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Modifying Power Quality's Indices of Load by Presenting an Adaptive Method based on Hebb Learning Algorithm for Controlling DVR

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Having electricity with high quality is one of the more important aims in electrical systems. Disturbances in distribution systems can change voltage waveform. There are some methods to prepare high power quality for sensitive loads. In this research we use "Dynamic Voltage Restorer" to compensate the harmful effects of disturbances on voltage. Since power systems fundamentally have complicated dynamic behavior, especially during faults, "Hebb" learning self-tuning controller, which is a powerful adaptive controller, has been used. In order to improve the performance of this controller from point of view of power quality's indices, such as flash and sensitive load voltage THD, a new structure is proposed for this controller with fuzzification method. Simulation results indicate better operation of the system for the case of proposed controller. Voltage sag and harmonics in faulty conditions are both improved by the proposed controller. According to simulation results, it works better than both classical PI controller and conventional Hebb learning controller.

Key words: DVR, Sensitive load, Power quality, Fuzzy membership function, Multi-objective Hebb learning algorithm, Self-tuning controller

Promjena indikatora kvalitete električne energije trošila predstavljanjem adaptivne metode za upravljanje DVR-om zasnovane na Hebbovom algoritmu učenja. Jedan od važnijih ciljeva elektroenergetskog sustava visoka je kvaliteta električne energije. Poremećaji u distribucijskom sustavu mogu neželjeno izmijeniti valni oblik napona. Postoji nekoliko metoda kako osigurati visoku kvalitetu energije za osjetljiva trošila. U istraživanju koristimo "dinamičku obnovu napona" za kompenziranje štetnih efekata poremećaja u naponu. Kako energetski sustavi u osnovi imaju složeno dinamičko ponašanje, posebno tijekom kvarova, korišten je vrlo moćan adaptivni regulator: "Hebbov" samopodešavajući regulator sa sposobnošću učenja. Da bi se unaprijedilo vladanje spomenutog regulatora s aspekta indikatora kvalitete energije kao što su parcijalna izbijanja i THD osjetljivog trošila, predložena je nova struktura regulatora s uključenim metodama neizrazite logike. Simulacijski rezultati pokazuju bolji rad sustava uz korištenje predloženog regulatora. Regulator smanjuje propade napona i poboljšava harmonični sastav sustava u kvarnim uvjetima. Rezultati simulacija također pokazuju bolje ponašanje u odnosu na uobičajeni PI regulator te konvencionalni Hebbov regulator s učenjem.

Ključne riječi: DVR, osjetljivo trošilo, kvaliteta energije, neizrazita funkcija pripadnosti, višekriterijski Hebbov algoritam učenja, samopodesivi regulator

1 INTRODUCTION

Nowadays by increasing the number of sensitive loads, demand for accessing stable and high-quality electrical power has increased significantly. In industrial competitive environment, as the tendency of manufacturing units towards utilizing power electronic devices, computer processors and nonlinear loads increases, any interruption or deviation in delivered power quality exceeding the standard range causes economic losses. This economic loss can be studied from various aspects such as manufacturer's lost competitive opportunities, efficiency reduction and production cost increase, low-quality products, reduced equipment lifetime and increased repair cost, production interruption and energy losses. Thus, access to high power quality, applies a great influence on the asset savings and economic advantages for a firm [1].

Disturbance in power distribution system causes harmful defects in distribution system such as interruption, voltage sag, voltage swell, and flicker. Among the above disturbances the most important is voltage sag. According to the IEEE standard, it is a sudden voltage decrease in the range of 10% to 90% for 0.5 cycles to 1 min [2]. That is the result of natural phenomena such as system asymmetric errors and electromagnetic phenomena like start and inrush current.

