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Artificial neural network based voltage controller for the single phase true sine wave inverter – a repetitive control approach

Streszczenie. *W artykule przedstawiono metodę budowy neuronowego regulatora napięcia dla falownika o sinusoidalnym napięciu wyjściowym. Regulator uczony jest w trybie on-line. Algorytm adaptacji wag sieci uwzględnia powtarzalność procesu poprzez odpowiednią definicję funkcji celu oraz uaktualnianie wag sieci raz na okres sygnału zadanego. Synteza układu regulacji nie wymaga identyfikowania modelu obiektu (podejście typu model-free). Zaproponowana topologia regulatora umożliwia jego wykorzystanie również do sterowania innymi procesami powtarzalnymi. Regulator pozwala na utrzymanie wysokiej jakości napięcia wyjściowego również dla okresowych obciążeń nieliniowych (**Neuronowy regulator napięcia dla jednofazowego falownika o sinusoidalnym wyjściu – sterowanie procesem powtarzalnym**)*

***Abstract**. The paper presents novel error backpropagation based neurocontroller for true sine wave inverter. The controller is trained in on-line mode. Adaptation algorithm takes into account repetitiveness of the process to be controlled. The cost function evaluates performance of the controller over the whole period of the reference signal and the weights are updated only once a period of this signal. A model-free concept is employed and hence no neural (or of any other type) model of the plant is needed. Proposed topology does not limit its area of implementation to the discussed converter. The controller is capable to maintain a high-quality output voltage waveform in the presence of periodic disturbance caused by nonlinear loads.*

Słowa kluczowe: adaptacyjny regulator neuronowy, falownik o sinusoidalnym napięciu wyjściowym, sterowanie procesem powtarzalnym.
Keywords: adaptive neurocontroller, true sine wave converter, iterative learning control, repetitive control.

Introduction

Many control tasks encountered in power electronic converters can be categorized as repetitive ones. Yet in many well-established industrial approaches to controller synthesis for such a system this repetitiveness is ignored. Standard feedback control for a true sine wave inverter, such as cascaded inductor current and capacitor voltage [1] (or capacitor current and capacitor voltage [2, 3]) control, along with their extension to deadbeat control [4-6] and hysteresis control [7], or sliding mode control [8], do not have a built-in algorithm that is able to adjust the control signal using information from previous pass (trial). Their performance deteriorates with increasing absolute value of load current derivative. This is very common problem since many industrial and commercial appliances have diode rectifier as a front-end converter. The current drawn by such a load is nonlinear (rich in harmonics) but constant in its shape (in its harmonic content) over time if load power is constant. The repetitiveness of the trajectory often occurs in robotics (e.g. assembly line robotic arm control) and thus many control schemes that take it into account, like iterative learning control (ILC), were originally derived and tested for motion control [9]. Recently these synthesis methods attract also attention of power electronics engineers due to a class of CACF (constant-amplitude constant-frequency) inverters with true sine output voltage wave. This arises from continuous development of UPS (uninterrupted power supply) systems and distributed power generation from renewables. Linear control laws for the discussed class of converters are usually derived using repetitive process control theory [10, 11]. This includes also examples of iterative learning control for DC/AC converters [12]. Various schemes that are derived using multioscillatory (multiresonant) controllers [13] also prove to be effective. Nonlinear solutions for repetitive process control often employ ANN (artificial neural network) systems. It is to notice that any ANN controller with learning algorithm kept active during regular operating mode of the system constitutes the learning control system and this learning takes place in iterative manner. Adaptive on-line trained ANN controllers have been already successfully incorporated into various control tasks in e.g. electric motor drive systems [14] and variable-speed power generation systems [15, 16]. In those systems no repetitiveness of the control signal is present over known time interval. Our main goal is to investigate new approach to ANN controller design for a repetitive processes and to test it on a single-phase true sine inverter. Some authors have already proposed ANN-based solutions aimed to improve ILC schemes for repetitive processes. Other propose ILC-like solutions that base solely on ANN architecture. A fairy representative set of such solutions can be found in [17-22]. As mentioned above the iterative learning control term can be misleadingly used for any on-line trained ANN controller. However, throughout this paper the term ILC is reserved to describe control system that explicitly takes into account the repetitiveness of the reference signal and thus ANN weight update procedure involves not only current error signal but also information from previous pass (trial).

