Enhancing microgrid performance with AI-based predictive control establishing an intelligent distributed control system

Hasani, Afshin; Heydari, Hossein; Golsorkhi, Mohammad Sadegh

Published in:
IET Generation, Transmission & Distribution

DOI:
10.1049/gtd2.13191

Publication date:
2024

Document version:
Final published version

Received: 10 December 2023 | Revised: 29 April 2024 | Accepted: 19 May 2024

IET Generation, Transmission & Distribution

DOI: 10.1049/gtd2.13191

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Enhancing microgrid performance with AI-based predictive control: Establishing an intelligent distributed control system

Afshin Hasani[1] | **Hossein Heydari**[1] | **Mohammad Sadegh Golsorkhi**[2]

[1]Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran

[2]Centre for Industrial Electronics, Department of Mechanical and Electrical Engineering, University of Southern Denmark, Sønderborg, Denmark

Correspondence
Hossein Heydari, Electrical Engineering Department, Iran University of Science and Technology, Tehran, Iran.
Email: heydari@iust.ac.ir

Abstract

Microgrids play a pivotal role in modern power distribution systems, necessitating precise control methodologies to tackle challenges such as performance instability, especially during islanding operations. This paper introduces an advanced control strategy that employs artificial intelligence, specifically deep neural network (DNN) predictions, to enhance microgrid performance, particularly in an islanding mode where voltage and frequency (VaF) deviations are critical concerns. By utilizing real-time data and historical trends, the proposed controller accurately forecasts power demand and generation patterns, enabling proactive planning and optimization of efficiency, reliability, and sustainability in microgrid management. One significant aspect of this approach is to establish an intelligent distributed control system that minimizes reliance on communication devices while ensuring that VaF remains within acceptable limits. Moreover, it consolidates the roles of primary and secondary controllers within the microgrid and facilitates the prediction of load changes and load injection processes. This capability significantly reduces microgrid VaF deviations, enhancing system performance through precise power distribution and balanced coordination among distributed generators. Consequently, it ensures the stability and reliability of the system. In summary, the integration of DNN-based predictive control represents a significant advancement in microgrid management, providing a solution to address performance challenges and optimize operational efficiency, reliability, and sustainability.

1 | INTRODUCTION

Microgrids represent adaptable power distribution systems capable of operating either connected to or independently from the main grid. They efficiently manage energy generation and consumption by optimizing energy sources and controlling demand [1]. These grids deploy two primary management strategies: communication-based and non-communication methods [2].

To enhance microgrid management, hierarchical control structures are implemented, consisting of primary, secondary, and tertiary levels [3]. Primary control (PC) methods, utilizing droop characteristics like active power–frequency (P–f) and reactive power–voltage (Q–V), effectively manage power distribution. However, they may inadvertently result in voltage and frequency deviations (VaF) [4].

Secondary control (SC) frameworks come in two primary forms. The centralized framework, despite its prevalence, faces challenges due to heavy communication and computation loads [5]. In contrast, the distributed control framework, based on local information exchanges, has gained significant attention. Within this framework, distributed generators (DGs) communicate through a network to mitigate VaF deviations [6]. Tertiary control further optimizes microgrid operation by establishing set points, thereby enhancing efficiency and performance [7].

Numerous methodologies have been explored in microgrid control. For example, a decentralized SC introduced in reference [8] utilizes the average frequency of all DGs instead of individual output frequencies for each DG. Additionally, references [9] and [10] highlight the implementation of SC, which involves receiving VaF information from the DGs within the microgrid. This information is used to adjust the frequency of each DG source back to its nominal value, correcting deviations from the DG's nominal values. Moreover, reference [11] introduces a pinning control strategy for SC in microgrids with distributed pinning. This strategy selectively involves a small subset of DGs with access to the frequency reference, guiding the remaining DGs accordingly. Furthermore, reference [12] proposes a distributed SC method aimed at managing voltage variations through feedback linearization, leveraging microgrid parameters exclusively. Another approach outlined in references [13–17] suggests a general SC structure based on distributed averaging proportional-integral (PI) control. However, utilizing a low-bandwidth SC in this case to address VaF deviations results in slow operation for the microgrid.

The mentioned articles underscore the critical necessity of continuous information exchange and periodic data transfer among DGs in microgrids. However, microgrid operations face challenges due to communication issues, resulting in disruptions such as delays in data transmission, sudden disconnections, and reduced efficiency. These faults can lead to instability in network control, data loss, and significant impacts on decision-making processes. Addressing these communication challenges is crucial for ensuring the reliable and efficient operation of microgrids. References [18] and [19] introduce a distributed framework for frequency control and intrusion detection in isolated microgrids, addressing challenges associated with continuous information exchange. This framework enhances microgrid flexibility by mitigating the impact of communication channel limitations. The operation of AC microgrids presents inherent challenges, such as achieving optimal settling time, maximum tolerable overshoot, and minimizing steady-state error. These challenges must be addressed concurrently with reducing reliance on continuous information exchange in microgrid control. Achieving excellent performance in terms of transient response and steady-state frequency recovery is particularly crucial for microgrids operating in island mode within low-inertia systems. The variability in power output and fluctuations of renewable energy sources (RES), coupled with uncertain load consumption, pose significant challenges for microgrid systems. These challenges can lead to dynamic stability issues, including transient power surges, unacceptable frequency deviations, and voltage fluctuations. Hence, there is a pressing need for more comprehensive research to address these critical aspects. References [20–25] focus on controllers designed for VaF in a droop-based microgrid control system operating in island mode. These studies emphasize the reduction of reliance on communication networks through the implementation of communication-less control systems. Traditionally, data collected during microgrid operations has been seldom leveraged to address the challenges at hand, particularly in expediting stability attainment during transient states induced by load changes. In reference [26], it is suggested that by adopting data-driven approaches in microgrid analysis, it is possible to identify the dynamic network without previous structural knowledge. However, this adoption presents challenges, particularly in managing large volumes of raw data, necessitating the development of advanced data processing techniques. The integration of artificial intelligence (AI) into large-scale electrical microgrids holds promise, enabling efficient processing of system information and facilitating various applications, including electrical grid analysis and control. The primary objective of this paper is to present a method utilizing deep neural networks (DNNs) for effective microgrid control. Through training the DNN network, it becomes capable of managing load changes within the microgrid and adjusting the output power of the DG system. To comprehend and formulate the DNN, it is necessary to train the model using information received from the SC, along with voltage and current measurements taken at the output of each DER. These data originate from an AC microgrid regulated by P–f and Q–V droop characteristics under steady-state conditions and various operating modes, with control implemented in a distributed manner. This specific microgrid serves as the dataset for training the DNN network. Leveraging this data, it becomes feasible to predict the voltage and current trends of any distributed generation source through artificial intelligence. Consequently, this approach eliminates the need for periodic communication and integrates the tasks of PC and SC within microgrids to form an intelligent distributed control (IDC) system. Additionally, by preprocessing the acquired data, filtering out the information causing voltage and current fluctuations during transient states, and replacing it with stable data, it becomes feasible to predict the trends of voltage and current changes during transient states. Consequently, this aids in achieving a seamless transition from transient to steady state. The second chapter of the article explores the fundamentals of PC, while the third chapter examines distributed SC. The fourth chapter emphasizes the integration of AI in microgrid control, while the fifth chapter showcases simulation results using Simulink MATLAB. Finally, the concluding chapter summarizes the implications of integrating AI into microgrid control.

