

ADAPTIVE TUNING OF A FUZZY PID CONTROLLER FOR LYOPHILIZATION PLANT

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Abstract: A design methodology for adaptive tuning of a fuzzy PID type controller is presented. The adaptation of the fuzzy PID gain coefficients is done by implementing a simple internal model scheme by Hammerstein fuzzy-neural predictive model and a gradient optimization procedure. Simulation experiments to control a nonlinear relation in Lyophilization plant are made.

АДАПТИВНА НАСТРОЙКА НА РАЗМИТ ПИД РЕГУЛАТОР ЗА ПРОЦЕСА ЛИОФИЛИЗАЦИЯ

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Резюме: В този доклад е представена методология за адаптивна настройка на размит ПИД регулатор. Адаптацията на параметрите на регулатора е осъществена на база опростен подход с вътрешен невронно-размит Хамерщайн модел и градиентен оптимизационен алгоритъм. Направени са симулационни експерименти за управлението на процеса лиофилизация.

1. INTRODUCTION

Control of nonlinear systems is difficult in the absence of a systematic procedure as available for linear systems. Many techniques are limited in their application to special class of systems. Therefore, more commonly available methods as fuzzy logic and neuro-fuzzy techniques which are heuristic in nature can reduce the arbitrariness in the design of a controller to a great extent [1].

The fuzzy logic control method is a type of intelligent language control. It adopts manual control rules or rules established upon experts experience and simulates logically consequent processes of human brain. It does not rely on the model of the system and can deal with the nonlinearity of parameters and uncertain problems. The fuzzy logic control method is flexible and adaptive; however, its stability is insufficient [2]. Also, one of the major problems of the fuzzy logic control is the tuning of the controller gains by trial and error procedures, which more often leads to unsatisfactory system performance [1].

Since, major industrial processes are often nonlinear a fuzzy controller with fixed parameters will derive poor control performance in such cases. To overcome this problem it can be used adaptive control schemes.

Nowadays, fuzzy-neural systems have been proved to be a promising approach to solve complex nonlinear control problems. This motivated many researchers to combine its advantages for solving complex control problems. Fuzzy-neural models have been proposed as an advantageous alternative to pure feed forward neural networks schemes for learning the nonlinear dynamics of a system from input-output data. Also, its capability

to be combined with an optimization procedure expands the potentials for constructing many nonlinear adaptive control schemes.

This paper investigates the performance of a fuzzy PID controller when the controller gains are under adaptation in each sampling period by implementing a simple internal model tuning procedure based on a fuzzy-neural Hammerstein predictive model and a gradient optimization procedure. Thus, the presented approach implements the idea for multiple FPID control which is suitable in control of nonlinear plants such as lyophilization.

2. DESIGN OF THE ADAPTATION PROCEDURE FOR FPID CONTROLLER

Fuzzy control is a practical alternative for a variety of challenging control applications since it provides a convenient method for constructing nonlinear controllers via the use of heuristic information. A natural Mamdani fuzzy controller using an expert rule base and triangular/gaussian membership functions gives a fuzzy PD control law. Thus, the integral part of the FPID controllers is introduced by different hybrid FPID structures [3]. One of them, most applied in practice is shown on Fig. 1. A disadvantage of the fuzzy PID controllers is to define a proper tuning of the gain coefficients in order a higher system performance to be obtained, since classical PID tuning strategies are not applicable in this case.

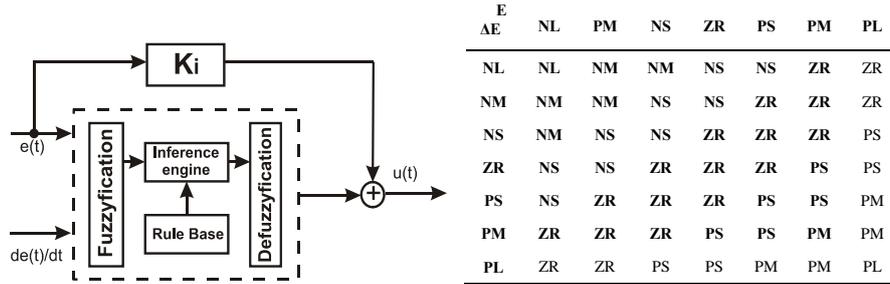


Fig. 1 Fuzzy PID type controller and expert PD type rules table

In order an accurate tuning coefficients for the FPID controller to be obtained, the implementation of a simple internal model which predicts the process dynamics and a simple optimization procedure which computes the values of the gains by minimization of an objective function at each sampling interval is considered. Thus, implementing a predictive feature into the FPID controller will simplify the tuning procedure and strength its robustness in notion to the nonlinear process under control.