Model-free ANN control scheme for a repetitive process

There are two main approaches to ANN controller synthesis: model based one and model-free one. The former one involves system identification stage before control design stage. The main drawback of model-based approach, besides its complexity, is that the performance of the ANN controller is highly dependent on the accuracy of the plant identification. On the other hand, the model-free concept does not require any emulator of the plant [15, 16]. In such a concept the ANN works as a compensator (Fig. 1) with a cost function containing only current control error:

$$E_{ANN}(k) = \frac{1}{2}\left(y^{ref}(k) - y(k)\right)^2 \tag{1}$$

where y denotes SISO system output and k is an integer time index (unbounded).

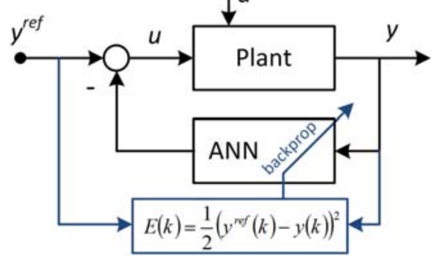

Fig.1. Adaptive model-free control system (no repetitiveness of the process is assumed)

Our idea is to rearrange the above control system to explicitly accommodate repetitiveness of the process. The SISO plant is here assumed. The cost function (1) is redefined to correspond to mean square error over the entire pass (i.e. over one period of the reference signal):

$$E_{ANN}^{ILC}(k)=\frac{1}{2}\sum_{p=1}^{\alpha}\left(y^{ref}(p)-y(k,p)\right)^2 \tag{2}$$

where α is a finite pass length, k is from now on an integer pass index, and p is an integer time index inside every pass (i.e. set to 1 at the beginning of every pass). This gives control system depicted in Fig. 2. The memory block stores control errors from previous pass. In the case of repetitive process this topology can be modified further. The plant output can no longer be explicitly connected to the input of the controller. Proposed control system topology is depicted in Fig. 3. In the most basic topology the ANN has only one input – a sawtooth wave of period equal to the period of a reference signal. This signal can be interpreted as a time base. The goal for the ANN is to learn to approximate feedback signal over entire pass that minimizes (2). The loop is organized as follows:

step 1: apply the control signal to the plant over entire pass of length α,
step 2: run one iteration of ANN gradient-based supervised training using (2) as the cost function,
step 3: go to step 1.

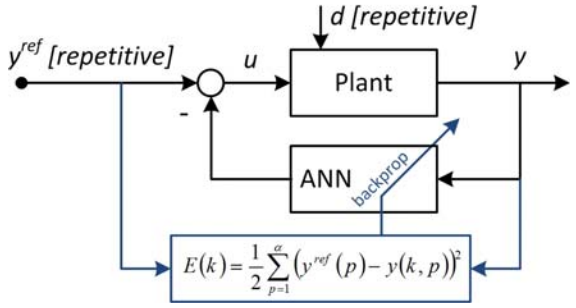

Fig.2. Adaptive model-free controller for repetitive process concept

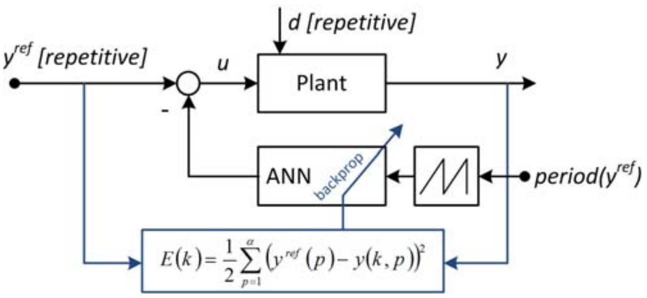

Fig.3. Adaptive model-free controller for repetitive process with sawtooth signal as the only ANN input