2 | FOUNDATIONS AND PRACTICAL IMPLEMENTATIONS OF PC

In AC microgrid systems, inverters play an essential role in regulating voltage and current based on the amplitude and frequency of the distributed voltage. Droop properties, such as P–f and Q–V, are crucial in microgrid control, particularly in scenarios without communication devices. These characteristics define the VaF values for various power levels, with the goal of keeping them within acceptable limits [27, 28], and [29]. The control formula for P–f is given by:

$$f = f^* - m(P - P^*) \tag{1}$$

Here, utilizing control coefficients denoted by m and power references (P^*), the active power (P) is adjusted to stabilize the frequency (f) around a desired value (f^*). Similarly, reactive power and voltage are controlled using a similar formula. Similarly, the control formula for Q–V is given by:

$$E = E^* - n(Q - Q^*) \tag{2}$$

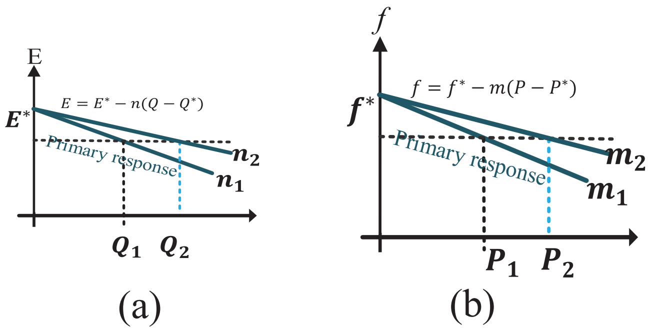

FIGURE 1 P/Q (active power/reactive power) droop characteristic: (a) q-axis; (b) d-axis.

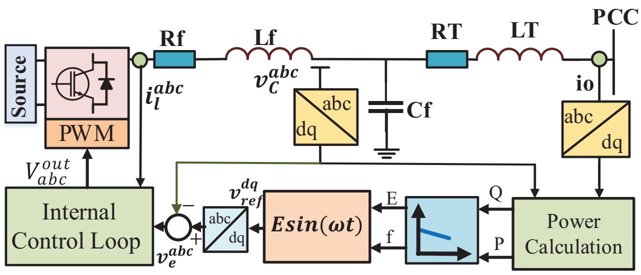

FIGURE 2 Schematic diagram of the primary control system.

Here, the reactive power (Q) is adjusted using a control coefficient 'n' and a reference value (Q^*), which determines the sensitivity to voltage fluctuations. E represents the current system voltage, while E^* indicates the desired voltage, typically aligned with the nominal or expected voltage [30, 31]. Figure 1 depicts the P/Q droop characteristic for the q-axis and d-axis, following Equations (1) and (2). The diagram in Figure 2 illustrates the PC system, employing P/Q droop control to calculate the reference voltage for the inverter. A cascaded voltage–current control loop, equipped with PI controllers, is employed to regulate the voltage within acceptable limits. This enhances the voltage stability of the microgrid and ensures reliable inverter operation through pulse width modulation (PWM) switching [32].

3 | DISTRIBUTED SECONDARY CONTROL IN MICROGRIDS

In the microgrid, PC manages each DG locally and focuses on individual DG operations, while SC provides a higher level of coordination among all DGs. This involves sharing information regarding output power, voltage, frequency, and other relevant factors for making system-wide decisions. The SC employs various methods, including consensus control and droop control techniques, to coordinate DGs and adjust their key parameters, thereby enhancing the overall performance of the system. By promoting coordination between DGs, SC aims to achieve system-wide objectives such as load sharing, voltage regulation, and frequency stability [33–36].

The synergy between PC and SC ensures the efficient and reliable operation of a DG system by leveraging the capabilities and compatibility of DG units while maintaining stability and quality throughout the wider power system. The proposed method integrates communication system information to collect data from different DGs and employs a control approach to optimize system performance and ensure proper operation.

Here is a breakdown of how SC operates in relation to frequency, voltage control, and reactive power sharing.

When frequency deviates significantly, it adjusts individual DGs' power output to restore nominal frequency, maintaining system stability. The control signal, δf_{DG_k}, is calculated using a PI controller formula [28]:

$$\delta f_{DG_k} = k_{Pf}\left(f_{MG}^* - \bar{f}_{DG_K}\right) + k_{If}\int\left(f_{MG}^* - \bar{f}_{DG_K}\right)dt$$
$$\bar{f}_{DG_K} = \frac{\sum_{i=1}^{N} f_{DG_i}}{N} \tag{3}$$

In this equation, k_{Pf} and k_{If} represent the parameters of the PI controller. f_{MG}^* is the reference frequency for the microgrid. $\bar{f}_{DG_K}$ denotes the average frequency across all DG units. δf_{DG_k} is the control signal produced by the SC system of DG_k at every sample time. In this context, i ranges from 1 to N, where N represents the number of packages (frequency measurements) received through the communication system, and K ranges from 1 to n, where n represents the number of DG units.

In voltage control, maintaining voltage levels within acceptable bounds is crucial. The SC system adjusts DGs to match a reference voltage. This adjustment, δE_{DG_k}, is calculated using a PI control approach:

$$\delta E_{DG_k} = k_{PE}\left(E_{MG}^* - \bar{E}_{DG_K}\right) + k_{IE}\int\left(E_{MG}^* - \bar{E}_{DG_K}\right)dt$$
$$\bar{E}_{DG_K} = \frac{\sum_{i=1}^{N} E_{DG_i}}{N} \tag{4}$$

In this equation, δE_{DG_k} signifies the voltage adjustment signal for DG_k, while k_{PE} and k_{IE} represent the PI controller parameters, respectively. E_{MG}^* denotes the microgrid voltage reference, and $\bar{E}_{DG_K}$ signifies the average voltage of all DG units. Additionally, N indicates the number of voltage measurements received via the communication system, providing insights into the system's voltage status.

