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Research to Design Predictive Controller for Nonlinear Object based on Fuzzy Model

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Abstract - *Model predictive control (MPC) is a control method that is used quite commonly in industrial processes. However, most predictive controllers are designed based on the linear model of the System, so the quality of control is limited when the System operates on a large area. In the predictive control system, building the object model has decisive significance to the quality of the control system. The paper proposes a method to build nonlinear object modeling using Takagi-Sugeno fuzzy model. The research applied on subjects is a double-linked tank system. The simulation results show the accuracy and feasibility of the model.*

Keywords — *Model predictive control, Takagi-Sugeno fuzzy model, Coupled-tanks systems.*

I. INTRODUCTION

Predictive control is a control method widely used in industry because it can control multivariable systems with strict constraints [1]. Although recently proposed and developed, the predictive model driver is interested in research and application in both theory and practice [2], [3]. Although it has been applied successfully in many fields, especially in industrial processes, the predictive control model still has many limitations in practical operation [4]. One of the main reasons is that most predictive controllers are designed based on a linear model of a system that can only accurately describe a certain operating point's "neighborhood" system. Meanwhile, in reality, the systems are all nonlinear systems with a large area of operation, so the use of linear models limits the predictive controller's ability. Therefore, later studies focus on nonlinear model predictive control to maintain stable control quality when it operates over a large working area. In recent years, fuzzy nonlinear models have been studied and applied successfully in predictive control of nonlinear systems in the industry [5-8].

A double-linked tank system is a typical industrial process system such as water treatment, boiler, reactor, distillation column; for these systems, the control of the tanks' liquid levels is a very important control problem. In recent years, many studies on control design have been successfully applied on double-linked tank systems such as fuzzy logic control [9], using artificial hydrocarbon networks [10], especially in battles. predictive control strategy based on model [11] - [13]. However, most of them are predictive control studies based on linear models [11], [12], and there are very few studies on predictive control using nonlinear models of double-coupled sink systems, for example, neural network model [13-18] or fuzzy model.

Predictive control is a method based on the real system model to predict future responses, on that basis, a target function optimization algorithm will be used to compute the credit chain. Control effect so that the deviation between the model's predictive and reference response is minimal. The general structure of the predictive control system is shown in Fig. 1.

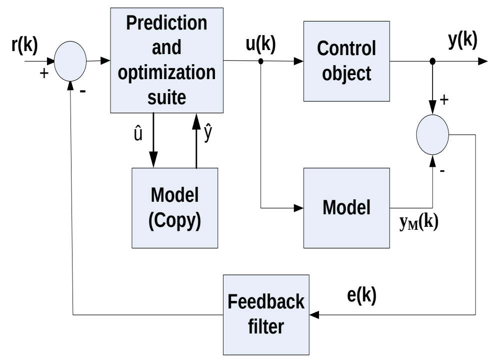


Fig. 1 The general structure of the predictive control system

Where: r(k) is the reference signal of the model at time k, and it is the desired output state of the control object; y(k) is the output signal of the real System; $y_M(k)$ is the output of the model; u(k) is the object control signal at time k; $\hat{u}, \hat{y}$ is the predictive control signal and corresponding future predictive output of the System based on the model.

Predictive control techniques are flexibly applied in process control by adjusting the controller structure to a given control object according to the binding parameters and operational requirements. System. A predictive controller consists of the following 5 basic components: System model and noise distribution model; The target function; Binding conditions; Method of solving optimization problems; Control strategy gradually translates into the future.

