Analysis and Design of Artificial Neural Network Based Droop Control for Autonomous Hybrid Microgrid

Aditya Sharma
Department of Electrical Engineering
Rajasthan Technical University
Kota, INDIA
aditya_sharma18391@yahoo.in

Vishal Nagar
Department of Electrical Engineering
Rajasthan Technical University
Kota, INDIA
vishalnagar3005@gmail.com

D. K. Palwalia
Department of Electrical Engineering
Rajasthan Technical University
Kota, INDIA
dkpalwalia@rtu.ac.in

***Abstract*— Microgrids have become a valuable approach for incorporating distributed generation into broader power systems, though they face challenges in maintaining consistent voltage and frequency during autonomous load sharing. In addition, the injection of perturbations of loads has the potential of reducing the power quality of the system. Traditional droop control is used for effective load sharing, frequency and voltage stabilization among multiple parallel inverters but is sensitive to load change and accurate coefficient parameters. To overcome these challenges artificial neural network (ANN) based droop control is proposed. Proposed microgrid integrates a PV system and wind energy conversion systems (WECS) as multiple distributed generations (DG) through parallel connected inverters. The modeling of a microgrid operating in island mode was carried out using MATLAB/SIMULINK. Results demonstrate the accuracy of the Artificial Neural Network (ANN) based control strategy in managing load fluctuations and minimizing the total harmonic distortion of the inverter output.**

Keywords*— *Artificial Neural Network (ANN), Droop Control, Grey Wolf Optimization (GWO), Microgrid, PV system, Voltage Source Converter (VSC)

I. Introduction

The integration of hybrid distributed generation (DG) systems, combining solar and wind energy sources, into microgrids represents evolution of sustainable energy solutions within the electrical power sector. This integration is driven by the increasing demand for renewable energy sources that are reducing dependency on traditional fossil fuels[1]-[3]. Microgrids, as localized energy networks, offer a unique platform for the deployment of solar and wind DGs, enabling optimized energy production and distribution tailored to specific geographical and climatic conditions [4]. The ability of microgrids to operate in both grid-connected and island modes further enhances their versatility, ensuring continuous energy supply even during grid outages. However, the variability inherent in solar and wind energy generation presents significant challenges in terms of maintaining stable power output, frequency, and voltage within the microgrid. Addressing these challenges requires innovative control strategies and advanced technological solutions to ensure the seamless integration of hybrid DGs, thereby maximizing the reliability, efficiency, and sustainability of microgrid operations [5].

Solar photovoltaic (PV) systems and wind energy conversion systems (WECS) represent two of the most rapidly advancing renewable energy sources in recent years. Unlike conventional generators that run on controllable fossil fuels, the output from renewable sources like solar and wind is less predictable due to their dependence on variable natural resources. Despite this variability, the use of advanced power electronic converters allows for some degree of control over the output from these renewable energy (RE) sources, enhancing their integration and reliability within the power system [6],[7]. Multiple optimization techniques are implemented for PV system and WECS for a reliable output under various climatic conditions [8]. Droop control emerges as a fundamental mechanism in the operational dynamics of microgrids, particularly in distributed generation (DG) resources for effective load sharing and frequency stabilization [9],[10]. By simulating the behavior of conventional power systems, where the output power adjusts in response to changes in frequency and voltage, droop control facilitates a seamless balance between supply and demand within the microgrid by replicating the inertia of larger power systems [11]. Some limitation of droop control is its inability to maintain precise voltage and frequency under varying load conditions. Additionally, droop control does not inherently compensate for line impedance, which can skew power sharing among distributed generators, particularly in microgrids with diverse generation sources and complex topologies [12]. Another significant challenge is the need for accurate parameter settings; incorrect droop coefficients can lead to inefficient operation and even system instability. Moreover, the integration of renewable energy sources introduces variability and unpredictability, exacerbating the difficulty of maintaining stable operation solely through droop control [13].

