Fuzzy Hammerstein Model Based States Space Identification Approach of Nonlinear Dynamics Systems

JÉSSICA A. SANTOS
Federal University of Maranhão
Department of Electrical Engineering
Av. dos Portugueses, S/N, Bacanga
São Luís - MA, Brazil
jessica.almeida.santos@hotmail.com

GINALBER L. O. SERRA
Federal Institute of Maranhão
Department of Electrotechnical and Electronic
Av. Getúlio Vargas, 04, Monte Castelo
São Luís - MA, Brazil
ginalber@ifma.edu.br

Abstract: This paper presents a novel methodology for evolving fuzzy identification of nonlinear systems in state space based on Hammerstein models. The nonlinear static characteristic is approximated by an evolving Takagi-Sugeno fuzzy model and the linear dynamics by a state space model. The recursive estimation of the linear model in state space is performed based on the system Markov parameters applied to the algorithm of minimum realization ERA. Computational results illustrate the effectiveness of the proposed method in the online identification of nonlinear systems.

Key–Words: Evolving fuzzy systems, Hammerstein models, state space systems, Markov parameters.

1 Introduction

Modern systems are each day more complex and demand more acurace of the models. New development of modeling techniques increase its effort to incorporate issues like nonlinearities, uncertainties and temporal variation. However, there is not standard and unified mathematical method to describe the complex behavior of processes [1] [2] [3].

Several methods to identify systems and their nonlinearities are currently studied [6] [13]. Block-oriented models are widely used to describe nonlinear systems, and are successfully applied to various problems [5] [7]. Hammerstein model, a typical block oriented model, consists of a static nonlinear block cascading with a linear dynamic block [8]. This type of model has been proven as an efficient tool in the modeling of biological, chemical and electrical nonlinear systems [9].

Takagi-Sugeno (TS) fuzzy systems have been shown to be efficient in modeling the complexities of many systems. In [4], a new modeling methodology based on evolving Takagi-Sugeno neuro-fuzzy network used to forecast seasonal time series, is proposed. In [10], an algorithm for obtaining TS fuzzy models based on ant colony optimization algorithm, is presented. In [11], an extension of the FLEXFIS algorithm is proposed for the construction of more generalized, but less complex, fuzzy models, is proposed

A wide variety of methods have been developed to identify Hammerstein model. In [12] a methodology for identification of Hammerstein models in state space is presented. The static nonlinearity is modeled by polynomial parameterization. This approach requires *a priori* knowledge of the polynomial order. Moreover, the signal applied for identification is difficult to reproduce experimentally. In [13], a batch identification method of Hammerstein models based on correlation analysis, is proposed. This method uses a neuro-fuzzy network to identify the nonlinear static characteristic and the linear part is approximated by an autoregressive model. For the implementation of this technique is also necessary to apply two separate special signals.

This paper presents a novel methodology for evolving identification of nonlinear systems in state space based in Hammerstein models. The main contributions of the proposed methodology as the following:

- Is does not depend on the use of specifics signals for static nonlinearity estimation and linear dynamics as in others methodologies from the literature;

- The application of an evolving Takagi-Sugeno fuzzy system. These models are able to adapt their structure online according to data;

- The new evolving fuzzy modeling algorithm produces models in state space of minimum order, based on system Markov parameters.

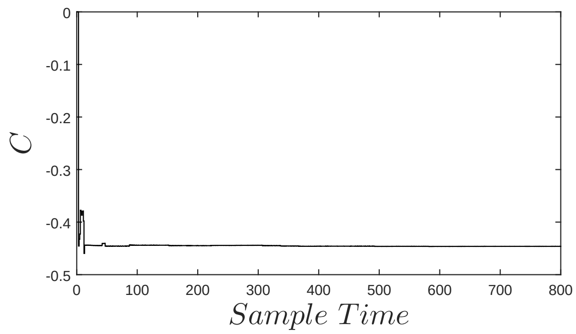

Figure 11: Parameters variation of the linear dynamic model: parameters variation of matrix C.