This equation combines both immediate voltage deviations (proportional term) and accumulated discrepancies over time (integral term) to ensure stable voltage regulation.

By guiding DGs based on these control signals, the SC system effectively maintains voltage within acceptable limits, supporting a high-quality power supply.

Effective sharing of reactive power among DGs is vital for voltage stability. The SC system collects data on reactive power generation and compares it to predefined criteria. If imbalances are detected, specific DGs are instructed to adjust their reactive power output, restoring equilibrium.

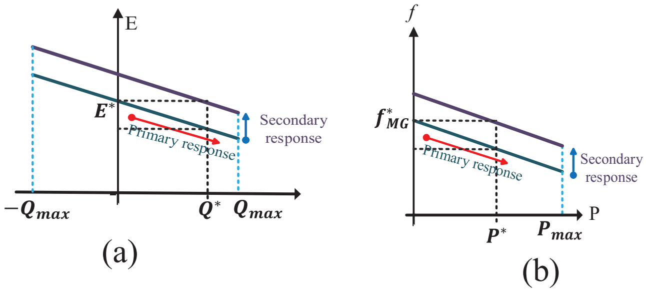

FIGURE 3 Effect of secondary control on P/Q (active power/reactive power) Droop Charateristic: (a) q-axis; (b) d-axis.

The control signal, δQ_{DG_k}, is determined as follows:

$$\delta Q_{DG_k} = k_{PQ}\left(Q^*_{MG} - \bar{Q}_{DG_K}\right) + k_{IQ}\int\left(Q^*_{MG} - \bar{Q}_{DG_K}\right)dt$$

$$\bar{Q}_{DG_K} = \frac{\sum_{i=1}^{N} Q_{DG_i}}{N} \tag{5}$$

In this equation, δQ_{DG_k} denotes the reactive power adjustment signal for DG_k, while k_{PQ} and k_{IQ} stand for the PI controller parameters, respectively. Q^*_{MG} signifies the microgrid's reactive power reference, and $\bar{Q}_{DG_K}$ represents the average reactive power of DG units. Additionally, N indicates the number of measurements received through the communication system. This equation facilitates the proper sharing of reactive power, promoting voltage stability and balanced operation.

The described controller system adopts a fully distributed approach, with each DG unit incorporating both PC and SC. The SC is strategically positioned between the communication infrastructure and the PC. This control framework empowers the management of frequency and voltage as well as the equitable distribution of reactive power. Additionally, it is adaptable enough to extend its capabilities to include active power sharing in microgrids characterized by high R/X ratios.

In this setup, the SC embedded in each DG unit collects data, including frequency, voltage amplitude, and reactive power, from other DG units through the communication system. It then calculates the average of these measurements and determines the required control signal to transmit to the PC, effectively eliminating steady-state errors.

Figure 3 illustrates the successful reduction of frequency and voltage deviations introduced by the PC within the microgrid units, thanks to the SC. It demonstrates that the SC exclusively enhances the primary response until the frequency returns to its nominal value, even when dealing with DGs of varying power ratings. This approach can be applied similarly to distributed frequency control, where each inverter evaluates the voltage error and works to alleviate voltage deviations stemming from the Q–V droop control. By employing the averaging method, the SC effectively mitigates voltage deviations induced by the PC within each DG unit, as illustrated in Figure 3a.

Furthermore, Figure 4 presents a comprehensive overview of the conventional distributed control framework for a DG

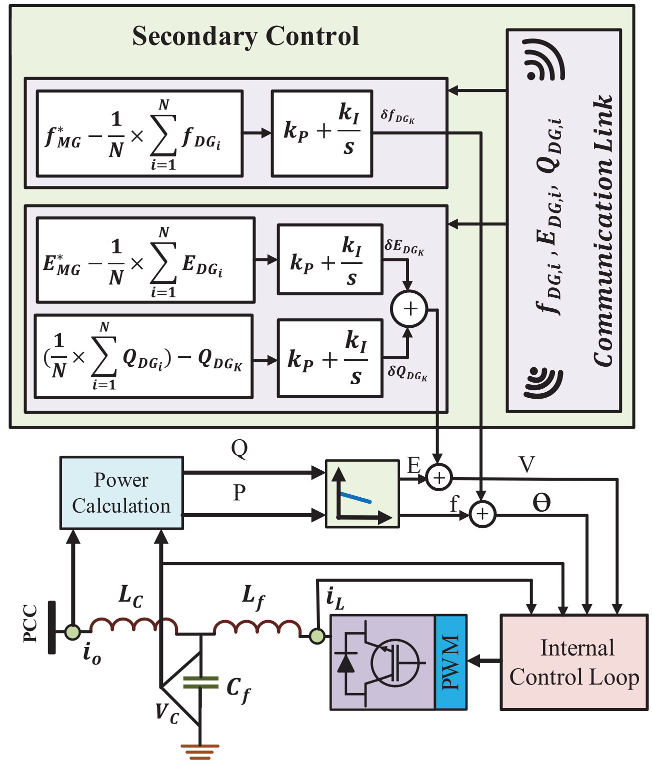

FIGURE 4 Traditional distributed control system scheme for each distributed generation unit in a microgrid.

unit operating in island mode, with a specific focus on the DG_k unit. This process involves the measurement and comparison of voltage and current levels within the microgrid against their designated reference values. Upon detecting any deviations, the relevant information is transmitted to the compensators at the PC level of all DG units.

