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Secondary Voltage and Frequency Control in Islanded Microgrids: Online ANN Tuning Approach

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Abstract— **This paper presents an intelligent control approach to optimally tune control parameters utilized in the control structure of a microgrid (MG) so that the voltage and frequency of islanded MGs return to the nominal values under occurring sudden changes in load. The proposed approach is based on restoring the voltage and frequency by using online tuning of the control parameters by means of an intelligent self-optimizing-based MG central controller (MGCC). The MGCC is used in order to implement an optimal secondary voltage/frequency control. An online ANN tuner is applied to the system to adjust the secondary controllers' parameters. The main advantage of online ANN-based MGCC is independency from human actions under occurring disturbances and also in industrial and uncertain environments. Simulation results are presented to show the feasibility of the proposed intelligent approach.**

I. Introduction

Microgrids (MGs) are local grids including several different technologies such as power electronic devices, renewable energy sources (RESs), telecommunications and storage devices that can be operated in two operating modes: connected and islanded modes. Due to existence of these technologies diversity in MGs, uncertainty in the RESs as well as other modern power systems components, and physical disturbances, intelligent control structures are essential to provide stability and effective operation of MGs. To preserve desirable performance and economic operation, various control units such as active/reactive power control, voltage and frequency regulation, angle synchronization process between MG and the main grid, energy management, economic optimization and system recovery are used in MGs [1].

According to IEEE Standard 1547 [2], the existing controls must supply the required active and reactive powers and provide frequency and voltage stability. In MGs, a hierarchical control structure with different levels has been defined. Typical control structure of a MG is shown in Fig. 1 [1]. There are two local controllers: microsource controller (MC) and load controller (LC). The MCs locally control voltage and frequency of each distributed generation (DG) and the LCs provide load control capabilities at the controllable loads [1]. In [3], three control layers: primary (local), supplementary (secondary) and global (tertiary) are defined in order to standardize MGs operation. The primary control consists of initial voltage and current control loops in the DGs. To achieve zero deviations of voltage and frequency of the MG after every change in load or generation, the supplementary control is considered. The global control manages the MG to work as economic and to organize the relation with the main grid in the connected mode.

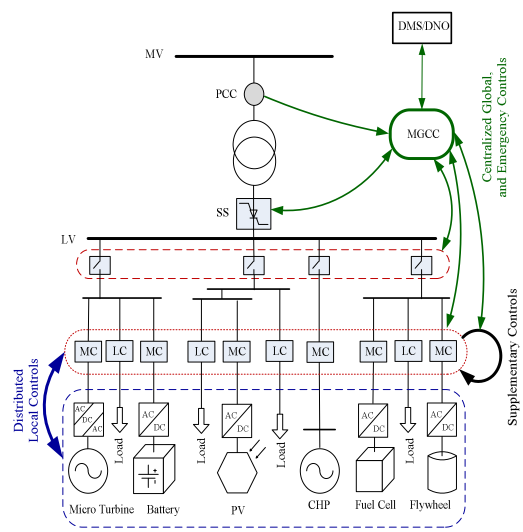

Fig. 1. A hierarchical control for reliable operation of a MG [1].

In [1], another layer named emergency control is presented. The emergency control is responsible to identify all types of contingencies and to select proper preventive and corrective actions. This preventive/corrective decisions are exported from the MG central controller (MGCC). The MGCC exchanges information with distribution management system/distribution network operator (DMS/DNO) to manage the MG operation in the connected mode.

Recently, two online intelligent secondary controllers in islanded MGs [4], [5] are proposed. In both works, intelligent techniques such as fuzzy logic (FL) combined with particle swarm optimization (PSO) and artificial neural network (ANN) are used for optimal tuning of the conventional proportional-integral (PI) controllers. The PI parameters are

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automatically tuned according to the online measurements. The online controller provides a desirable performance in different operating conditions. But, these control structures have been only applied to the frequency model of MGs and a complete model of MG has not been considered. In this paper, a control structure containing inner control loops, droop and secondary control loops for automatic regulation of the MG's voltage and frequency is presented. In order to minimize the voltage and frequency deviations of MGs caused by change in load, a self-tuning structure based on ANNs changes value of the control loop parameters, optimally.