To address these issues a new ANN based droop control is proposed realizing a feed forward neural network (FFNN) trained on scaled conjugate gradient algorithm. ANN-based systems can dynamically adjust control parameters to maintain system frequency and voltage within desired ranges, thereby enhancing the overall efficiency and effectiveness of microgrid operations. The data set to train ANN model is taken from a single DG system of microgrid. The suggested Artificial Neural Network (ANN) enhanced droop control method effectively maintains inverter voltage and frequency stability amidst variations in load and irradiance levels. The entire system was modeled and tested using the MATLAB/SIMULINK toolbox, with outcomes illustrating the efficiency of the proposed control strategy.

II. System description

The proposed microgrid system consist of two individual parallel connected inverters with PV system and WECS as

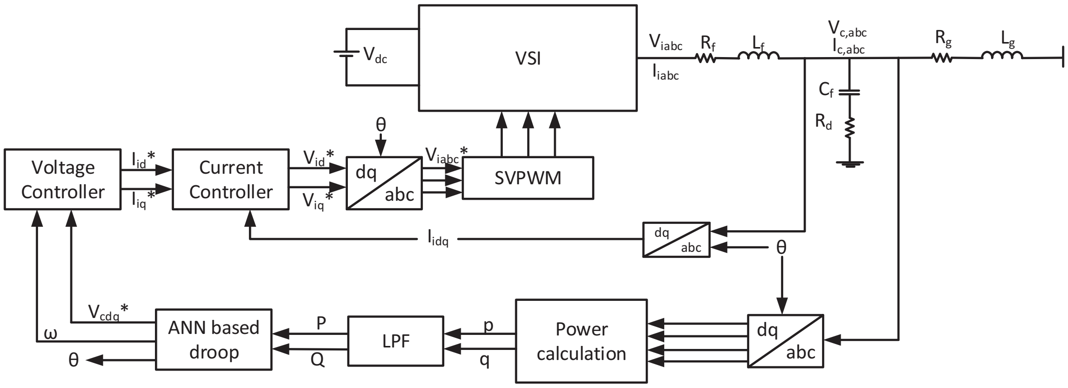

Figure 1. Control Strategy of individual DER

distributed sources. Control strategy for an individual inverter is shown in Fig. 1. Traditional droop controller is replaced by ANN based droop control under this control scheme. Microgrid study system is shown in Fig. 2 which depicts two inverters connected parallel to supply the load demands. DG1 is the PV system connected to its respective voltage source inverter (VSI) through a DC-DC boost converter using Grey Wolf Optimization (GWO) algorithm technique for maximum power point tracking (MPPT). Similarly, WECS is connected to its respective VSI through an AC-DC converter. Both inverters are coupled at common point of coupling (PCC) through an LC filter and coupling inductor. The droop control method is used to share power among these inverters. To maintain frequency and voltage of microgrid in autonomous mode, an artificial neural network (ANN) model utilizing a feed forward neural network (FFNN) is implemented which is trained by the scaled conjugate gradient technique. Nonlinear loads are connected at the point of common coupling and a step change in load is introduced in simulation for load perturbation.

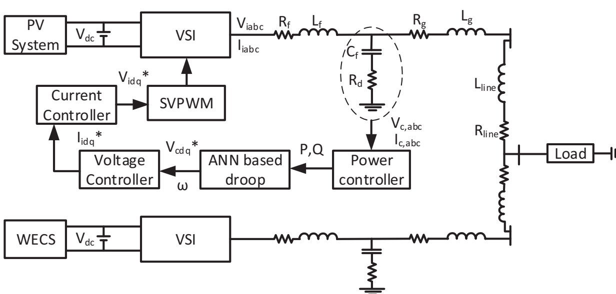

Figure 2. Microgrid study system

III. SYSTEM CONTROL

The controls of proposed microgrid configurations consists of MPPT control, ANN based droop control and nested control for current voltage loop.