4 | EMPOWERING CONTROL SYSTEMS WITH AI

AI is indeed a tool that can establish relationships between inputs and outputs based on validated data. Its primary advantage lies in its ability to learn from this data and use it to predict future outputs when new inputs are provided. By leveraging advanced algorithms and modelling techniques, AI can analyse patterns and make informed predictions or decisions. This predictive power makes AI a valuable tool in various domains, ranging from machine learning and data analysis to natural language processing and image recognition [37]. The distributed control system relies on the communication network as its backbone, making it prone to various communication challenges, especially when the communication links are disrupted. This paper aims to address these challenges by proposing an IDC network that has a virtual communication link facilitated by AI. Developing such a controller requires significant amounts of training data. To collect this data, we have utilized a distributed control network, as discussed in sections two and three of this article. Using artificial intelligence, the controller predicts the

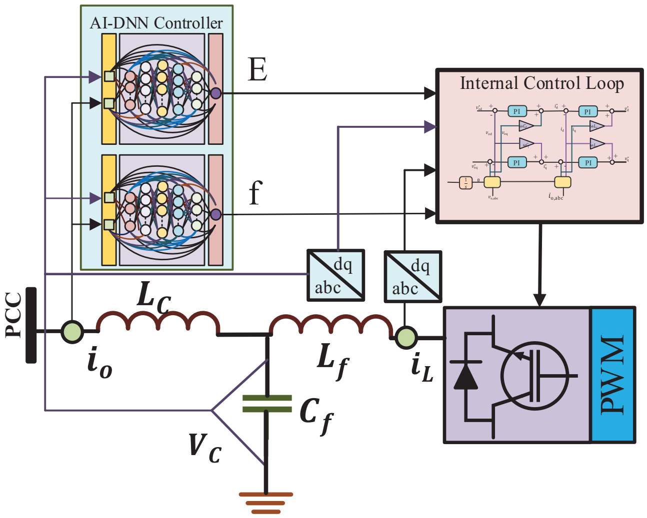

FIGURE 5 An intelligent distributed control scheme for each distributed generation unit in a microgrid.

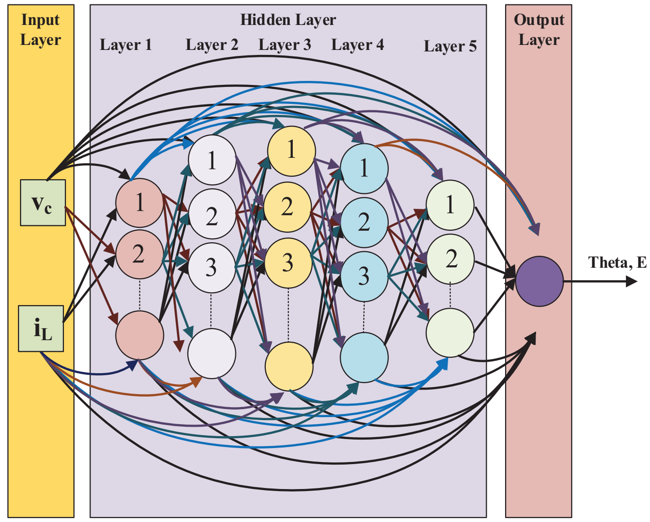

FIGURE 6 The proposed deep neural network controller architecture for active and reactive power control of microgrid.

data sent by each DG, thereby eliminating the periodic need for direct communication. In a typical distributed control system, variations in the output load cause voltage and current fluctuations in each DG. Each DG requires time to synchronize its power injection with others to meet the load demand based on its rated capacity. To address this issue, a PI controller is employed in the distributed control system to minimize the disparity between the actual and desired voltage and current. By leveraging historical data, the controller determines the necessary power injection from each DG for any alterations in load demand. Through the learning process of a DNN, the system anticipates the trend of load variations. By integrating PC and SC in diverse scenarios and loads, the controller achieves precise allocation of active and reactive power, aiming to minimize VaF deviations. Consequently, voltage and current fluctuations are effectively mitigated. Preparing and normalizing the extra data acquired from microgrid control before training the DNN is crucial for making the data more suitable and consistent. Techniques such as feature scaling, normalization, or data transformation can be applied to prepare the data, ensuring it is well-suited for efficient learning and convergence during the DNN training process. This step contributes to enhancing the accuracy and performance of the DNN model as a whole. Figure 5 illustrates the IDC circuit within the microgrid, employing artificial intelligence. Additionally, Figure 6 illustrates the architecture of the proposed controller, structured as a DNN. The first architecture takes the input voltage and output current of frequency DGs and performs the role of a *P–f* controller along with the secondary controller in the microgrid. The second architecture utilizes the output voltage and current of DGs to control the voltage, adjust reactive power, and perform the role of a *Q–V* controller along with the secondary controller in the microgrid. The architecture of neural networks consists of several layers, with each layer containing a specific number of neurons. Here is a breakdown of the neuron configuration for each layer in Table 1.

TABLE 1 Number of neurons in deep neural network architectures used for active and reactive power control.

	Active power control architecture	Reactive power control architecture
First hidden layer	5 neurons	10 neurons
Second hidden layer	20 neurons	30 neurons
Third hidden layer	30 neurons	50 neurons
Fourth hidden layer	20 neurons	30 neurons
Fifth hidden layer	5 neurons	10 neurons

These neuron configurations define the structure and capacity of the neural network models used in the proposed controller.

Incorporating multiple hidden layers empowers the network to engage in deep learning, enabling it to extract intricate patterns and information from the input data. This capability proves advantageous for tasks demanding a thorough understanding and processing of complex data. The DNN architecture enhances the model's capacity to learn and has the potential to enhance its performance across various applications.

The proposed neural network architecture employs a "dense" or "fully connected" structure, where the neurons in each layer are connected to all the neurons in other layers. This type of connectivity enables information to flow freely between any two neurons in the network, regardless of their position in the layer. This connection pattern is advantageous for preventing network saturation during training. Saturation occurs when neuron activations reach extreme values (close to 0 or 1), hindering effective learning. By allowing connections between non-adjacent neurons, the information flow becomes more dynamic, preventing saturation and potentially enhancing the learning process. The fully connected architecture empowers the network to capture

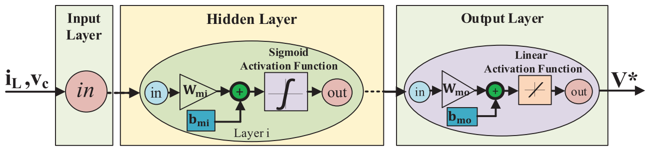

FIGURE 7 Architecture of neurons in a proposed deep neural network.

