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Design and Genetic Algorithms Based Optimisation of Industrial Adaptive PID FLC System of Liquid Level

Abstract

The level control of the precarbonised solution in a soda ash production plant requires intelligent approaches that can tackle process complexity, nonlinearity and industrial environment impact. Therefore, model-free fuzzy logic controllers (FLC) with empirical tuning are suggested which are implemented in a general purpose programmable logic controller (PLC) and operate in real time control. Online adaptation improves the FLC parameters tuning. The aim of the present research is to optimise the adaptation strategy and the parameters of an adaptive PLC PID FLC using genetic algorithms (GA) and simulations for reducing both the system error and the control variance. The PID FLC is based on a PD FLC and a parallel integrator of the system error. A Sugeno model is used for adaptation of the PID FLC tuning parameters. Depending on the level it defines empirically via its input membership functions three linearisation zones and performs soft blending of the local for each zone PD FLC gains and integrator time-constants. Two adaptation strategies are suggested for online auto-tuning of the integrator time-constant only, and together with the PD FLC gain. The local parameters, in turn, are GA optimised. Simulations show that the best system performance is achieved by auto-tuning both PID FLC parameters with optimised local values.

Keywords: carbonisation, fuzzy logic adaptive control, genetic algorithms optimisation, industrial implementation, system simulations

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Проектирование и оптимизация генетическими алгоритмами промышленной системы с адаптивным нечетким ПИД регулятором уровня жидкости

Задача регулирования уровня предварительно карбонизированного раствора на технологической установке по производству кальцинированной соды требует применения не традиционных, классических, а современных интеллектуальных подходов, позволяющих учитывать сложность процесса, его нелинейность и воздействия промышленных помех. Для решения данной задачи в работе предлагается использовать безмодельные контроллеры нечеткой логики FLC с эмпирической онлайн-настройкой, реализованные в режиме реального времени в программируемом логическом контроллере общего назначения PLC. Целью исследования является параметрическая оптимизация генетическим алгоритмом стратегии адаптивного PID FLC регулятора. При этом для адаптации параметров настройки PID FLC используется модель Sugeno. Здесь PD FLC регулятор, в зависимости от значения регулируемого уровня, эмпирически

определяет с помощью своих функций принадлежности три зоны линеаризации и выполняет для каждой зоны мягкое смешивание коэффициентов передачи усилителя и интегратора. Предложены две стратегии адаптации для онлайн-автоматической настройки постоянной времени интегратора совместно с коэффициентами передачи усилителя и дифференциатора PD FLC. Локальные параметры системы регулирования технологической установки, в свою очередь, автоматически оптимизируются генетическим алгоритмом. Компьютерное моделирование и промышленные эксперименты показали высокую эффективность синтезированной системы регулирования за счет автоматической настройки параметров PID FLC с оптимизированными локальными значениями.

Ключевые слова: технологический процесс карбонизации, адаптивное управление с нечеткой логикой, параметрическая оптимизация генетическим алгоритмом, компьютерное моделирование, промышленные эксперименты

1. Introduction and state-of-the-art

Carbonisation is an essential process in the production of synthetic soda ash. In a carbonisation column (CCI) a reversible exothermic reaction of a precarbonised solution mainly of ammonia brine solution (a solution of water H_2O , salt $NaCl$ and ammonia NH_3) with carbon dioxide (CO_2) gases in counterflow takes place. As a result crystals of sodium bicarbonate ($NaHCO_3$) are produced taken away by the cooling water at the output valve on the CCI bottom. On industrial scale several CCI operate in parallel with a common supply of precarbonised solution. Besides, CCI alternates operation mode with washing mode keeping a prescribed ratio of CCI in operation and in washing mode [1].

The control of level in a CCI is important for the quality of the soda ash produced. It is also a challenging task because of the plant complex nonlinear behaviour and the impact of the industrial disturbances. The main disturbance is the measured pressure P in the common supply collector, which changes randomly. The reference for level also changes as it depends on the load of the CCI measured by the flowrate of the CO_2 gases and on the distribution of the produced precarbonised solution among the CCI in operation mode.