The ANN training parameters tuning can be done by means of evolutionary optimization like e.g. in [23]. Here the trial-and-error method has been used. There is one significant difference between a classical ILC control law (e.g. [12]) and the above learning law in terms of reaction delay to load change. In the classical ILC control signal is corrected in each sample time (sample after sample). Whereas here all α consecutive control signal values are corrected in one learning procedure call only once over entire reference signal period using (2) as a cost function. This could be seen as a profound drawback. However, this is not a disqualifying feature in the system if control correction delayed by one period of the reference signal is acceptable from application point of view. What we mean here by this is the ability to operate within acceptable control errors during one pass after disturbance change because during the pass only errors are collected (no sample after sample control signal update takes place) and control signal is updated just at the beginning of the next pass. This is the case if inverter with an output LC filter is considered. In low-performance power supplies this type of converter can work solely in open-loop mode. In high-performance power supplies the loop is closed to improve output voltage waveform when nonlinear loads are connected.

True sine wave inverter

Proposed approach to ANN-based repetitive control has been tested in single phase inverter with an LC filter. The system is sketched schematically in Fig. 4. Some key parameters are given in Tab. 1.

Table 1. Selected parameters of the system

Output filter	0.12mH, 80μF, 0.6Ω [*]
Load 1	Diode rectifier: 100μH, 3mF, 2.5kW (crest factor of 3.5)
Load 2	Resistive: 3.5kW
Load 3	Diode rectifier: 100μH, 3mF, 3.5kW (crest factor of 3.4)
Number of neurons	24 (trial-and-error method)
Type of neurons	*tansig* (incl. output neuron)
Training method type	Levenberg-Marquardt backpropagation (Matlab *trainlm* implementation)
Training method selected parameters	Initial momentum: 0.001 Momentum decrease factor: 0.1 Momentum increase factor: 10 Maximum momentum: 10^{10}
Measurement noise	2%
System noise	0.5% noise introduced to control signal
Signal conditioning (noise cancellation filters)	None
Reference signal	Sinusoidal: 230Vrms, 50Hz
Sampling time	20kHz (400 points per one pass)
ANN input scaling	Yes, into [-1,1]
Measurement and reference scaling	None
ANN output signal gain	k_1 = 200 (trial-and-error method)
Control error gain (scaling done before error backpropagation)	k_2 = 1/500 (trial-and-error method)

[*] The resultant resistance of the circuit, incl. choke resistance as well as IGBT, diode, connections and wires resistances.

It was tested that the system can be started with random ANN's weights but this entails highly corrupted output voltage waveform during system start-up which could be harmful for loads. Thus, in this experiment the ANN has been pre-tuned for no-load conditions. The output voltage waveform evolution during pre-tuning is shown in Figs. 5-7. Then the system is tested against disturbances. An exemplary test scenario includes switching between linear resistive loads and diode rectifiers with capacitor filter, and varying power drawn from the inverter by this two types of loads (see Tab. 1). All following diagrams have been obtained in numerical model of the system coded in Matlab/Simulink/Plecs environment.

