International Journal on "Technical and Physical Problems of Engineering" (IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

December 2014 | Issue 21 | Volume 6 | Number 4 | Pages 88-93

INTEGRATION OF ONLINE SYSTEM IDENTIFICATION AND PREDICTIVE CONTROLLER FOR INVERTER OPTIMAL CONTROL

I. Banisaeed [1] J. Barati [2]

1. Department of Electrical Engineering, College of Electrical Engineering, Mahshahr Branch, Islamic Azad University, Mahshahr, Iran, esmaeel.bs58@gmail.com
2. Department of Electrical Engineering, College of Electrical Engineering, Ramhormoz Branch, Islamic Azad University, Ramhormoz, Iran, tj_barati62@yahoo.com

Abstract- In this paper, integrative scheme of online identification algorithm and model-based predictive control is used for voltage control of three-phase inverter with inductive-capacitive output filter. In online system identification stage, evolving Takagi-Sugeno fuzzy model of system is constructed using input-output data. The model is adapted instantaneously on system parameters (changes of load magnitude, power factor, …). Online data clustering and weighted recursive least squares are used for structure identification and parameter identification, respectively. Also, a criteria are proposed for elimination of excessive rules and combination of very close rules. System model is used to predict future values of output voltage based on past and present values of output voltage and current. Different prediction steps and same or different voltage vectors for future steps are evaluated and their corresponding *THD* values are compared. Effectiveness of the proposed integrated scheme is proved using simulation results. Also, it has been shown that three step ahead prediction and application of same voltage vectors for future steps is better than other choices.

Keywords: Online Identification, Predictive Controller, Inverter, Voltage Prediction.

I. INTRODUCTION

Inverters are among of all-purpose circuits in electricity industry. Using adequate switching commands, amplitude and frequency of output voltage is controlled and excessive harmonic components are minimized, such that output voltage quality will be convenient regardless of load characteristics such as magnitude, power factor and non-linearity. It is possible to improve output voltage quality using output LC filter. However, controller design and parameter adjustment will be more difficult.

Several control schemes are proposed for inverter control such as deadbeat control [1], multi-loop feedback control [2], adaptive control based on resonance filters bank [3], repetition-based controllers [4] and predictive controllers [5-6].

Regardless of complexity, adaptive controllers does not take into account nonlinear uncertainties. Some improvements are necessary for robustness of deadbeat control method. Also, most of proposed control methods are not optimal. A discrete offline model of load is considered in [6] to predict future values of load current. However, it is obvious that model errors and uncertainties can make problems, specially for time-variant loads which exist in many applications. Regarding to defects of present control methods and abundant importance of inverters control, it is very necessary to investigate new control methods and modeling algorithms.

Model-based predictive control methods are very attractive for control of power converters because of their rapid dynamic response and optimization of system response [5-6]. These methods are needy to a system model to predict output values for a future time horizon. Optimal control sequence is calculated such that a cost function is minimized. These controllers consider system constraints in controller design step in a straight way. They make it possible to consider system nonlinearities in its model. Also, it is simple to generalize them to a multi-variable systems. Other benefits of Predictive control methods are easy tuning and applicability in a delayed, unstable and non-minimum phase systems [7]. Different cost functions are used to minimize output error and control signals, and to keep important variables in an allowable area.

In this paper, an algorithm for online identification of an evolving model for inverter and its load is proposed to identify load characteristics changes such as nonlinearity, power factor, magnitude, etc. Based on well-defined parameter called 'potential', the importance of each I/O data-point in sense of its beneficial information is evaluated. A solution is presented to decrease calculations complexity without any effect on system performance. New criteria are proposed to add a new rule or replace an old rule with a better rule. Also, because of changes in characteristics of time-variant systems, some rules may lose their importance and their effect on model accuracy.

Therefore, a criterion is proposed to remove less-effective rules and their additional computational load. Benefits of multi-step ahead prediction of important parameters and their application for predictive control of an inverter with inductive-capacitive filter are discussed. Various numbers are considered as a prediction horizon and related results are compared. Also, the effect of different and similar voltage vectors is investigated.

II. SYSTEM IDENTIFICATION

Quality of predictive model is an important parameter on performance of predictive controller. Type and structure of predictive model is one of main differences of predictive control family members [7].