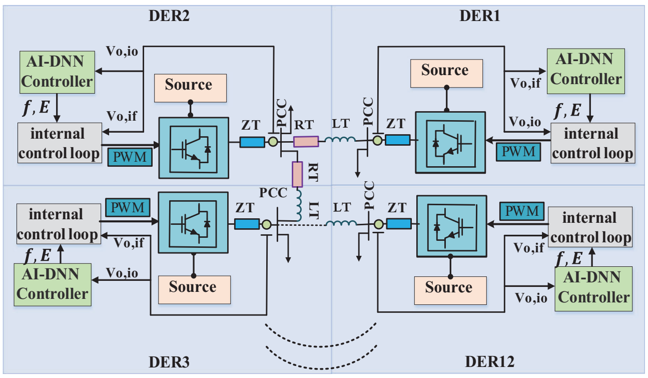

FIGURE 8 A simulated model depicting a microgrid comprising 12 distributed generation units.

and transmit information from various parts of the network, making it easier to extract complex patterns and improving the network's ability to understand intricate relationships within the input data. In the described neural network, the activation function plays a vital role in transforming inputs into desired outputs while capturing the complex and non-linear relationships present in the data. As depicted in Figure 7, a sigmoid activation function, also known as the logistic function, is employed in the hidden layer. This function maps inputs to values between 0 and 1, commonly applied in deep learning for tasks such as binary classification or when the output is intended to represent probabilities. As depicted in Figure 8, a sigmoid activation function, also known as the logistic function, is employed in the hidden layer. This function maps inputs to values between 0 and 1, commonly applied in deep learning for tasks such as binary classification or when the output is intended to represent probabilities. In contrast, the output layer utilizes the linear activation function. The linear function generates an output that is directly proportional to the input, making it well-suited for regression tasks or situations where non-linear transformations are not needed. By using different activation functions in the hidden and output layers, the network can learn complex and non-linear data patterns while ultimately generating linear outputs. However, the choice of activation functions depends on the specific problem, with different scenarios warranting different activation functions for optimal results.

The training of the proposed controller, utilizing a DNN and the Levenberg–Marquardt algorithm, undergoes a sequence of stages aimed at enhancing the network's performance. It commences with the initialization of the network's weights and biases. Subsequently, a dataset featuring input data and target outputs is employed for forward propagation and error assessment. Gradients are computed through backpropagation, guiding adjustments to the weights and biases to minimize the error. The Levenberg–Marquardt algorithm streamlines this process, dynamically adapting learning rates based on error surface curvature.

This iterative process continues until a predefined stopping criterion is met, such as a set number of iterations or achieving the desired training data performance. This approach amalgamates elements from gradient descent and Gauss–Newton methods, offering more efficient optimization compared to conventional gradient-based techniques. Since the output ranges are significantly different, one related to the angle and the other to the voltage, separate and specialized networks should be used. Moreover, it is worth noting that discrete networks tend to converge faster and more effectively in such scenarios. This is because each network is exclusively trained on its own data set and requires minimal adaptation to other data sets. Also, due to the complexity of this network, trying to develop and train it can bring more challenges. Therefore, it was decided to use two separate networks with the same inputs. By distributing tasks among these networks, the overall complexity becomes more manageable.

5 | SIMULATION RESULTS

The proposed method was simulated using Simulink within the MATLAB environment. The configuration, depicted in Figure 8, delineates the overall structure of the simulated models for a microgrid consisting of 12 DG units. As illustrated in Figure 8, each DG system incorporates a renewable energy source, represented by DC sources. The power electronic interface, typically a DC/AC converter, is a vital component within every DG system. Each DG unit has the option of a direct connection to a predefined load or a connection to a shared AC bus for power distribution. DC/AC inverters play a pivotal role in this process.

The microgrid is equipped with energy sources of the same rated power. Thorough modelling has been performed for the DG units, including their interface inverters. Each power source connects to the shared bus through unique impedance lines and supplies power to the loads at the common coupling point. A comprehensive array of control parameters necessary for the simulation of the microgrid using the proposed control method is outlined in Table 2. It is important to note that, in this simulation, all DG units maintain consistent control parameters. Throughout the design phase of this proposed system, it was crucial to secure a significant volume of input and output data to facilitate effective neural network training. This goal was accomplished by utilizing data collected from both the primary and secondary controllers under different loading conditions and during DG entry and exit at various time intervals.

The dataset has been segregated into two separate subsets: a training set and a test set. In the context of a DNN, 80% of the data is designated for training, and the remaining 20% is set aside for testing and evaluation.

TABLE 2 Parameters for electrical and control in the simulated microgrid.

Parameter	Symbol	Value
Rated phase voltage	V^*	220 V_{rms}
Rated frequency	f^*	50 Hz
LCL filter components	L_f	8.6 mH
	C_f	25 µF
	Lo	1.8 mH
Impedance of the load	R_L	100 or 50 Ω
Droop control		
Active power droop factor	K_{pP}	0.00001 Ws/rd
Integral contribution to active power droop	K_{iP}	0.0008 Ws/rd
Coefficient for reactive power droop	R_{pQ}	0.16 VAr/V
First-level control loop		
Voltage proportional component	k_{PV}	0.35
Voltage integral component	k_{IV}	400
Current proportional component	k_{PC}	0.35
Current integral component	k_{IC}	200
Secondary control		
Proportional component of frequency	K_{pf}	0.001
Integral component of frequency	K_{if}	4/s
Amplitude voltage proportional factor	K_{pE}	0.001
Integral part of voltage	K_{iE}	0.6/s
Reactive power proportional factor	K_{pQ}	0.0001 Var/V
Reactive power integral gain	K_{iQ}	0.3 Var/V

Throughout the training process, the DNN progressively enhances its capacity to create a mapping from input data to the desired output by iteratively fine-tuning its weights and biases. The training set serves as the cornerstone of this procedure, facilitating the step-by-step adjustment of DNN parameters until the model attains the desired level of accuracy. Once the training phase is concluded, the test set is utilized to evaluate the model's performance and its ability to generalize.

The test set comprises data that the DNN has not been exposed to during training, enabling an independent assessment of the model's proficiency in handling input it has not encountered before. Through the assessment of the DNN's performance on the test set, one can estimate the model's effectiveness in dealing with new and unfamiliar data. This evaluation offers valuable insights into the DNN's ability to extrapolate learned patterns and make predictions regarding data it has not previously encountered. The practice of dividing a dataset into training and testing subsets is a fundamental technique in machine learning designed to combat overfitting. Overfitting happens when a DNN becomes excessively focused on learning specific features within the training data, which can hinder its ability to generalize to new, unseen data. The creation of a distinct test set facilitates an unbiased evaluation of DNN performance on this novel and unfamiliar data, ultimately reducing the potential risks associated with overfitting.

