MODELING OF A LYOPHILIZATION PLANT BY MEANS OF HYBRID FUZZY-NEURAL WIENER-HAMMERSTEIN MODEL

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Abstract: It is presented in this paper a design methodology for a hybrid Wiener-Hammerstein Fuzzy-Neural process model. The nonlinear part of the model is common for each sub model and it is approximated by means of a simple fuzzy inference system. The linear parts are introduced separately. The learning procedure for the designed model is based on the minimization of an instant error. There are made simulation experiments in modeling of a nonlinear Lyophilization plant.

МОДЕЛИРАНЕ НА ЛИОФИЛИЗАЦИОНЕН ПРОЦЕС ПОСРЕДСТВОМ НЕВРОННО-РАЗМИТ ВИНЕР-ХАМЕРЩАЙН МОДЕЛ

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Резюме: В този доклад е представена методология за проектиране на хибриден невронно-размит Винер-Хамерщайн модел. Нелинейната част на модела е обща за всеки под модел и тя е апроксимирана посредством опростена размита система. Линейните части в модела са въведени отделно. Обучаващият алгоритъм за модела е базиран на минимизацията на моментната грешка. Направени са симулационни експерименти с лиофилизационен процес.

1. INTRODUCTION

Identification theory for nonlinear systems is almost as old as identification theory for linear systems. In many different fields of application, the structure of the nonlinear system is obtained from physical laws describing the various components as well as interconnection laws describing the interconnection structure. Identification then reduces to estimating unknown parameters appearing in the mode structure on the basis of measured signals. The analysis and solution of a nonlinear identification problem with known model structure but unknown parameters parallels the analysis and solution of linear identification problems [1].

For both problems, one first needs to check whether the parameters that one seeks to estimate are identifiable, which essentially amounts to checking whether the predicted outputs are sensitive to these parameters. For a long time, attempts were made to go beyond the identification of nonlinear systems with known structure by introducing special classes of nonlinear black-box models such as Wiener, Hammerstein, and Wiener-Hammerstein models. Black-box models refer, as in the linear case, to model structures that have not been derived from physics laws and whose parameters therefore have a priori no physical significance. A Wiener model is a linear dynamic model with a static nonlinearity at the output, while a Hammerstein model has the static nonlinearity at the input; the Wiener-Hammerstein model combines both nonlinearities. The search for universal classes of nonlinear black-box models gathered steam with the introduction of broader classes of basis functions, such as splines, neural networks, wavelets, and radial basis functions [1].

The Wiener and Hammerstein models are successfully applied for nonlinear system representation in a number of practical approaches in the areas of chemical processes, biological processes [2], signal processing [3], communication and control [4].

For instance, the nonlinear effects encountered in some industrial processes, such as distillation columns, pH-neutralization, heat exchangers, or electro-mechanical systems can be effectively modeled by a Hammerstein or Wiener model.

It is presented in this paper a new approach for designing a hybrid Wiener-Hammerstein Fuzzy-Neural model (FNWH), based on so called “one step solutions” [5]. When the model is identified with the help of linguistic rules and data, gathered from the process, it has the potential to be transparent and easily interpretable [6].The proposed model is evaluated to model a nonlinear Lyophilization plant.

2. FUZZY-NEURAL WIENER-HAMMERSTEIN MODEL

The classical Wiener and Hammerstein models have the following structures (Fig.1):

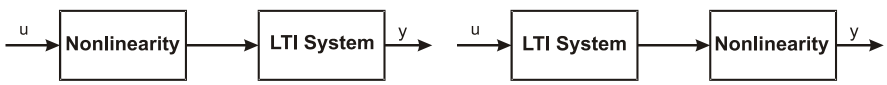

Fig.1. Structures of classical Hammerstein and Wiener models

When these structures are combined, both they give a new hybrid Wiener-Hammerstein model (Fig.2).

Fig.2. Structure of a hybrid Wiener-Hammerstein model

Using a simple fuzzy-neural approach the static nonlinearity can be easily approximated as a set of linear functions. For this purpose it is used the Takagi-Sugeno fuzzy-neural technique. As it is well known the Takagi-Sugeno fuzzy-neural technique is suitable to model a class of nonlinear dynamic systems, which can be described in discrete time by the NARX (Nonlinear AutoregRessive model with eXogenous inputs) input-output model. The used model for nonlinearity approximation is also taken in the NARX type:

$$s(k) = f_v(x(k)) \tag{1}$$

where the elements of the considered regression vector *x(k)* are given by:

$$x(k) = [v(k),.........v(k-n_v)] \tag{2}$$

$$v(k) = \frac{B(q^{-1})}{A(q^{-1})}u(k) \tag{3}$$

where

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + ... + a_m q^m \; ; \quad B(q^{-1}) = b_o + b_1 q^{-1} + b_2 q^{-2} + ... + b_n q^n \; ; \quad (4)$$