Fuzzy systems, especially Takagi-Sugeno systems, are very efficient choice for system modeling and function approximation [8]. Evolving fuzzy models are presented to overcome offline identification drawbacks such as computational complexity, need to large memory and failure to comply with new specification of system, specifically in time-variant systems. There is no need to save large amount of data. Each data point is used only in a limited number of training epochs, and its effect on main parameters of evolving model is applied simultaneously using recursive calculations.

A. Structure of Takagi-Sugeno Fuzzy Model

In a T-S fuzzy model, *i*th rule will be [9]:

$$R_i: \text{ if } (x_1 \text{ is } A_{i1}) \text{ and ... and } (x_n \text{ is } A_{in}) \quad \text{then } y^i = x_e^T \pi^i \,;\; i = \{1, R\} \tag{1}$$

where $\boldsymbol{A_{ij}}$ are fuzzy sets of antecedent part, $\boldsymbol{R}$ is the number of fuzzy rules and y^i is output of *i*th rule:

$$y^i = [y_1^i, y_2^i, \ldots.., y_m^i] \tag{2}$$

The x_e (extended input vector) and π^i (matrix of consequent parameters) are defined as follow:

$$x_e = \left(1, x^T\right)^T = \left(1, [x_1, x_2, \ldots, x_n]^T\right)^T \tag{3}$$

$$\pi^i = \begin{bmatrix} a_{01}^i & a_{02}^i & \cdots & a_{0m}^i \\ a_{11}^i & a_{12}^i & \cdots & a_{1m}^i \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1}^i & a_{n2}^i & \cdots & a_{nm}^i \end{bmatrix} \tag{4}$$

Each if-then rule is a linear sub-model. Linearity of Sub-models is very useful property, especially for model-based predictive controllers. In these controllers, an optimization problem should be solved in each sampling period. Using nonlinear models as a predictor, the optimization problem will be nonlinear, which has no analytical solution and should be solved by complicated time-consuming methods.

No computation is done in a first layer of model. Membership functions of input variables are calculated in second layers:

$$\mu_{ij} = \exp\left(-\frac{\left(x_{ij} - c_{ij}\right)^2}{\sigma_i^2}\right) \,;\; i = \{1, R\} \,,\; j = \{1, n\} \tag{5}$$

where c_{ij} is the center of Gaussian membership function of fuzzy set (*j*th element of *i*th cluster center) and σ_i is width of membership functions of *i*th rule. Each node in third layer represents one fuzzy rule and calculate its activation level:

$$\varphi_i(x) = \prod_{j=1}^{n} \mu_{ij}(x_i) = \exp\left(-\sum_{j=1}^{n} \frac{\left(x_j - c_{ij}\right)^2}{\sigma_i^2}\right) \tag{6}$$

Activation level of rules is normalized:

$$\lambda_i = \varphi_i / \sum_{k=1}^{R} \varphi_k \tag{7}$$

*j*th output is calculated as:

$$y_j = \sum_{i=1}^{R} \lambda_i y_j^i \tag{8}$$

The problem of T-S model identification is divided in two parts: structure identification (to find canonical points of clusters and width of membership functions) and parameter identification (to determine parameters of antecedent part of rules) [11].

B. Structure Identification

Subtractive clustering is one of most effective clustering methods [12-13]. In this algorithm, 'potential' of each data-point is defined as a measure of its ability to be a cluster center. At start of online clustering, first data-point is selected as a center of first cluster. The potential of each new data-point is defined as:

$$p_k(z_k) = \frac{1}{1 + \frac{1}{(k-1)} \sum_{l=1}^{k-1} \sum_{j=1}^{n+m} \left(d_{lk}^j\right)^2} \;;\; k = 2, 3, \ldots \tag{9}$$

where $p_k(z_k)$ is a potential of *k*th data point and $d_{lk}^j = z_l^j - z_k^j$ is a distance of z_k^j and z_l^j, projected on '*j*' axis. Equation (9) is'not recursive and its calculation is time-consuming. Therefore, following recursive equation is proposed for a potential to overcome this problem:

$$p_k(z_k) = \frac{(k-1)}{(k-1)(\omega_k + 1) + \tau_k - 2\nu_k} \tag{10}$$

where, $\omega_k = \sum_{j=1}^{n+m} \left(z_k^j\right)^2$; $\tau_k = \sum_{l=1}^{k-1} \sum_{j=1}^{n+m} \left(z_l^j\right)^2$ and

$$\nu_k = \sum_{j=1}^{n+m} z_k^j \beta_k^j \;;\; \beta_k^j = \sum_{l=1}^{k-1} z_l^j$$