The used process model in this study represents a simple Hammerstein fuzzy-neural model (FNH) in which the structural nonlinearity is approximated by Takagi-Sugeno inference system [4]. The used model for nonlinearity approximation is taken in the NARX type:

$$u_m = f_u(x(k)) \quad (1)$$

where the elements of the considered regression vector $\mathbf{x}(k)$ are given by:

$$x(k) = [u(k), \dots, u(k - n_u)] \quad (2)$$

The unknown nonlinear functions f_u can be approximated by Takagi-Sugeno type fuzzy rules:

$$R^{(i)}: \text{if } x_j \text{ is } \tilde{A}_j^{(i)} \text{ and } x_p \text{ is } \tilde{A}_p^{(i)} \text{ then } f_u^{(i)}(k) \quad (3)$$

$$f_u^{(i)}(k) = d_1^{(i)}u(k) + d_2^{(i)}u(k-1) + \dots + d_{n_u}^{(i)}u(k-n_u) + d_0^{(i)} \quad (4)$$

($i=1, 2, \dots, N$), where N is the number of the fuzzy rules, A_i is an activated fuzzy set defined in the universe of discourse of the input $x=[x_1, x_2, \dots, x_p]$ and the crisp coefficients d_{ji} are the coefficients into the Sugeno function f_u . From a given input vector, the output of the fuzzy model is inferred by computing the following equation:

$$u_m(k) = f_u^{(i)}(k)g_u^{(i)} \quad \text{where} \quad g_u^{(i)} = \prod_{i=1}^N \mu_{ui}^{(i)} \quad (5)$$

where μ_{ui} are the degrees of fulfillment in notion to ui -th activated fuzzy membership function.

Afterwards the linear part is introduced into the fuzzy model as follows:

$$f_s^{(i)}(k) = a_1^{(i)}y(k-1) + \dots + a_{n_y}^{(i)}y(k-n_y) + b_1^{(i)}u_m(k) + \dots + b_{n_u}^{(i)}u_m(k-n_u) + b_o \quad (6)$$

Finally the output of the designed Fuzzy-Neural Hammerstein model is computed as:

$$\begin{aligned} y(k+1) &= \sum_{j=1}^N \left(\sum_{i=1}^{n_a} a_i y(k-i+1) + \sum_{i=1}^{n_b} b_i u_{mj}(k-i-n_d+1) \right) \\ &= \sum_{j=1}^N \left(\sum_{i=1}^{n_a} a_i y(k-i+1) + \sum_{i=1}^{n_b} b_i d_j g_{uj}(u(k-i-n_d+1)) \right) \end{aligned} \quad (7)$$

In the FNH model it is needed to determine the unknown parameters – the number of membership functions, their shape and the parameters of the function f_u in the consequent part of the rules. This is an identification procedure for which have been proposed numerous approaches. In this work is applied a simplified fuzzy-neural approach, with learning procedure described in [4], [5].

To compute the FPID gains, an optimization task by a simple gradient algorithm is solved. For this purpose the following cost function in notion the predicted system output is defined:

$$J(k, u(k)) = \frac{1}{2} \hat{e}^2(k+1) = \frac{1}{2} (r(k+1) - \hat{y}(k+1))^2 \quad (8)$$

Gradient vector ∇P in the n -dimensional space have n -components which are partial derivatives on cost function on each parameter rules in point $x^{(k)}$, an exactly:

$$\nabla P(x^{(k)}) = \left(\frac{\partial P(x^{(k)})}{\partial x_i} \right)_{i=1, n} \quad (9)$$

From any starting point $x^{(k)}$, the passage toward next $x^{(k+1)}$ can be made iteratively by the following expressions, respectively for finding the extremum.