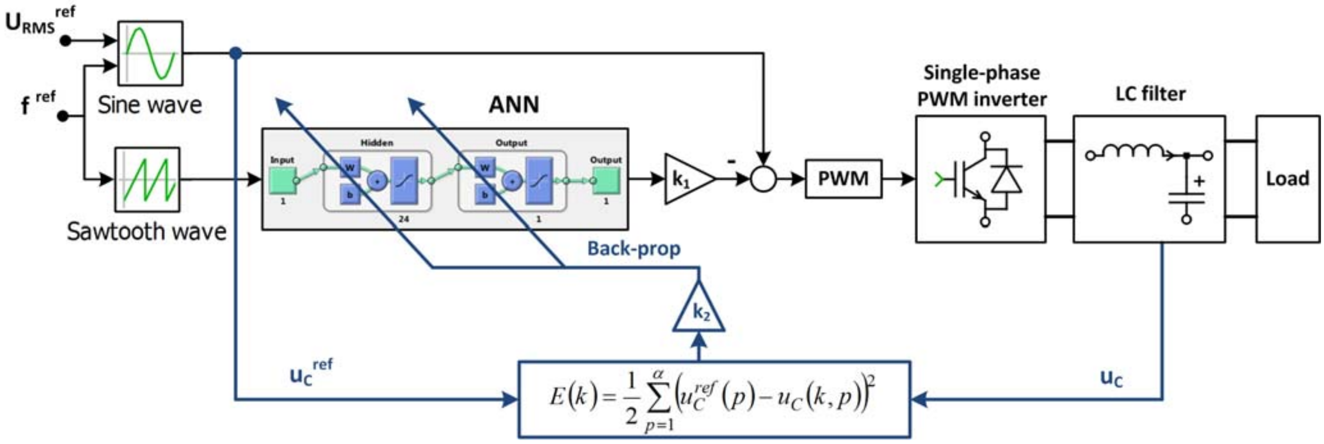

Fig.4. Schematic diagram of the inverter with an ANN-based ILC-like controller

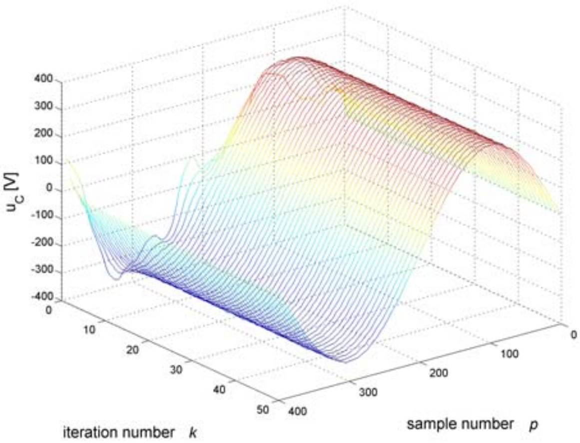

Fig.5. Pre-tuning for no-load conditions: the evolution of output voltage

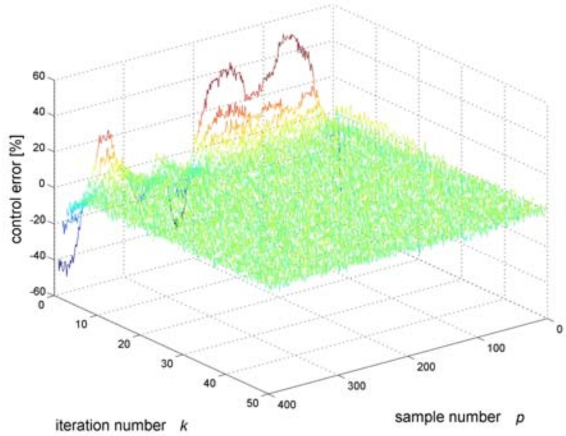

Fig.6. Pre-tuning for no-load conditions: the evolution of control error

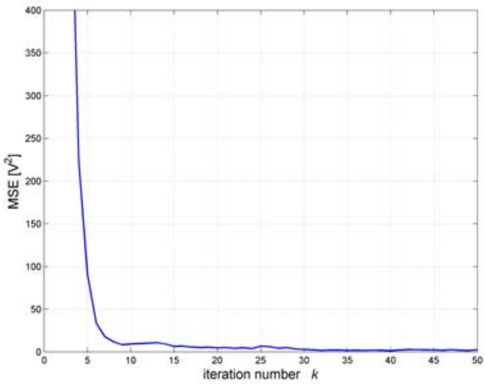

Fig.7. Pre-tuning for no-load conditions: the evolution of MSE

System and measurement noise is accommodated in this model. Figures 9-12 illustrate performance of the system when exposed to load current shown in Fig. 8. The MSE (mean squared error) of output voltage versus consecutive trials is presented in Fig. 11. This graph clearly indicates that the learning takes place and that after increase caused by a change in load (its type and/or its power) the error is forced to go down to reasonable levels. It is to note that the MSE possible lowest value is determined by the number of neurons and noise level. In this system the number of neurons is fixed. Preliminary results indicate that is