II. Control Structure

A. Power and Inner Controllers

Consider an islanded MG as shown in Fig. 2. This MG consists of three inverter interfaced Distributed Generations (IIDGs) (220V, 50Hz) and two load banks [6]. Control structure of each IIDG is depicted in Fig. 3. All the measured signals in this structure are in the *d-q* frame. The power section consists of inverter, a pulse width modulator (PWM), an output LC filter and a coupling inductor. In comparison with fast dynamic of inverter, the DC side can be considered as an ideal DC source and its dynamics can be neglected [7]. The local controllers are divided into three parts: power, voltage and current controllers. The power control loop sets the voltage magnitude and frequency as reference values for the inverter output voltage/frequency according to the droop characteristics of *P/f* and *Q/v* [6, 8]. Then, the voltage and current controllers are designed to reject high frequency disturbances [9]-[11].

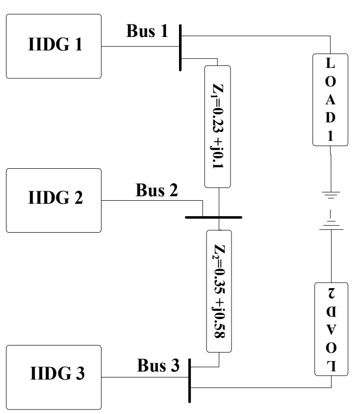

Fig. 2. An islanded MG with three IIDGs and two load banks

Fig. 4 shows scheme of the power controller. In order to remove instantaneous fluctuations in the power calculations, instantaneous active and reactive power components p and q are passed through two low-pass filters with cut-off frequency ω_c. In order to locally supply the required power among IIDGs, the *P/f* and *Q/v* droop controls are designed for determining the frequency and voltage magnitude references. Interested readers can find a simplified mathematical model for a MG with various DGs in [4, 12]. As shown in Fig. 4, *m* and *n* are the frequency and voltage conventional droop coefficients. The conventional frequency and voltage droop methods (*P/f* and *Q/v* droop characteristics), taken from conventional power system controls have limitations, especially when the line impedances between the IIDGs and loads have a significant resistive component. Considering that the proposed intelligent MGCC monitors the MG system as online, hence this problem can be appropriately solved by online tuning of the PI secondary voltage and frequency controllers. Here, the output voltage magnitude reference is aligned to the *d*-axis and the *q*-axis reference is set to zero.

Fig. 5 shows the inner control loops containing initial voltage and current controllers. Two conventional PI controllers are implemented to track the voltage magnitude reference and to control output filter inductor current. The feedforward terms shown in Fig. 5 are used to improve transient performance and compensate for the coupling of the *d* and *q* dynamics [11]. Here, *F* is the feedforward voltage controller gain.

B. Secondary Controllers

Secondary controllers are classified into central controllers cluster and they are used in order to compensate steady state errors uncompensated by droop controllers. Secondary voltage magnitude and frequency controllers used in this paper are shown in Fig. 6.

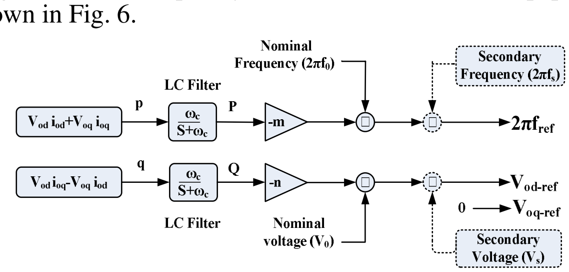

Fig. 4. Power controller.