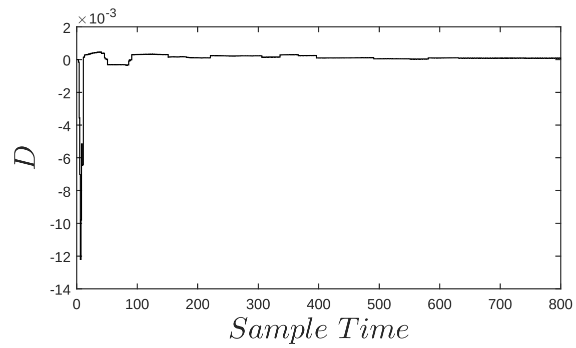

Figure 12: Parameters variation of the linear dynamic model: parameters variation of matrix D.

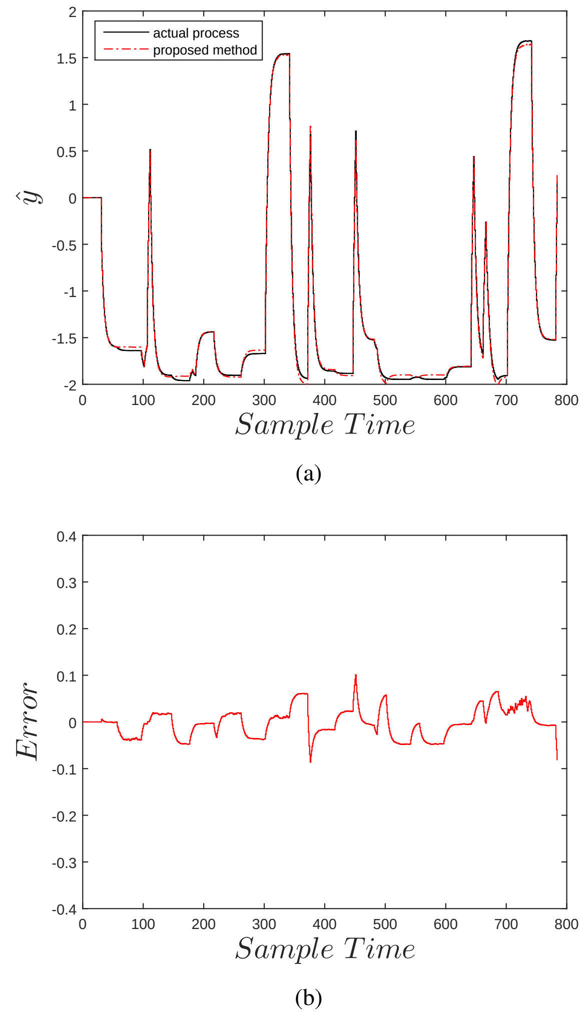

Figure 13: Validation result. (a) solid black line: actual process output y; dashed dotted red line: estimated output by proposed method $\hat{y}$. (b) prediction error.

4 Conclusion

The novel methodology proposed in this paper is efficient in identification of systems with complex nonlinearities. The identification of the static nonlinear block by an evolving TS fuzzy model shows to be satisfactory for estimation of the static nonlinear characteristic in all operations regions of the nonlinear system, with a smaller number of rules. Moreover, the proposed method varies the antecedent and consequent structure according experimental data. The recursive identification of the linear block, through the ERA algorithm presented good performance. Thus, the results presented in this paper show that both nonlinear block and linear block approximation were considered satisfactory. The comparison analysis the with methods in [13] shows that the proposed methodology presents better results with lower number of rules.

Table 1: Comparative analysis for the proposed methodology.

Model	MSE^*	MSE^+
Proposed	2.7088×10^{-4}	9.1415×10^{-4}
Neuro-fuzzy	5.2323×10^{-4}	9.9665×10^{-4}
Polynomial	4.3000×10^{-3}	7.6000×10^{-3}

MSE^* - training.
MSE^+ - validation.

References:

[1] Q. Jin, H. Wang, Q. Su, B. Jiang and Q. Liu, A novel optimization algorithm for MIMO Hammerstein model identification under heavy-tailed noise. ISA transactions, 2017.