could be profitable to adapt number of neurons to various types of loads. The higher harmonic content of load current the higher harmonic content of desired ANN output signal. The good number of *tansig* neurons is dictated by the shape of control signal to be constructed. For linear load several neurons would be enough whereas for diode rectifier with low inductance several dozens of neurons would be needed to achieve similar accuracy in terms of MSE value. Here 20 to 25 neurons were chosen as a trade-off between accuracy for non-linear loads and tendency to overlearn in no-load or linear load conditions. For comparison purposes the open-loop operation is demonstrated in Figs. 13-16.

Several other test scenarios have been investigated. This includes different LC filter parameters and noise levels. For all technically feasible values for these parameters it is possible to find values for k_1 and k_2 that ensure stable operation. However, the stability of the method has not yet been investigated.

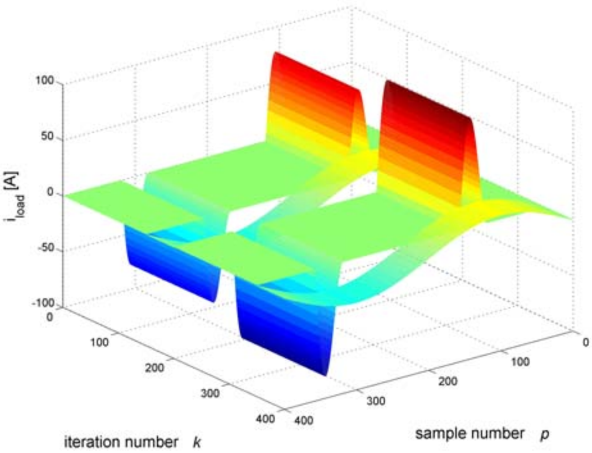

Fig.8. Test load current (disturbance)