The plant is difficult to be modelled and hence to be controlled applying classical control techniques. Model-free fuzzy logic controllers (FLC) ensure high performance control based on expert empirical knowledge about the plant instead of a classical mathematical model [2]. Various FLC are suggested for level control [3-9]. Adaptation and genetic algorithms (GA) parameter optimisation are the most often used approaches to FLC tuning [4-6]. In [7-9] FLC for industrial applications are developed based on programmable logic controllers (PLC) and embedded low cost technique, which, however, are tested only in laboratory environment.

Several model-free FLC for the control of the level of the solution in the CCI are designed and empirically tuned in [10-12]. They all are implemented in

the industrial general purpose PLC and applied for the real time online level control in an operating CCI of the "Solvay Sodi" AD plant in the town of Devnya, Bulgaria. First, a PI single-input single-output (SISO) FLC is developed in [10] with the system error as input. The SISO FLC avoids the use of the rate of error as a second input in the classical PI FLC which numerical computation in industrial environment by the means of the PLC is highly noise sensitive. In order to reduce the disturbance impact a PI two-input (2I) FLC is designed in [11] where the deviation of the pressure from its mean value is introduced as a second input and a corresponding rule base derived. In [12] a PID FLC based on a 2ISO PD FLC and a parallel linear integrator of the system error is designed. The post-processing gain K_d of the PD FLC or the integrator time-constant T_i are online auto-tuned depending on the degree of belonging of the current measured level H or its reference H_r to three overlapping plant linear operation zones. The linearization zones are defined by the input membership functions (MF) of a Sugeno model which performs a soft blending of the local for each zone empirically determined gains K_{dj} or integration time-constants T_{ij} . The real time industrial experiments show that the system with adaptive online tuning of T_i as function of the level H has the best performance and therefore is accepted as a basis of the present paper.

The aim of the new investigation is to develop an approach for design and study via simulations of an adaptive PID FLC system for the control of the level of the precarbonised solution in a CCI with two adaptation strategies for online auto-tuning as function of H — only of T_i and of both K_d and T_i by PDC soft blending of GA optimised local values in order to improve the performance of the system.

The GA optimisation of the local gains and integration time-constants uses for computation of the fitness function system simulations and data from the real time level control system with the best adaptive PID FLC with online auto-tuning of T_i as function of H for empirically determined K_d and local T_{ij} . The derivation of the system simulation

model and the simulation investigations are based on MATLABTM/Simulink and its toolboxes for fuzzy logic and GA [14, 15], on the industrial PLC completion of the PID FLC [13] and the data from the real time experiments.

The paper is organized as follows. Chapter 2 presents the theoretical background and the problem formulation. The derivation and validation of a system simulation model of the existing real world operating closed loop system with the PLC adaptive Sugeno PID FLC from [12] is described in Chapter 3. Chapter 4 is devoted to the off-line GA optimisation of the local parameters T_{ij} and K_{dj} based on system simulation. It also contains simulation investigations and comparison of the performance of the systems with empirically determined and GA optimised local parameters in the two adaptation strategies. Chapter 5 presents a conclusion and ideas for future research.

2. Theoretical background and problem formulation

The most often used model-free PID FLC are based on a fuzzy unit (FU) with two normalised in the range $[-1, 1]$ inputs — the system error e^n and the rate of error de^n that comprises a 2ISO PD FLC which operates either with a PI post-processing or with a linear integrator in parallel as the developed in [12]. The rate of error is responsible for the D component which is important for the system stability and fast response due its prediction property. The noise sensitivity of the numerical computation of the rate of error, however, hinders its wide industrial implementation. Therefore, different numerical and filtering methods are developed to reduce the impact of noise and disturbances. In [12] the computed rate of error as a finite difference is smoothed using sliding average technique. The model-free PID FLC tuning also is a problem and most often relies on empirical approaches based on subjective human expertise, various assumptions, many and slow experiments which are difficult to control in industrial environment. To compensate the trial-and-error imprecise tuning, a simple mechanism for online auto-tuning is suggested in [12]. The PID FLC adaptation stems from the principle of parallel distributed compensation (PDC) [16, 17] for building of nonlinear control by soft blending of the outputs of local linear controllers. The PDC is designed on the basis of a TSK model of the nonlinear plant which assumes that the plant operates in a few overlapping linearisation zones and in each zone it can be described by a local linear model. A Sugeno model defines the linearisa-

tion zones via the input MF and performs soft blending of local linear plant models. In the same way, the PDC performs soft blending of the outputs of the local linear controllers in the PDC rules conclusions on the basis of the common with the TSK plant model predicate in the If-Then rules. Each local for the linearisation zone linear controller is designed using the linear control theory methods accounting for the corresponding local linear plant model.