For more computational efficiency, β_k^j and τ_k are calculated recursively:

$$\tau_k = \tau_{k-1} + \sum_{j=1}^{n+m} \left(z_{k-1}^j\right)^2 \tag{11}$$

$$\beta_k^j = \beta_{k-1}^j + z_{k-1}^j \tag{12}$$

To update the potential of cluster centers, we have:

$$p_k(c_l) = \frac{(k-1) p_{k-1}(c_l)}{[k - 2 + p_{k-1}(c_l) + p_{k-1}(c_l) \sum_{j=1}^{n+m} \left(d_{k(k-1)}^j\right)^2]} \tag{13}$$

where $p_k(c_l)$ is potential of center of cluster number l in kth sampling period.

It is important to note that except of cluster centers, there is no need to save the previous data points or their potential for calculation of potential of new data point . This is a vital property, regarding to reduction of computational load and needed memory.

C. Recursive Estimation of Consequent Parameters

Fixing the antecedent parameters, the estimation of consequent parameters can be formulated as a least square problem:

$$\hat{y}_{k+1} = \psi_k^T \hat{\theta}_k \; ; \quad k = 2,3, \ldots \tag{14}$$

where θ is vector of consequent parameters and ψ is vector of input variables, weighted by activation level of rules:

$$\theta_k = [\pi_1^T, \pi_2^T, ..., \pi_R^T]^T \tag{15}$$

$$\psi_k = [\lambda_1 x_e^T, \lambda_2 x_e^T, ..., \lambda_R x_e^T]^T \tag{16}$$

Local optimal rules are obtained by minimization of following weighted cost function:

$$J_L = \sum_{i=1}^{R} (Y - X^T \pi_i)^T \Lambda_i (Y - X^T \pi_i) \tag{17}$$

where X is a matrix $(X \in R^{N(n+1)})$ obtained from x_{ek} and Λ_i is a diagonal matrix, which its diagonal elements are $\lambda_i(x_k)$. Also, π_i is calculated as:

$$\pi_{ik} = \pi_{i(k-1)} + C_{ik} x_{e(k-1)} \lambda_i(x_{k-1})(y_k - x_{e(k-1)}^T \pi_{i(k-1)}) \tag{18}$$

Covariance matrices are updated as here:

$$C_{ik} = C_{i(k-1)} - \frac{\lambda_i(x_{k-1}) C_{i(k-1)} x_{ek-1} x_{ek-1}^T C_{i(k-1)}}{1 + \lambda_i(x_{k-1}) x_{ek-1}^T C_{ik-1} x_{ek-1}} \tag{19}$$

where k = 2,3, … and initial conditions are as here:

$$\hat{\pi}_1 = 0 \quad ; \quad C_{i1} = \Omega I \tag{20}$$

Covariance matrices are separate for each rule:

$$C_{ik} \in R^{(n+m)\times(n+m)}; \quad i = [1, R] \tag{21}$$

When a new rule is added (R = R+1), its Parameters are calculated using (18). Parameters of previous rules are obtained from previous iteration:

$$\pi_{ik} = \pi_{i(k-1)}; \quad i = [1, R] \tag{22}$$

When a rule replaced by another rule, parameters of all rules remain constant (22). Covariance matrix of new rule is initiated as follow:

$$C_{(R+1)k} = \Omega I \tag{23}$$

Covariance matrices of previous rules are obtained from previous iteration:

$$C_{ik} = C_{i(k-1)} \quad , i = [1, R] \tag{24}$$

D. Online Identification Algorithm for Evolving T-S Models [9-10]

1- Primary structure of rule-base is determined. There is no need to any initial information about the system. First rule is obtained from first I/O data-point:

$$k = 1; \quad R = 1; \quad x_1^* = x_k; \quad p_1(c_1) = 1$$
$$\theta_1 = \pi_1 = 0; \quad C_1 = \Omega I \tag{25}$$

where x_1^* is canonical point (center) of first rule.