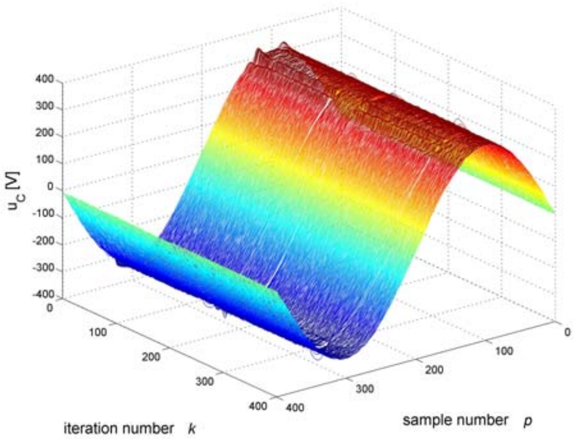

Fig.9. Closed-loop operation: the evolution of output voltage

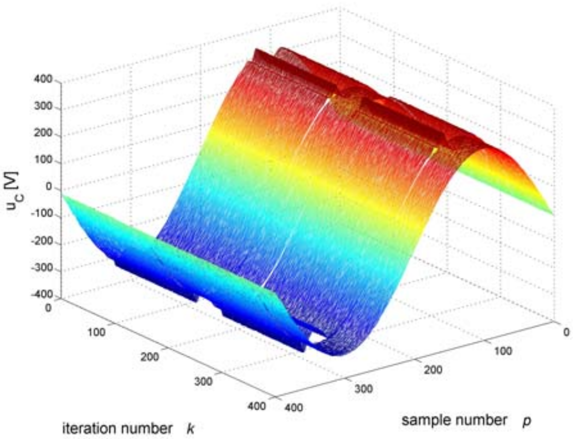

Fig.13. Open-loop operation: the evolution of output voltage

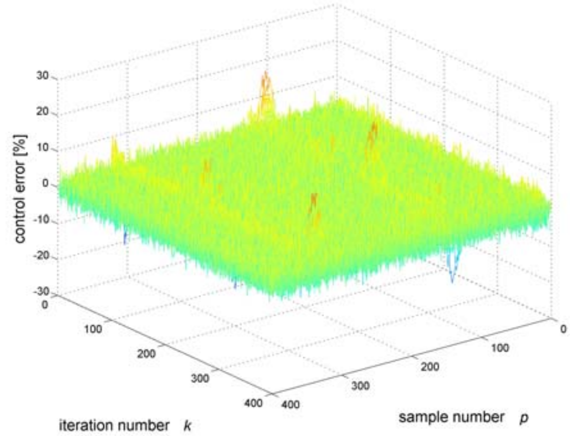

Fig.10. Closed-loop operation: the evolution of control error

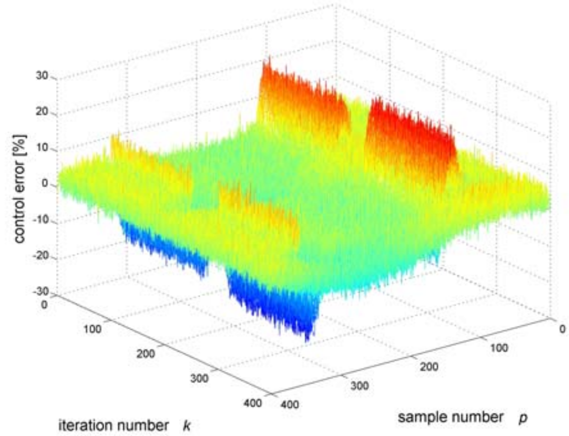

Fig.14. Open-loop operation: the evolution of control error

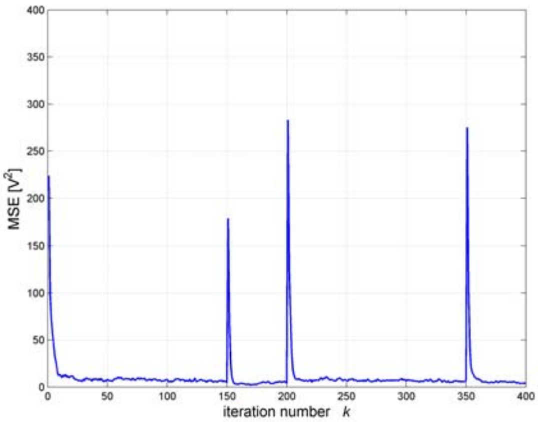

Fig.11. Closed-loop operation: the evolution of MSE

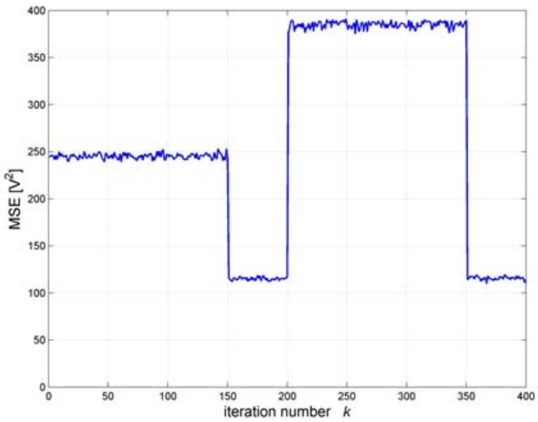

Fig.15. Open-loop operation: the evolution of MSE

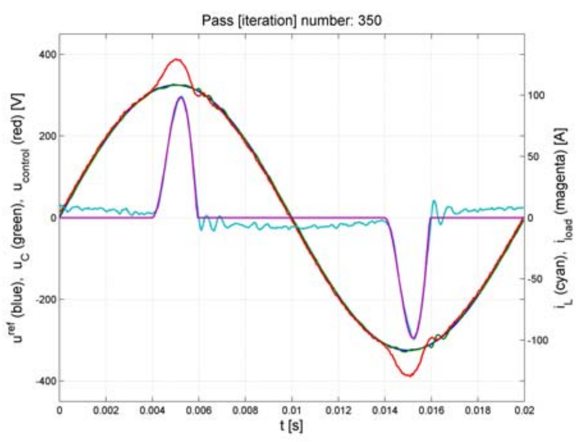

Fig.12. Closed-loop operation: selected iteration (pass/trial)

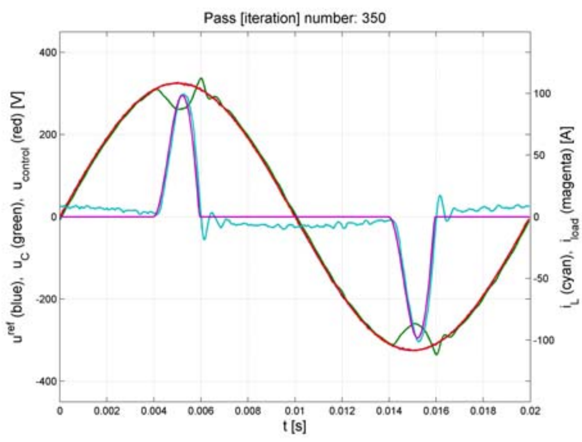

Fig.16. Open-loop operation: load conditions as in Fig. 12

Conclusions

The ANN-based repetitive controller for the single-phase true sine inverter has been proposed and investigated numerically. The repetitiveness of the process has been accommodated in the ANN adaptive controller design. The cost function for error back-propagation has been defined to be the MSE over entire period of the reference voltage. The key problem related to a fixed ANN topology has been identified. Further research will include hybridization of the controller by plugging it into linear controller for LC filter to reduce discrepancy between desired ANN output for various types of loads (the ANN would only do a fine tuning of the control signal), and we would like also to investigate the