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Voltage Quality Improvement with Neural Network-Based Interline Dynamic Voltage Restorer

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Abstract – Custom power devices such as dynamic voltage restorer (DVR) and DSTATCOM are used to improve the power quality in distribution systems. These devices require real power to compensate the deep voltage sag during sufficient time. An interline DVR (IDVR) consists of several DVRs in different feeders. In this paper, a neural network is proposed to control the IDVR performance to achieve optimal mitigation of voltage sags, swell, and unbalance, as well as improvement of dynamic performance. Three multilayer perceptron neural networks are used to identify and regulate the dynamics of the voltage on sensitive load. A backpropagation algorithm trains this type of network. The proposed controller provides optimal mitigation of voltage dynamic. Simulation is carried out by MATLAB/Simulink, demonstrating that the proposed controller has fast response with lower total harmonic distortion.

Keywords: IDVR, Artificial neural network, Voltage sag, Fast response, THD

1. Introduction

The application of voltage-sensitive equipment, such as automatic production lines, computer centers, hospital equipment, programmable logic controllers (PLC), adjustable speed drives (ASD), and air-conditioning controllers [1, 2], has been increasing.

Voltage sag is defined as the reduction in voltage RMS between 0.1 and 0.9 PU within 0.5 cycles to a few seconds [3].

Swell is defined as an increase in nominal voltage between 1.1 and 1.8 PU during 0.5 cycles to 1 minute.

Faults or large induction motors starting in the power system may cause voltage sags or swell. Consequently, other equipment may shut down [3, 4].

A solution for power quality improvement is to use custom power devices like a dynamic voltage restorer (DVR). External energy storage is necessary to provide the requirement for real power. Thus, the maximum amount of real power that can be provided to the load during voltage sag mitigation is a deciding factor of the capability of a DVR. However, the energy requirement cannot be met by the application of such phase advance technology alone to compensate the deep sag of long duration; in addition, since there are the limitations in the provider of these energy devices, it is necessary to minimize energy injection [5].

An interline DVR (IDVR) provides a way to replenish dynamically the energy in the common DC link energy storage. The IDVR is similar to the interline power flow controller (IPFC), which is used in transmission systems [6]. In this type of device, several DVRs prevent sensitive load voltage interruption in the distribution feeders emanating from different grid substations that share a common DC link energy storage. The DC links of these DVRs can be connected to a common terminal in the form of an IDVR system. This would reduce the cost of the custom power device as sharing a common DC link reduces the size of the DC link storage capacity substantially compared to that of a system in which loads are protected by clusters of DVRs with separate energy storage systems [7].

The control system of the IDVR plays an important role in the requirements for fast response against voltage sags and variations in the connected load.

The IDVR must be controlled properly to obtain the best compensation effects. In recent years, most studies have presented several methods for the design of IDVR controllers using linear control strategies. In such case, the system equations are linearized at a specific operating point, and the PI controllers are tuned based on the linearized model in order to have the best possible performance. The drawback, however, of such PI controllers is that their performance degrades as the system operating conditions change. On the other hand, nonlinear adaptive controllers can provide suitable control capabilities over a wide range of operating conditions, but they have a more complex configuration and are more difficult to implement compared with linear controllers. In addition, they need a mathematical model of the system to be controlled [8, 9].

Artificial neural networks (ANNs) present a solution to this problem as they can identify and model a nonlinear

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system. This technique is currently being regarded as a new tool to design a DSTATCOM control system. The ANN presents two principal characteristics. First, it is not necessary to obtain specific input–output relationships, but they are formulated through a learning process or an adaptive algorithm. Second, ANN can be trained online without requiring large amount of database [10].

In this paper, a new voltage disturbance detection method with neural network control is presented. With the proposed method, the amplitude of each phase voltage is tracked instantaneously and the delay time of recovery from voltage disturbance can be minimized even under deep unbalanced voltage conditions. It is proposed that a new modified d-q transformed voltage regulator for single-phase inverter is used to obtain quick dynamic response and robustness, where three phase inverters are controlled by neural network controller. Therefore, the trained ANN-based estimator can correctly predict a set of proper control variables for the control system of the IDVR to meet a certain control goal.

2. The Proposed IDVR in a Distribution System Based on Neural Network

The proposed system configuration of the IDVR is shown in Fig. 1. The power circuit of the IDVR is composed of two DVRs in two different feeders, where each DVR is composed of a voltage source inverter, common DC link, and filter circuit and injection transformer.