In [12] in absence of a TSK plant model three linearization zones around the most often used references for the level 40, 50 and 60 % are assumed. The adaptation comprises soft blending either of the gains $K_d = [K_{d1} = 40, K_{d2} = 50, K_{d3} = 70]$ % for a constant integration time-constant T_{io} or of $T_i = [T_{i1} = 18, T_{i2} = 84, T_{i3} = 102]$ s for a constant K_{do} . The constant and the local values are determined via experiments. Five different control strategies are experimented based on PLC PID FLC:

- Strategy 1 with fixed empirically tuned $K_d = 50$ % and $T_i = 138$ s;
- Strategy 2 with soft blending of the local values of T_i for constant $K_{do} = 55$ %;
- Strategy 3 with soft blending of the local values of K_d for constant $T_{io} = 138$ s.

Strategy 2 and Strategy 3 use two variants of parameters soft blending — depending on the degree of belonging of the current measured level H (H is the Sugeno model input) or of its reference H_r (H_r is the Sugeno model input) to all defined linearization zones in the Sugeno model input MF. In this way were done Strategy 4 and Strategy 5. All experiments are performed on the operating CCl with PLC implementation of the designed PID FLC by the use of ordinary logic functions for the description of MF, fuzzy rules, aggregation, implication, accumulation and defuzzyfication. The best system performance is assessed from the adaptation of T_i as fuzzy function of H which turns the integrating component in the adaptive PID FLC from linear into nonlinear. The empirical tuning of K_{do} and T_{ij} or K_{dj} and T_{io} is rather subjective and slow and it is not applicable for a great number of tuning parameters in case both K_{dj} and T_{ij} are auto-tuned.

The problem is to apply an objective approach — optimisation of the local tuning parameters in the strategies for auto-tuning of T_i and of both K_d and T_i in order to improve the performance of the best empirically tuned adaptive PLC PID FLC system.

GA are selected as a proper technique for optimisation of a nonlinear fitness function of many parameters without analytical expression with respect to its parameters [18]. They provide parallel random

search of the parameter space for global optimum without getting trapped in a local optimum. The GA are inspired from the Darwin's theory on the evolution of the human intelligence. The new better with respect to the accepted fitness function generation is raised by mating of properly selected individuals (parents), exchange of genes within specified areas between them and small random gene mutations to escape from the low level of the parents' generation and trapping in local optimum. The individual is viewed upon as a possible solution — a combination of values for the parameters for which the fitness function gets an optimal value, usually minimum. It is an analogue to the chromosome that comprises an array of genes, each representing a coded value of the corresponding tuning parameter. The optimisation starts with the random generation of the initial population of M individuals. Then the individuals are rated according to the computed value of the accepted fitness function. The mating, the genes crossover and mutation are based on different methods and continue till the new generation is completed with M offsprings with better ratings than their parents. The optimisation ends after a given number of generations and then the optimal parameters may not ensure the desired minimum of the fitness function or after the expected minimum is reached.

In the present investigation the GA are applied off-line using system simulations to compute the fitness function which ensures fast and objective results without interfering of the real world system that may cause for some generated chromosomes system instability or unacceptable performance. By GA two types of optimisation problem are solved in the present investigation. The first is a modelling problem. It is expressed in optimisation of the parameters of a designed model in order to minimise a fitness function of the modelling error between the outputs of the model and the modelled real world system, plant or controller. Both model and real world system are subjected to the same input recorded from the real time operation of real world system. This problem appears in the derivation of a TSK plant model [16, 17] and a PID FLC from real time experiments of the level control with the PLC implementation of the best Sugeno adaptive PID FLC [12]. The second optimisation problem is related with the computing of the optimal controller's parameters which minimise a fitness function of

specific closed loop control system performance indicators. In both problems the necessary input/output data used are a result of well-designed experiments in order to ensure that the signals cover the whole range of operation of the real world system and are rich in magnitudes and frequencies. Then the data are pre-processed to decrease the length of the sample and to eliminate noise and correlation. Usually the data from the real world experiments are split into data used in the GA optimisation and data (1/3 of all) used for model validation after the end of the optimisation.