2- Potential of new data-point is calculated and potentials of centers of existing rules are updated using (10) and (13), respectively.

3- Existing rules are improved or a new rule is added using this criteria: If the potential of new data-point is larger than all cluster centers:

$$p_k(z_k) > p_k(c_i) \quad ; \quad i = [1, R] \tag{26}$$

then a new rule is added (R = R+1). New data-point will be the center of new rule:

$$R = R + 1 \quad ; \quad x_R^* = x_k \quad ; \quad p_k(c_R) = P_k(z_k) \tag{27}$$

Consequent parameters and covariance matrices are updated.

If potential of new data-point is larger than all cluster centers, and new data-point is very close to the cluster center number j^*, such that

$$\frac{P_k(z_k)}{\max_{i=1}^{R} P_k(c_i)} - \frac{\delta_{\min}}{\|c\|} \geq 1 \tag{28}$$

where

$$\delta_{\min} = \min_{i=1}^{R} \|z_k - c_i\| \tag{29}$$

Then cluster center number j^* is replaced by new data-point:

$$c_{j^*} = \arg \min_{i=1}^{R} \left(\|z_k - c_i\| \right) \tag{30}$$

$$p_k(c_{j^*}) = p_k(z_k) \tag{31}$$

Antecedent parameters and covariance matrices of new rule are as same as those of replaced rule:

$$\hat{\pi}_k = \pi_k^{j^*} \quad ; \quad C_k = C_k^{j^*} \tag{32}$$

4- Less-effective rules are Deleted : assume that there is 'R' rules in rule-base at instant k. $d_{\min}$ and $p_{\max}$ are defined as:

$$d_{\min} = \min \left\{ \exp(-\frac{2\|c_i - \sigma_l\|}{\|\sigma_i\| + \|\sigma_l\|}) \right\}; \quad i = 1:R; \quad l = 2:R \tag{33}$$

$$p_{\max} = \max_{i=1}^{R} p_k(c_i) \tag{34}$$

Also, assume that c_a and c_b are nearest cluster centers and $p_k(c_b) > p_k(c_a)$. If (35) is satisfied, Then rule number 'a' will be removed:

$$\frac{d_{\min}}{\|\sigma_a\|} + \frac{p_k(c_a)}{p_{\max}} < 1 \tag{35}$$

5- Update consequent parameters by WRLS (18 and 19).

6- Model output for next sampling period (k+1) is calculated using (14). It is a prediction of real system output for (k+1).

7- Return to step 2.

By simple changes in sorting of I/O data of identification algorithm, It is possible to predict real system output for other future instants (k+2, k+3, ...).

III. PREDICTIVE CONTROL OF INVERTER

Block-diagram of predictive control scheme combined with online identification which is applied in this paper is shown in Figure 1. The 'online identifier' is responsible for online identification of evolving fuzzy model of inverter and its load, using a limited number of past values of output voltage and currents according to algorithm explained in previous part. Hence, we have an evolving predictive model which is updated in each sampling period.

Future values of output voltage over prediction horizon ($v_c(k+1)$, …, $v_c(k+N)$) are estimated using this predictive model. Present values of output voltage $v_c(k)$, inverter output current $i_f(k)$ and load current $i_o(k)$ are used as model input data. Predicted values of output voltage are used in minimization of the cost function and calculation of optimal control sequence for inverter. Equations of Generalized predictive control method [7] are used as predictive controller. All switching states are evaluated in any moment to find an optimal state. First element of control sequence is applied to inverter. These operations are repeated each sampling period.

A. Cost Function

For simplicity, output voltage error (difference between reference voltage and predicted values of output voltage) is considered as main term of cost function .Cost function is defined as

$$J=\sum_{n=1}^{N_P}\left(v_{c\alpha}^{*}-v_{c\alpha}^{p}(k+n)\right)^2+\sum_{n=1}^{N_P}\left(v_{c\beta}^{*}-v_{c\beta}^{p}(k+n)\right)^2+i_{\lim} \quad (36)$$