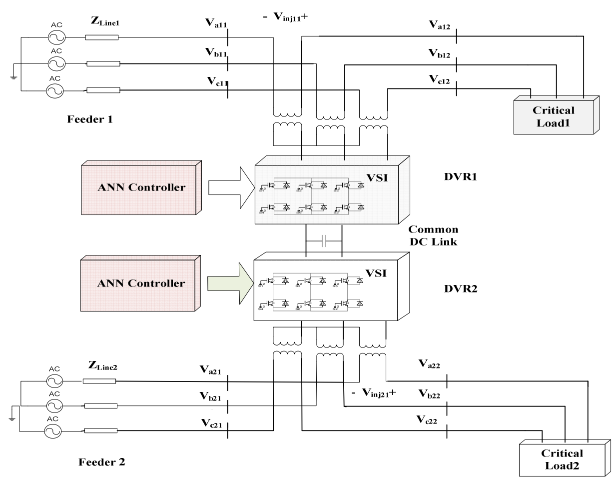


Fig. 1. The proposed IDVR in a distribution network based on ANN

When one of the DVRs compensates for voltage sag, the other DVR in the IDVR system operates in power flow control mode to restore the common DC link, which is depleted to the real power taken by the DVR working in the voltage sag compensation.

3. Control Strategy

The proposed control strategy is based on minimal energy strategy [10]; therefore, this controller optimizes energy balance between two feeders. For a given load and balanced sag, if voltage phasor V_{DVR1} is perpendicular to the load current I_{L1}, then the active power injection is not required to restore the voltage by the DVR. Fig. 2 shows the phasor diagram for this control strategy. In this diagram, δ, and α are the angles of V_{L1} and V_{DVR1}, respectively. In this case, α can be obtained from the following:

$$\alpha = \frac{\pi}{2} - \varphi + \delta \tag{1}$$

The δ is calculated using the following equation:

$$\delta = \varphi - \cos^{-1} \frac{V_{L1}.\cos\varphi}{V_{S1}} \tag{2}$$

If the supply voltage parameters satisfy the following condition, then the δ can be defined as follows:

$$V_{L1}.\cos\varphi \le V_{S1} \tag{3}$$

Eq. (3) means that the level of voltage sag is shallow sag. Hence, the injected active power of the DVR is equal to zero and the optimum α is obtained from (1). If inequality (3) is not satisfied, then level of voltage sag will be deep sag and the active injected power is not equal to zero [11].

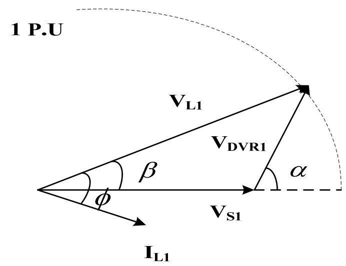


Fig. 2. The block diagram of the control strategy

4. ANN Controller Based on IDVR

Fig. 3 illustrates the control system of one of the DVRs in the proposed IDVR. In this proposed method, the injected three voltages by the phase locked loop (PLL) tracks the phase of the load voltage. The load voltage is transformed to V_d, V_q, and V_o based on park transformation according to Eqs. (4), (5), and (6), respectively. For the regulation of load voltage, they are compared with reference signals V_{dref}, V_{qref}, and V_{oref}

and produce errors. The errors, $e(k)$, are considered as ANN controller inputs.

$$V_d = \frac{2}{3}\left[V_a \cos\omega t + V_b \left(\cos\omega t - \frac{2\pi}{3}\right) + Vc(\cos\omega t+2\pi 3)\right] \quad (4)$$

$$V_q = \frac{2}{3}\left[V_a \sin\omega t + V_b \sin\left(\omega t - \frac{2\pi}{3}\right) + V_c \sin\left(\omega t + \frac{2\pi}{3}\right)\right] \quad (5)$$