At $t = 3$ s, the load connects to the microgrid, and power is supplied to the load by distributed generation sources. The proposed control system accurately allocates power among the DG units and effectively corrects errors in active and reactive power division. As depicted in Figure 9a, the active power increases from 0 to 913 W at $t = 3$ s and stabilizes within about half a second. In contrast, the controllers referenced in [21] and [23] compensate for active power division errors relatively slowly and exhibit power fluctuations. The observed errors stem from communication delays and power fluctuations resulting from power coupling, phenomena absent in the outcomes of the proposed method. Previous studies exhibit prolonged stabilization periods and significant fluctuations in active power before achieving stability. Nonetheless, the proposed method adeptly mitigates excessive active power and transient fluctuations, offering a solution to a prominent challenge observed in earlier methodologies.

In Figure 9b, the reactive power waveform stabilizes quickly with each load change at $t = 3$ s and $t = 15$ s, accurately distributing reactive power among DG units without fluctuations to achieve stability. In contrast, the referenced studies [14] and [22] require more time to achieve stability during load changes.

At $t = 15$ s, Figure 9a,e illustrates the active power waveform of each DG and the effective output current of each DG, respectively. These figures demonstrate that the microgrid, under the proposed control system, exhibits a rapid and dynamic response to load changes. Additionally, the microgrid maintains active power stability with minimal overcurrent, ensuring effective operation. Compared to the controller methods described in references [21] and [23], there is a notable improvement in stability attainment time during load changes, with negligible transient current. However, it is important to note that excessive active power may lead to higher currents from the inverter, posing risks to microgrid stability and inverter integrity. Therefore, implementing power sharing according to the capacity of each generation source is crucial to reducing overload and ensuring swift dynamics, thereby maintaining the stability and reliability of the microgrid.

The implementation of the proposed control system, as depicted in Figure 9c,d, significantly reduces VaF deviations, ensuring they remain within acceptable thresholds. Compared to the methods mentioned in reference [23], the proposed method achieves stability for a shorter duration when encountering deviations caused by changes in voltage and frequency load during the transient state. Additionally, the frequency oscillations exhibit less overshoot and undershoot, and they are damped in a smaller number of oscillations. The rapid attainment of voltage stability, as depicted in Figure 9c, underscores the dynamic and stabilizing capabilities of the proposed controller. It notably reduces the time required to achieve stability compared to the methods mentioned in [21] and [23]. Moreover, as evidenced in Figure 9a–e, the proposed controller demonstrates agile dynamics and effective stabilization with minimal overcurrent. In addition, integrating AI for predictive analytics can eliminate the periodic dependence on communication devices, thus reducing communication disruptions and

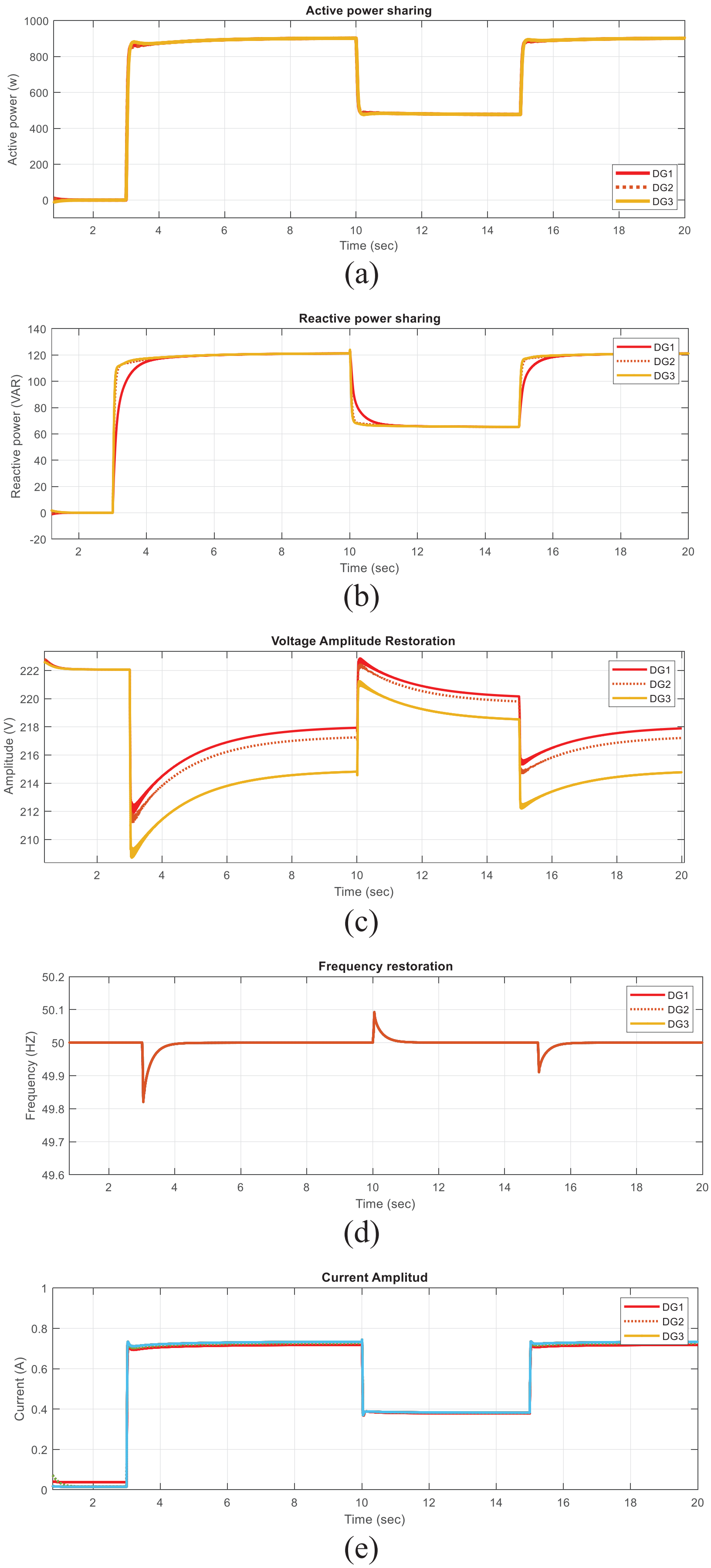

FIGURE 9 Performance of the proposed control method: (a) active power sharing; (b) reactive power sharing; (c) frequency restoration; (d) voltage amplitude restoration; (e) current amplitude.

TABLE 3 Comparative analysis of previous studies and current research.