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

$$R^{(i)} : if \;\; x_1 \;\; is \;\; \widetilde{A}_1^{(i)} \;\; and \;\; x_p \;\; is \;\; \widetilde{A}_p^{(i)} \;\; then \;\; f_v^{(i)}(k) \quad (5)$$

$$f_v^{(i)}(k) = r_1^{(i)} v(k) + r_2^{(i)} v(k-1) + ... + r_{nv}^{(i)} v(k-n_v) + r_0^{(i)} \quad (6)$$

(i)=1,2,…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 $x=[x_1, x_2, ..., x_p]$ and the crisp coefficients *r,* are the coefficients into the Sugeno function f_v. From a given input vector, the output of the fuzzy model is inferred by computing the following equation:

$$s(k) = f_v^{(i)}(k) g_v^{(i)} \;\; where \quad g_v^{(i)} = \prod_{i=1}^{N} \mu_{vi}^{(i)} \quad (7)$$

where μ_{vi} are the degrees of fulfilment in notion to $vi^{i\text{-}th}$ activated fuzzy membership function.

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

$$f_{v1}^{(i)}(k) = c_1^{(i)} y(k-1) + ... + c_{n_y}^{(i)} y(k-n_y) + d_1^{(i)} s(k) + ... + d_{n_v}^{(i)} s(k-n_v) + d_o \quad (8)$$

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

$$y(k+1) = \sum_{j=1}^{N} \left(\sum_{i=1}^{n_a} c_i y(k-i+1) + \sum_{i=1}^{n_b} d_i s_j(k-i-n_d+1) \right) = \sum_{j=1}^{N} \left(\sum_{i=1}^{n_a} c_i y(k-i+1) + \sum_{i=1}^{n_b} d_i r_j g_{vj}(v(k-i-n_d+1)) \right) \quad (9)$$

The designed FNWH model has the structure, as it shown on Fig. 3.

In the FNWH model it is needed to be determined the unknown parameters – the number of membership functions, their shape, the parameters of the function f_v in the consequent part of the rules and the parameters into the linear parts. This is an identification procedure for which they have been proposed numerous approaches. In this work it is applied a simplified fuzzy-neural approach, with a learning procedure described bellow [9].

2.1 LEARNING ALGORITHM FOR THE DESIGNED FUZZY-NEURAL WIENER-HAMMERSTEIN MODEL

It is used two steps simplified gradient learning procedure as a learning algorithm. This procedure is based on minimization of the instant error between the process output and the model output. It is needed to be adjusted two groups of parameters in the fuzzy-neural architecture – premise and consequent parameters.

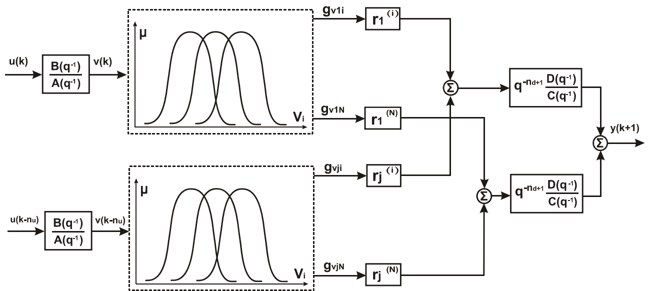

Fig. 3. Fuzzy-Neural Wiener-Hammerstein model

The consequent parameters are the coefficients r in the Sugeno function f_v and they are calculated by the following equations:

$$\beta_{ij}(k+1)=\beta_{ij}(k)+\eta(y(k)-y_M(k))\overline{g}_v^{(j)}(k)x_i(k); \quad \beta_{0j}(k+1)=\beta_{0j}(k)+\eta(y(k)-y_M(k))\overline{g}_v^{(j)}(k) \tag{10}$$

in which η is the learning rate and β_{ij} is an adjustable i^{-th} coefficient r_i in the Sugeno function f_v of the j^{-th} activated rule.