$$V_o = \frac{1}{3}\left[V_a + V_b + V_c\right] \quad (6)$$

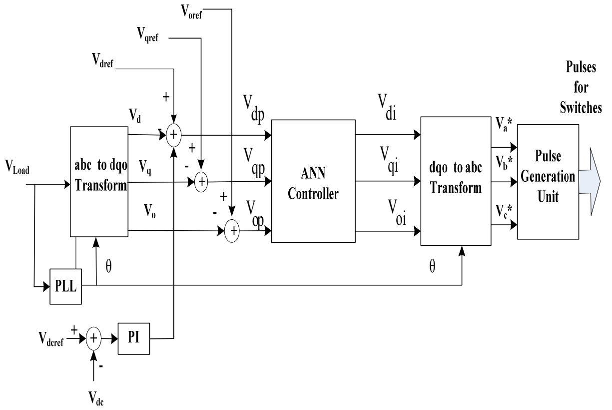


Fig. 3. The control system of the proposed IDVR

In a recent publication, an NN was considered for the implementation of instantaneous current control PWM [12], where the sinusoidal phase voltage commands were compared with the respective feedback voltages, and the resulting loop the pulse with signals through a feedback NN.

The converter can be controlled well as long as V_{di}, V_{qi}, and V_{oi} can be determined to the desired value. The V_{di}, V_{qi}, and V_{oi} are approximated by a neural network, where V_{dp} and V_{qp} are chosen as the network's inputs, as shown in Fig. 4. The network is expressed in following form:

$$\left(\hat{V}_{di}, \hat{V}_{qi}, \hat{V}_{oi}\right) = NN(V_{dp}, V_{dp}, V_{op}, W) \quad (7)$$

where $(\hat{V}_{di}, \hat{V}_{qi}, \hat{V}_{oi})$ is the estimate of (V_{di}, V_{qi}, V_{oi}), NN denotes the network used to approximate $(\hat{V}_{di}, \hat{V}_{qi}, \hat{V}_{oi})$, and W is the corresponding weight vector.

4.1. The Architecture of ANN

Fig. 4 illustrates the architecture of artificial neural network (ANN). The ANN controller used in this control system, consists of three neuron layers, the input layer, the hidden layer and the output layer. The input layer offers connection point to transmit the input signal to the hidden layer. The latter begins the learning process and the output layer continues the learning process and provides outputs. The hidden layer neurons have a tan sigmoid transfer function, and the output layer neurons have a linear transfer function. The ANN has three inputs that are the three phase voltage errors of the IDVR. It also has three outputs that are the three switching functions of the inverter legs.

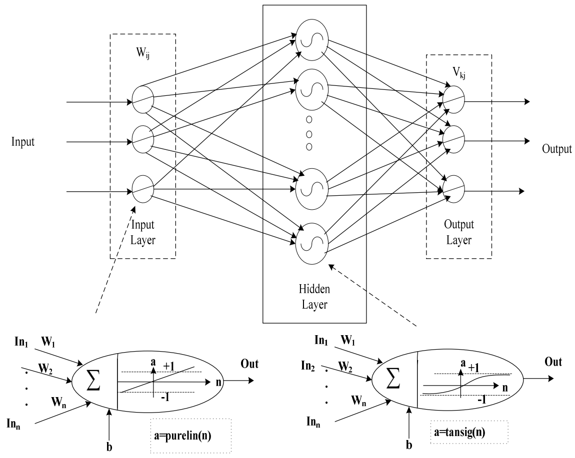


Fig. 4. MLP neural network configuration

The output of ANN controller is the reference variable for the PWM generator. Therefore, the output of ANN with varying amplitude and phase passes through a comparator and is compared with a carrier signal. When the ANN output's magnitude is more than carrier signal's magnitude, the PWM circuit generates high output and when the ANN output's magnitude is less than carrier signal's magnitude, the PWM circuit produces low output. The carrier signal is a saw tooth waveform at 20 kHz taking values between -1 and 1.

On introducing the input vector e_j where $e_j = [e_a \; e_b \; e_c]^T$ the equations associated with the signals flowing from each layer to the next layer are:

$$I_j = f(W_{hj}^T e_j^T + B_{hj}^T) \quad (8)$$

$$O_j = g(W_{oj}^T e_j^T + B_{oj}^T) \quad (9)$$

where I_j is the hidden layer output vector O_j is the output vector of the ANN, *f* is the transfer function of the hidden layer (nonlinear function), *g* is the transfer function of the output layer (linear function); W_h is the weight matrix of the hidden layer; W_o is the weight matrix of the output layer; B_h is the bias vector of the hidden layer neurons; and B_o is the bias vector or the output layer. In this paper, the functions of *f* and *g* are as follows:

$$f(x) = \frac{2}{1+e^{-\lambda x}} - 1 \quad (10)$$

$$g(x) = \begin{cases} 0 & x < 0 \\ 1 & x \geq 0 \end{cases} \quad (11)$$

where λ is the up ratio of the function, which is between 0 and 1 [13].