A. MPPT Control

The implementation of Maximum Power Point Tracking (MPPT) using Grey Wolf Optimization (GWO) in PV systems signifies a considerable advancement in solar technology. By employing the GWO algorithm, the MPPT controller intelligently regulates the operating point of the PV array to ensure that maximum power is extracted under varying environmental conditions [14]. This technique is essential because the optimal power point of a PV array changes with solar irradiance and temperature. The GWO algorithm, inspired by the social hierarchy and hunting technique of grey wolves, is utilized to search for the peak power point in an efficient and iterative manner. In the given system shown in Fig. 3, the GWO MPPT communicates with a PWM generator to modulate the duty cycle of power electronic switches, effectively regulating the output of dc-dc boost converter to match the current requirements while maintaining maximum energy harvest. The integration of capacitors for voltage stabilization and an inductor for current smoothing further enhances the system's efficiency, ensuring that the power delivered to the VSC is consistent and reliable. The output from PV array to GWO-MPPT unit are PV voltage (V_{PV}) and PV current (I_{PV}), through which the duty cycle D is obtained.

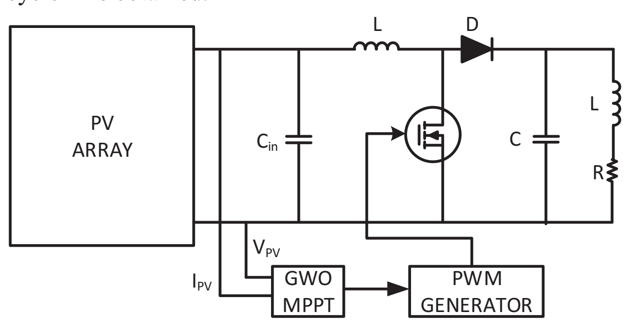

Figure 3. Control diagram of PV system

The algorithm depicted in Fig. 4 is a flowchart for the Grey Wolf Optimizer (GWO) used for MPPT in photovoltaic (PV) systems [15]. It starts by initializing a population of grey wolves, which represent potential solutions. Each iteration involves sensing the voltage and current from the PV array, calculating the power, and evaluating the fitness of each solution. If a better solution is found, it updates the maximum power. The best solution (G_best) is also updated if necessary. All wolves (solutions) are evaluated in turn, and their positions are updated based on certain equations. The algorithm iterates until convergence criteria are met, aiming to find the optimal operating point for maximum power output from the PV array.

The wind energy conversion system (WECS) was modeled based on the methodology presented in [16],[17]. A permanent magnet synchronous generator (PMSG) based WECS integrated with the microgrid was considered, employing a back-to-back voltage source converter topology. The machine-side converter utilized the sinusoidal pulse width modulation (SPWM) technique, while the grid-side converter implemented space vector pulse width modulation (SVPWM). To extract maximum power from the variable wind speeds, the optimal power control (OPC) scheme was adopted for maximum power point tracking (MPPT) control of the WECS. The DC-link voltage was regulated by the grid-side converter.

