СРАВНИТЕЛНО ИЗСЛЕДВАНЕ НА ИНТЕЛИГЕНТНИ АЛГОРИТМИ ЗА УПРАВЛЕНИЕ

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Резюме: В тази статия е представно едно сравнително изследване на интелгентни методи за управление. Проектирани са хибридни размити ПИД регулатори, чиято работа е сравнена с тази на обобщен предсказващ регулатор. Анализът на работата на отделните алгоритми е направен чрез симулационно изследване в средата на MATLAB/SIMULINK за управление на технологичен агрегат - топлообменник.

COMPARATIVE STUDY OF DIFFERENT INTELLIGENT CONTROL ALGORITHMS

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Abstract: In this paper it is presented a comparative study of different intelligent control algorithms. The study includes comparaison between hybrid fuzzy PID controllers and Generalized Predictive Controller (GPC). Analysis is made in MATLAB/SIMULINK environement to contol a temperature in a heat exchanger.

1. INTRODUCTION

The ever increasing technological demands of today call for very complex systems, which in turn require highly sophisticated controllers to ensure that high performance can be achieved and maintained under adverse conditions. There are needs in the control of these complex systems which cannot be met by conventional controllers and this is primarily due to the lack of precise knowledge about the process to be controlled. Acquisition of adequate system knowledge is often problematic or impractical due to system complexity and the fact that the structure and parameters in many systems change in significant and unpredictable ways over time. To address the control demands of such highly complex and uncertain systems one can enhance today's control methods using intelligent control systems and techniques [1].

The area of Intelligent Control is a fusion of a number of research areas in Systems and Control, Computer Science and Operations Research among others, coming together, merging and expanding in new directions and opening new horizons to address the new problems of this challenging and promising area. Intelligent control systems are typically able to perform one or more of the following functions: planning actions at different levels of detail, learning from past experience, identifying changes that threat the system behavior, such as failures, and reacting appropriately. This identifies the areas of Planning and Expert Systems, Fuzzy Systems, Neural Networks and hybrid Neuro-Fuzzy systems to mention, as existing research areas that are related and important to Intelligent Control.

During past years, fuzzy control has taken a position as an alternative of conventional control. At present, fuzzy systems are being used in a wide range of industrial and scientific applications where the main applications are as being fuzzy control, data analysis and knowledge based systems [1]. Fuzzy controllers, for instance, model the control strategy of a human expert to control a system for which no mathematical or physical model exists. They employ a set of linguistic rules to describe the human behavior.

Generalized Predictive Control (GPC) belongs to the class of Model Predictive Control (MPC) techniques and was first introduced by Clarke and his co-workers [2]. Model Predictive Control, also referred to as moving horizon control or receding horizon control, has become an attractive feedback strategy, especially for linear processes. Linear MPC refers to a family of MPC schemes in which linear models are used to predict the system dynamics [3]. Linear MPC approaches have found successful applications, especially in the process industries. Several researchers had extended the classical MPC scheme to Nonlinear Model Predictive Control (NMPC) that works with different types of nonlinear models. In NMPC a process dynamic model is used to predict future outputs over a prescribed period called prediction horizon. Afterward, the model outputs are used to compute the future control actions by minimizing a cost function. A class of models based on empirical data, such as artificial neural networks and fuzzy logic is commonly used in NMPC control scheme.

The described above control methods have a common nature and they can handle process nonlinearities in order to obtain a good system performance. In this way it is needed to be made a comparative study of its efficiency. It is presented in this paper a comparative study between different Mamdani Fuzzy PID control algorithms and Nonlinear Model Predictive Control strategy based on Takagi-Sugeno Fuzzy-Neural model and simplified gradient optimization algorithm, to control a temperature in a heat exchanger.

2. BASICS OF HYBRID FUZZY PID CONTROL

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. Such heuristic information may come from an operator who has acted as a “human-in-the-loop” controller for a process. In the fuzzy control design methodology, we ask this operator to write down a set of rules on how to control the process, then we incorporate these into a fuzzy controller that emulates the decision-making process of the human. In other cases, the heuristic information may come from a control engineer who has performed extensive mathematical modeling, analysis, and development of control algorithms for a particular process [4].