4.2 The procedure of training the ANN

The ANN is trained by varying the weights W_{ij} and the biases B_j. The training criterion is taken as the mean square error of the ANN output with a value of 0.0001 and the error function is defined as the following equation:

$$\mathrm{J} = \sum_{i=1}^{N} e(i)^2 \tag{12}$$

where N is the number of output neurons and $e(i)$ is the instantaneous error between the actual and estimated values of the output. The training is completed when the value of J is less than 0.0001 [14].

The hidden layer has no target values. Hence, a procedure is applied to back-propagate the output layer errors to the hidden layer neurons in order to optimize their weights and minimize the error. The training starts with a gradient algorithm. When the minimum is approached, the gradient takes lower values and the convergences toward this minimum is greatly retarded [15]. Before the start of the training, weights are initially given small random values to reduce the chance of premature saturation of the logistical neurons, thus reducing the training speed. The common principle of second-order algorithms is to compute a descent direction obtained by a linear transformation of the cost function gradient. For the gradient algorithm, the weights are updated at each step according to the following:

$$W(t+1) = W(t) + \Delta W \tag{13}$$

$$\Delta W_{ij} = -\eta \frac{\partial J}{\partial w_{ij}} \tag{14}$$

where η is the learning rate parameter., Learning occurs quickly if η is large; however, it may also lead to instability and increase in errors if η is too large [16].

Fig. 5 shows the training, validation, and test errors used to check the progress of training. This result is reasonable since the test set error and the validation set error have similar characteristics; it does not appear that any significant over fitting has occurred.

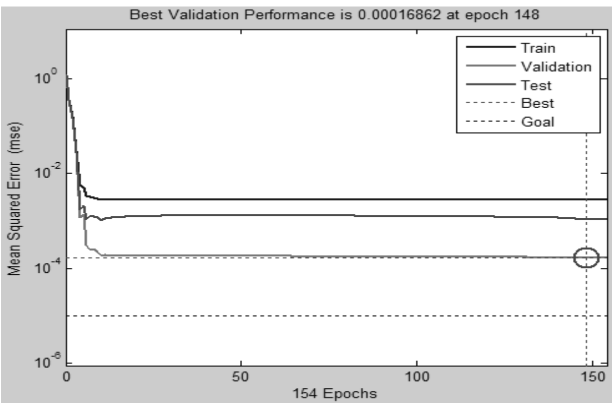


Fig. 5. Training validation and test curves of the neural network

The following figure shows the graphical output provided by postreg. The network outputs are plotted versus the targets as open circles. The best linear fit is indicated by a dashed line. The perfect fit (the output is equal to targets) is shown by the solid line. The output seem to track the targets reasonably with regression of 0.78.

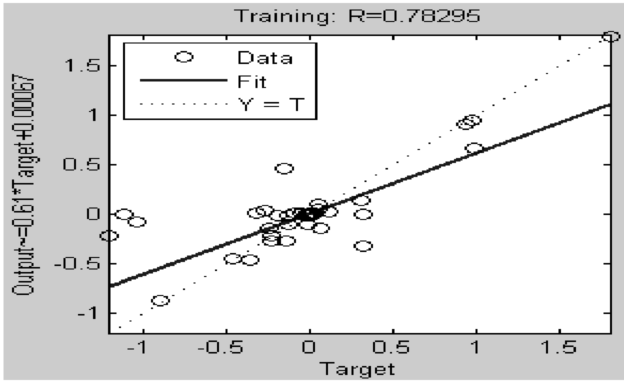


Fig. 6. The estimation of the function by the ANN

5. Results of Simulation

The proposed detailed IDVR based on ANN controller with a three-phase bridge converter connected into a distribution system is modeled and analyzed by using MATLAB/Simulink. The learning process of ANN is developed in MATLAB, aided by the toolbox neural network.

5.1 Power quality compensation

The most common power quality problem with compensation was investigated.