"Custom Power" device has been introduced by experts in order to compensate the harmful effects of disturbances on sensitive loads. Among these devices, DVR is capable of compensating voltage sag and swell effects for sensitive loads devices. The structure of DVR in simple terms consists of: electrical storage source, voltage source inverter and coupling transformer. Recognizing voltage sag in feeder connected to the sensitive load, DVR generates proper voltage using coupling transformer which is in series with sensitive load and injects proper voltage to the network and decreases voltage sag effect.

The classical PID method has poor flexibility since its parameters are fixed for a special work point. Furthermore, when it applies to a complicated system as power system, results can't be acceptable for all conditions [3]. Therefore, control strategies such as predictive control [4], sliding mode [5] and robust control [6] are used in order to control injected voltage. Also in [7] and [8] are used H_∞ controller and a controller based on iteration are used for having better operation in steady and transient states respectively. Also emotional controller is implemented as an adaptive controller in [9] for DVR control. In [10] fuzzy controller is utilized. In [11] multi-level inverter with optimal predictive control structure is used. In [10-11], improving voltage THD index has been considered as an objective and a control criterion. However, in all of the aforementioned references, algorithms are complex. Although applied control strategies are capable of reducing impulses caused by voltage flash in sensitive loads, but most of these approaches don't consider reducing voltage THD. These approaches do not pay much attention to short voltage interruptions both abrupt holes and gaps or overshoot in the beginning and end of flash [11]. In many sensitive loads such as medical equipment and adjustable speed motor drives, this level of sensitivity can be very important.

In most of the aforementioned researches, it is tried to use a stable controller in order to make it capable of reacting to various fault conditions in the best possible way. Consequently, a relatively new adaptive method based on artificial neural network structure is introduced. This adaptive method which is inspired by a single neuron neural network is used as a self-tuning and robust PI controller. This method has been invented by combining neural network and classical PID in order to modify drawbacks of classical PID which mentioned in this section. The advantages are having simple structure, low computations time and self-tuning ability. Therefore, this control algorithm can be utilized in real time controller.

In order to have an appropriate performance during voltage flash and sensitive load voltage THD, a two-objective structure is proposed. In this method, voltage THD is considered as second goal for DVR control system. Both of voltage sag and THD can be modified by this algorithm.

To investigate the efficiency of the proposed algorithm, performance of DVR compensator during various faults in a typical network is tested and compared with conventional Hebb and classical PI controller. Also, in order to validate good operation of proposed method, we compare the controller with presented controller in [9].

DVR operation is introduced in Section 2; PI controller based on Hebb learning algorithm is discussed in Section 3. Section 4 introduces the proposed method for making two-objective (two-input) with fuzzification, and the final section contains the simulation and results.

2 DVR'S STRUCTURE AND FUNCTIONALITY

DVR is one of the "custom power" devices in distribution network which is connected in series. Load voltage is fixed through injecting three output voltages during disturbance in the power system and controlling voltage amplitude, phase and frequency. Thus DVR is based on injection of necessary voltage when voltage sag occurs in order to compensate it. DVR functionality can be categorized as two modes: standby mode and injection mode [12]. In the standby mode a low voltage is injected into the network in order to cover voltage sag caused by transformer reactance losses. In second mode, in presence of voltage sag, DVR injects voltage to sensitive load.

DVR circuit includes in 5 main components. They are shown in Figure 1.

1. Series transformer: that its primary winding is connected to the inverter and its secondary winding is connected to the distribution network and sensitive load.
2. Voltage inverter: The inverter is connected to the injection transformer. Energy storage equipment has been considered for inverter. This inverter includes IGBT switches self-commutation by shunt diodes and PWM technique is applied for controling of it.
3. Energy storage equipment: Power storage resources such as batteries, capacitor banks, SMES and flywheels that have been used for providing adequate voltage and active power and compensating sag [13].
4. Passive filter: It is connected to the high voltage side of inverter to eliminate harmonics produced by switching.

5. Control system: Logical fundamental of control system is based on voltage sag detection, and providing appropriate switching strategies for inverter.