Reference no.	Frequency restoration	Active power sharing	Voltage restoration	Reactive power sharing	Resilient to communication disruptions	Data-driven
[11, 12, 17, 21]	Yes	Yes	No	No	No	No
[10, 15, 16, 23]	Yes	Yes	Yes	Yes	No	No
[14, 22]	No	No	Yes	Yes	No	No
[20, 25]	Yes	Yes	No	No	Yes	No
[26, 27]	Yes	Yes	Yes	Yes	No	Yes
This article	Yes	Yes	Yes	Yes	Yes	Yes

facilitating a smoother transition from transient to steady-state by anticipating process changes.

6 | CONCLUSION

This paper presents a novel distributed control system that effectively tackles the communication challenges inherent in traditional distributed control systems while capitalizing on their benefits. This system facilitates equitable power allocation among distributed energy sources without relying on periodic communication devices. By adeptly managing power distribution through VaF adjustments within specified limits, this approach enhances overall system performance. DNNs leverage data from existing control methods to adapt to changing conditions, predict outcomes, and handle complex non-linear behaviours. The integration of AI-based optimization algorithms enables efficient resource management by adapting to dynamic parameters. It swiftly stabilizes the microgrid in response to changes in output load and injected power, thereby improving microgrid dynamics.

This customized DNN-based control system enhances microgrid performance by dynamically adjusting output power based on various inputs. In summary, the integration of AI into microgrid control offers promising opportunities to boost performance, streamline operations, and enhance flexibility. This integration lays the groundwork for adaptive, predictive AI-based microgrid systems capable of effectively addressing the challenges of the evolving energy landscape.

Furthermore, Table 3 provides a comprehensive comparative analysis of previous studies and the current research across various aspects of microgrid control. These aspects include frequency restoration, active power sharing, voltage restoration, reactive power sharing, resilience to communication disruptions, and the utilization of data-driven approaches.

AUTHOR CONTRIBUTIONS

Afshin Hasani: Conceptualization; investigation; methodology; software; validation; writing—original draft. **Hossein Heydari**: Investigation; supervision; validation; writing—review and editing. **Mohammad Sadegh Golsorkhi**: Investigation; supervision; validation; writing—review and editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

ORCID

Afshin Hasani https://orcid.org/0009-0002-6976-9558

REFERENCES

1. Rokrok, E., Golshan, M.E.H.: Adaptive voltage droop scheme for voltage source converters in an islanded multibus microgrid. IET Gener. Transm. Distrib. 4(5), 562 (2010). https://doi.org/10.1049/iet-gtd.2009.0146
2. Baharizadeh, M., Esfahani, M.S.G., Kazemi, N.: Modified virtual frequency-voltage frame control scheme with zero sharing error for islanded AC microgrids. IET Gener. Transm. Distrib. 17(11), 2576–2586 (2023). https://doi.org/10.1049/gtd2.12837
3. Baharizadeh, M., Golsorkhi, M.S., Savaghebi, M.: Secondary control with reduced communication requirements for accurate reactive power sharing in AC microgrids. IET Smart Grid 6, 638–652 (2023). https://doi.org/10.1049/stg2.12127
4. Kallamadi, M., Sarkar, V.: Enhanced real-time power balancing of an AC microgrid through transiently coupled droop control. IET Gener. Transm. Distrib. 11(8), 1933–1942 (2017). https://doi.org/10.1049/iet-gtd.2016.1250
5. Hajian, M., Golsorkhi, M.S., Ranjbar, A., Shafiee, Q., Savaghebi, M.: V-I droop-based distributed event- and self-triggered secondary control of AC microgrids. IET Smart Grid 6(3), 271–283 (2023). https://doi.org/10.1049/stg2.12097
6. Bidram, A., Davoudi, A., Lewis, F.L., Guerrero, J.M.: Distributed cooperative secondary control of microgrids using feedback linearization. IEEE Trans. Power Syst. 28(3), 3462–3470 (2013). https://doi.org/10.1109/TPWRS.2013.2247071
7. Jadeja, R., Ved, A., Trivedi, T., Khanduja, G.: Control of power electronic converters in AC microgrid. In: Microgrid Architectures, Control and Protection Methods. pp. 329–355. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-23723-3_13
8. Li, Q., Peng, C., Wang, M., Chen, M., Guerrero, J.M., Abbott, D.: Distributed secondary control and management of islanded microgrids via dynamic weights. IEEE Trans. Smart Grid 10(2), 2196–2207 (2019). https://doi.org/10.1109/TSG.2018.2791398
9. Golsorkhi, M.S., Shafiee, Q., Lu, D.D.-C., Guerrero, J.M.: Distributed control of low-voltage resistive AC microgrids. IEEE Trans. Energy Convers. 34(2), 573–584 (2019). https://doi.org/10.1109/TEC.2018.2878690
10. Xu, Y., Sun, H., Gu, W., Xu, Y., Li, Z.: Optimal distributed control for secondary frequency and voltage regulation in an islanded microgrid. IEEE Trans. Ind. Informatics 15(1), 225–235 (2019). https://doi.org/10.1109/TII.2018.2795584