The premise parameters are the centre c_{ij} and the deviation σ_{ij} of an activated Gaussian fuzzy set. They can be calculated using the following equations:

$$c_{ij}(k+1)=c_{ij}(k)+\eta(y(k)-y_M(k))\overline{g}_v^{(j)}(k)[f_y^{(i)}(k)-\widehat{y}(k)]\frac{[x_i(k)-c_{ij}(k)]}{c_{ij}^2(k)} \tag{11}$$

$$\sigma_{ij}(k+1)=\sigma_{ij}(k)+\eta(y(k)-y_M(k))\overline{g}_v^{(j)}(k)[f_y^{(i)}(k)-\widehat{y}(k)]\frac{[x_i(k)-\sigma_{ij}(k)]^2}{\sigma_{ij}^3(k)} \tag{12}$$

To adjust the coefficients into the linear parts of the proposed FNWH model it is used the same gradient learning procedure as the described one above.

3. SIMULATION EXPERIMENTS

3.1 PLANT DESCRIPTION

The assumed plant process in the following simulation experiments is a Lyophlization plant.

Lyophilization process (Sublimation drying) 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. Using a Lyophilization plant the bound in product water is removed by its transition from ice to vapor phase with no melting.

Referring to Fig.5 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 those shelves the product is placed (6). The chamber is isolated from the condenser by valve (7). The vacuum system is placed after condenser. After the process is completed the condenser will be heated in order to be removed the frozen ice from its wall [8].

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

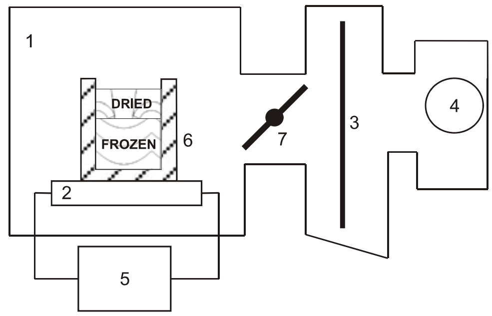

Fig.5.Diagram of simplified Lyophilization plant

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 it is assumed only the first stage of the drying process called primary drying.

3.2 SIMULATION EXPERIMENTS

It is made simulation experiments in *Matlab & Simulink* environment with the proposed FN Wiener-Hammerstein model. It has to be mentioned, that the reference point for the end of simulation experiments was taken the final value of the interface front at value $x=0.0001$ m. This is due to the nature of the Lyophilization process.

The modeling process is made during a lyophlization cycle and it is estimated the model error between the plant process and the artificial model.

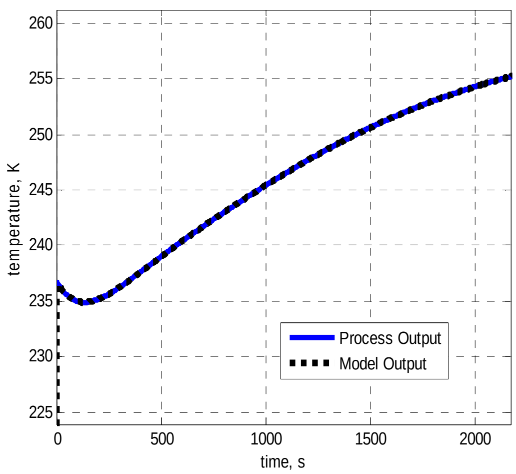

Fig.6. Process and Model outputs during a Lyophilization cycle

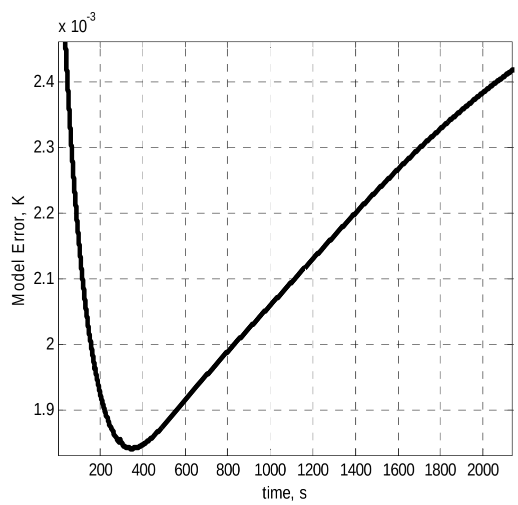

Fig.7. Model Error during a Lyophilization cycle

4. CONCLUSIONS

It is presented in this paper a design methodology for a hybrid Wiener-Hammerstein Fuzzy-Neural process model. The nonlinear part of the model is common for each sub model and it is approximated by means of a simple fuzzy inference system. The linear parts are introduced separately. The learning procedure for the designed model is based on the minimization of an instant error.

The simulation results show the efficiency of the proposed design approach. The predictive model follows the process output during the Lyophilization cycle and the error between both parameters is minimal.

The proposed model can be easily implemented in a classical Nonlinear Model Predictive Control Scheme.

5. REFERENCES

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