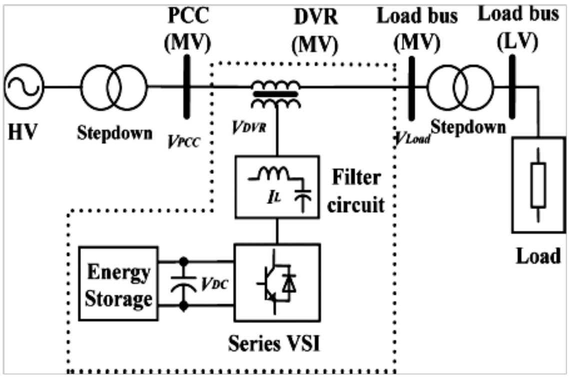

Fig. 1. DVR unit structure

Control system uses the abc-dq transformation to calculate v_d and v_q. During normal and balanceed conditions, the voltages v_d and v_q are: $v_d = 1$ and $v_q = 0$. But in fault condition, these voltages change [10]. We can control the variations of these signals by comparing these voltages with their references and giving their error signals to a PI controller.

3 PI CONTROLLER BASED ON HEBB LEARNING ALGORITHM

The fundamental structure of single neuron PID control system based on Hebb learning algorithm is revealed in Figure 2.

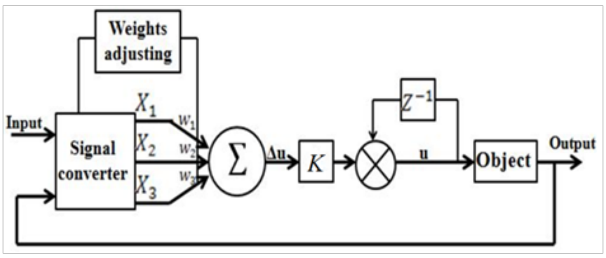

Fig. 2. Structure of single neuron PID control system based on Hebb learning algorithm

Where $x_1(k)$, $x_2(k)$ and $x_3(k)$ are proportion error, integral error and differential error at the kth time respectively. $X = \{x_1(k), x_2(k), x_3(k)\}$ is the neuron's input vector. Corresponding weights of neuron's input vector are $w_1(k)$, $w_2(k)$ and $w_3(k)$. It is important to normalize them because they are restrained from increasing infinitely in learning. The weights are normalized with (1):

$$w_i'(k) = w_i(k) / \sum_{i=1}^{3} |w_i(k)|. \qquad (1)$$

The output of neuron is described with (2):

$$u\,(k) = u\,(k-1) + k \cdot \sum_{i=1}^{3} w_i'\,(k) \cdot x_i(k). \qquad (2)$$

If e is considered as error, the neuron's input vector is defined in (3):

$$\begin{aligned} X_1 &= e\,(k) - e\,(k-1)\,, \\ X_2 &= e(k), \\ X_3 &= e\,(k) - 2e\,(k-1) + e(k-2), \end{aligned} \qquad (3)$$

where K is neuron proportion coefficient and its value is very important. With a large value, the control system speed increase. It should be proportional to the time delay of controlled object [14].

Up to now, several typical weights-learning algorithms are defined on the learning theory of neural network. These rules can be mentioned in categories such as Non-supervised Hebb learning, Supervised Delta learning, Supervised Hebb learning and improved Hebb learning. The last one is discussed in [3]. All of these rules are obtained in (4) to (6) respectively.