$v_{c\alpha}^{*}$ and $v_{c\beta}^{*}$ are real and imaginary parts of reference voltage vector (v_c^{*}). Also, $v_{c\alpha}^{p}(k+n)$ and $v_{c\beta}^{p}(k+n)$ are real and imaginary parts of predicted output voltage vector (v_c^{p}). 'N_p' is a prediction horizon, which is dependent to the accuracy of predictive model. It increased one-by-one to find the best number. Finally, $i_{\lim}$ is considered to limit output currents:

$$i_{\lim}=\begin{cases}0 & \text{if } \left|i_f(k+1)\right|\le i_{\max}\\ \infty & \text{if } \left|i_f(k+1)\right|\ge i_{\max}\end{cases} \quad (37)$$

For a given voltage vector, cost function will be infinite if $i_f(k+1)$ is greater than allowed maximum current $i_{\max}$, and this voltage vector is rejected. Otherwise, only output voltage error is considered in cost function. In each sampling period, firing pulses are calculated such that the cost function is minimized. In this paper, the magnitude of reference voltage from present instant (k) until ($k+N$) is considered constant and equal to $v_c^{*}(k)$.

B. Selection of Voltage Vector Sequences

In one-step ahead voltage prediction , the effect of one voltage vector in one sampling period is evaluated and only seven voltage vectors are investigated (Figure 2). In case of voltage prediction for N step ahead and consideration of separate voltage vector for each sampling period, 7^N sequence should be evaluated in each sampling period, which increases the difficulty and cost of practical implementation, because of extremely increase in computational load.

In order to decrease the computational load, we can apply same voltage vectors for future "N" step time. As will be seen, this leads to a simplified algorithm for predictive controller, with reasonable performance and lower cost with respect to simpler computations, compare to using different voltage vectors for future "N" step time. Also, this simplification does not drop voltage quality.

IV. SIMULATION RESULTS

The performance of 'online system identification' + 'model-based predictive control' is evaluated via MATLAB simulations on a three-phase inverter. *THD* is used to measure the quality of responses. System parameters are shown in Table 1.

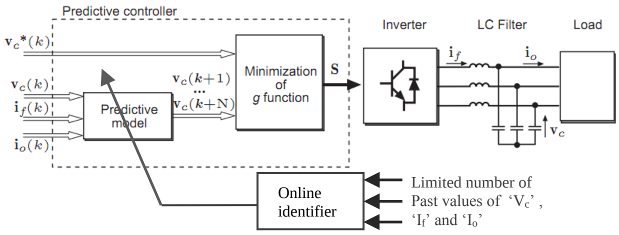

Figure 1. 'predictive control' + 'online identification' scheme for inverter control

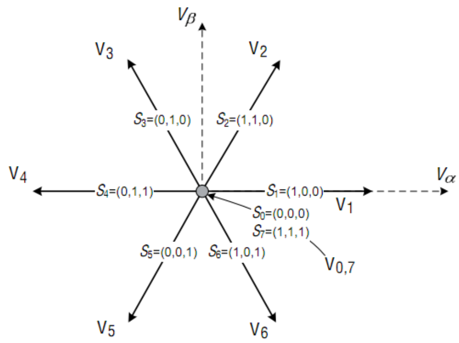

Figure 2. Voltage vectors of inverter

A. Performance for Resistive (Linear) Load

Output response for three-phase resistive load (10 ohm) and 3-step ahead prediction are shown in Figure 3. Related *THD* values are illustrated in Table 2.

Comparision of *THD* values shows that system performance variation for same and different voltage vectors is negligible in case of two and three ahead prediction.

Also, system performance for two and three steps prediction are considerably better than system performance in case of one-step ahead prediction. Keeping the load constant, prediction steps are increased to four and higher numbers. But we faced with a drop in system performance and *THD* increases (for example, *THD* was %1.55 for four step ahead prediction).

The main reason is that prediction accuracy reduced by increase of prediction steps. Hence, three steps ahead predicton is the best choice for resistive load and proposed identification method.

B. Performance for Non-Linear Load

A three-phase resistor and three single-phase diode bridge rectifiers are connected as a nonlinear load (Figure 4). Simulation results for three-step ahead prediction and same voltage vectors are shown in Figure 5.

For nonlinear load, Table 3 shows that three-step ahead prediction has better response, compare to one and two step prediction. On the other hand, utilization of similar voltage vectors decreases calculation load, while keeping good response quality. As same as linear load, any increase in prediction Steps larger than three steps deteriorates response quality.

