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# СУПЕРВАЙЗОРНА НАСТРОЙКА НА ПРЕДСКАЗВАЩ РЕГУЛАТОР

МАРГАРИТА ТЕРЗИЙСКА, ЯНЧО ТОДОРОВ, МИХАИЛ ПЕТРОВ

**Резюме:** *Един от основните проблеми при предсказващите регулатори е тяхната настройка. Стойностите на хоризонтите на предсказване и управление и тегловните коефициенти в целевия оптимизационен критерий обикновено се определят евристично. В настоящата статия е представен един подход за настройка посредством проектирането на супервайзор. Той осъществява адаптивната донастройка на тегловния коефициент ρ, като влияе директно върху изходната стойност на управлението, при постоянни хоризонти на предсказване. Предложеният алгоритъм за невронно-размито предсказващо управление е тестван в реални условия върху лабораторна топлинна система, която се намира в Машинния факултет на Техническия университет в Прага.*

**Ключови думи:** *предсказващо управление, невронно-размит модел, супервайзор, топлинна система, топлообменник*

# REAL-TIME SUPERVISORY TUNING OF PREDICTIVE CONTROLLER

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**Abstract:** *One of the main problems in predictive controllers is their tuning. The values of the prediction and control horizons and weighting factors in the optimization criterion are usually determined heuristically. This paper presents an approach of supervisory tuning of predictive controller. The supervisor carries out the adaptive adjustment of the weighting factor ρ that directly affects the output value of control in constant horizons of prediction. The proposed algorithm for neural-fuzzy predictive control has been tested in real conditions on a laboratory heating system, which is located in the Faculty of Mechanical Engineering of the Technical University in Prague.*

**Key words:** *predictive control, neuro-fuzzy model, supervisor, heating system, heat exchanger*

## 1. Introduction

Model Predictive Control (MPC) is an optimal control technique that relies on dynamic model of the process, used to predict the future response of a plant. Afterwards, an optimization procedure computes an optimal control policy by minimizing a prescribed cost function. In general, the industrial processes are inherently nonlinear and this implies the use of nonlinear models and respectively Nonlinear Model Predictive Control (NMPC) algorithms. Predictive controllers (linear or nonlinear) have several tuning parameters – control horizon, prediction horizon, and weighting factors in the cost function. The good system performance in predictive control scheme strongly depends on its values. In practice, there is no systematic way for tuning the predictive controller. This paper presents an approach of supervisory tuning of predictive controller. The supervisor carries out an adaptive adjustment of the weighting factor ρ that directly affects the output value of control, while prediction horizons are constant. The proposed algorithm for neural-fuzzy predictive control has been tested in real conditions on a laboratory heating system, which is located in the Faculty of Mechanical Engineering of the Technical University in Prague.

## 2. Neuro-fuzzy predictive control strategy

Nonlinear Model Predictive Control, or NMPC, is a variant of model predictive control (MPC) that is characterized by the use of nonlinear system models in the prediction. While NMPC application in the past have been mostly used in the processes with relatively slow dynamics, today it is wide spread as control strategy e.g., in the automotive industry, or even when the states are distributed in space.

In this paper NMPC based on fuzzy-neural predictive model is used to control a heating system with heat exchanger. In [3] it is described a fuzzy model based predictive control of a tubular heat exchanger system. Neural network based predictive control of a heat exchanger is proposed in [4]. Cascade Generalized Predictive Control algoritm for heat exchanger is described in [5]. In [6] is suggest simplified scheme for predictive control for a shell and tube heat exchanger.

NMPC as it is applied here with Takagi-Sugeno fuzzy-neural process model can be described in general with a block diagram, as it is depicted in Fig. 1.