possibility of introducing an on-line adaptation algorithm for ANN structure manipulation according to load current harmonic content. Also additional input signals for the ANN will be considered. But nonetheless, even this basic scheme proves to deliver learning capability in pass-to-pass direction. An experimental verification is pending. The obtained numerical results demonstrate the effectiveness of the method.

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REFERENCES

[1] Finn S.D., A high performance inverter technology, architecture and applications, *Proc. of the 8th Annual IEEE Applied Power Electronics Conference and Exposition APEC* (1993), 556-560

[2] Ryan M.J., Lorenz R.D., A high performance sine wave inverter controller with capacitor current feedback and "back-EMF" decoupling, *Proc. of the 26th Annual IEEE Power Electronics Specialists Conference. PESC*, 1 (1995), 507-513

[3] Ryan M.J., Brumsickle W.E., Lorenz R.D., Control topology options for single-phase UPS inverters, *Proc. of the Int. Conference on Power Electronics, Drives and Energy Systems for Industrial Growth*, 1 (1996), 553-558

[4] Gokhale K.P., Kawamura A., Hoft R.G., Dead beat microprocessor control of PWM inverter for sinusoidal output waveform synthesis, *IEEE Trans. on Industry Applications*, 23 (1987), n.5, 901-910

[5] Mihalache L., DSP control method of single-phase inverters for UPS applications, *Proc. of the 17th Annual IEEE Applied Power Electronics Conference and Exposition APEC*, 1 (2002), 590-596