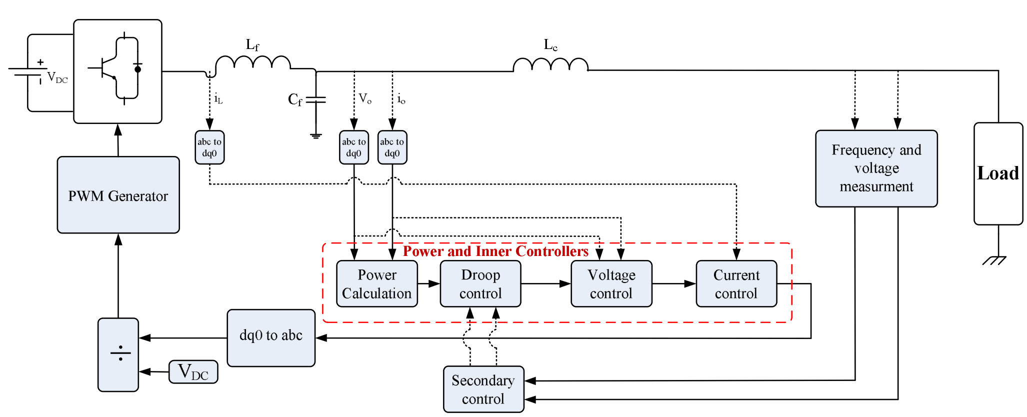

Fig. 3. Control structure of the IIDGs

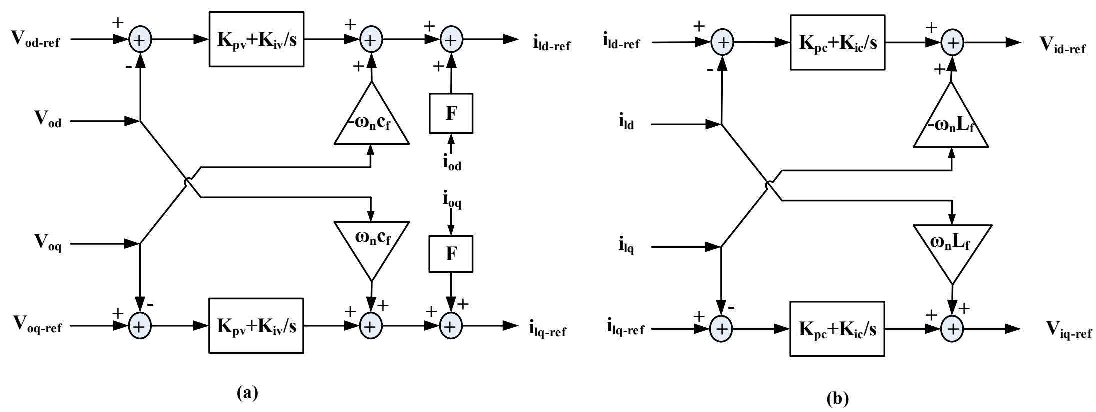

Fig. 5. Inner control loops: a) voltage controller, b) current controller.

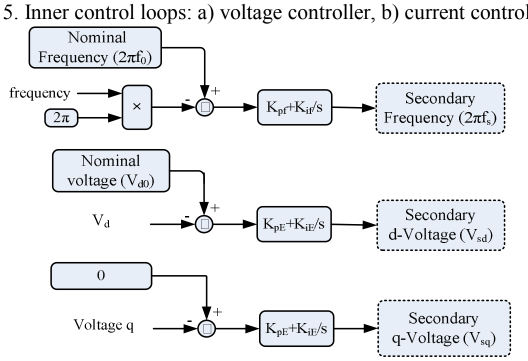

Fig. 6. Secondary voltage magnitude and frequency controllers

k_{pf}, k_{if}, k_{pE}, and k_{iE} are the PI controllers parameters. The frequency is instantaneously calculated and is compared with the nominal value. The frequency deviation after passing through the PI frequency controller is added into the power controller output (see Fig. 4). This process is reiterated for the voltage deviations. If these PI controller parameters are properly selected, the secondary PI controllers play in the role of voltage and frequency deviation minimizers.

III. ANN-Based Online Tuning

As explained, to return the system voltage and frequency to the nominal values, a supplementary control loop is used that is called secondary control. This control is commonly done by the conventional PI controllers to regulate the voltage and frequency deviations toward zero after every change in the load or supply. The PI parameters are applied to the system after initial tuning by try and error method. If operating conditions are varying, obtaining an optimal response will be difficult. Recently, [4], [5] and [13] have used intelligent and evolutionary algorithms to tune the control parameters. The main objective of such online tuning is to implement a self-tuning system so that could operate with a more independence from human actions in an industrial and uncertain environment [14]. In this section, an ANN-based MGCC is presented to automatically tune the PI parameters.

The ANN is a parallel computational system including several simple processing components connected together in a specific way in order to perform a particular task. Some advantages of ANNs are capability of parallel processing, learning, generalization and fault/noise tolerating. The weights updating and networks training is done by two basic methods: feedforward and feedback processes. The feedback process has three methods: supervised, unsupervised and reinforcement learning [15, 16].