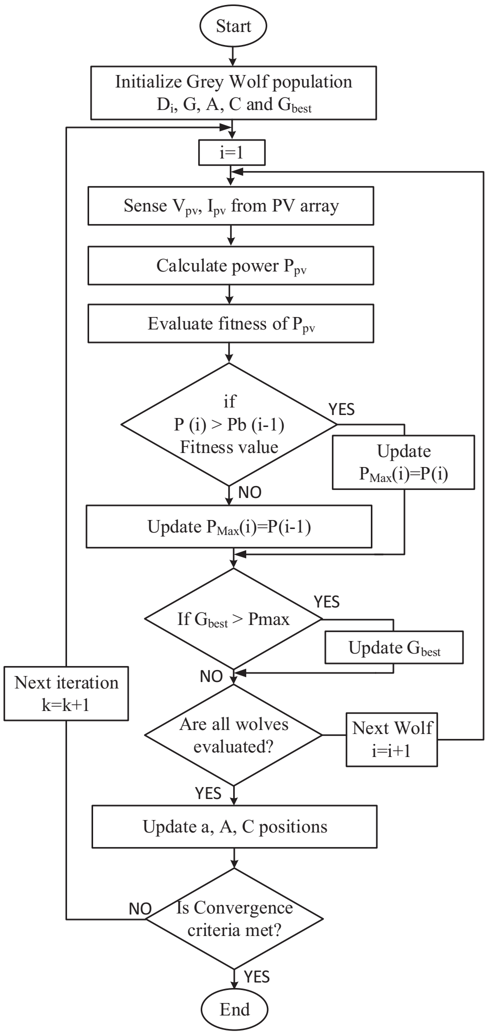

Figure 4. Grey wolf optimization flow chart

B. *Current and Voltage Control*

The local controller is designed using a Nested Control Topology. This system is composed of a dual-layered control mechanism: a primary current control loop and a secondary voltage control loop. The innermost layer, the current control, is optimized for rapid response and integrates load pole neutralization into its design. The load is represented by a resistor, while inductance and resistance are the line's contributions. The current control is precisely engineered to negate the poles generated by both the load and the line.

$$K_{pc} + \frac{K_{ic}}{s} = R + sL \quad (1)$$

$$\frac{sK_{pc}+K_{ic}}{s} = R + sL \quad (2)$$

Using the above equations, one can align the coefficients and solve for the PI controller gains, K_P and K_I, within the Current Control Loop. This loop is responsible for producing the Voltage Reference needed for the Space Vector Pulse Width Modulation (SVPWM) that, in turn, controls the inverter's gate signals. The outer layer, the voltage control loop, is tasked with creating reference current inputs for the current control loop. Its design aims to minimize the discrepancy between actual and target voltages, ensuring precise reference current tracking is relayed to the Current Control Loop.

To determine the PID gains for the controller, the 'pidtunes' command was utilized within the MATLAB script. Given the switching frequency of 10kHz, the Current Control Loop's bandwidth was set at 1kHz, while the Voltage Control Loop's bandwidth was set at 100Hz to aid in the calculation of the controller gains.

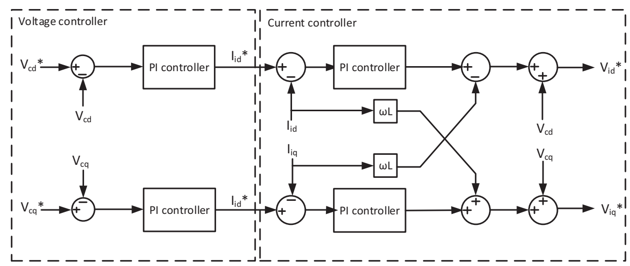

Figure 5. Voltage and current controller diagram

Figure 5 illustrates the control loop for voltage and current, highlighting the inclusion of cross-coupling and feed-forward elements. The voltage control mechanism utilizes a conventional proportional-integral (PI) regulator that evaluates the difference between the sampled output voltage and the target value provided by the power controller. The mathematical representation of the voltage control process is detailed in the subsequent equations.

$$\dot{\varphi_d} = V_{cd}^* - V_{cd} \quad (3)$$

$$\dot{\varphi_q} = V_{cq}^* - V_{cq} \quad (4)$$

$$I_{id}^* = K_{pv}\,(V_{cd}^* - V_{cd}) + K_{iv}(\varphi_d) \quad (5)$$

$$I_{iq}^* = K_{pv}\,\left(V_{cq}^* - V_{cq}\right) + K_{ic}\left(\varphi_q\right) \quad (6)$$

K_{pv}, K_{iv} are the proportional and integral PI controller gains of voltage respectively.