[6] Tzou Y.-Y., DSP-based fully digital control of a PWM DC-AC converter for AC voltage regulation, *Proc. of the 26th Annual IEEE Power Electronics Specialists Conference PESC*, 1 (1995), 138-144

[7] Kawamura A., Hoft R., Instantaneous feedback controlled PWM inverter with adaptive hysteresis, *IEEE Trans. on Industry Applications*, 20 (1984), n.4, 769-775

[8] Carpita M., Marchesoni M., Experimental study of a power conditioning system using sliding mode control, *IEEE Trans. on Power Electronics*, 11 (1996), n.5, 731-742

[9] Rogers E., Galkowski K., Owens D.H., *Control Systems Theory and Applications for Linear Repetitive Processes* (Lecture Notes in Control and Information Sciences 349), Springer, 2007.

[10] Escobar G., Valdez A.A., Leyva-Ramos J., Mattavelli P., Repetitive-based controller for a UPS inverter to compensate unbalance and harmonic distortion, *IEEE Trans. on Industrial Electronics*, 54 (2007), n.1, 504-510

[11] Zhou K., Wang D., Zhang B., Wang Y., Plug-in dual-mode-structure repetitive controller for CVCF PWM inverters, *IEEE Trans. on Industrial Electronics*, 56 (2009), n.3, 784-791

[12] Kulawinek R., Galkowski K., Grzesiak L., Kummert A., Iterative learning control method for a single-phase inverter with sinusoidal output voltage, *Proc. IEEE Industrial Electronics Society 37th Annual Conf. IECON* (2011), 1402-1407

[13] Kaszewski A., Grzesiak L.M., Ufnalski B., Multi-oscillatory LQR for a three-phase four-wire inverter with L3nC output filter, *Proc. IEEE Industrial Electronics Society 38th Annual Conf. IECON* (accepted for publication) (2012)

[14] Grzesiak L.M., Meganck V., Sobolewski J., Ufnalski B., On-line trained neural speed controller with variable weight update period for direct-torque-controlled AC drive, *Proc. of the Power Electronics and Motion Control EPE-PEMC 12th Int. Conference* (2006), 1127-1132

[15] Grzesiak L.M., Sobolewski J., Energy flow control system based on neural compensator in the feedback path for autonomous energy source, *Bulletin of the Polish Academy of Sciences – Technical Sciences*, 54 (2006), nr.3, 335-340

[16] Sobolewski J., *Neuro-control system for converter based electrical energy source with combustion engine*, Ph.D. Thesis, Warsaw University of Technology, 2008

[17] Efe M.O., Neural network-based control, Chapter III in *The Industrial Electronics Handbook: Intelligent Systems*, CRC Press, 2011

[18] Sarangapani J., *Neural Network Control of Nonlinear Discrete-Time Systems*, CRC Press, 2006

[19] Kalkkuhl J., Hunt K.J., Zbikowski R., Dzielinski A. eds., *Applications of neural adaptive control technology* (World Scientific Series in Robotics and Intelligent Systems, 17), World Scientific, 1997

[20] Tanomaru J., Takahashi Y., A general structure for neurocontrol of dynamical systems, *Proc. of the IEEE IECON Int. Conf.*, 1 (1993), 304-309

[21] Potocnik P., Grabec I., Adaptive self-tuning neurocontrol, *Mathematics and Computers in Simulation*, 51 (2000), nr.3-4, 201-207

[22] Wang Y.-C., Chien C.-J., Lee D.-T., An output recurrent fuzzy neural network based iterative learning control for nonlinear systems, *Proc. of the IEEE World Congress on Computational Intelligence*, FUZZ-IEEE 2008, 1563-1569

[23] Ufnalski B., Grzesiak L.M., Particle swarm optimization of artificial-neural-network-based on-line trained speed controller for battery electric vehicle", *Bulletin of The Polish Academy of Sciences – Technical Sciences*, 60 (2012), n.3

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