Table 1. Parameters of system under simulation

DC Link Voltage (V_{dc})	500 V
Filter Inductance (L)	2.2 mH
Filter Capacitance (C)	20 μF
Sample time	50 μs

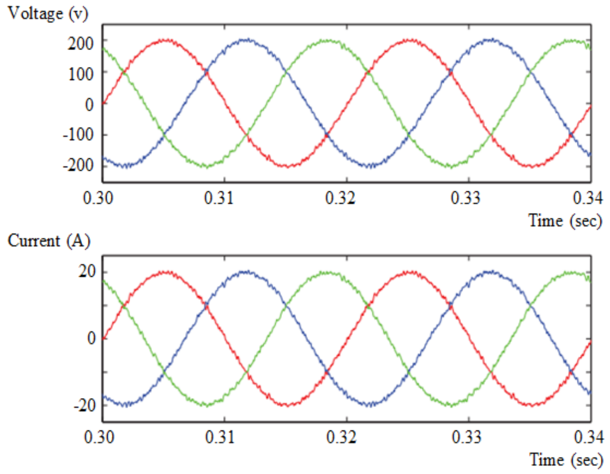

Figure 3. output voltage and current for resistive load, three step ahead prediction and same voltage vectors

Table 2. *THD* values for resistive load

	Same vectors	Different vectors
one step ahead prediction	%2.05	-
two step ahead prediction	%1.48	%1.45
three step ahead prediction	%1.37	%1.33

V. CONCLUSIONS

A combination of "online identification algorithm" and "predictive controller" has been presented for inverter control. A novel algorithm is proposed for online identification and adaptation of evolving predictive model of unknown system. Criteria are presented for rule creation, enhancement or deletion of rules. Model parameters are calculated recursively to reduce calculation load and needed memory. This model is used to predict future values of output voltage of inverter for one, two and greater number of steps ahead.

Predicted values of output voltage are used to calculate optimal firing signals for inverter switches by minimization of cost function. In order to reduce needed calculations, the effect of same voltage vectors instead of different voltage vectors is investigated.

Simulation results shows that best *THD* value for both linear and nonlinear load is achieved using three step ahead prediction. Also, it has been shown that *THD* values using same and different voltage vectors are very close. So, it is preferable to use same voltage vectors because of less computational load.

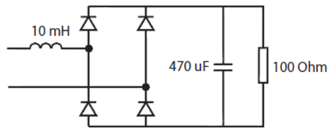

Figure 4. Part of nonlinear load

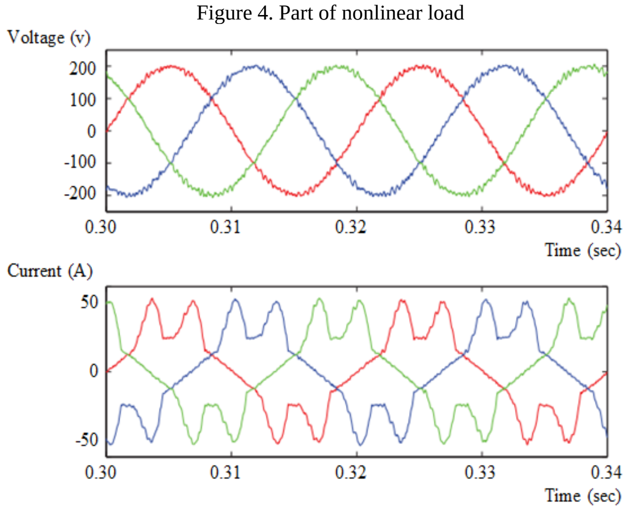

Figure 5. Output voltage and current for nonlinear load, three step ahead prediction and same voltage vectors

Table 3. *THD* values for nonlinear load

	Same vectors	Different vectors
one step ahead prediction	%2.19	-
two step ahead prediction	%2.06	%2.03
three step ahead prediction	%1.95	%1.93

Main advantages of proposed scheme are daptation to converter & load conditions, reduced calculative load and optimization of system behavior, which makes it very attractive for practical implementation.

For future work, it suggested to consider additional terms in cost function, to enhance other parameters of inverter such as switching frequency and dc line voltage balancing. Also, it is suggested to make more enhancements on identification algorithm in order to predict system output with higher accuracy for more than three steps and improve system performance.