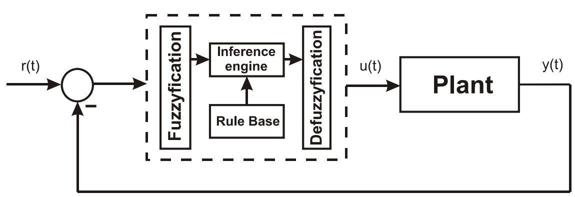

Fig. 1 Classical fuzzy controller

Fuzzy control provides a formal methodology for representing, manipulating, and implementing a human’s heuristic knowledge how to control a system. In this section we seek to provide a philosophy of how to approach the design of fuzzy controllers. The classical Mamdani type fuzzy controller block diagram is given in Figure 1, where is shown a fuzzy controller embedded in a closed-loop control system. The plant output is denoted by $y(t)$, the input is denoted by $u(t)$, and the reference input is denoted by $r(t)$. The fuzzy controller has four main components: (1) the “rule-base” holds the knowledge, in the form of a set of rules, of how best to control the system; (2) the inference mechanism evaluates which control rules are relevant at the current time and then decides what the input to the plant should be; (3) the fuzzification interface simply modifies the inputs so that they can be interpreted and compared to the rules in the rule-base; and (4) the defuzzification interface converts the conclusions reached by the inference mechanism into the inputs to the plant. Basically, the fuzzy controller is an artificial decision maker that operates in a closed-loop system in real time. It gathers plant output data $y(t)$, comparing it to the reference input $r(t)$, and then decides what the plant input $u(t)$ should be to ensure that the performance objectives will be met. To design a fuzzy controller, the control engineer must gather information on how the artificial decision maker should act in the closed-loop system. Sometimes this information can come from a human decision maker who performs the control task, while at other times the control engineer can come to understand the plant dynamics and write down a set of rules how to control the system without outside help. In practice frequently are used unified expert rule bases (Fig. 3), which gives a natural way to bear a resemblance with classical conventional control laws.

It is typical method of PID control to make control signal by summing proportional, integral and derivative signal of the tracking error. However, fixed gain PID controllers generally do not work well for nonlinear or high order systems. To overcome this weakness, they were implemented fuzzy PID type controllers (FPID) [5]. A natural Mamdani fuzzy controller using an expert rule base gives a fuzzy PD control law. Thus, the integral part of the FPID is introduced by a different hybrid FPID structures. Some of them, most applied in practice are shown in Fig. 2, Fig. 3.

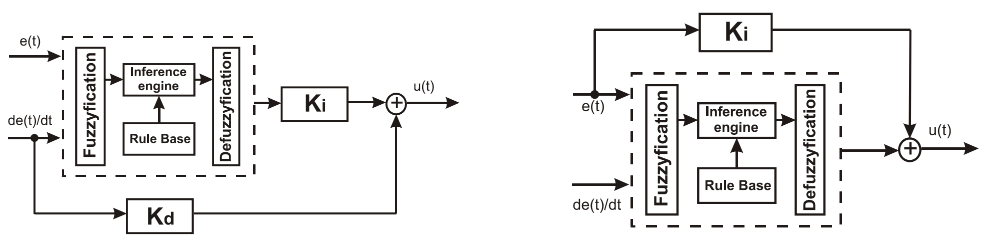

Fig.2 FPID controller with parallel differentiator/ integrator

E / ΔE	NL	PM	NS	ZR	PS	PM	PL
NL	NL	NM	NM	NS	NS	ZR	ZR
NM	NM	NM	NS	NS	ZR	ZR	ZR
NS	NM	NS	NS	ZR	ZR	ZR	PS
ZR	NS	NS	ZR	ZR	ZR	PS	PS
PS	NS	ZR	ZR	ZR	PS	PS	PM
PM	ZR	ZR	ZR	PS	PS	PM	PM
PL	ZR	ZR	PS	PS	PM	PM	PL