Like the voltage control loop, the current controller minimizes current error by employing a PI controller to assess the difference between the filtered sampled current and the reference current specified by the voltage controller.

$$\dot{\gamma_d} = I_{id}^* - I_{id} \quad (7)$$

$$\dot{\gamma_q} = I_{iq}^* - I_{iq} \quad (8)$$

$$V_{id}^* = K_{pc}(I_{id}^* - I_{id}) + K_{ic}(\gamma_d) - \omega L I_{iq} + V_{cd} \quad (9)$$

$$V_{iq}^* = K_{pc}\left(I_{iq}^* - I_{iq}\right) + K_{ic}\left(\gamma_q\right) + \omega L_f I_{iq} + V_{cd} \quad (10)$$

K_{pc}, K_{ic} are the proportional and integral PI controller gains of current respectively.

C. *ANN based Droop Control*

Droop control is a method used in the parallel operation of inverters without direct communication, maintaining system stability even if an inverter fails. It compensates for the absence of inherent inertia in inverters, where an increase in load typically leads to a reduction in frequency. Droop control emulates inertia by adjusting frequency (ω) and output voltage (v) based on changes in load, using predefined droop coefficients (m and n) tied to active (P) and reactive (Q) power [18],[19]. This technique is crucial for inverters during isolated operation, as it allows them to self-regulate frequency and voltage in the absence of a grid reference.

$$\omega^* = \omega_n - mP \tag{11}$$
$$v^* = v_n - nQ \tag{12}$$

Lately, methods such as artificial intelligence (AI), adaptive network-based fuzzy inference system (ANFIS), and heuristic algorithms have become popular for addressing the operational and control challenges of microgrids. For addressing issues related to voltage and frequency stability in microgrids, an ANN-based droop control approach has been chosen. A feedforward neural network, trained using the scaled conjugate gradient technique, is the selected model for this purpose. The performance of a neural network is affected by several factors, including the number of neurons in the hidden layer, the activation functions utilized by the hidden layer, and the algorithm employed for training. A standard feedforward neural network (FFNN) features an input layer, one hidden layer, and an output layer, as illustrated in Figure 6. The input signal is processed sequentially through the layers of the network. Each connection, or 'link', between the nodes is associated with a weight. These weights, denoted as W^{ih} for input-to-hidden layer and W^{oh} for hidden-to-output layer, are fine-tuned throughout the training phase. The hidden layer's neurons make use of a nonlinear tangent-sigmoid activation function, whereas the neuron in the output layer adopts a linear activation function. The mathematical expression for the outputs generated by the neurons in the hidden layer is as follows:

$$\varphi_h = \frac{2}{1+\exp(-2*(W^{ih}*X_i+b^{ih}))}\ \text{, for } i = 1,2 \text{ and } h = 1,2....5. \tag{13}$$

The mathematical expression for output is expressed as,

$$Y_1 = W^{oh} * \varphi_h + b^0\ \text{, for } h = 1,2....5. \tag{14}$$

Where X_i is the input variables (P_i *and* Q_i), b^{ih} is the hidden layer and b^o is the output layer.

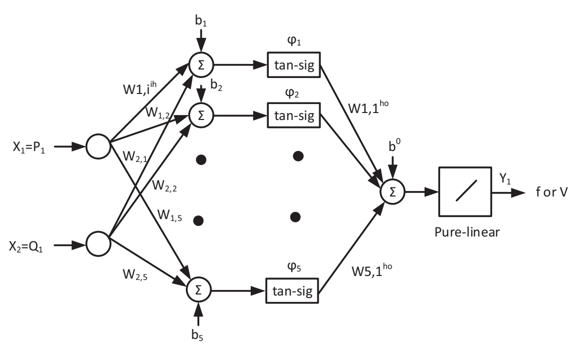

Figure 6. Feed forward neural network structure

Training of the above network is performed on a singular DG microgrid system utilizing the conventional droop control method. Under this method reference voltage and frequency is used from Eq. (11) and Eq. (12). The structure of the FFNN consists of an input layer with two neurons (representing P_i *and* Q_i), a hidden layer comprising five neurons, and an output layer for either frequency (f) or voltage (V), leading to the use of two distinct FFNNs, one for creating a voltage and frequency reference respectively. The training regimen for the FFNN employs the scaled conjugate gradient technique, facilitated by the Matlab/Neural Network Toolbox. To train the network, a dataset of 45,000 input and output pairs collected from the single DG system is used. The FFNN's training process is divided into three main stages: training, validation, and testing.