Fig. 7 shows schematic diagram of the proposed central controller scheme for the ANN-based online tuning MG voltage and frequency control. When the operating conditions of the MG changes due to change in loads or outgoing a DG, the voltage and frequency of the MG are deviated from its nominal values. The settled coefficients of the PI secondary voltage and frequency controllers tuned by try and error method may cannot immediately return the voltage and frequency to their nominal values. In case of a more serious event or a contingency, the previous coefficients of the secondary controllers may not return the MG voltage and frequency to the nominal values or even it leads the MG to be collapsed. To avoid this problem and for better performance of the MG under events and sudden changes in load, an ANN-based intelligent control unit named MGCC collects the information about the voltage and frequency of all DGs and Loads. The collected data are considered as the ANN inputs. A corrective decision for optimizing the secondary controllers' behavior is sent to each DG. The ANN plays role of an online optimizer for the PI control parameters. By getting input-output data based on some certain ANN learning rules namely the back-propagation rules, the weights are adjusted and an appropriate control signal is recommended to each DG control structure.

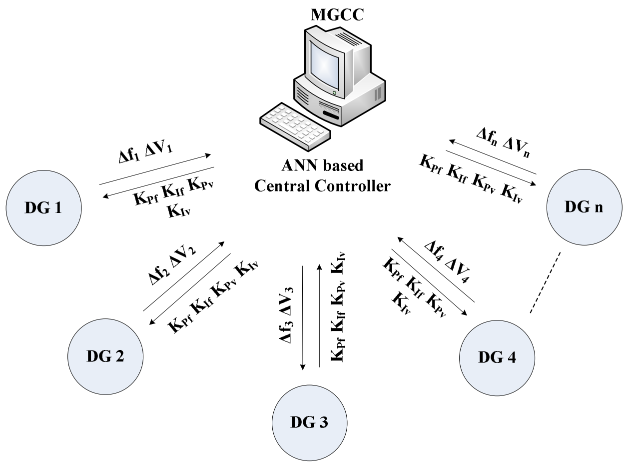

Fig. 11. Overall structure of online central controller.

To use ANNs in the optimization tasks, it is necessary to have a mathematical model for neural networks. Fig. 8 shows a simple mathematical model for a neuron as the basic element of an ANN. A neuron consists of three basic components: weights W_j=[w_1 w_2 … w_n], bias θ, and a single activation function *f(net)*. The inputs x_j are multiplied by related weight of the neuron connection. The bias θ is the magnitude offset that is applied to the activation function of the *k*th node output $y(k)$ as follows [17]:

$$y(k) = f\left(\sum_{j=1}^{n} w_j x_j(k) + \theta\right) \tag{1}$$

The activation function *f(net)* can be selected as logsigmoid, sign, tansigmoid or other functions. For learning algorithms such as back-propagation, derivative of the activation function $f^{'}(net)$ is necessary. So, the selected activation function must be differentiable.

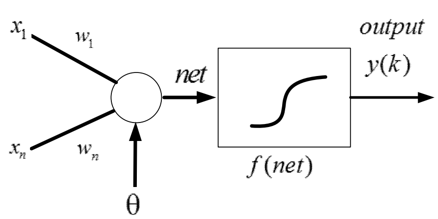

Fig. 8. Typical mathematical model of a neuron.

The employed ANN structure for tuning the control parameters is shown in Fig. 9. The desired frequency f_d and voltage V_d are considered as the input vectors. Usually, number of hidden layer's neurons are selected as twice of the input layer's neurons. In this structure by try and error method, ten linear neurons, and twenty nonlinear neurons are considered for input and hidden layers, respectively. The advantage of using the nonlinear functions is to perform a smooth updating of weights. There are three IIDGs in the MG shown in Fig. 2 and each IIDG has two secondary controllers (voltage and frequency controllers). The number of output layer's neurons is equal to the number of the control parameters. Therefore, twelve linear neurons are considered for the output layer. W_1 and W_2 are weight vectors of the hidden and output layers, respectively. In the feed-forward process, the values of hidden layer and then the output layer are provided by applying the input vector. The outputs of frequency (*f*) and voltage (*V*) of each IIDG are compared with desired vectors y_d (nominal values: 220V and 50Hz). As shown in Fig. 9, the feedback process is based on supervised learning. There are several learning methods for supervised learning such as widrow-hoff, back-propagation, and correlation learning methods. In the proposed structure, the back-propagation is selected. Flowchart of the back-propagation learning algorithm is shown in Fig. 10. The learning procedure is done to minimize the function given by (2), where *y* and y_d are measured and desired output variables, respectively.