Table 1 Expert PD type rule base table

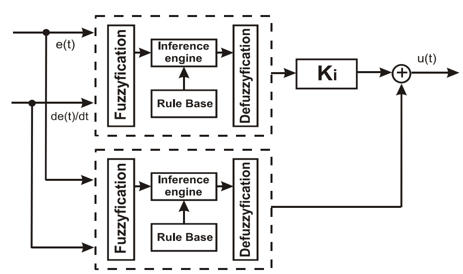

Fig.3 FPID controller with parallel FPI+FPD

3. BASICS OF NONLINEAR MODEL PREDICTIVE CONTROL STRATEGY

In general, the predictive control problem is formulated as solving on-line a finite horizon open-loop optimal control problem subject to system dynamics.

Nonlinear Model Predictive Control (NMPC) as it was applied with the Takagi-Sugeno fuzzy-neural process model can be described in general with a block diagram, as it is depicted in Figure 4.

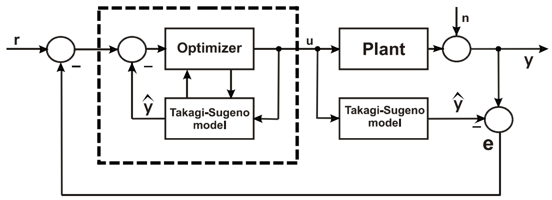

Fig.4 Block diagram of model predictive control system

The Takagi-Sugeno fuzzy-neural models are suitable to model a class of nonlinear systems. As it is well known a wide class of nonlinear dynamic systems can be described in discrete time by the NARX (Nonlinear Auto Regressive 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:

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

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

(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_i 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. In the Takagi-Sugeno fuzzy model is need 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 it has been proposed numerous approaches. In this work is applied a simplified fuzzy neural approach described in several previous works [6]. It is used two steps gradient learning procedure as a learning algorithm of the internal fuzzy neural model. This procedure is based on minimization of the instant error between the process and model output.

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:

$$J(k,u(k))=\sum_{i=N_1}^{N_2}(r(k+i)-\hat{y}(k+i))^2+\rho\sum_{i=1}^{N_u}\Delta u(k+i-1)^2 \tag{4}$$

where $\hat{y}$ is the predicted model output, r is the 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, 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: $\nabla J[k,U(k)]=0$

4. SIMULATIN EXPERIMENTS

4.1 PLANT DESCRIPTION

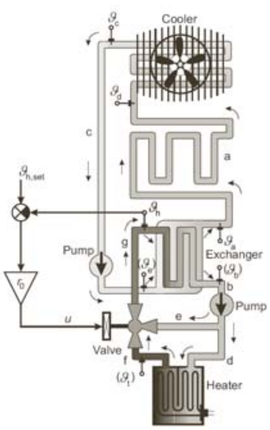

Fig.5 Heat exchanger

The considered plant process is a heating system which consists of two heating circuits with the circulation of the heat medium (water) accomplished by two pumps (one in each circuit). The heat source of the system is an electric heater, located in the primary circuit. The heat exchange between the two circuits, which is controlled by the mixing valve, takes place in the multi-plate heating exchanger. The last component of the system is an air-water cooler located in the secondary circuit. As can be seen in Fig. 5, the components of the system are connected by the piping lines that provide the most important delays in the system. The control objective is to maintain the temperature *θh* at desired set point. The plant process can be represented by the following equations [7]:

$$T_d \frac{d\Delta\vartheta_d(t)}{dt} = -\Delta\vartheta_d(t) + K_d \Delta\vartheta_a(t-\tau_d) \qquad (5)$$

$$T_c \frac{d\Delta\vartheta_c(t)}{dt} = -\Delta\vartheta_c(t-\eta_c) + K_c \Delta\vartheta_d(t-\tau_c) \qquad (6)$$

$$T_h \frac{d\Delta\vartheta_h(t)}{dt} = -\Delta\vartheta_h(t-\eta_h) + K_b \Delta\vartheta_a(t-\tau_b) + K_u \Delta\vartheta_{h,set}(t-\tau_u) \qquad (7)$$

$$T_a \frac{d\Delta\vartheta_a(t)}{dt} = K_a\,[\,\Delta\vartheta_h(t) - \frac{1+q}{2}\Delta\vartheta_a(t) - \frac{1+q}{2}\Delta\vartheta_c(t-\tau_c)] - [\,\Delta\vartheta_a(t) - \Delta\vartheta_a(t-\tau_c)] \qquad (8)$$