Figure 7 illustrates a consistent decrease in the mean square error throughout the training epochs, culminating in a minimum error of 7.3372e-05 at the 125 epoch. This suggests that the network gradually improved in correlating the input with the output values, achieving this accuracy at epoch 125. Fig. 8 regression chart, indicated by the correlation coefficient (R), demonstrates that the FFNN was proficiently trained with the selected data sets. The network's validation, testing, and cumulative performance are also deemed adequate, noting that an R value of 1 would signify flawless correlation. Once the training was deemed effective, the capabilities of the proposed FFNN controller were tested on an isolated microgrid system.

IV. Results and Discussion

The proposed autonomous microgrid shown in Fig. 1 simulation is performed on MATLAB toolbox with ANN based droop control. Microgrid is connected to the PCC which is further connected to nonlinear loads. Under islanded mode in simulation, a step change load of 200Ω and 1.5mH is introduced at simulation time of 0.4 sec to the existing load of 50Ω and 1mH in parallel.

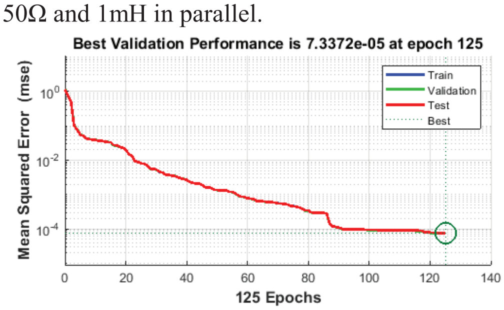

Figure 7. Performance plot of ANN

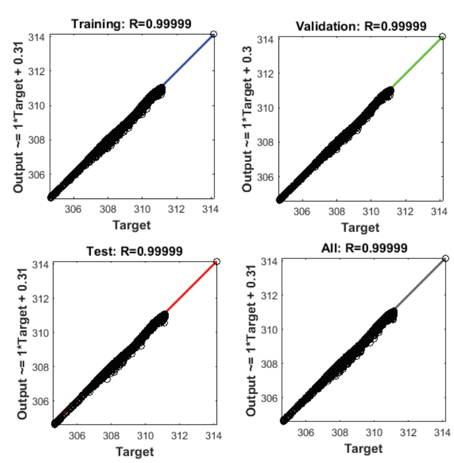

Figure 8. Regression Plot of ANN

Output voltage of both inverters under traditional droop control are given in Fig. 9 showing a stable voltage with total harmonic distortion of 6.12%. The system looks stable with output voltage of each inverter, VSC1 and VSC2 to be stable sinusoidal waveform with voltage amplitude of 310V as peak value. Fig. 10 depicts output voltage of parallel connected inverters while using ANN based droop control method. It is observed output voltage of inverters are stable with a total harmonic distortion of 5.11%.