$$e = \frac{1}{2}\sum_{i=1}^{n}(y_d - y)^2 \tag{2}$$

Here, y_d is the nominal values of voltage and frequency (y_d=[220 50]). The error (e) is employed to update the weights as follows.

$$W_2(k+1) = W_2(k) + \Delta W_2 = W_2(k) + \eta\delta_k H_j \tag{3}$$

$$W_1(k+1) = W_1(k) + \Delta W_1 = W_1(k) + \eta\sigma X \tag{4}$$

where, ΔW_1 and ΔW_2 are obtained by equations (5) and (6), respectively.

$$\begin{cases} \Delta W_2 = -\eta\dfrac{\partial e}{\partial W_2} \\ \dfrac{\partial e}{\partial W_2} = \dfrac{\partial e}{\partial y}\dfrac{\partial y}{\partial u}\dfrac{\partial u}{\partial net_k}\dfrac{\partial net_k}{\partial W_2} \\ \dfrac{\partial net_k}{\partial W_2} = f^{'}(net_k) \\ \dfrac{\partial net_k}{\partial W_2} = H_j \\ \dfrac{\partial e}{\partial y}\dfrac{\partial y}{\partial u}\dfrac{\partial u}{\partial net_k} = \delta_k \\ \Delta W_2 = \eta\delta_k H_j \end{cases} \tag{5}$$

$$\begin{cases} \Delta W_1 = -\eta\dfrac{\partial e}{\partial W_1} \\ \dfrac{\partial e}{\partial W_1} = \dfrac{\partial e}{\partial y}\dfrac{\partial y}{\partial u}\dfrac{\partial u}{\partial net_k}\dfrac{\partial net_k}{\partial H_j}\dfrac{\partial H_j}{\partial net_j}\dfrac{\partial net_j}{\partial W_1} \\ \dfrac{\partial u}{\partial net_k} = f^{'}(net_k) \\ \dfrac{\partial net_k}{\partial H_j} = W_2 \\ \dfrac{\partial H_j}{\partial net_j} = f^{'}(net_j) \\ \dfrac{\partial net_j}{\partial W_j} = X \\ \Delta W_1 = \eta\delta_k f^{'}(net_k) W_2 f^{'}(net_j) X = \eta\sigma_j X \end{cases} \tag{6}$$

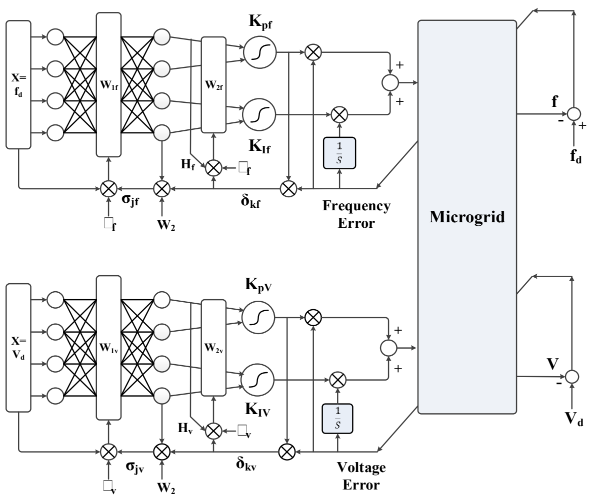

Fig. 9. ANN structure used for tuning the MG control parameters.