$$x^{(k+1)} = x^{(k)} - s_k \nabla P(x^{(k)}) \quad (10)$$

Usually, the discrete PID controller has the following structure:

$$u(k) = u(k-1) + K_1 e(k) + K_2 e(k-1) + K_3 e(k-2) \quad (11)$$

Thus, the PID controller gains can be adjusted by minimizing the above performance index according to the following equation:

$$K_i(k) = K_i(k-1) - \gamma(r(k+1) - \hat{y}(k+1)) \frac{\partial \hat{y}(k+1)}{\partial u(k)} \frac{\partial u(k)}{\partial K_i} \quad (12)$$

where γ is the learning rate according to controller parameters K_i

3. SIMULATION EXPERIMENTS

The assumed plant process in the following simulation experiments is a Lyophilization plant. Lyophilization process is widely used in pharmaceutical and food industries, preparing stable dried medications and foodstuffs for astronauts and alpinists. The main objective of the Lyophilization process is to remove the preliminary frozen water which takes part from the product structure by its sublimation. Referring to Fig.1 a simplified diagram of the main components of the Lyophilization plant is shown. The plant consists particularly of a drying chamber (1); temperature controlled shelves (2), a condenser (3) and vacuum pump (4). The major purposes of the shelves are to cool and freeze or to supply heat to the product. This is supported by the shelves heater and refrigeration system (5). On these shelves the product is placed (6). The chamber is isolated from the condenser by valve (7). The vacuum system is placed after the condenser. After the process is completed the condenser is heated in order the frozen ice from its wall to be removed [6], [7].

After the product is entirely frozen, the chamber is evacuated in order to increase the partial vapor water pressure difference between the frozen ice zone and the chamber. The shelf heating system starts to provide enthalpy for the sublimation process. The sublimation takes place at a moving ice front, which proceeds from the top of the frozen material downwards. At the end of the primary drying, all the unconstrained water has been removed and what remains is the water which is constrained in the solution. At this point, the product can be removed, but in practice the water content is too high to guarantee biological stability. The stage in which the remaining water content is further reduced is called secondary drying, which takes place at higher temperature. In this contribution only the first stage of the drying process called primary drying is assumed.

The participating ice is the unconstrained water accumulated in the small cylindrical tubes. Throughout the primary drying the product, which consists of the dried layer on the top and the frozen core at the bottom, stays below a certain temperature to insure that no melting occurs.

In this contribution is assumed a small scale Lyophilization plant, for drying of 50 vials filled with glycine in water adjusted to pH 3, with hydrochloric acid. The schematic diagram on Fig. 2 depicts the sublimation process occurring at the interface which is located at a distance x from the vial bottom. During sublimation the interface moves in a negative

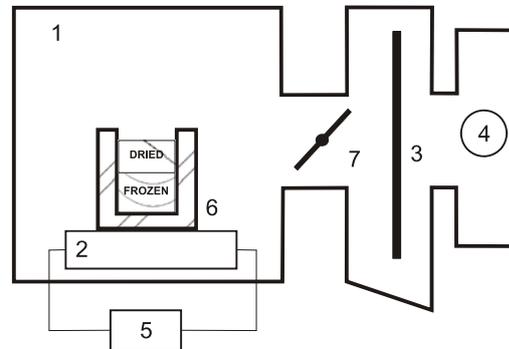


Fig.2. Simplified Lyophilization plant

direction, while the product height remains constant. The sublimated water leaves product through the already dried product layer.

Energy inside the frozen product layer is lost due to the sublimated water and the conducted heat to the dried product layer. The heat flux from the chamber to the condenser depends on the thickness of the crystallized water at the condenser wall.

The following initial conditions for simulation experiments are assumed:

- Initial shelf temperature, before the start of the primary drying $T_{s,in} = 228\text{ K}$
- Initial thickness of the interface front $x=0.0023\text{ m}$
- Thickness of the product $L=0.003\text{ m}$
- Reference product temperature $T_p=255\text{ K}$

In the primary drying stage it is required to maintain the shelf temperature about 298 K , until the product is dried, which requires about 45 min. It has to be mentioned, that for a reference point for the end of the simulation experiments was taken the final value of the interface front at value $x=0.0001\text{ m}$. This is due to the nature of the Lyophilization process.