$$\begin{cases} w_1(k) = w_1\,(k-1) + \eta_P x_1\,(k-1)\,u\,(k-1) \\ w_2(k) = w_2\,(k-1) + \eta_I x_2\,(k-1)\,u\,(k-1) \\ w_3(k) = w_3\,(k-1) + \eta_D x_3\,(k-1)\,u\,(k-1) \end{cases}, \qquad (4)$$

$$\begin{cases} w_1(k) = w_1\,(k-1) + \eta_P e\,(k-1)\,u\,(k-1) \\ w_2(k) = w_2\,(k-1) + \eta_I e\,(k-1)\,u\,(k-1) \\ w_3(k) = w_3\,(k-1) + \eta_D e\,(k-1)\,u\,(k-1) \end{cases}, \qquad (5)$$

$$\begin{cases} w_1\,(k) = w_1\,(k-1) + \eta_P e\,(k-1)\,x_1\,(k-1)\,u\,(k-1) \\ w_2(k) = w_2\,(k-1) + \eta_I e\,(k-1)\,x_2\,(k-1)\,u\,(k-1) \\ w_3\,(k) = w_3\,(k-1) + \eta_D e\,(k-1)\,x_3\,(k-1)\,u\,(k-1) \end{cases}, \qquad (6)$$

where η_P, η_I and η_D are proportion learning speed, integral learning speed and differential learning speed coefficients. The most vital factor is error signal, the second one is first order differential equation of error and the last one is its second order differential equation. As the results show, each coefficient should be adjusted according to its importance.

4 MULTI-OBJECTIVE MAKING WITH FUNCTION OF FUZZY MEMBERSHIP

There are several methods to analyze multi-objective (multi-input) neural networks. Up to now, multi-objective methods introduced [15-18]. In [15] there are three objectives. These three objectives are integrated into an objective function through weighting factors and the problem with minimum objective function value is solved. Also, in [16], fuzzification objectives are used. In [17-18], pareto base approach is used. Most of these methods have efficiency in evolutionary and off-line algorithms. It's possible that many of these inputs (objectives) aren't homogeneous and some of these methods aren't useful. Therefore, we should use special methods to making them homogeneous**.**

Hence, in this paper each objective is described in the form of membership function in fuzzy set environment. Then combine them using appropriate weighting coefficients in the form of a satisfactory fuzzy objective function [19] are defined. We can use the objective function of (7) to control the objectives of voltage THD and sag:

$$F = w_1 \cdot \mu_T + w_2 \cdot \mu_D, \tag{7}$$

where μ_T is the rate of membership function; THD and voltage sag of sensitive load, μ_D is the rate of membership function and w_1 and w_2 are respectively weight coefficients equal to mentioned objectives.

By determination of appropriate membership functions and weighting coefficients associated in each objective, the process control can be employed. Fuzzy membership functions for the purpose of objectives control indicates the objective desirability changes in the interval [0, 1]. The proposed membership functions for each objective are described in continued.

4.1 Voltage sag Membership Function

In voltage sag, it is tried to minimize difference between base bus voltage and real bus voltage. This voltage sag is caused from system faults. The voltage error obtains as (8).

$$D{=}\max\left|v_b{-}v_l\right|, \tag{8}$$

where v_b is base bus voltage of sensitive load, v_l is sensitive load voltage. If the maximum bus voltage sag decreases, it takes more satisfier value and vice versa. According to IEEE-519 standard, bus voltage can have any value between 0.95 and 1.05. In this paper, we considered $D_{min} = 0$ and $D_{max} = 0.05$. The membership function is specified in (9) and Figure 3:

$$\mu_D = \begin{cases} \frac{D_{max}-D}{D_{max}-D_{min}} & \text{for } D_{min} \le D \le D_{max} \\ 1 & \text{for } D \le D_{min} \\ 0 & \text{for } D \ge D_{max} \end{cases} . \tag{9}$$