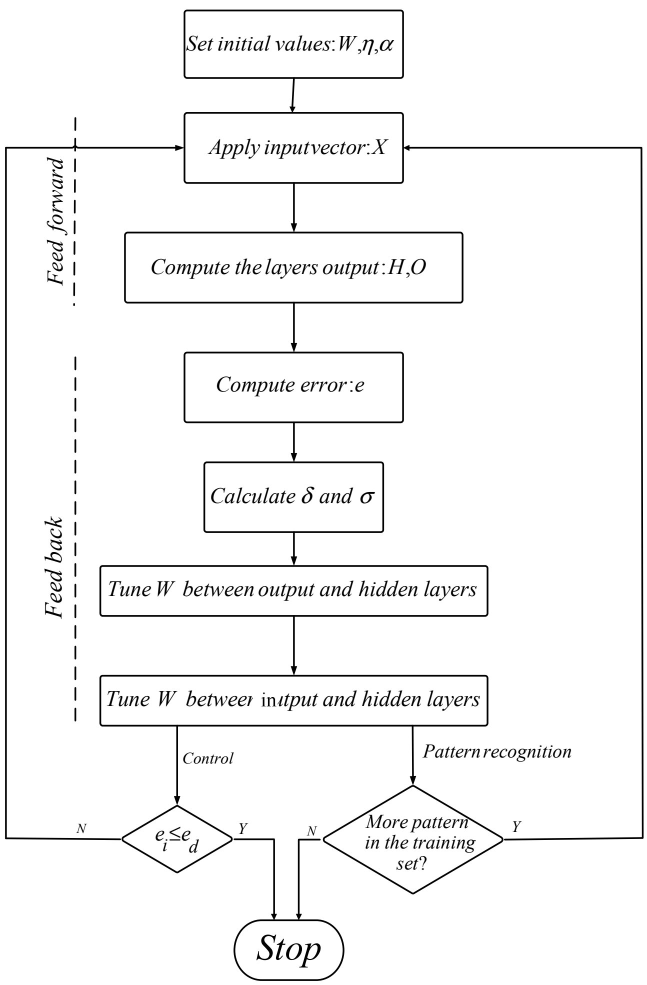

Fig. 10. Flowchart of back-propagation learning algorithm for updating weights [17].

All symbols used in Equations (5) and (6) can be visible in Fig. 10. The small positive constant is the learning rate. The learning process will continue to reach the defined minimum error [16, 17].

IV. Simulation Results

To evaluate performance of the proposed control structure, the islanded MG shown in Fig. 2 is carried out under various load changes. To illustrate the dynamic response of the MG system, the proposed control system is examined in face of a multiple step changes in load. In times 0.3, 0.5, 0.7, 0.9 and 1.1, step changes are occurred in loads 1 and 2 as given in Table I. All numerical data of IIDGs and lines have been given in [6]. After applying the load changes scenario to the MG, the system response including voltage and frequency profiles are obtained as shown in Fig. 11 and Fig 12, respectively. these results shows that existence of the proposed ANN-based MGCC remains the MG's voltage and frequency profiles in the nominal values range under occurring severe disturbances such as sudden changes in load.

The ANN-based-online tuning shows a desirable performance in terms of settling time and minimization of the voltage and frequency deviations (steady state errors).

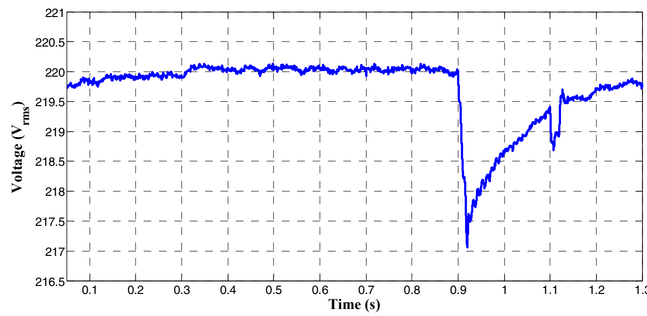

Fig. 11. Voltage profile under sudden load changes.

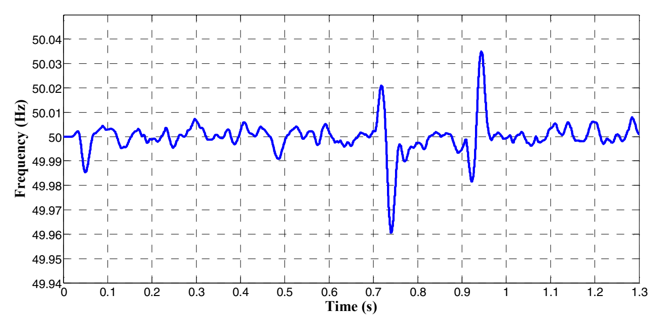

Fig. 12. Frequency profile under sudden load changes.

