logic based Control in Micro-grids," *2019 FISE-IEEE/CIGRE Conference - Living the Energy Transition (FISE/CIGRE)*, Medellin, Colombia, pp. 1-8, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] Shakil Mirza, and Arif Hussain, "New Approaches in Finite Control Set Model Predictive Control for Grid-Connected Photovoltaic Inverters: State of the Art," *Solar*, vol. 4, no. 3, pp. 491-508, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Yang Sun et al., "Artificial Neural Network for Control and Grid Integration of Residential Solar Photovoltaic Systems," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 4, pp. 1484-1495, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[14] IIhab S. Mohamed et al., "A Neural-Network-Based Model Predictive Control of Three-Phase Inverter with an Output LC Filter," *IEEE Access*, vol. 7, pp. 124737-124749, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Md. Masudur Rahman et al., "Design of a High-Performance Resonant Controller for Improved Stability and Robustness of Islanded Three-Phase Microgrids," *IEEE Access*, vol. 10, pp. 119206-119220, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[16] Amirnaser Yazdani, and Reza Iravani, *Voltage-Sourced Converters in Power Systems: Modeling, Control, and Applications*, John Wiley & Sons, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[17] C.D. Schauder, and R. Caddy, "Current Control of Voltage Source Inverters for Fast Four-Quadrant Drive Performance," *1981 Annual Meeting Industry Applications Society*, Philadelphia, PA, USA, pp. 592-599, 1981. [Google Scholar] [Publisher Link]

[18] C. Schauder, and H. Mehta, "Vector Analysis and Control of Advanced Static VAR Compensators," *IEE Proceedings C (Generation, Transmission and Distribution)*, vol. 140, no. 4, pp. 299-306, 1993. [CrossRef] [Google Scholar] [Publisher Link]

[19] M. Karthikeyan, D. Manimegalai, and Karthikeyan RajaGopal, "Power Control of Hybrid Grid-Connected Renewable Energy System using Machine Learning," *Energy Reports*, vol. 11, pp. 1079-1087, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Yu Lu et al., "Deep Reinforcement Learning Based Optimal Scheduling of Active Distribution System Considering Distributed Generation, Energy Storage and Flexible Load," *Energy*, vol. 271, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Mehmet Önder Efe et al., "A Modified Levenberg Marquardt Algorithm for Simultaneous Learning of Multiple Datasets," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 71, no. 4, pp. 2379-2383, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] P.A. Dahono, A. Purwadi, and Qamaruzzaman, "An LC Filter Design Method for Single-Phase PWM Inverters," *Proceedings of 1995 International Conference on Power Electronics and Drive Systems. PEDS 95*, Singapore, vol. 2, pp. 571-576, 1995. [CrossRef] [Google Scholar] [Publisher Link]