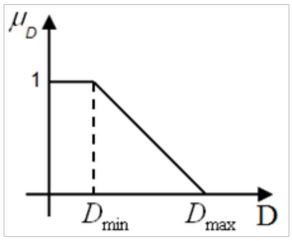

Fig. 3. Voltage sag Membership Function

4.2 Voltage THD Membership Function

The THD may cause irreversible effects on the sensitive load. Thus voltage harmonic minimization can be an attractive objective. THD index is intended to determine the harmonic distortion that the membership function is specified in (10) and Figure 4:

$$\mu_T = \begin{cases} \frac{T_{max}-T}{T_{max}-T_{min}} & \text{for } T_{min} \le T \le T_{max} \\ 1 & \text{for } T \le T_{min} \\ 0 & \text{for } T \ge T_{max} \end{cases} . \tag{10}$$

In this function, $T_{min} = 0$ and $T_{max} = 0.05$. Since according to IEEE-519 standard, the value of acceptable THD voltage is determined under 5%.

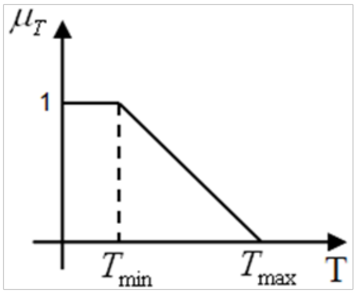

Fig. 4. Voltage THD Membership Function

4.3 Proposed control algorithm

Firstly, each objective (input) convert to its special membership function fuzzy. Then by using mentioned objective function in (7), input of Hebb learning algorithm create. Values of each weight coefficients can be consider with operator (designer) comment. Different values are tested for both of objectives in Section 5.

5 SIMULATION AND RESULTS

The case study is a power distribution system consists of two voltage buses that one of them includes sensitive load. The simple schematic of electrical network is shown in Figure 5 and its parameters introduced in Table 1.

The distractive effect of fault increases by decreasing distance between event locations to sensitive load. To simulation of more critical conditions, two faults are simulated. The first fault is occurred just after series injection transformer and the second one is occurred in near of non sensitive load. These faults led to decrease buses voltages about 50 percent of nominal line voltage of system. However, according to IEEE-519 standard, acceptable voltage sag and swell must not be over 5 percent. Therefore we have to compensate these voltages that stay in the range. In this research, to control the DVR, Hebb learning algorithm proposed. Then this method compared with another controller.

DVR Control has been carried out under different faults in network using classical PID controller, Hebb learning (single-objective) controller and proposed Hebb learning (two-objective) controller. Proposed Hebb learning controller is applied with weighting coefficients $w_1 = 0.75$ and $w_2 = 0.25$.

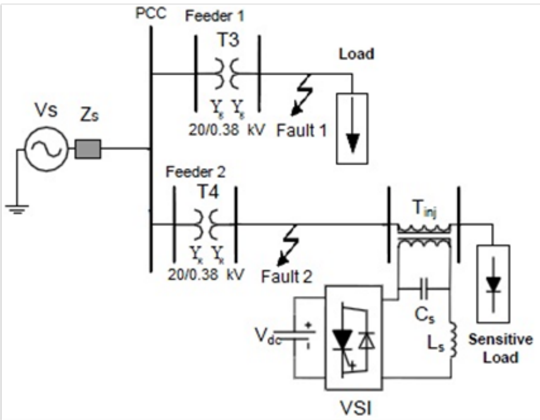

Fig. 5. Power distribution system schematic

The voltage THD signal is as its second objective. Both mentioned cases in Table 2 are simulated and diagrams of PCC bus voltage, sensitive load voltage in the network, and injected voltage to the sensitive load by compensator and voltage flash signal are shown respectively in Figures (6-11). Voltage flash signal is obtained by subtracting real value of voltage from its desired value (one per-unit). Figures 6, 7 and 8 show the first fault condition in the system which is controlled by classical PI controller, Hebb learning controller and proposed Hebb learning controller respectively.

Also, figures 9, 10 and 11 show the second fault condition in the system which is controlled by classical PI controller, Hebb learning controller and proposed Hebb learning controller respectively.