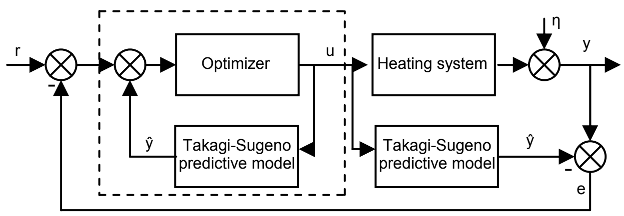


***Fig. 1.** Block diagram of a typical model predictive control system*

The Takagi-Sugeno fuzzy-neural models are suitable to model nonlinear systems, as well as heating systems with heat exchangers. As it is well known a wide class of nonlinear dynamic systems can be described in discrete time by the NARX (Nonlinear AutoregRessive model with eXogenous inputs) input-output model. The used model in this paper is also taken in the NARX type:

$$y(k) = f_y(x(k)) \tag{1}$$

where the unknown nonlinear function $f_y$ can be approximated by Takagi-Sugeno type fuzzy rules:

$$R^{(i)} : if\ x_1\ is\ \widetilde{A}_1^{(i)}\ and\ x_p\ is\ \widetilde{A}_p^{(i)}\ then\ f_y^{(i)}(k) \tag{2}$$

$$\begin{aligned} f_y^{(i)}(k) &= a_1^{(i)}y(k-1)+a_2^{(i)}y(k-2)+\cdots+a_{ny}^{(i)}y(k-n_y) \\ &+b_1^{(i)}u(k)+b_2^{(i)}u(k-1)+\cdots+b_{nu}^{(i)}u(k-n_u)+c_0^{(i)} \end{aligned} \tag{3}$$

where (i)=1,2,…N, N is the number of the fuzzy rules, $A_i$ is an activated fuzzy set defined in the universe of discourse of the input xi and the crisp coefficients $a_1$, $a_2$,...$a_{ny}$, $b_1$, $b_2$,...$b_{nu}$ are the coefficients into the Sugeno function $f_y(k)$.

In the Takagi-Sugeno fuzzy-neural model it is needed to be determined the unknown parameters – the number of membership functions, their shape and the parameters of the function $f_y$ in the consequent part of the rules. This is an identification procedure for which have been proposed numerous approaches. In this work it is applied a simplified fuzzy neural approach.

### 2.1 Learning algorithm for the designed fuzzy-neural process model

It is used two steps gradient learning procedure as a learning algorithm of the internal fuzzy-neural model. This procedure is based on the 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 and they are: premise and consequent parameters. The consequent parameters are the coefficients $a_1$, $a_2$...$a_{ny}$, $b_1$, $b_2$...$b_{nu}$ in the Sugeno function $f_y$ and they are calculated at first step by the following equations:

$$\beta_{ij}(k+1)=\beta_{ij}(k)+\eta(y(\kappa)-y_M(\kappa))\overline{\mu}_y^{(j)}(k)x_i(k) \tag{4}$$

$$\beta_{0j}(k+1)=\beta_{0j}(k)+\eta(y(\kappa)-y_M(\kappa))\overline{\mu}_y^{(j)}(k) \tag{5}$$

where η is the learning rate and $\beta_{ij}$ is an adjustable i-th coefficient ($a_i$ or $b_i$) in the Sugeno function $f_y$ of the $j^{-th}$ activated rule.

The premise parameters are the centre $c_{ij}$ and the deviation $\sigma_{ij}$ of a Gaussian fuzzy set. They can be calculated at second step using the following equations:

$$c_{ij}(k+1)=c_{ij}(k)+\eta(y(\kappa)-y_M(\kappa))\overline{\mu}_y^{(j)}(k)[f_y^{(i)}(\kappa)-\hat{y}(k)]\frac{[x_i(k)-c_{ij}(k)]}{c_{ij}^2(k)} \tag{6}$$

$$\sigma_{ij}(k+1)=\sigma_{ij}(k)+\eta(y(\kappa)-y_M(\kappa))\overline{\mu}_y^{(j)}(k)[f_y^{(i)}(\kappa)-\hat{y}(k)]\frac{[x_i(k)-\sigma_{ij}(k)]^2}{\sigma_{ij}^3(k)} \tag{7}$$

Using the Takagi-Sugeno fuzzy-neural model, the Optimization Algorithm computes the future control actions at each sampling period, by minimizing the following cost function:

$$J(k,u(k))=\sum_{i=N_1}^{N_2}(r(k+i)-\hat{y}(k+i))^2+\rho\sum_{i=1}^{N_u}\Delta u(k+i-1)^2 \qquad (8)$$

where y is the predicted model output, r is the system reference and u is the control action. The tuning parameters of the predictive controller are: $N_1$, $N_2$, $N_u$ and ρ. $N_1$ is the minimum prediction horizon, $N_2$ is the maximum prediction horizon, $N_u$ is the control horizon and ρ is the weighting factor penalizing changes in the control actions.