(a) Voltage sag: This refers to a reduction of the normal voltage level between 10% and 90% of the nominal RMS voltage at the power frequency during half-cycle to one minute [17]. Fig. 7 shows the efficiency

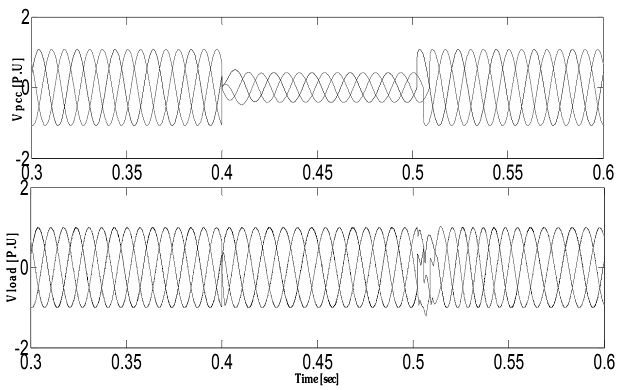


Fig. 7. The voltage sag compensation by one of the DVR in the IDVR based on ANN

of the proposed control structure based on ANN control in regulating the point common coupling (PCC) voltage at 1.0 PU; the voltage sag occurred at t = 0.4 seconds for a duration of 0.1 seconds by fault in feeder 2.

(b) Voltage swell: A voltage swell is an increase in the RMS voltage in the domain of 1.1–1.8 PU during greater than half a main cycle and less than 1 minute [17]. Fig. 8 shows the voltage swell at t = 0.4 seconds for a duration of 0.1 seconds; the IDVR injects series voltage with phase angle of 180° voltage supply and compensates the voltage swell.

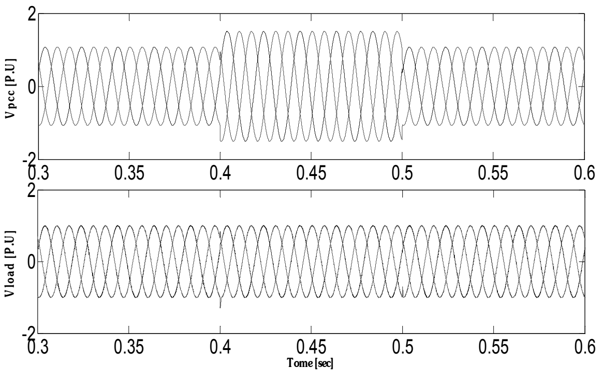


Fig. 8. The voltage swell compensation by one of the DVR in the IDVR based on ANN

(c) Unbalance voltage: This is a voltage variation in a three-phase system in which the three voltage magnitudes or the phase angle differences between them are not equal. Fig. 9 presents an unbalance voltage and its compensation by an ANN-based IDVR.

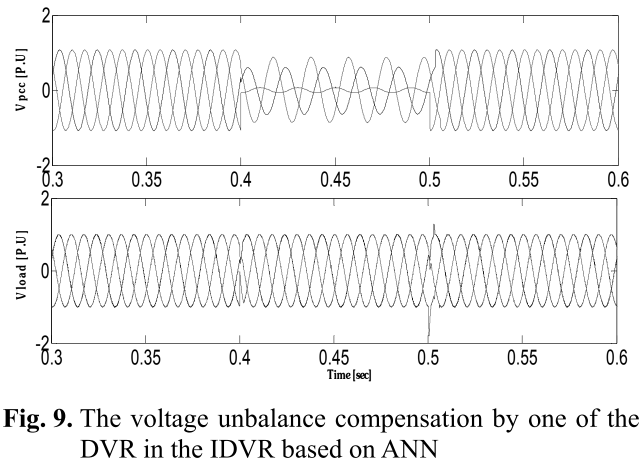


Fig. 9. The voltage unbalance compensation by one of the DVR in the IDVR based on ANN

5.2 The characteristic of the proposed controller

The IDVR with fast dynamics compensates power quality problems. Fig. 10 shows a comparison between the load voltage waveform by using PI controller and ANN controller for voltage sag compensation. The voltage sag occurred at 0.4 seconds. The neural network controller clearly provides better performance than the PI controller; the ANN has fast dynamic response and produces low harmonic.