4.2 SIMULATION RESULTS

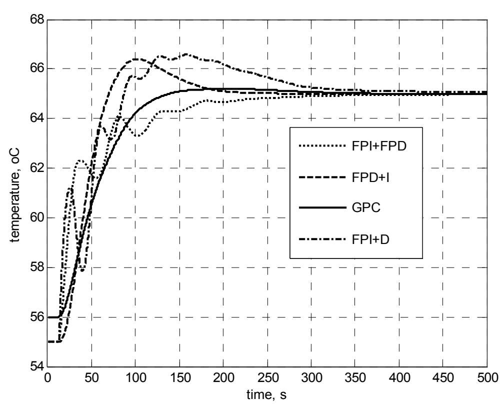

Fig. 6 Transient process responses at system reference r=65 oC and different control algorithms

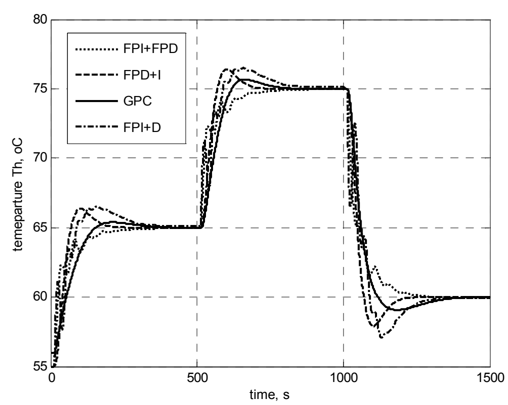

Fig. 6 Transient process responses at variable system reference and different control algorithms

5. CONCLUSIONS

In this paper it is presented a comparative study between Generalized Predictive Controller, based on a Takagi-Sugeno fuzzy-neural model and a simple optimization procedure, and different Fuzzy PID type control algorithms in case of temperature control of a heat exchanger. The simulation results show that the studied GPC algorithm ensures a good system performance in both cases of variable and set system reference which is a result of its adaptiveness according to system changes. When using fuzzy PID algorithms, one can see that the structure of each Fuzzy PID controller is an important issue in notion to system dynamics. The Fuzzy PI+D and PI+PD controllers lead to similar process responses with undesirable overshoots, in both cases in contrast to Fuzzy PD+I which gives a better system performance. The gain coefficients of each FPID controller must be retuned in order to be well tracked the variable system reference. When the fuzzy PD+I controller is well tuned and its rule base is extended with additional rules, its performance can be improved as close to GPC control.

6. ACKNOWLEDGEMENTS

The authors would like to acknowledge the Ministry of Education and Science of Bulgaria Research Fund Project No: BY-TH-108/2005.

7. REFERENCES

[1] Passino K, Yourkovic S., *Fuzzy Control*, Adisson-Wesley, 1998
[2] Clarke D. W., Mohtadi C., Tuffs P. C., *Generalized Predictive Control - Part 1: The Basic Algorithm*, Automatica, Volume 23, 1987, pp 137-148.
[3] Findeisen R., Allgower F., *An introduction to nonlinear model predictive control*, 21st Benelux Meeting on Systems and Control, 2002, Veldhoven
[4] L. Zheng, "*A Practical Guide to Tune of Proportional and Integral (PI) Like Fuzzy Controllers*," IEEE 1992.
[5] Berhm T., Rattan K., *Hybrid Fuzzy logic PID controller*, Proceedings of the 1994 IEEE International Conference on Fuzzy Systems, Orlando, FL, June 1994.
[6] M. Georgieva, M.Petrov, A. Taneva, *RLS method for training of TS fuzzy neural model*, Summer School, 2004, Graz, Austria.
[7] Vyhlidal T., *Analysis and synthesis of time delay system spectrum,Ph.D. thesis, Czech Technical University of Prague.*

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