When the criterion function is a quadratic one and there are no constraints on the control action, the cost function can be minimized analytically. If the criterion J is minimized with respect to the future control actions u, then their optimal values can be calculated by applying the condition:

$$\nabla J[k,U(k)]=\left[\frac{\partial J[k,U(k)]}{\partial u(k)},\frac{\partial J[k,U(k)]}{\partial u(k+1)},\dots,\frac{\partial J[k,U(k)]}{\partial u(k+N_u-1)}\right]=0 \qquad (9)$$

Each element from this gradient vector can be calculated using the following equation:

$$\frac{\partial J[k,U(k)]}{\partial U(k)}=\left[-2\left[R(k)-\hat{Y}(k)\right]^T\frac{\partial \hat{Y}(k)}{\partial U(k)}+2\rho\,\hat{U}(k)^T\frac{\partial \hat{U}(k)}{\partial U(k)}\right] \qquad (10)$$

From the above expression can be seen that it is needed to obtain two groups of partial derivatives. The first one is $\left[\frac{\partial \hat{Y}(k)}{\partial U(k)}\right]$, and second one is $\left[\frac{\partial \hat{U}(k)}{\partial U(k)}\right]$. Each element from the first group of partial derivatives is calculated with the following equations:

$$\frac{\partial \hat{y}(k)}{\partial u(k)}=\sum_{i=1}^{N} b_1^{(i)}\bar{\mu}_y^{(i)}(k) \qquad (11)$$

$$\frac{\partial \hat{y}(k+1)}{\partial u(k)}=\sum_{i=1}^{N}\left[a_1^{(i)}\frac{\partial \hat{y}(k)}{\partial u(k)}+b_2^{(i)}\right]\bar{\mu}_y^{(i)}(k+1) \qquad (12)$$

$$\frac{\partial \hat{y}(k+2)}{\partial u(k)}=\sum_{i=1}^{N}\left[a_1^{(i)}\frac{\partial \hat{y}(k+1)}{\partial u(k)}+a_2^{(i)}\frac{\partial \hat{y}(k)}{\partial u(k)}\right]\bar{\mu}_y^{(i)}(k+2) \qquad (13)$$

$$\frac{\partial \hat{y}(k+N_2)}{\partial u(k)}=\sum_{i=1}^{N}\left[\begin{array}{l} a_1^{(i)}\dfrac{\partial \hat{y}(k+N_2-1)}{\partial u(k)}+\dots \\ +\,a_2^{(i)}\dfrac{\partial \hat{y}(k+N_2-2)}{\partial u(k)}\end{array}\right]\bar{\mu}_y^{(i)}(k+N_2) \qquad (14)$$

The second group partial derivatives have the following form:

$$\frac{\partial \hat{U}(k)}{\partial U(k)}=\begin{bmatrix}\dfrac{\partial \Delta u(k)}{\partial u(k)} & \cdots & \dfrac{\partial \Delta u(k)}{\partial \Delta u(k+N_u-1)} \\ \cdots & \cdots & \cdots \\ \dfrac{\partial \Delta u(k+N_u-1)}{\partial u(k)} & \cdots & \dfrac{\partial \Delta u(k+N_u-1)}{\partial \Delta u(k+N_u-1)}\end{bmatrix} \qquad (15)$$

Since $\Delta u(k)=u(k)-u(k-1)$, this is:

$$\frac{\partial \hat{U}(k)}{\partial U(k)}=\begin{bmatrix}1 & 0 & 0 & 0 & 0\\ -1 & 1 & 0 & 0 & 0\\ 0 & -1 & 1 & 0 & 0\\ 0 & 0 & -1 & 1 & 0\\ 0 & 0 & 0 & -1 & 1\end{bmatrix} \qquad (16)$$