The functional block diagram of the adaptive PID FLC to be optimised is presented in Fig. 1. It integrates two PDC adaptation strategies — the best for auto-tuning of T_i for constant K_d from [12] (position "1" of the Switch) and a new one with the additional functionality to auto-tune both K_d and T_i (position "2" of the Switch). The measured level H_m is noise filtered by an exponential filter with transfer function $W_f(s) = (12s + 1)^{-1}$. The result is compared with the reference H_r to yield the system error $e = H_r - H$. The rate of error de is numerically computed in the block "de/dt" and then smoothed for 30 points in the block "Sliding average". The gains $K_e = K_{de} = 0.05$ for normalisation of e and de in the range $[-1 \ 1]$ are computed based on the maximal expected absolute system error of 20 %.

The fuzzy unit represents in a 2ISO Sugeno model a number of PLC ordinary logic expressions for the MF, the fuzzy rules and the derivation of the final defuzzyfied conclusion.

Standard orthogonal triangle and trapezoidal at the range ends MF for the inputs and singletons for the output MF and a standard soft rule base with fuzzy rules R_p , $p = 1-15$ are used. The MF of the normalised inputs are the following:

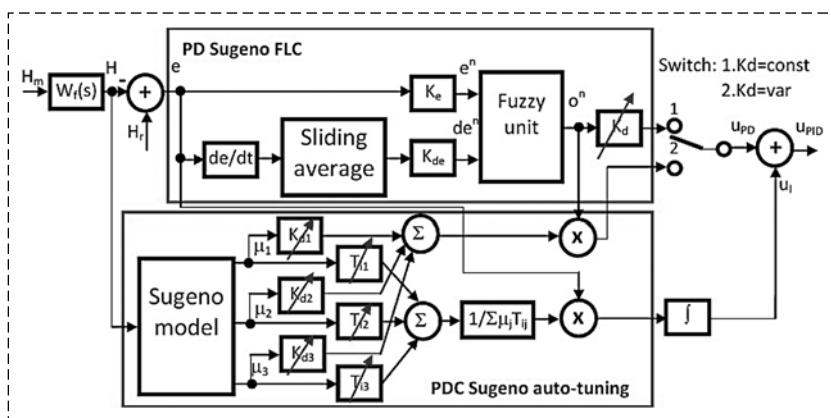


Fig. 1. Functional block diagram of the Sugeno PID FLC with on-line PDC adaptation only of T_i (Switch in "1") and of both K_d and T_i (Switch in "2") as function of the level H

— for the system error e^n with labels $Le = [Le_m] = [NG_e N_e Z_e P_e PG_e]$, $m = 1-5$, where $NG_e = [-1 -1 -0.6 -0.2]$, $N_e = [-0.6 -0.2 0]$, $Z_e = [-0.2 0 0.2]$ — Norm, $P_e = [0 0.2 0.6]$, $PG_e = [0.2 0.6 1 1]$;

— for the rate of error de^n with labels $Lde = [Lde_l] = [N_e Z_e P_e]$, $l = 1-3$, where $N_{de} = [-1 -1 -0.3 0]$, $Z_{de} = [-0.3 0 0.3]$ — Norm, $N_{de} = [0 0.3 1 1]$, NG is Negative Great, N — for Negative, Z — for Zero, P — for Positive and PG — for Positive Great.

The MF of the output o^n are singletons labelled $Lo = [Lo_r] = [NG NS N Z P PS PG]$, $r = 1-7$, where $NG = -1$, $NS = -0.6$, $N = -0.2$, $Z = 0$, $P = 0.2$, $PS = 0.6$, $PG = 1$ and PS and NS stand for Positive Small and Negative Small respectively.