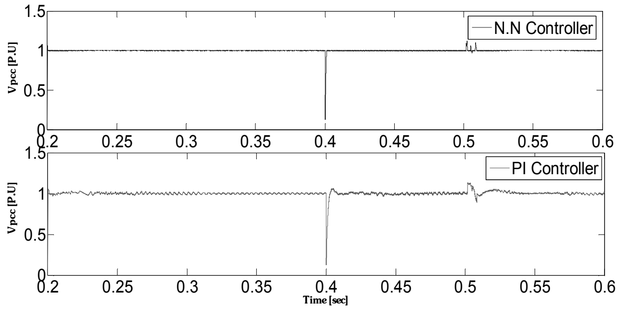


Fig. 10. The comparison between the load voltage waveform in PI and ANN controller

6. Discussion on the total harmonic distortion

The total harmonic distortion (THD) is determined in the following form:

$$THD = \frac{1}{V_1}\sqrt{\sum_{n=2,3,\ldots}^{\infty} V_n^2} \tag{15}$$

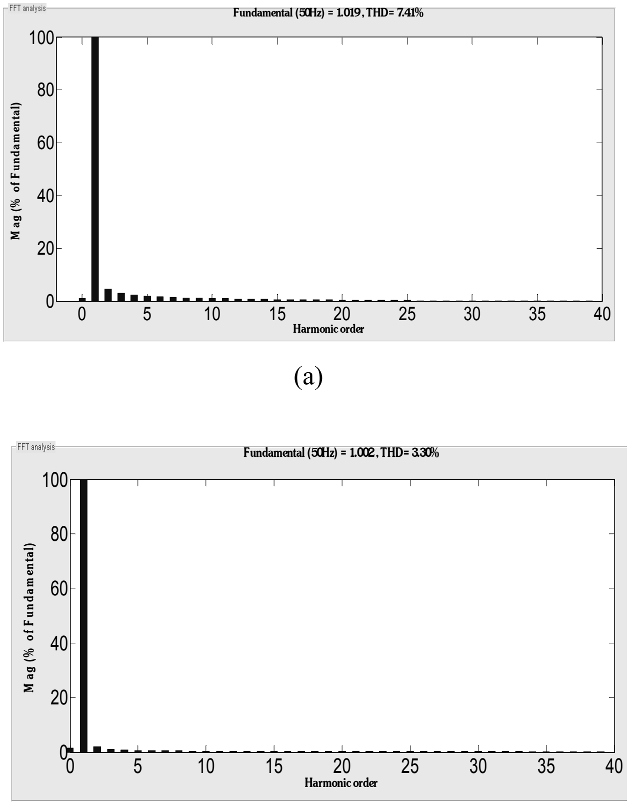
where V_1 is the magnitude of the main harmonic in terms of RMS and V_n is the magnitude of the nth harmonic. According to the *IEEE* standard 519–1992 "the objective of the current limits the maximum individual frequency voltage harmonic to 3% of the fundamental and the voltage THD to 5% for the system without a major parallel resonance at one of the injected harmonic frequencies" [18].

Fig. 11 compares the THD of the load voltage after compensation by the IDVR based on PI and ANN controllers in the compensation case with ANN controller after passive filter: $THD \leq 3.3\%$. Hence, the load voltage containing minimum harmonic and the resulting loss of inverter is less.

The delay time of recovery is the time at which the load voltage is restored to the initial state. Therefore, if this time is reduced, the dynamic response of the DVR will be fast.

Table 1 compares the THD and delay time of recovery of the load voltage in different control systems.

Therefore, when power quality problems occur, the proposed system has a fast transient response. The IDVR-based neural network compensates power quality problems better than a PI controller.



(a)

(b)

Fig. 11. The THD of the load voltage after compensation by IDVR based on a) PI controller and b) neural network controller

Table 1. The comparison between THD and delay time of recovery

Control system	Max THD	Delay time of recovery
PI (classic controller)	7.41	15.2 msec
Neural network controller	3.30	2.7 msec

7. Conclusion

In this paper, a novel control concept using ANN-based estimator for the IDVR system was presented. Simulation results show that the trained ANN-based estimator can correctly estimate the patterns of IDVR control variables. The ANN for the IDVR is proven to be very effective and robust in compensation deep voltage sag and in power quality problem. The proposed controller has fast dynamic response, and the THD of the injected voltage or load voltage is always kept below the standard limits by using this control strategy.

Appendix

Table 2 shows the applied parameters in the simulation of IDVR and system.

Table 2. The applied value in the simulation of IDVR and system

Parameter	Value
Power supply	380 Vrms (line to line); 50 Hz
Single-phase injection transformer	55/110 Vrms; 3 kVA leakage; inductance 0.03 PU
Carrier frequency	20 kHZ
Inverter filter	Inductance L_f = 22 mH; capacitance C_f = 50 uF
DC link capacitor	C_{dc} = 20 mF

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