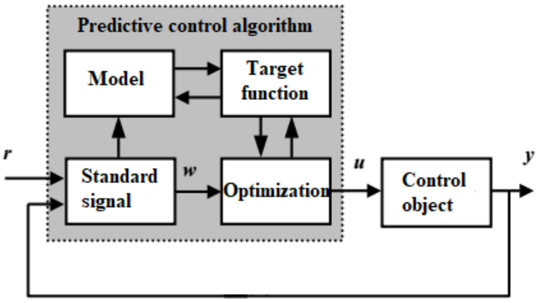


Fig. 2 Block diagram of a predictive control system

The biggest difficulty when applying predictive control is building models and solving optimization problems. This work is more difficult for nonlinear systems because it is difficult to build a good model that accurately describes the System's properties. The optimization algorithm is often complex, with a large number of calculations and time. Implementation is prolonged due to solving the problem of nonlinear optimization. Therefore, according to statistics, over 2200 commercial applications use predictive control techniques, most of which focus on linear systems. Therefore, the research and application of predictive control for nonlinear systems are of much interest to many scientists, and it has great significance in both theory and practice. For nonlinear dynamic systems, the model is constructed in two ways: the physical model or the white-box model, and the black or gray-box model is the model using the general approximation and the I/O data set. of the System. The physical model is only suitable for simple systems, and the properties of the System can be described by differential equations, while the black or gray-box model is suitable for complex systems or in the case of not knowing much about the System when modeling. Due to the complex nature of nonlinear systems, the black and gray box models are often used in practice. In predictive control, an important standard for the application of black-box modeling techniques is: The model structure is simple, reliable, and allows to exploit the known amount of information about the System fully; the model is not too complicated, that is, the number of parameters is not too large; easy to apply online optimization algorithm (online) to calibrate model parameters. This paper proposes a method to build a nonlinear object model using Takagi-Sugeno fuzzy model.

II. BUILDING OBJECT MODEL WITH TAKAGI-SUGENO FUZZY MODEL

A. Controller Object

Considering the control object is a dual tank system (Fig. 3)

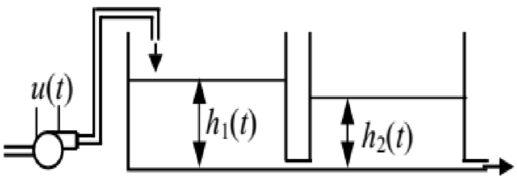


Fig. 3 Model of dual tank system

Described by the System of equations:

$$\begin{cases} \dot{h}_1 = \dfrac{1}{A}\left(ku - a_1\sqrt{2g\left(h_1 - h_2\right)}\right) \\ \dot{h}_2 = \dfrac{1}{A}\left(a_1\sqrt{2g\left(h_1 - h_2\right)} - a_2\sqrt{2gh_2}\right) \end{cases}$$

In which: A = 200 cm^2 is the cross section of 2 tanks; a_1 = 1cm^2 is the cross-section of the pipe connecting the two tanks; a_2 = 0.5 cm^2 is the drainage pipe cross-section in tank 2; g = 9.81 m/s^2 = 981cm/s^2 is the acceleration of gravity; maximum pump flow Q_{max} = 18 dm^3/min = 300 cm^3/sec.

The system control problem requires keeping the liquid level in the second tank following a given reference trajectory. The flow of water pumped into the first tank is shown in component k.u, where u is the control voltage varying from 0 to 24VDC, and k is the pump amplification factor. In practice, k is a nonlinear coefficient depending on the characteristics of the pump motor. For simplicity, in this paper, choose k as a constant, then the flow rate of water pumped into the tank is linear according to voltage u. So with the maximum flow Q_{max} = 300 cm^2/sec, then k=12.5.

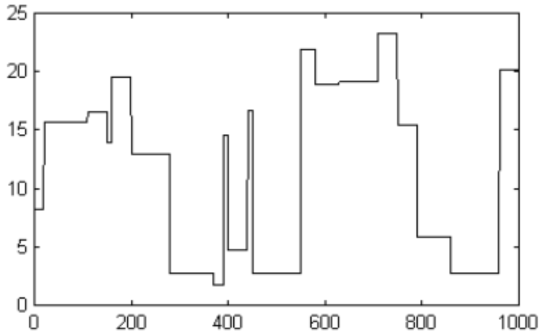


Fig. 4 Dual tank input signal

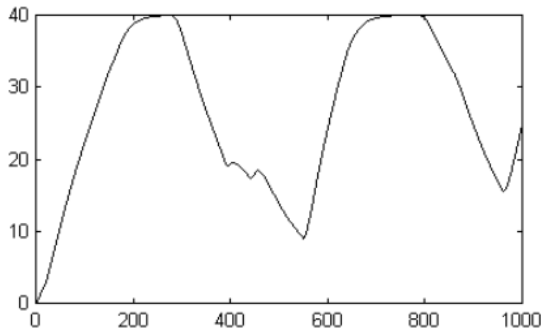


Fig. 5 Dual tank output signal

The semi-random input data set (Fig. 4) responds to the System's output (water level h_2); it is shaped like Fig. 5. Observing the system response, we see: The inertia of the large System; the System does not respond to rapidly varying input signals (high-frequency control signals); Output range from 0 to 40 cm due to the physical limitation of the storage tank.