## 3. Tuning of predictive controllers

The tuning parameters of a model predictive controller are: prediction horizon $N_2$, control horizon $N_u$ and weighting factors in the cost function (8). Recently they are selected heuristically, by “trial and error” procedures based on simulations results [1, 2]. In [7] it is proposed heuristic on-line tuning algorithm for Nonlinear Model Predictive Controllers, which automatically adjusts the prediction horizon $N_2$ and the diagonal elements of the input weight matrix Λ. The control horizon $N_u$ is left constant. The tuning algorithm is designed using the fuzzy logic concepts. Simple auto-tuning rules for MPC are described in [8]. A method for optimal tuning parameters of the dynamic matrix predictive controller with constraints based on genetic algorithms is proposed in [9]. How to use genetic algorithms for tuning the parameters of generalized predictive control is described in [10]. In [11] it is derived an analytic expression to determine the move suppression parameter $\lambda_j$ for mono and multivariable systems, in order to obtain an automatic tuning method.

In this paper it is proposed an idea for adaptive tuning of the weighting factor ρ in optimization criterion (8), maintaining the other parameters as constants. The modified MPC control scheme with the applied fuzzy-neural supervisor is shown on Fig.2

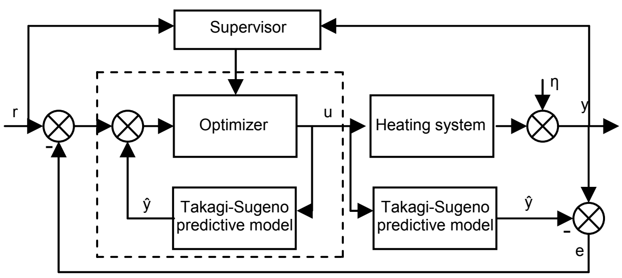


***Fig.2.*** *MPC control scheme with a fuzzy-neural supervisor*

The used Fuzzy-Neural Supervisor is easily implemented as a simple fuzzy-neural Takagi-Sugeno type architecture. This fuzzy-neural network has the same structure as that one used as a predictive model. It can be expressed in the following form:

$$\rho(k) = f_{\rho}(x(k)) \tag{17}$$

where $x(k) = [\rho(k-1), \rho(k-2), e(k), e(k-1)]$ and e is the system error.

The unknown nonlinear function fρ can be approximated by Takagi-Sugeno type fuzzy rules:

$$Q^{(i)} : if\ x_1\ is\ \tilde{C}_1^{(i)}\ and\ x_p\ is\ \tilde{C}_p^{(i)}\ then\ f_{\rho}^{(i)}(k) \tag{18}$$

$$f_{\rho}^{(i)}(k) = c_1^{(i)}\rho(k-1) + c_2^{(i)}\rho(k-2) + c_3^{(i)}e(k) + c_4^{(i)}e(k-1) + c_0^{(i)} \tag{19}$$

(i)=1,2,…M, where M is the number of the fuzzy rules, $C_i$ is an activated fuzzy set defined in the universe of discourse of the input xi and the crisp coefficients $c_1$, $c_2$, $c_3$, $c_4$, $c_0$ are the coefficients into the Sugeno function $f_{\rho}$.

As a learning procedure of the presented adaptive fuzzy supervisor it is considered the same two steps gradient algorithm discussed above (Equations (4) - (7)).

## 4. Description of the laboratory heating system

The considered plant is situated in Czech Technical University in Prague, Faculty of Mechanical Engineering. The laboratory heating system (Fig. 3) is designed as a multiple input multiple output (MIMO) system. The system consists of two closed independent heating circuits, in which the water is the heat transfer medium. Both the circuits are equipped with a heater, cooler, pump and valves, by which the heat transfer within the circuit can be controlled. The heat flow can also be transferred between the circuits through a multi-plate heat exchanger. The used heat exchanger is Zilmet Z 1/8 with heat transfer up to 3 kW and it consists from 5 plates. Monitoring of the heating system state is done via twelve thermometers and four flow-rate-meters. The whole system is controlled either by a PC equipped with data acquisition cards or by a modular industrial PLC Tecomat NS950 with analogue input-output modules. In the Fig. 3 it is presented the photograph of the laboratory heating system. As it can be seen the main subsystem units of the system are connected by pipe lines. It is used the five-layer aluminum plastic composite pipes Seacomppipe 16x2, with inner diameter 12 mm., because of its very good isolation features.