11. Zhou, Q., Shahidehpour, M., Yan, M., Wu, X., Alabdulwahab, A., Abusorrah, A.: Distributed secondary control for islanded microgrids with mobile emergency resources. IEEE Trans. Power Syst. 35(2), 1389–1399 (2020). https://doi.org/10.1109/TPWRS.2019.2942269
12. Lu, L.-Y., Liu, H.J., Zhu, H., Chu, C.-C.: Intrusion detection in distributed frequency control of isolated microgrids. IEEE Trans. Smart Grid 10(6), 6502–6515 (2019). https://doi.org/10.1109/TSG.2019.2906573
13. Baker, K., Bernstein, A., Dall'Anese, E., Zhao, C.: Network-cognizant voltage droop control for distribution grids. IEEE Trans. Power Syst. 33(2), 2098–2108 (2018). https://doi.org/10.1109/TPWRS.2017.2735379
14. Eskandari, M., Li, L., Moradi, M.H.: Decentralized optimal servo control system for implementing instantaneous reactive power sharing in microgrids. IEEE Trans. Sustain. Energy 9(2), 525–537 (2018). https://doi.org/10.1109/TSTE.2017.2747515
15. Heydari, R., Dragicevic, T., Blaabjerg, F.: High-bandwidth secondary voltage and frequency control of VSC-based AC microgrid. IEEE Trans. Power Electron. 34(11), 11320–11331 (2019). https://doi.org/10.1109/TPEL.2019.2896955
16. Hashmi, K., et al.: An energy sharing scheme based on distributed average value estimations for islanded AC microgrids. Int. J. Electr. Power Energy Syst. 116, 105587 (2020). https://doi.org/10.1016/j.ijepes.2019.105587
17. Dashtdar, M., et al.: Frequency control of the islanded microgrid based on optimised model predictive control by PSO. IET Renewable Power Gener. 16(10), 2088–2100 (2022). https://doi.org/10.1049/rpg2.12492
18. Sheikhahmadi, H., Batmani, Y., Khayat, Y., Konstantinou, C.: H∞ optimal frequency control in islanded AC microgrids: A zero-sum dynamic game approach. IET Renewable Power Gener. 17(7), 1826–1834 (2023). https://doi.org/10.1049/rpg2.12717
19. Aghaee, F., Dehkordi, N.M., Bayati, N., Karimi, H.: A distributed secondary voltage and frequency controller considering packet dropouts and communication delay. Int. J. Electr. Power Energy Syst. 143, 108466 (2022). https://doi.org/10.1016/j.ijepes.2022.108466
20. Rey, J.M., Marti, P., Velasco, M., Miret, J., Castilla, M.: Secondary switched control with no communications for islanded microgrids. IEEE Trans. Ind. Electron. 64(11), 8534–8545 (2017). https://doi.org/10.1109/TIE.2017.2703669
21. Chen, Y., et al.: Distributed self-triggered control for frequency restoration and active power sharing in islanded microgrids. IEEE Trans. Ind. Informatics 19(10), 10635–10646 (2023). https://doi.org/10.1109/TII.2023.3240738
22. Andreotti, A., Caiazzo, B., Fridman, E., Petrillo, A., Santini, S.: Distributed dynamic event-triggered control for voltage recovery in islanded microgrids by using artificial delays. IEEE Trans. Cybern. 1–14 (2024). https://doi.org/10.1109/TCYB.2024.3364820
23. Khan, M.Y.A., Liu, H., Zhang, R., Guo, Q., Cai, H., Huang, L.: A unified distributed hierarchal control of a microgrid operating in islanded and grid connected modes. IET Renewable Power Gener. 17(10), 2489–2511 (2023). https://doi.org/10.1049/rpg2.12716
24. Saleem, M.I., Saha, S., Roy, T.K., Ghosh, S.K.: Assessment and management of frequency stability in low inertia renewable energy rich power grids. IET Gener. Transm. Distrib. 18, 1372–1390 (2024). https://doi.org/10.1049/gtd2.13129
25. Ahmadi, F., Batmani, Y., Bevrani, H.: Model Reference Adaptive Controller for Simultaneous Voltage and Frequency Restoration of Autonomous AC Microgrids. vol. XX(Xx), 1–10. https://doi.org/10.35833/MPCE.2023.000277
26. Ingalalli, A., Kamalasadan, S.: Data-driven decentralized online system identification-based integral model-predictive voltage and frequency control in microgrids. IEEE Trans. Ind. Informatics 20, 1963–1974 (2023). https://doi.org/10.1109/TII.2023.3280308
27. Dehghani, M., Kavousi-Fard, A., Dabbaghjamanesh, M., Avatefipour, O.: Deep learning based method for false data injection attack detection in AC smart islands. IET Gener. Transm. Distrib. 14(24), 5756–5765 (2020). https://doi.org/10.1049/iet-gtd.2020.0391
28. Shafiee, Q., Guerrero, J.M., Vasquez, J.C.: Distributed secondary control for islanded microgrids—A novel approach. IEEE Trans. Power Electron. 29(2), 1018–1031 (2014). https://doi.org/10.1109/TPEL.2013.2259506
29. Sati, T.E., Azzouz, M.A.: An adaptive virtual impedance fault current limiter for optimal protection coordination of islanded microgrids. IET Renewable Power Gener. 16(8), 1719–1732 (2022). https://doi.org/10.1049/rpg2.12474
30. Parallel, V.I., Considering, S.: An improved droop control method for voltage-source inverter parallel systems considering line impedance differences. Energies 12(6), 1158 (2019). https://doi.org/10.3390/en12061158
31. Huang, L., Sun, W., Yan, Z., Li, Q., Li, W.: Average voltage observer based distributed secondary sliding mode control with reactive power sharing for microgrids. In: 2023 IEEE 6th International Electrical and Energy Conference (CIEEC) Hefei, China. pp. 2473–2478 (2023). https://doi.org/10.1109/CIEEC58067.2023.10166907
32. Baharizadeh, M., Golsorkhi, M.S., Savaghebi, M.: Secondary control with reduced communication requirements for accurate reactive power sharing in AC microgrids. IET Smart Grid 6(6), 638–652 (2023). https://doi.org/10.1049/stg2.12127
33. Nguyen, D.H., Khazaei, J.: Unified distributed control of battery storage with various primary control in power systems. IEEE Trans. Sustainable Energy 12(4), 2332–2341 (2021). https://doi.org/10.1109/TSTE.2021.3091976
34. Wong, Y.C.C., Lim, C.S., Cruden, A., Rotaru, M.D., Ray, P.K.: A consensus-based adaptive virtual output impedance control scheme for reactive power sharing in radial microgrids. IEEE Trans. Ind. Appl. 57(1), 784–794 (2021). https://doi.org/10.1109/TIA.2020.3031884
35. Chen, P., Liu, S., Chen, B., Yu, L.: Multi-agent reinforcement learning for decentralized resilient secondary control of energy storage systems against DoS attacks. IEEE Trans. Smart Grid 13(3), 1739–1750 (2022). https://doi.org/10.1109/TSG.2022.3142087
36. Bidram, A., Nasirian, V., Davoudi, A., Lewis, F.L.: Cooperative synchronization in distributed microgrid control. In: Advances in Industrial Control. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-50808-5
37. Yeganeh, M.S.O., Oshnoei, A., Mijatovic, N., Dragicevic, T., Blaabjerg, F.: Intelligent secondary control of islanded AC microgrids: A brain emotional learning-based approach. IEEE Trans. Ind. Electron. 70(7), 6711–6723 (2023). https://doi.org/10.1109/TIE.2022.3203677

How to cite this article: Hasani, A., Heydari, H., Golsorkhi, M.S.: Enhancing microgrid performance with AI-based predictive control: Establishing an intelligent distributed control system. IET Gener. Transm. Distrib. 18, 2499–2508 (2024). https://doi.org/10.1049/gtd2.13191