B. Fuzzy Modeling

Using the Takagi-Sugeno fuzzy System with two regression inputs u(k-1) and h_2(k-1) and one output h_2(k) to describe the dual tank system. For the convenience of notation, in this paper, choose the symbol h(k-1) instead of h_2(k-1) and h(k) instead of h_2(k). Constraints on I/O signal:

$$\begin{cases} 0 \le u(k) \le 24 \\ 0 \le h(k) \le 40 \end{cases}$$

Please choose the number of input fuzzy sets u(k-1) is 2, having a Gaussian distribution with two centers at c_1=7.2 and c_2 = 16.8; variance σ ≈ 8.

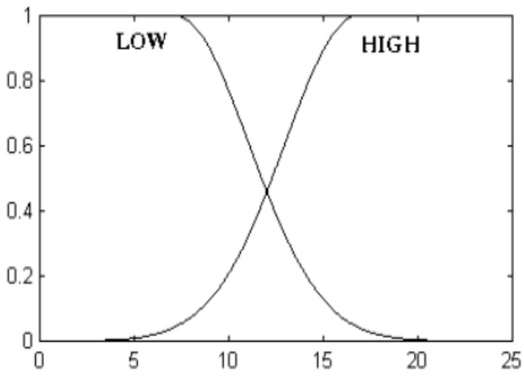


Fig. 6 Set of input fuzzy u(k-1)

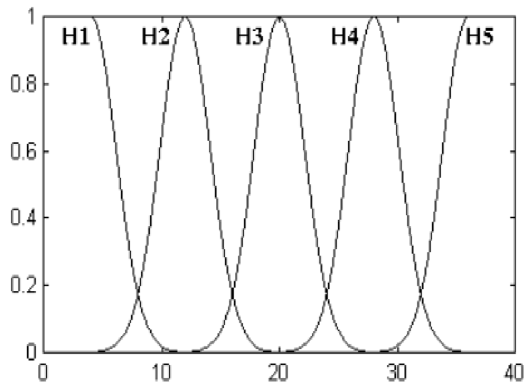


Fig. 7 Set of fuzzy output h(k-1)

Choose the number of input fuzzy sets h(k-1) is 5, having the form of the Gaussian distribution with centers at c_1 = 4, c_2 = 12, c_3 = 20, c_3 = 28 and c_4 = 36; variance σ ≈ 2.

The general fuzzy rule set for the Takagi-Sugeno fuzzy model has the form:

R_j: If h(k-1) is $A_{j,1}$ and u(k-1) is $A_{j,2}$ then: $h_j(k) = w_{j,0} + w_{j,1}u(k-1) + w_{j,2}h(k-1)$

Since the number of input fuzzy sets u(k-1) is 2 and the number of input fuzzy sets h(k-1) is 5, a maximum of 2x5 = 10 fuzzy rules are built. That is j = 1...10. Thus we need to determine the number of parameters for the model is 3x10 = 30 parameters.

The output of the control object model is summarized as follows:

$$h(k) = \sum_{j=1}^{10}\left(w_{j,0} + w_{j,1}u(k-1) + w_{j,2}h(k-1)\right)\Phi_j\left([u,h],c_j,\sigma_j\right) \quad (1)$$

Inside:

$$\Phi_j\left([u,h],c_j,\sigma_j\right) = \frac{\mu_j}{\sum_{j=1}^{10}\mu_j} \qquad (2)$$

$$\sum_{j=1}^{10}\Phi_j = 1 \qquad (3)$$

μ_j is the dependence of the regression signals in the j law on fuzzy sets with the Gaussian distribution and the values determined by:

$$\mu_j = \exp\left(-\frac{1}{2}\frac{\left(u(k-1)-c_{j,1}\right)^2}{\sigma_{j,1}^2}\right).\exp\left(-\frac{1}{2}\frac{\left(h(k-1)-c_{j,2}\right)^2}{\sigma_{j,2}^2}\right) \qquad (4)$$

c_j, σ_j are centroids and corresponding variance of fuzzy sets having values given in fuzzy input sets above.