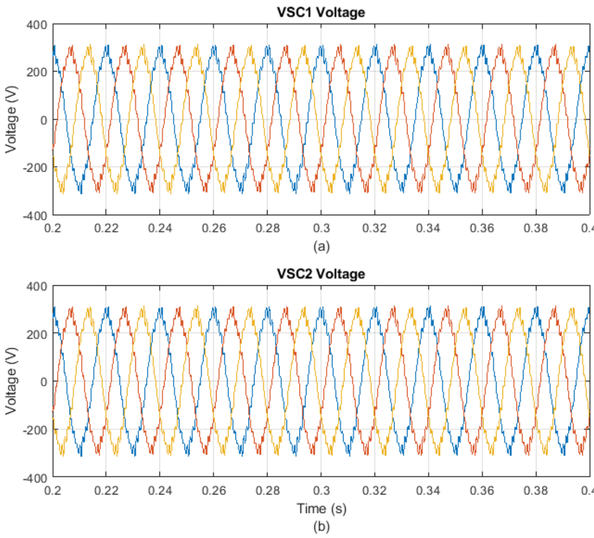

Figure 9. Output voltage of both inverter without ANN

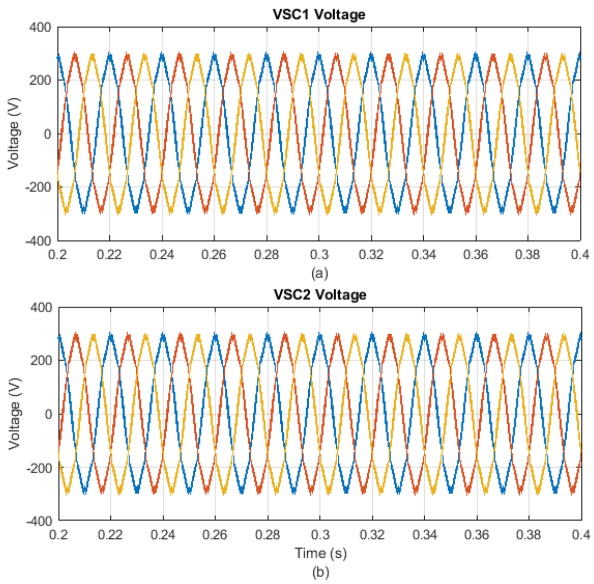

Figure 10. Output voltage of both inverter with ANN

After the introduction of the step disturbance by introducing a load of 200Ω and 1.5mH at simulation time of 0.4 sec, the voltage profile seems to be stable and the current profile across the load increases accordingly. The values can be seen below in the current output profile in Fig. 11. Output voltage RMS profile of one inverter from each model with ANN and without ANN is compared in Fig. 12. It is evident that voltage is stabilized efficiently under ANN based droop control method.

Frequency of inverter are compared in Fig. 13 and it is reported that ANN based droop control technique stabilizes frequency under desired limits more effectively than traditional droop control. Output voltage waveform from each inverter based both controllers is reported to have a total harmonic distortion (THD) of 6.12% with traditional droop control method and 5.11% with ANN based droop control method as shown in Fig 14.