The FU final output o^n is computed via weighted average defuzzification in the same way as in the PLC PID FLC implementation:

$$o^n = \left(\sum_{p=1}^{15} Lo_p w_p \right) / \sum_{p=1}^{15} w_p,$$

where $Lo_p = Lo_1 - Lo_7$ is the singleton in the p^{th} rule conclusion and $w_p = \min(Le_m, Lde_l)$ is the p^{th} rule activation degree. The final PID FLC output u_{PID} is computed as:

$$u_{PID}(t) = u_{PD}(t) + \frac{1}{T_i} \int e(t) dt,$$

where $u_{PD}(t) = K_d o^n(t)$ is the PD FLC output and the PD FLC gain K_d and the integration time-constant T_i are the PID FLC tuning parameters.

The PDC auto-tuning mechanism is based on a SI3O Sugeno model. The Sugeno model input is the filtered measured level H with MF labeled $LH = [LH_j] = [LowH NormH HighH]$, $j = 1-3$, $LowH = [0 0 35 50]$, $NormH = [35 50 65]$, $HighH = [50 65 100 100]$ to describe the empirically accepted three linearisation zones. The output MF are the singletons 0 and 1. Specific fuzzy rules R_j ensure mapping of the three MF in the three outputs (3O), i.e. each output yields the degree of belonging of the current H to the corresponding linearisation zone, or output $\mu_j = \mu_j$:

R_1 : If H is LowH
Then $output_1^1 = 1$, $output_2^1 = 0$, $output_3^1 = 0$

R_2 : If H is NormH
Then $output_1^2 = 0$, $output_2^2 = 1$, $output_3^2 = 0$

R_3 : If H is HighH
Then $output_1^3 = 0$, $output_2^3 = 0$, $output_3^3 = 1$.

E.g. for current measured level $H_k = 46\%$ at time instant t_k the predicate of R_1 is fulfilled with degree $\mu_1 = 0.3$, of R_2 — with $\mu_2 = 0.7$ and of R_3 — with $\mu_3 = 0$, i.e. the degree of belonging of H_k to linearization zone LowH is $\mu_1 = 0.3$, to NormH is $\mu_2 = 0.7$ and to HighH is $\mu_3 = 0$. The Sugeno model outputs are computed applying the weighted average defuzzification and considering that the MF of the inputs are orthogonal $\left(\sum_{j=1}^3 \mu_j = 1 \right)$:

$$output_1 = \sum_{j=1}^3 output_j^1 \mu_j =$$

$$= 1\mu_1 + 0\mu_2 + 0\mu_3 = \mu_1 = 0.3;$$

$$output_2 = \sum_{j=1}^3 output_j^2 \mu_j =$$

$$= 0\mu_1 + 1\mu_2 + 0\mu_3 = \mu_2 = 0.7;$$

$$output_3 = \sum_{j=1}^3 output_j^3 \mu_j =$$

$$= 0\mu_1 + 0\mu_2 + 1\mu_3 = \mu_3 = 0.$$

The degree of belonging μ_j of the level H_k to the corresponding linearization zone appears as Sugeno model output $output_j$ which scales the respective local gain K_{dj} and integration time-constant T_{ij} in this zone. Thus the expression of the smooth nonlinear adaptation algorithm for online tuning of the PID FLC parameters as function of H is the following:

$$K_d(t) = \sum_{j=1}^3 \mu_j(H(t)) K_{dj}, \quad T_i(t) = \sum_{j=1}^3 \mu_j(H(t)) T_{ij}.$$

3. Simulation modelling and validation of adaptive PID FLC system

The derivation and validation of a simulation model of the existing real world closed loop system is based on MATLABTM/Simulink and its toolboxes Fuzzy Logic and GA [14, 15]. The simulation model is necessary in the GA optimisation of the parameters of the adaptive PID FLC and in the simulation investigations for assessment and comparison of the performance of the designed systems with empirical and optimised local parameters using two adaptation strategies. The system simulation model consists of a Simulink model of the adaptive PID FLC and a TSK plant model. Their derivation and validation uses data from the real time experiments of the best PLC PID FLC system from [12].