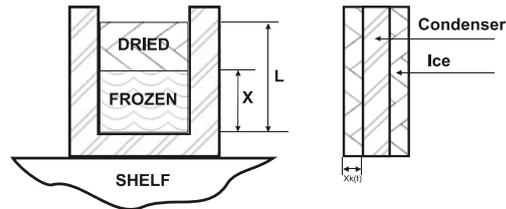


Fig.2. Sublimation in a vial

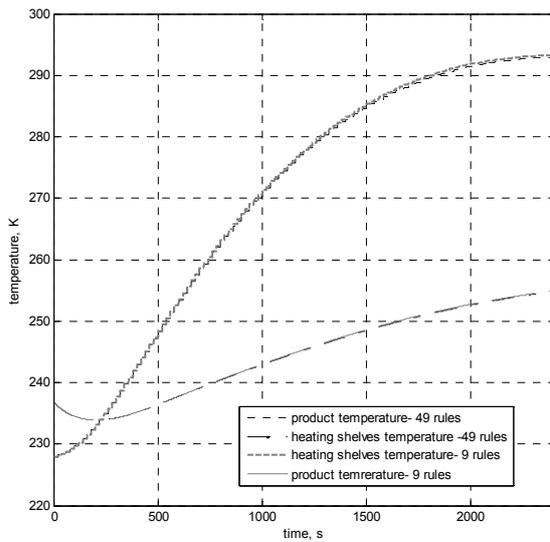


Fig.3. Process responses in case of using 3 and 7 membership functions

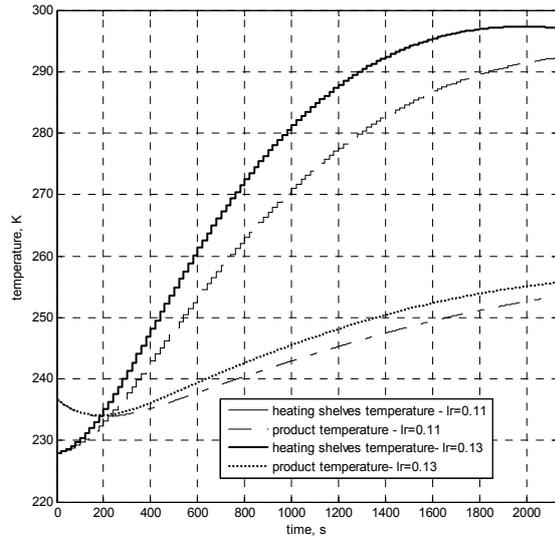


Fig.4. Influence of the learning rate into the tuning optimization procedure

4. CONCLUSIONS

An adaptive tuning of procedure for Fuzzy PID type controller is presented. The adaptation procedure for the controller gains is done by implementing a simple internal fuzzy-neural Hammerstein predictive model and a gradient optimization algorithm calculating the appropriate gain values by minimizing a cost error function with respect to current process conditions.

Simulation experiments with 3 and 7 input/output triangular membership functions in the fuzzy PID structure and different values of the learning rate into the optimization procedure are made.

The simulation results show the efficiency of the proposed approach. The adaptation procedure insures calculation of appropriate values of the FPID gains according to the natural process conditions which facilitate the FPID tuning procedure and also its capability to handle the process nonlinearities. Changing the number of the membership functions does not affect significantly the process response as it is done by the learning rate of the tuning optimization procedure.

REFERENCES

- [1] Mohanadas K., Shaik K., Fuzzy and Neuro-Fuzzy modelling and control of nonlinear systems, (2001) Eleco'2001 2th International conference on electrical and electronics engineering, Bursa, Turkey.
- [2] Zhao C., Zhu Shi J., He Qi-Wei, Fuzzy-PID control method for two-stage Vibration isolation system. (2007) Journal of Theoretical and Applied Mechanics, Vol. 45(1), pp. 171-177.
- [3] Passino K., Yourkovic S., Fuzzy Control, (1998) Adisson-Wesley.
- [4] Terziyska M., Todorov Y., Petrov M., Nonlinear Model Predictive Controller using a Fuzzy-Neural Hammerstein model. (2006) *International conference "Modern Trends in Control", Kosice, Slovak Republic.*
- [5] Todorov Y., Terziyska M., Petrov M., Nonlinear Model Based Predictive Controller of using a Fuzzy-Neural Wiener-Hammerstein model, (2007) *International Conference "Process Control'07", Stribske Pleso, Slovak Republic.*
- [6] Shoen, M.P. A simulation model for primary drying phase of the freeze-drying, (1995) *International Journal of Pharmaceutics.*
- [7] Mellor, J.D. Fundamentals of Freeze Drying. (1981) Academic Press, New York.

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