C. The Algorithm for Recognition of the Takagi-Sugeno Fuzzy Model

Select a data set to identify model parameters including 2000 quasi-random input and output data samples in the direction of covering the entire possible operating area of the System to bring into play all the properties of the local models. . The data set has the form:

$$\theta_j = \begin{bmatrix} w_{j,0} & w_{j,1} & w_{j,2} \end{bmatrix}^T \qquad (5)$$

$$\psi_j = \begin{bmatrix} 1 & u(k-1) & h(k-1) \end{bmatrix}^T \qquad (6)$$

Using LOLIMOT algorithm with the above identification data set to identify the parameters of the model, we get:

$$\theta_j = \left(\psi_j^T Q_j \psi_j\right)^{-1}\psi_j^T Q_j h_d \qquad (7)$$

With:

h_d = $[h_d(1), h_d(2),..., h_d(2000)]^T$: Set of 2000 identification output samples.

Ψ_j = $[\psi_j(1), \psi_j(2), ..., \psi_j(2000)]^T$: Matrix of input regression signals.

Q_j = diag(Φ_j([u(1), h(1)], c_j, σ_j), ..., Φ_j([u(2000), h(2000)], c_j, σ_j)): is a cross-block matrix and is called an input weight matrix. The components u(i), h(i), (i = 1...2000) are discrete values of a given identity data set.

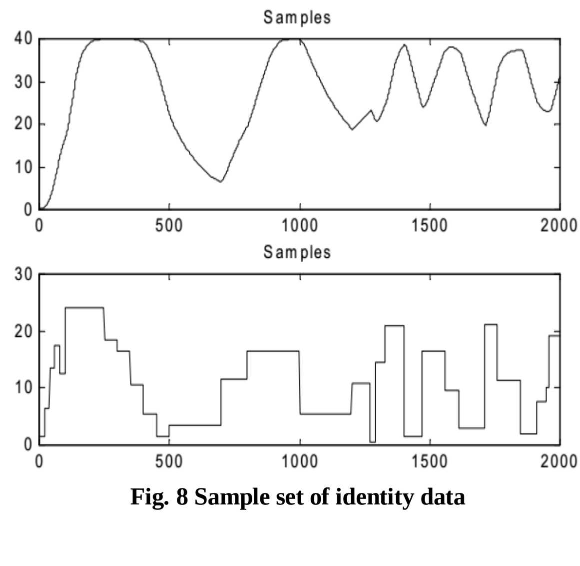


Fig. 8 Sample set of identity data

R_1: If h(k-1) is H1 and u(k-1) is LOW then: $h_1(k)=0.0023 + 0.0159u(k-1) + 0.9873h(k-1)$

R_2: If h(k-1) is H1 and u(k-1) is HIGH then: $h_2(k)=0.642 + 0.0068u(k-1) + 1.0115h(k-1)$

R_3: If h(k-1) is H2 and u(k-1) is LOW then: $h_3(k)=0.0048 + 0.0047u(k-1) + 0.9919h(k-1)$

R_4: If h(k-1) is H2 and u(k-1) is HIGH then: $h_4(k)=0.5609 – 0.0173u(k-1) + 1.005h(k-1)$

R_5: If h(k-1) is H3 and u(k-1) is LOW then: $h_5(k)=-0.2142 + 0.0315u(k-1) + 0.9989h(k-1)$

R_6: If h(k-1) is H3 and u(k-1) is HIGH then: $h_6(k)=-0.7215 + 0.0228u(k-1) + 1.0220h(k-1)$

R_7: If h(k-1) is H4 and u(k-1) is LOW then: $h_7(k)=0.0805 + 0.0189u(k-1) + 0.9881h(k-1)$