The modelling and the validation of the adaptive PID FLC simulation model is based on the block

diagram in 1 which describes the PLC implemented PID FLC. The derived Simulink simulation model of the best adaptive PLC PID FLC is presented in Fig. 2 (see the third side of the cover) where $K_d = 55\%$, $T_{i1} = 18$ s, $T_{i2} = 84$ s and $T_{i3} = 102$ s. It contains Transport Delay blocks for the inputs and a Switch at its output to keep zero output for the time-delay (here 4000 s). This time-delay is needed for the nonlinear controller to reach initial steady state, i.e. the initial conditions to settle ensuring equilibrium. Then the recorded and smoothed signals from the PLC real time control system are applied to the inputs of the Simulink PID FLC model. These signals are the noise filtered level H_{is} , its reference H_{exp} , the control action U_{is} , the on-line auto-tuned T_{iexp} and the normalised rate of error $dEns_sh$. They are obtained as a result of experiments with successive step changes of the level reference in the sequence 50–60–50–40–50 % carried out during the PLC real time control with the adaptation of T_i . The disturbance P changes randomly in each experiment. The FU and the Sugeno model in Fig.1 are designed by the help of the Fuzzy Logic toolbox each to identically represent in a single block "FLC" of MATLABTM/Simulink a number of PLC ordinary logic expressions for the MF, the fuzzy rules and the derivation of the final defuzzified conclusion. All other Simulink blocks model precisely the PLC blocks from the adaptive PID FLC implementation. The only difference concludes in the computation of de^n . Therefore, the Simulink module "de/dt", shown in Fig. 2 (see the third side of the cover), is suggested to approximate the PLC PID FLC blocks for the computation of the rate of error "de/dt" and "Sliding average" in Fig. 1. First, the finite difference of the error is computed $de_k \approx e_k - e_{k-1}$ using previous time instant signal from the block "1/z". Then the result is smoothed by additional exponential filter with transfer function $W_d(s) = k(Ts + 1)^{-1}$. The filter parameters k and T are obtained after a GA minimisation of the mean squared modelling error between the normalised de^n computed by the Simulink PID FLC model and the processed rate of the error signal computed by the PLC PID FLC during the real time control experiments. The optimised values are $k = 70$ and $T = 30$ s. The step responses to $H_r = 50-60-50-40-50\%$ of the normalised system error e^n and rates of error of the PID FLC from simulation de^n with input data H_{is} , U_{is} from experiments and $de_{is}^n = dEns_sh$ from PLC real time experiments are shown in Fig. 3 (see the third side of the cover). The rate of error e^n is close to de_{is}^n which is a proof

of high approximation accuracy. The step responses of the control actions U and T_i from adaptation of the PID FLC simulation model and $de_{is}^n = dEns_sh$ from experiments and U_{is} and $T_{is}(H)$ from experiments are also close to U_{is} and T_{iis} of the best adaptive PLC PID FLC as seen in Fig. 4 (see the third side of the cover). This confirms that the developed PID FLC simulation model is accurate.

The derivation of the TSK plant model uses the same Sugeno model from the T_i auto-tuning and a dynamic part of three parallel local linear models — one for each linearization zone, shown in Fig. 5. The local linear models are described by the transfer functions of timelags $P_j(s) = K_j(T_j s + 1)^{-1}$. An additional common for the three zones timelag $P_4(s) = (T_4 s + 1)^{-1}$ is introduced in series to increase the order of the local plants with a small number of the TSK plant model parameters $\mathbf{q}_{TSK}^T = [K_1 \ K_2 \ K_3 \ T_1 \ T_2 \ T_3 \ T_4 \ y_0]$ to be determined. The initial level $y(0)$ is accepted as a model parameter since it plays an important role in the behaviour of the nonlinear plant. This structure of the TSK plant model is accepted based on the assumption of three linearization zones around the most often used references and the expert knowledge about the dynamic behaviour of the plant in these zones. The unknown parameters \mathbf{q}_{TSK}^T are computed in a GA optimisation procedure. For this purpose a closed loop system simulation model is built of the TSK plant model and the designed model of the PID FLC with adaptation of T_i from Fig. 2 (see the third side of the cover) that controls $y_{TSK} = H_{TSK}$. The fitness function $F = \frac{1}{N} \sum_{k=1}^N (y_{TSKk} - H_{is_k})^2$ is the mean squared modelling error between the output of the TSK plant model y_{TSK} in the closed loop system simulation model and the smoothed measured level H_{is} from the closed loop control system real time experiments for step reference changes $H_r = 50-60-50-40-50\%$, where N is the sample length, i.e. the number of measurements (here $N = 5050$). Delay blocks and zero output for the same