***Fig.3.*** *A photograph of the laboratory heating system*

The heating system can be divided into two parts that is call left and right circuit, respectively. The main difference between these two circuits is the heater. For the investigations here it is used only one circuit – the left side one.

In the left circuit it is used an accumulation-type heater SHU 5 S STIEBEL ELTRON 071754. The performance of this heater is 2 kW and its capacity is 5 l. For the right circuit, a flow-type heater was designed. The performance of the heater is 2 kW and its capacity is 1.5 l. The used left circuit can be described by the following equations:

$$T_d \frac{d\Delta\vartheta_d(t)}{dt} = -\Delta\vartheta_d(t) + K_d\Delta\vartheta_a(t-\tau_d) \tag{20}$$

$$T_c \frac{d\Delta\vartheta_c(t)}{dt} = -\Delta\vartheta_c(t-\eta_c) + K_c\Delta\vartheta_d(t-\tau_c) \tag{21}$$

$$T_h \frac{d\Delta\vartheta_h(t)}{dt} = -\Delta\vartheta_h(t-\eta_h) + K_b\Delta\vartheta_a(t-\tau_b) + K_u\Delta\vartheta_{h,set}(t-\tau_u) \tag{22}$$

$$T_a \frac{d\Delta\vartheta_a(t)}{dt} = K_a[\Delta\vartheta_h(t) - \frac{1+q}{2}\Delta\vartheta_a(t) - \frac{1+q}{2}\Delta\vartheta_c(t-\tau_c)] - [\Delta\vartheta_a(t) - \Delta\vartheta_a(t-\tau_c)] \tag{23}$$

where $T_a$, $T_d$, $T_c$ and $T_h$ are the time constants, $K_a$ is the heat transfer coefficient, $K_d$, $K_c$, $K_b$ and $K_u$ are the static gain coefficients, $\tau_e$, $\tau_d$, $\tau_c$ and $\tau_b$ are the time delays.

## 5. Real-time experiments

The results are obtained via Matlab Real-time Toolbox with the next initial conditions:

$N_1$=1, $N_2$=5, $N_u$=3,

System reference r=65°C;

Consequent changes of the system reference r=65°C; 75°C; 60°C

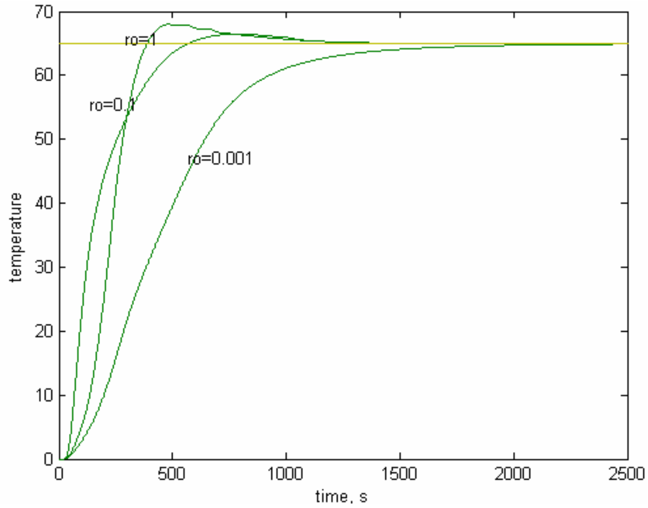


***Fig. 4.*** *Transient process responses in case of set system reference with different initial values of the weighting factor ρ*

At Fig.4 are presented experiments with the proposed supervisory GPC control algorithm in case of different initial values of the weighting factor *ρ*. The results show that there is no system overshoot into the transient responses and the settling time of the process is increased when using smaller values of *ρ* and vice versa**.** It can be mentioned also that the used in simulation initial values of *ρ* are valid only for the considered heating system.