Significant performance improvement of DVR with Hebb learning controller in comparison with PI classical controller is perceptible in both fault conditions. This improvement can be related to its high capability of responding to dynamic behaviors. This improvement can be seen not only in voltage flash compensating but also in voltage THD.

For more improvement of compensation, the modified Hebb learning controller can be used. From Table 3 one can get more detailed information about how power quality indices are improved in each of three control approaches. In this Table, two indices mentioned above and percentage of improvements of both (single-objective) and modified (two-objective) Hebb learning controller over classical PI controller are mentioned. In addition, results of another

Table 1. Network parameters

PARAMETERS	VALUES
network ferquency power supply voltage	F_n=50 (Hz) V_s=22500 (V)
active and reactive power for sensetive load	P=2000 (W) Q_l = 40 (VAR) Q_C = 10 (VAR)
active and reactive power for non-sensetive load	P=2500 (W) Q_l=40 (VAR)
distribution transformer rated power and ratio	P_n=3200 (W) 20000/380
distribution transformer impedances	R_l=0.0003 (P.U.) X_l=0.001 (P.U.) R_m=X_m=500 (P.U.)
serie transformer rated power and ratio	P_n=1500 (W) 100/1000
serie transformer rated power and ratio impedances	R_l=0.00001 (P.U.) X_l=0.0003 (P.U.) R_m=X_m=500 (P.U.)
DVR switching frequency	f_S=10000 (Hz)
DC voltage source	V_{DC}=200 (V)
impedances for shunt and serie filter	R_S=0.2 (Ω) L_S=6 (mH) R_P=0.2 (Ω) C_P=20 (μF)

Table 2. Fault parameters

States	fault point	fault period	fault resistance	earth resistance
1	1) A,B	[0.025 0.085]	4.6	0.1
	2) A, B,C	[0.12 0.16]	4.6	0.1
2	1) A, C	[0.025 0.085]	4.6	0.1
	2) B	[0.12 0.16]	4.6	0.1