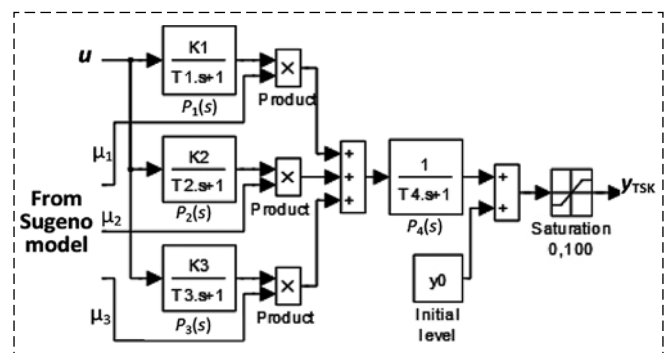


Fig. 5. Dynamic part of the accepted TSK plant model in Simulink

time-delay like in Fig. 2 (see the third side of the cover) ensure start of the simulation experiments after a reached initial equilibrium — important for nonlinear systems. The minimisation of the fitness function computed by the help of system simulations yields the following optimal parameters for which $F_{\min} = 0.5986$:

$$\mathbf{q}_{\text{TSK}}^{\text{Topt}} = [K_1 = 0.31; K_2 = 0.75; K_3 = 0.99; \\ T_1 = 24 \text{ s}; T_2 = 219 \text{ s}; T_3 = 481 \text{ s}; \\ T_4 = 164 \text{ s}; y_0 = 29 \%].$$

The step responses with respect to level, control action and tuning parameter of the best adaptive PID FLC closed loop system from simulation (Hisim, Uisim, Tisim) and from PLC real time control without data smoothing (Hi, Ui, Ti) are presented in Fig. 6 (see the third side of the cover). They show that Hisim is smooth and very close to Hi (Hism \approx Hi) while Hi is subjected to the impact of industrial disturbances. The T_i adaptations are almost identical Tism \approx Ti. The control actions differ in the final for each step response values which can be explained by the disturbance impact. The closed loop systems step responses for fixed $K_d = 50 \%$ and $T_i = 138 \text{ s}$ demonstrate the same relationship between the simulation and the real time data which validates the developed simulation models of the PID FLC and of the plant. The validation gives grounds to trust all further simulation results in testing of other adaptation strategies and in GA optimisation of the PID FLC parameters.

The TSK plant model enables the study of the plant. Its step responses from simulation are depicted in Fig. 7 (see the fourth side of the cover) where the MF of the Sugeno model are added. The step responses demonstrate the nonlinearity of the plant since for equal step changes Δu of the input u the step response at settling time of the plant output $\Delta H_{\text{TSK}}(\infty)$ is different in the different operating points — it is lowest about $H_{\text{TSK}} = 40 \%$ (linearisation zone "LowH"), highest about $H_{\text{TSK}} = 50 \%$ (linearisation zone "NormH") and medium about $H_{\text{TSK}} = 60 \%$ (linearisation zone "HighH"). So, the gains of the local linear plants $K_j = \Delta H_{\text{TSK}_j}(\infty)/\Delta u$ in the three linearisation zones change from low through high to medium. This serves as information for determining of the ranges for the PID FLC tuning parameters in their further GA optimisation.

4. GA optimisation of PID FLC parameters

The empirical parameters tuning of the PID FLC is the only approach in case of scanty expert know-

ledge about the control of the plant. It is based on a lot of trial-and-error experiments with different values for the parameters during the operation of the plant. The experiments take a long time, can hardly be controlled in presence of industrial disturbances and are not applicable for tuning of many parameters. Besides, the assessment of the system performance improvement is difficult and approximate. The PDC based adaptation of the PID FLC parameters about empirically determined local values in [12] is introduced as compensation of the subjectivity, the impact of industrial disturbances and the imprecision in tuning. Even in this case the approach is applicable for a small number of tuning parameters and the result may be still far from the optimal. The empirical tuning is useful as it provides a new knowledge to the control of the plant which enables application of objective optimisation techniques.