TABLE I
LOAD CHANGE SCENARIO

Time duration [s]	Load 1	Load 2
0-0.3	100 +200mH	150 +100mH+30μF
0.3-0.5	50 +100mH	100 +10μF
0.5-0.7	0	0
0.7-0.9	40 +5μF	10 +50μF
0.9-1.1	5 +10mH	200 +10mH+150μF
1.1-1.3	5 +10mH	500 +10μF

V. Conclusion

An important issue in the ac microgrids is simultaneous regulation of voltage and frequency in the presence of disturbances such as sudden load changes. In practice, simple PI controllers usually used. These controllers have a poor performance in the presence of serious disturbances. This paper has introduced an intelligent centralized control strategy to restore the voltage and frequency of islanded MGs by adjusting the secondary controllers' parameters. In the proposed control structure, utilizing an ANN, an MG central controller (MGCC) has implemented to the MG for online tuning/updating of the secondary voltage/frequency controllers parameters under occurring disturbances. The simulation results showed that the proposed control strategy has a desirable performance in restoring voltage and frequency of MG and removing steady state errors.

REFERENCES

[1] H. Bevrani, M. Watanabe, and Y. Mitani, "Microgrid controls," *Standard handbook for electrical engeneers*, Section 16, 16th Edition, H. Wayne Beaty (Ed), New York: McGraw Hill, 2012.

[2] IEEE Standard for Interconnecting Distributed Resources With Electric Power Systems, IEEE Std 1547-2003, pp. 0_1-16, 2003.

[3] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuña, and M. Castilla, "Hierarchical control of droop-controlled AC and DC microgrids—a general approach toward standardization," *Industrial Electronics, IEEE Transactions on,* vol. 58, pp. 158-172, 2011.

[4] H. Bevrani, F. Habibi, P. Babahajyani, M. Watanabe, and Y. Mitani, "Intelligent Frequency Control in an AC Microgrid: Online PSO-Based Fuzzy Tuning Approach," *Smart Grid, IEEE Transactions on,* vol. 3, no. 4, pp. 1935-1944, 2012.

[5] H. Bevrani, F. Habibi, and S. Shokoohi, "ANN-Based Self-Tuning Frequency Control Design for an Isolated Microgrid," *Meta-Heuristics Optimization Algorithms in Engineering, Business, Economics, and Finance*, pp. 357, 2012.

[6] H. Bevrani, and S. Shokoohi, "An Intelligent Droop Control for Simultaneous Voltage and Frequency Regulation in Islanded Microgrids," *Smart Grid, IEEE Transactions on,* vol. 4, no. 3, pp. 1505-1513, 2013.

[7] N. Hatziargyriou, M. Donnelly, S. Papathanassiou, J. P. Lopes, M. Takasaki, H. Chao, J. Usaola, R. Lasseter, A. Efthymiadis, and K. Karoui, "Modeling new forms of generation and storage," *Cigre TF38,* vol. 1, 2000.

[8] S. Ahmadi, S. Shokoohi, and H. Bevrani, "A fuzzy logic-based droop control for simultaneous voltage and frequency regulation in an AC microgrid," *International Journal of Electrical Power & Energy Systems,* vol. 64, no. 0, pp. 148-155, 1//, 2015.

[9] N. Pogaku, M. Prodanovic, and T. C. Green, "Modeling, analysis and testing of autonomous operation of an inverter-based microgrid," *Power Electronics, IEEE Transactions on,* vol. 22, no. 2, pp. 613-625, 2007.

[10] M. Prodanovic, "Power quality and control aspects of parallel connected inverters in distributed generation," Imperial College London (University of London), 2004.

[11] M. N. Marwali, and A. Keyhani, "Control of distributed generation systems-Part I: Voltages and currents control," *Power Electronics, IEEE Transactions on,* vol. 19, no. 6, pp. 1541-1550, 2004.

[12] H. Bevrani, *Robust power system frequency control*, the 2nd Edition: Springer, 2014.

[13] S. Shokoohi, *Analysis and Control of Microgrids in Different Operating Modes (in Persian)*, M.SC Thesis, University of Kurdistan, 2012. Available: http://www.shoreshshokoohi.com/Downloads/M.Sc%20Thesis_Analysis%20and%20Control%20of%20Microgrids%20in%20Different%20Operating%20Modes%20(by%20Shoresh%20Shokoohi).pdf

[14] H. Bevrani, and T. Hiyama, *Intelligent automatic generation control*: CRC Press, 2011.

[15] M. M. Gupta, L. Jin, and N. Homma, *Static and dynamic neural networks: from fundamentals to advanced theory*: John Wiley & Sons, 2004.

[16] M. T. Hagan, H. B. Demuth, and M. H. Beale, *Neural network design*: Pws Pub. Boston, 1996.

[17] J. Sarangapani, *Neural network control of nonlinear discrete-time systems*: CRC press, 2006.