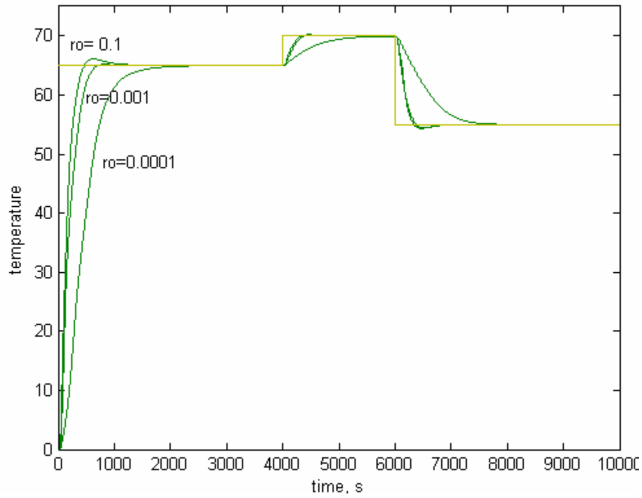


***Fig. 5****. Transient process responses in case of variable system reference and with different initial values of the weighting factor ρ*

Another part of experiments are made in case of variable system reference (Fig. 6). From the results it can be observed a similar system dynamics as in the above considered case of invariable system reference.

The proposed method for supervisory tuning of predictive controller is compared with another method for supervisory tuning, which is based on the Mamdani mechanism and is described in detail in [12], and with a standard neural-fuzzy generalized predictive controller. The results are shown in Fig. 6. Comparison between different types of control schemes was done under the same conditions. The value of the weighting factor for GPC control is assumed to be ρ = 0.001, respectively, and the initial values for both methods with a supervisor.

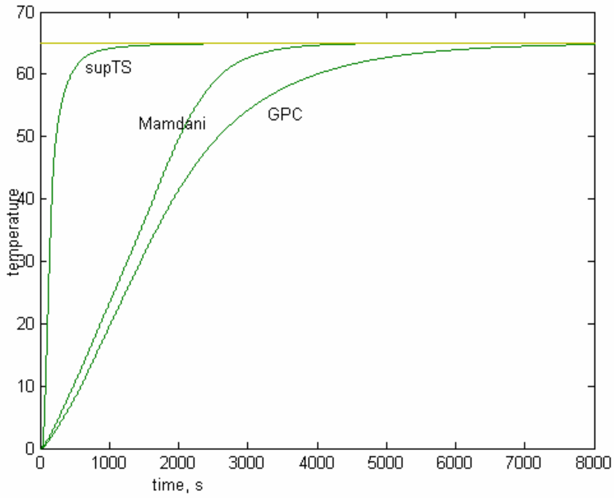


***Fig.6****. Transient process responses in case of set system reference, GPC, TS supervisory GPD and Mamdani supervisory GPC (ρ=0.001) control schemes*

## 6. Conclusion

An adaptive predictive supervisory algorithm to the temperature control of a heating system with a heat exchanger it is presented in this paper. The nonlinear predictive control strategy is designed on the basis of a Takagi-Sugeno fuzzy-neural model and a simple optimization procedure. An additional supervisory level in the control system is introduced for adaptive tuning of a weighting factor in the predefined optimization criterion. The obtained real time results show the efficiency of the proposed approach. The proposed algorithm performs well in a variety of conditions.

The results in Fig. 6 show that the control algorithm using an additional level supervising structures of fuzzy Takagi-Sugeno gives the best results. Adaptive tuning of the weighting factor provides performance and process quality. Despite the fact that the presence of modifications of model predictive control scheme associated with additional calculations resulted in a significant influence on the transition time, in this case does not affect the performance to reach the desired value. In the method using Mamdani approach for tuning of ρ that is not the case. It can be concluded that a system with supervisory level using Takagi-Sugeno model is a better option for control the heating system that provides better quality and efficiency of the process.

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