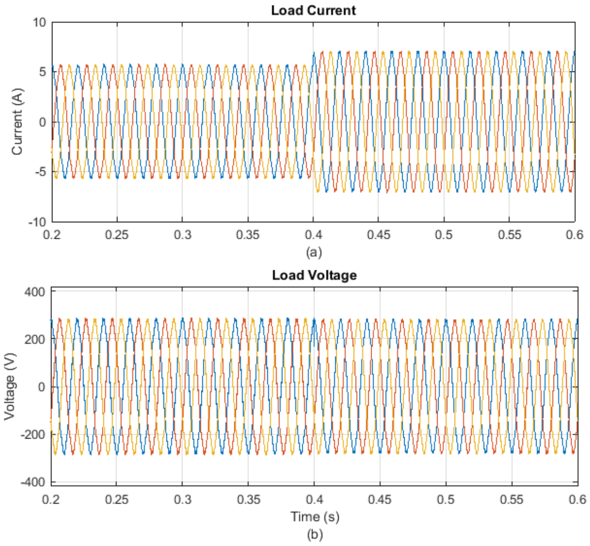

Figure 11. Load current and voltage with step change

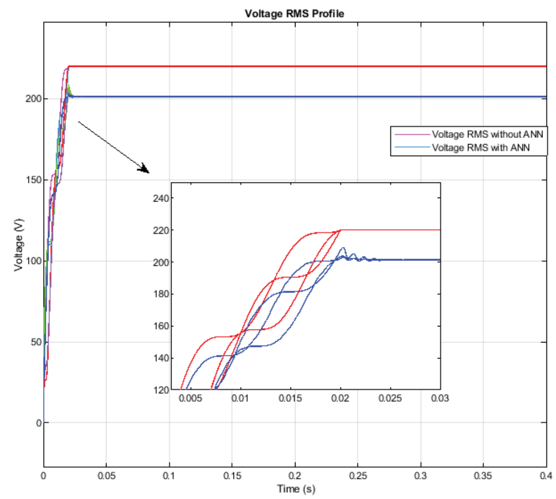

Figure 12. Voltage RMS profile

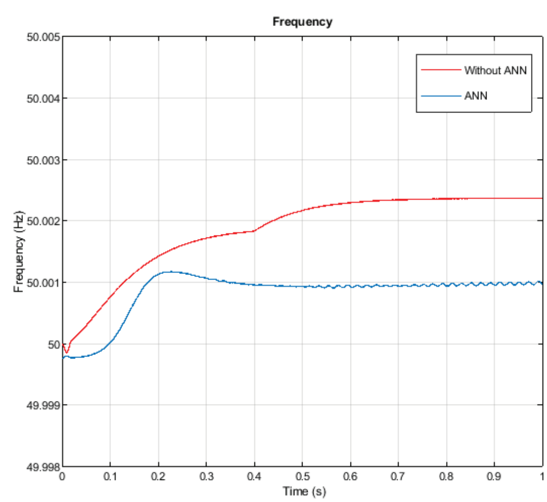

Figure 13. Frequency comparison

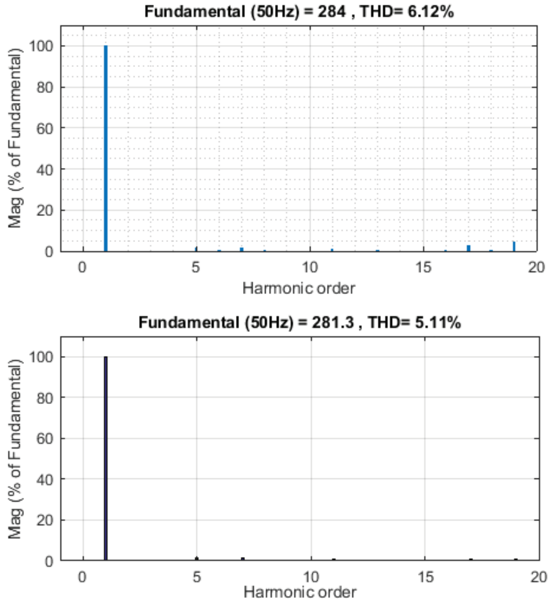

Figure 14. Total harmonic distortion (THD) comparison

The control method without ANN shown in Fig 13 exhibits a noticeable deviation from the nominal frequency, undershooting below 50 Hz before gradually stabilizing. This indicates that the non-ANN system is initially more affected by the disturbance and takes longer to recover to a stable frequency. On the other hand, the ANN-based control demonstrates a quicker and more damped response to the same disturbance, with less deviation from the nominal frequency. The frequency in the ANN-controlled system stabilizes much closer to 50 Hz much quicker than the system without ANN, indicating that the ANN-based control provides a more robust and effective response to load change

V. Conclusion

The proposed ANN based droop control strategy offers significant advantages over traditional droop control methods for microgrids with multiple parallel inverter-interfaced distributed generations. Results demonstrate the ANN controller's superior performance in maintaining stable voltage and frequency under dynamic load conditions. The reduced total harmonic distortion iindicates improved power quality with the ANN approach. Additionally, the simulation results showcase better frequency tracking ability compared to conventional droop control during transient events. When subjected to a load change disturbance, the ANN controller exhibited better voltage and frequency regulation, confirming its robustness and stability. By employing a feedforward neural network (FFNN) trained via the scaled conjugate gradient algorithm, the ANN-based system dynamically adapts control parameters, ensuring voltage and frequency remain within optimal ranges, a key advantage over fixed-gain traditional methods. Overall, the ANN based droop control strategy emerges as a highly effective solution for reliable and efficient microgrid operation by enhancing power quality, dynamic response, and system stability.

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