R_8: If h(k-1) is H4 and u(k-1) is HIGH then: $h_8(k)=-0.5766 + 0.0264u(k-1) + 1.0111h(k-1)$

R_9: If h(k-1) is H5 and u(k-1) is LOW then: $h_9(k)=-0.4922 + 0.0196u(k-1) + 0.0077h(k-1)$

R_{10}: If h(k-1) is H5 and u(k-1) is HIGH then: $h_{10}(k)=1.1091 + 0.0035u(k-1) + 0.9908h(k-1)$

The output of the fuzzy model is synthesized by formula (1).

III. SIMULATION RESULTS

Select the control signal set of 1000 semi-random samples with the shape as shown in Fig. 6. The accuracy of the model is calculated by the formula:

$$VAF = 100\%\left(1-\frac{\operatorname{var}\left(Y_m - Y\right)}{\operatorname{var}\left(Y\right)}\right) \qquad (8)$$

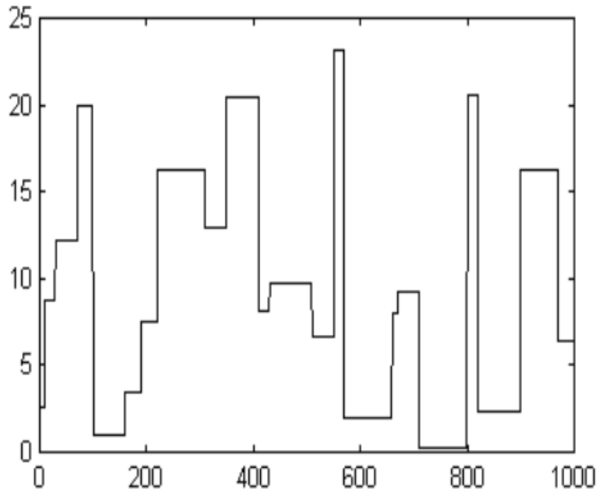
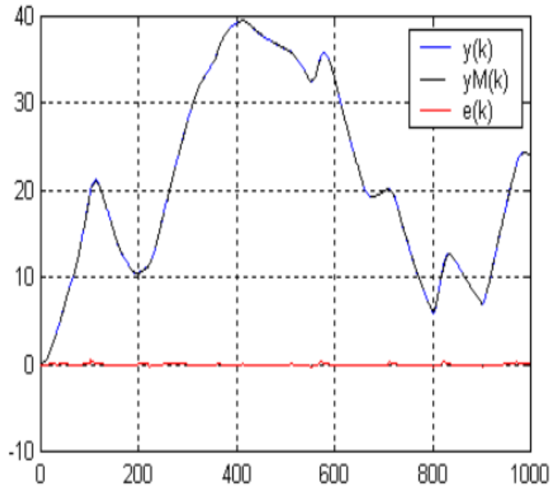
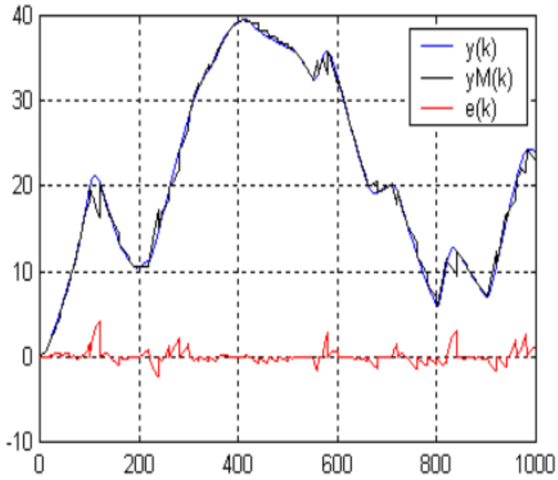


Fig. 9 Sample set of control data

Y is the output of the System, and Ym is the predictive output from the model. Putting the control data sample set simultaneously on the model identified above and the control object, we get the results shown in Fig. 7a, b, and Fig. 8. In which: Fig. 7a is the forecast result. one step forward; Fig. 7b shows the result of forecasting 20 steps forward.



a)



b)

Fig. 10a, b: Results of one-step forecast and forecast of 20 steps
a) Model accuracy 99.994%; b) Model accuracy 99.485%

IV. CONCLUSION

Through the above results, we realize that: although there are still errors in the model, especially in the forecast of 20 steps forward, the above model can be completely applied in the predictive control algorithm. The main reason is that the forecast range is always limited; when the forecast range increases, it will increase the algorithm's execution time. In the scope of this article, the forecast range only changes in the range from 1 to 20, corresponding to the accuracy of the model from 99,992% to 99,5138%.