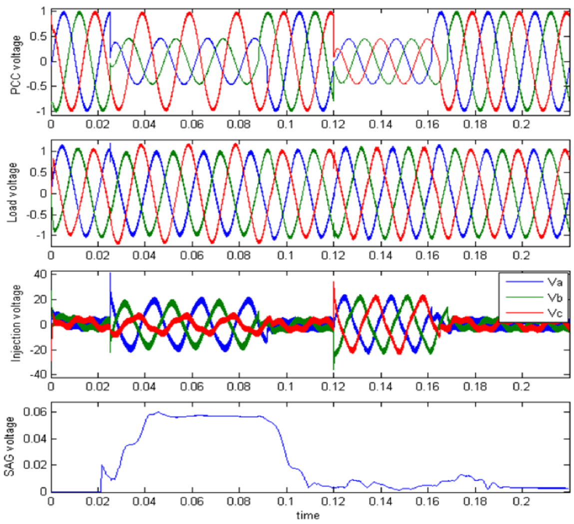

Fig. 6. DVR control with classical PI in first state

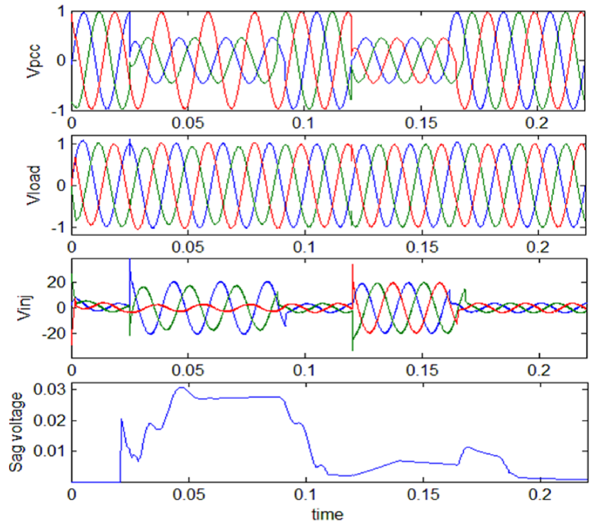

Fig. 8. DVR control with two-objective Hebb learning controller in first state

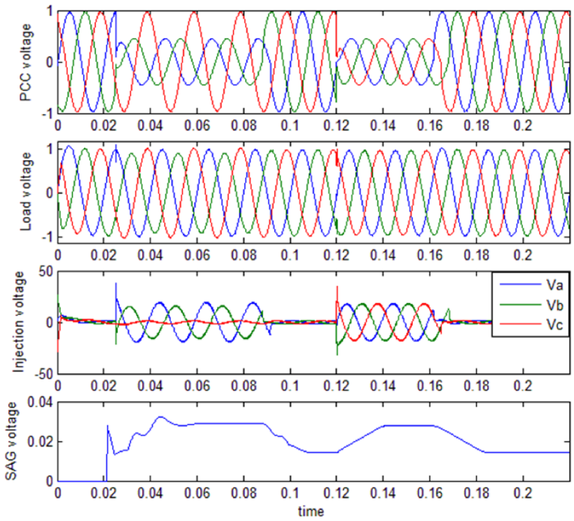

Fig. 7. DVR control with Hebb learning controller in first state

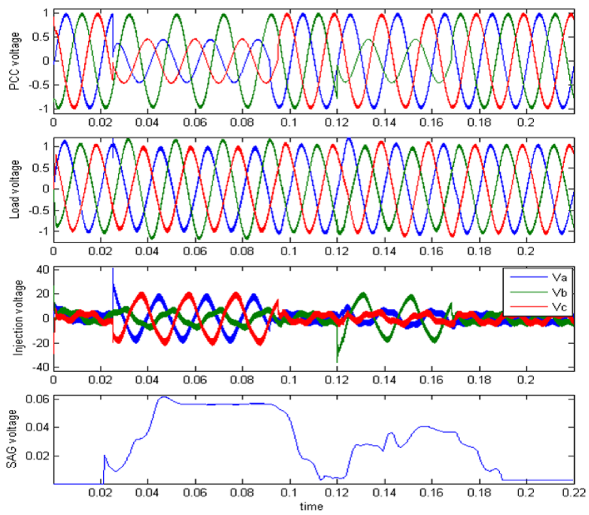

Fig. 9. DVR control with classical PI in second state

controller that have been introduced in [9] is obtained in Table 3. The method described a controller based on emotional learning.

It is clear that performance of proposed Hebb learning controller is improved in comparison with Hebb learning controller. In proposed controller both voltage flash and voltage THD indices have decreased in comparison to the conventional Hebb learning controller. In the other words, by considering control signal of voltage THD as second objective, this index not only has been improved but also the main objective, voltage flash, has been reduced. Considering of voltage THD as second objective modify voltage sag and THD seriously.

The emotional learning controller has good performance on DVR compensating. However, according to results presented in Table 3, we can understand that modified Hebb learning controller (bi-objective) operated better than other methods.

In (7), we saw that different weighting coefficients can be attributed to w_1 and w_2. The simulated cases are listed in Table 4. Also values of indices power quality such as voltage THD and sag have been mentioned in it.

According to the results in Table 4, by increasing w_1, the voltage sag and THD improve. There are an optimum