REFERENCES

[1] P. Mattavelli, "An Improved Dead-Beat Control for UPS Using Disturbance Observers", IEEE Trans. on Industrial Electronics, Vol. 52, No. 1, pp. 206-212, February 2005.

[2] P.C. Loh, D.G. Holmes, "Analysis of Multi-Loop Strategies for LC/CL/LCL-Filtered Voltage-Source and

Current-Source Inverters", IEEE Trans. on Industry Applications, Vol. 41, No. 2, pp. 644-654, March/April 2005.
[3] M.N. Uddin, H. Wen, "Development of a Self-Tuned Neuro-Fuzzy Controller for Induction Motor Drives", IEEE Transactions on Industrial Applications, Vol. 43, No. 4, pp. 1108-1116, July-August. 2007.
[4] G. Escobar, A.A. Valdes, J. Leyva Ramos, P. Mattavelli, "Repetitive-Based Controller for a UPS Inverter to Compensate Unbalance and Harmonic Distortion", IEEE Trans. on Industrial Electronics, Vol. 54, No. 1, pp. 504-510, February 2007.
[5] P. Cortes, M.P. Kazmierkowski, R.M. Kennel, D.E. Quevedo, J. Rodriguez, "Predictive Control in Power Electronics and Drives", IEEE Transactions on Industrial Electronics , Vol. 55, No. 12, pp. 4312-4324, Dec. 2008
[6] J. Rodriguez, J. Pontt, C. Silva, P. Correa, P. Lezana, P. Cortes, U. Ammann, "Predictive Current Control of a Voltage Source Inverter", IEEE Transactions on Industrial Electronics, Vol. 54, No. 1, pp. 495-503, February 2007.
[7] E.F. Camacho, C. Bordons, "Model Predictive Control", Springer, 2004.
[8] W. Wang, J. Vrbanek, "An Evolving Fuzzy Predictor For Industrial Applications", IEEE Transactions on Fuzzy Systems, Vol. 16, No. 6, pp. 1439-1449, December 2008.
[9] P. Angelov, E. Lughofer, X. Zhou, "Evolving Fuzzy Classifiers Using Different Model Architectures", Elsevier, Fuzzy Sets and Systems, Vol. 159, pp. 3160-3182, 2008.
[10] E. Banisaeed, S.M.R. Rafiei, M.H. Zarif, "An Improved Algorithm for Online Identification of Evolving TS Fuzzy Models", 8th WSEAS International Conference on Fuzzy Systems (FS'07), Vancouver, Canada, pp. 132-138, June 18-20, 2007.
[11] M.A. Perez, P. Cortes, J. Rodriguez, "Predictive Control Algorithm Technique for Multilevel Asymmetric Cascaded H-Bridge Inverters", IEEE Transactions on Industrial Electronics, Vol. 55, No. 12, pp. 4354-4361, December 2008.
[12] T. Geyer, G. Papafotiou, M. Morari, "Model Predictive Direct Torque Control - Part I: Concept, Algorithm, and Analysis", IEEE Transactions on Industrial Electronics, Vol. 56, No. 6, pp. 1894-1905, June 2009.
[13] A. Banakar, M.F. Azeem, "Parameter Identification of TSK Neuro-Fuzzy Models", Elsevier, Fuzzy Sets and Systems, Vol. 179, pp. 62-82, 2011.

BIOGRAPHIES

Ismail Banisaeed was born in Ramhormoz, Iran, 1979. He received the B.Sc. degree from Shahid Chamran University (Ahvaz, Iran) and the M.Sc. degree from Shahrood University (Shahrood, Iran) both in Electrical Engineering, in 2003 and 2006, respectively. Currently, he is a lecturer in Electrical Engineering at Mahshahr Branch, Islamic Azad University, Mahshahr, Iran. His research interests include power electronics, fuzzy systems and system identification.

Jamshid Baratai was born in Baghmalek, Iran, 1984. He received the B.Sc. and M.Sc. degrees in Electrical Engineering from Shahid Chamran university (Ahvaz, Iran) in 2006 and 2009, respectively. Currently, he is a Lecturer at Islamic Azad University, Ramhormoz Branch, Ramhormoz, Iran. His research interests include power system dynamic stability, control and stability of FACTS devices.