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REFERENCES

[1] E. F. Camacho, C. B. Alba, Model Predictive Control,Springer, (2007).

[2] L. Wang, Model Predictive Control System Design and Implementation Using MATLAB®, Advances in Industrial Control, Springer, (2009).

[3] D. Q. Mayne, Model Predictive Control: Recent Developments and Future Promise, Automatica,50(2014) 2967-2986.

[4] M. G. Forbes, R. S. Patwardhan, H. Hamadah, R. B. Gopaluni, Model Predictive Control in Industry: Challenges and Opportunities, IFAC – Papers On-Line,48-8(2015) 531-538.

[5] S. Joe Qin, Thomas A. Badgwell.,An Overview of nonlinear Predictive Control Application, IEEE.((2000).

[6] I. Boulkaibet, K. Belarbi, S. Bououden, T. Marwala, M. Chadli, A New T-S fuzzy Model Predictive Control for Nonlinear Processes, Expert Systems With Applications,88, (2017) 132-151.

[7] J. Mendes, R. Araújo, F. Souza, Adaptive Fuzzy Identification and Predictive Control for Industrial Processes, Expert Systems with Applications, 40(2013) 6964-6975.

[8] M. H. Khooban, N. Vafamand, T. Niknam,T–S Fuzzy Model Predictive Speed Control of Electrical Vehicles,ISA Transactions, 64(2016) 231-240.

[9] S. Yordanova,Fuzzy Logic Approach to Coupled Level Control,Systems Science & Control Engineering,4(2016) 215-222.

[10] H. Ponce, P. Ponce, H. Bastida, A. Molina,A Novel Robust Liquid Level Controller for Coupled-Tanks Systems Using Artificial Hydrocarbon Networks, Expert Systems with Applications, 42(2015),8858-8867.

[11] M. U. Khalid, M. B. Kadri,Liquid Level Control of Nonlinear Coupled Tanks System Using Linear Model Predictive Control,Proceedings of the IEEE 2012 International Conference on Emerging Technologies (ICET)Islamabad, Pakistan.,)(2012),8-9

[12] M. Awais, H. Alam, A. Muhammad,Model Predictive Control Design for Coupled Tank System,Proceedings of The InternationalconferenceQualityTime17(2017) 26-27 Kyrgyzstan.

[13] F. Zhou, H. Peng, Y. Qin, X. Zeng, W. Xie, J. Wu,RBF-ARX Model-Based MPC Strategies with Application to A Watertank System, Journal of Process Control,34,(2015) 97-116.

[14] Nguyen Minh Hoa, Identification of Coupled-Tanks Systems with Fuzzy Models based on Measurement Data from Simulation and Experimental Apparatus, The University of Da Nang Journal of Science and Technology, 124,(2018) 28-32.

[15] Babuska, J.M Sousa, HB Verbrugen,Predictive Control of Nonlinear System Basic on Fuzzy and Neural Models, IEEE.

[16] Rolf Findeisen, Frank Allgower (2001),An Introduction to nonlinear model Predictive Control" IEEE transaction on fuzzy System.,(2000).

[17] S. Mollov, R. Babuska, J. Abonyi, H. B. Verbruggen, "Effective Optimization for Fuzzy Model Predictive Control,IEEE Transactions on Fuzzy Systems,12, (2004) 661-675.

[18] Qilun Zhu, Simona Onori, Robert Prucka,Nonlinear Economic Model Predictive Control for SI Engines based on Sequential Quadratic Programming,American Control Conference (ACC), Boston, MA, (2016) 1802-1807.