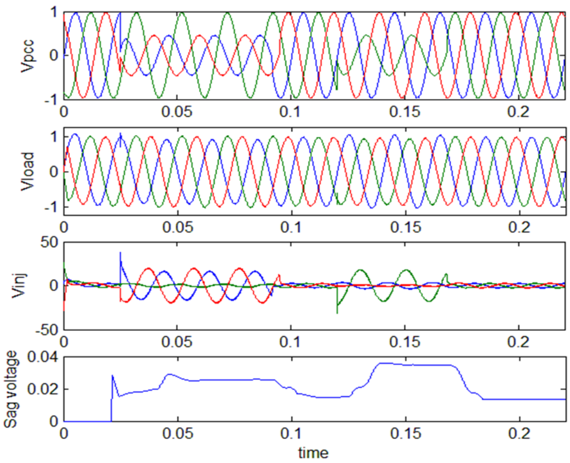

Fig. 10. DVR control with Hebb learning controller in second state

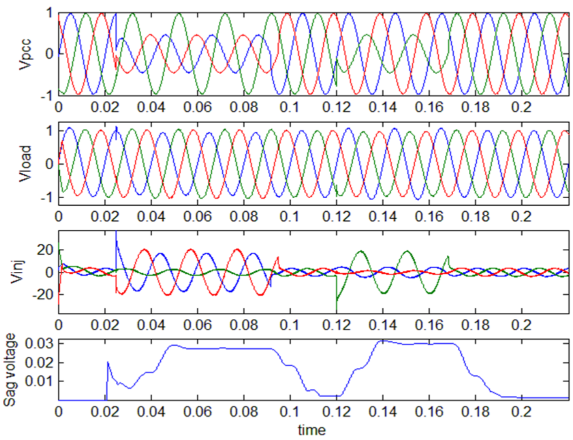

Fig. 11. DVR control with two-objective Hebb learning controller in second state

point in $w_1 = 0.75$ and $w_2 = 0.25$. It is the best point for making fuzzification of suggested objectives (inputs).

As it can be seen, during whole period of simulation IEEE-519 harmonic standard requirements are observed. These requirements force load voltage THD to be under 5%. It should be note that stability analysis is not our purpose in this research. Our study is in distribution systems. Consequently, it can be said that this controller can be an appropriate controller under different dynamic fault in the network and also it can improve power quality indices.

6 CONCLUSION

According to the results obtained by applying the proposed algorithm to the test network, it can be said that this algorithm is a good approach for improving power quality for customers. As it is clear, due to dynamic behaviors of power system under normal and fault conditions it is difficult to have a good model. So, to achieve fast and accurate performance of compensators, adaptive control algorithms should be used. The proposed controller has shown a very good performance under test cases. Also can been said that the Hebb learning controller and its proposed format are absolutely self-adjusting without any primary training and initializing. This controller mainly was designed to have a better performance in voltage THD index of sensitive load, but it was shown that by improving this index, a better compensation in voltage flash can also be achieved. Designing this controller does not have much complexity. It should be noted that the good performance of proposed approach is obtained without using specific additional equipment which can make it more cost-effective.

Table 3. Results of voltage THD and sag indice in each three control methods

		Voltage sag average		**THD (%)**	
Controllers	***states***	***value***	***Improve (%)***	***value***	***Improve (%)***
Classical PI	1	0.0205	-	4.87	-
	2	0.0273	-	3.94	-
Emotional Controller	1	0.0177	13.66	0.61	87.47
	2	0.0203	25.64	0.63	84.01
hebb learning controller	1	0.0198	3.41	0.61	87.47
	2	0.0215	21.24	0.65	83.5
Modified hebb learning controller	1	0.0129	37.07	0.56	88.50
	2	0.0164	39.92	0.60	84.77

Table 4. The values voltage THD and sag with different weight coefficients in two conditions

	First state		**Second state**	
Values of indices	***Sag***	***THD***	***sag***	***THD***
w_1=0.5 , w_2=0.5	0.0215	0.58	0.0264	0.56
w_1=0.6 , w_2=0.4	0.0157	0.57	0.0197	0.58
w_1=0.7 , w_2=0.3	0.0132	0.56	0.0169	0.58
w_1=0.75 , w_2=0.25	0.0129	0.56	0.0164	0.58
w_1=0.8 , w_2=0.2	0.0138	0.59	0.017	0.62
w_1=0.9 , w_2=0.1	0.0171	0.60	0.0194	0.65

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