[2] L. Shang, J. Liu and Y. Zhang, Recursive Fault Detection and Identification for Time-Varying

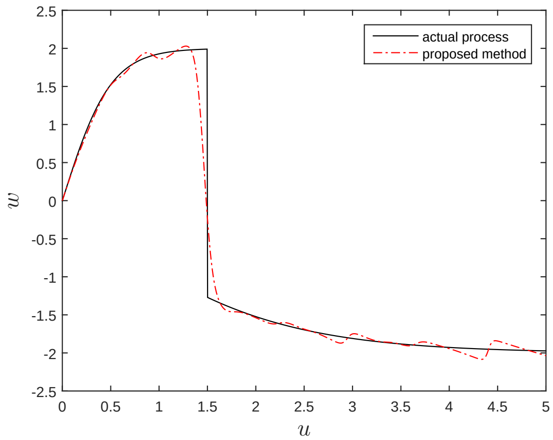

Figure 14: Nonlinear static function. Solid black line: actual process; dashed dotted red line: proposed method.

Processes. Industrial & Engineering Chemistry Research 55.46 (2016): 12149-12160.

[3] E. Costa, and G. Serra, Swarm optimization based adaptive fuzzy control design from robust stability criteria. Journal of Intelligent & Fuzzy Systems 32.3 (2017): 1787-1804.

[4] S. Rodrigues Júnior and G. Serra, A novel intelligent approach for state space evolving forecasting of seasonal time series. Engineering Applications of Artificial Intelligence 64 (2017): 272-285.

[5] M. Jafari, M. Salimifard and M. Dehghani, Identification of multivariable nonlinear systems in the presence of colored noises using iterative hierarchical least squares algorithm. ISA transactions 53.4 (2014): 1243-1252.

[6] W. Zhao, H. Chen and R. Tempo, Recursive Nonparametric Identification of Nonlinear Systems with Adaptive Binary Sensors. IEEE Transactions on Automatic Control (2017).

[7] R. Rattanawaorahirunkul, P. Sanposh and C. Panjapornpon, Nonlinear system identification of pH process using Hammerstein-Wiener model. Electronics, Information, and Communications (ICEIC), 2016 International Conference on. IEEE, 2016.

[8] S. Lajnef, N. Boulejfen and F. Ghannouchi, Cartesian Augmented Hammerstein Model for Nonlinearity and I/Q Impairments Compensation in Concurrent Dual-Band Transmitters. IET Communications (2017).

[9] Jalaleddini, Kian, and Robert E. Kearney, Subspace identification of SISO Hammerstein systems: application to stretch reflex identification. IEEE Transactions on Biomedical Engineering 60.10 (2013): 2725-2734.

[10] S. Tsai, and Y. Chen, A Novel Fuzzy Identification Method Based on Ant Colony Optimization Algorithm. IEEE Access 4 (2016): 3747-3756.

[11] E. Lughofer, C. Cernuda and M. Pratama, Generalized flexible fuzzy inference systems. Machine Learning and Applications (ICMLA), 2013 12th International Conference on. Vol. 2. IEEE, 2013.

[12] K. Hammar, T. Djamah and M. Bettayeb, Fractional Hammerstein system identification using polynomial non-linear state space model. Control, Engineering & Information Technology (CEIT), 2015 3rd International Conference on. IEEE, 2015.

[13] L. Jia, X. Li and M-S. Chiu. The identification of neuro-fuzzy based MIMO Hammerstein model with separable input signals. Neurocomputing 174 (2016): 530-541.

[14] E. Lughofer, FLEXFIS: A robust incremental learning approach for evolving Takagi–Sugeno fuzzy models. IEEE Transactions on fuzzy systems 16.6 (2008): 1393-1410.

[15] E. Lughofer, Evolving fuzzy systems-methodologies, advanced concepts and applications. Vol. 53. Berlin: Springer, 2011.

[16] C-Y. Wu, J.S-H. Tsai, S-M. Guo, L-S. Shieh, J. Canelon, F. Ebrahimzadeh and L. Wang, A novel on-line observer/Kalman filter identification method and its application to input-constrained active fault-tolerant tracker design for unknown stochastic systems. Journal of the Franklin Institute 352.3 (2015): 1119-1151.

[17] J-N. Juang and M. Phan. Identification and control of mechanical systems. Cambridge University Press, 2001.

[18] L. Ljung, System identification. Signal analysis and prediction. Birkhäuser, Boston, MA, 1998. 163-173.

[19] J-N. Juang, M. Phan, L. Horta, R. Longman, Identification of observer/Kalman filter Markov parameters: theory and experiments. Journal of Guidance, Control, and Dynamics 16.2 (1993): 320-329.