The task in this chapter is to use the developed system simulation model of validated controller's model and TSK plant model on the basis of the empirically tuned best adaptive PLC PID FLC in order to GA optimise the PID FLC tuning parameters and study two adaptation strategies:

— Strategy 1 — PDC online auto-tuning of T_i with optimised K_d and local T_{ij} . This strategy is used in the best adaptive PLC PID FLC from the real time level control but with empirically determined K_d and local T_{ij} ;

— Strategy 2 — PDC online auto-tuning of both T_i and K_d with optimised local T_{ij} and K_{dj} . This strategy is based on online auto-tuning of more parameters, which have first to be optimised and explores the possibility for a greater improvement of the system performance.

The simulation model of the system with the two adaptation strategies used in the GA parameter optimisation is shown in Fig. 8 (see the fourth side of the cover). In adaptation strategy 1 the tuning parameters of the block "Kd = var" are reduced to one by assigning $K_{d1} = K_{d2} = K_{d3} = K_d$.

The suggested fitness function to be minimized is $F = F_1 + 0.1F_2/F_3$. It integrates two criteria. The first criterion aims at increasing of the system dynamic accuracy by minimisation of the mean squared system error $F_1 = \frac{1}{N} \sum_{k=1}^N (H_{rk} - y_{\text{TSK}k})^2 = \min$. The second criterion $\frac{F_2}{F_3} = \min$ demands a reduction of the variance of the control action per unit reference $F_2 = \text{var} \left(\frac{u}{H_r} \right)$ relative to the variance of the main disturbance $F_3 = \text{var}(P)$ accounting in this way for

Performance indicators of the investigated systems via simulation

Systems	System 1 $F^{opt} = 17.7, F_1^{opt} = 10.6$				System 2 $F^{opt} = 14.5, F_1^{opt} = 8.7$				System 3 $F^{opt} = 13.93, F_1^{opt} = 10.6$			
Performance indicators	$\sigma, \%$	t_s, s	$U_{peak}/U_\infty, \%$	$ \Delta U _{max}, \%$	$\sigma, \%$	t_s, s	$U_{peak}/U_\infty, \%$	$ \Delta U _{max}, \%$	$\sigma, \%$	t_s, s	$U_{peak}/U_\infty, \%$	$ \Delta U _{max}, \%$
$H_r = 50-60 \%$	30	1100	80/35	48	8	800	85/35	55	0	700	59/35	27
$H_r = 60-50 \%$	35	1500	8/29	25	10	1100	0/29	33	5	900	0/29	31
$H_r = 50-40 \%$	33	1800	0/25	30	12	1100	0/25	26	7	1100	0/25	25
$H_r = 40-50 \%$	35	1300	75/29	50	20	1300	82/29	50	15	1300	63/29	36
mean	33	1425	40.8	38.3	13	1075	41.8	41	7	1000	30.5	29.8

the impact of the random disturbance. The minimisation of the control variance responds to the requirement for prolonging of the lifetime of the expensive final control elements for the level control in the CCI.

The GA optimisation yields the following optimal PID FLC parameters:

— for the first strategy $\mathbf{q}_{PDC1}^{opt} = [K_d = 63 \%; T_{i1} = 26 s, T_{i2} = 202 s, T_{i3} = 186 s], F^{opt} = 14.5, F_1^{opt} = 8.7;$

— for the second strategy $\mathbf{q}_{PDC2}^{opt} = [K_{d1} = 51 \%, K_{d2} = 32 \%, K_{d3} = 89 \%; T_{i1} = 34 s, T_{i2} = 374 s, T_{i3} = 179 s], F^{opt} = 13.93, F_1^{opt} = 10.6.$

The step responses with respect to level H , control action U and adapted parameters T_i and K_d from simulation of the investigated PID FLC systems are shown in Fig. 9 (see the fourth side of the cover), where the designations are the following:

— (Hi, Ui, Ti) for System 1 with T_i PDC auto-tuning and empirically determined K_d and $T_{ij};$

— (Hio, Uio, Tio) for System 2 with T_i PDC auto-tuning and optimised K_d and $T_{ij};$

— (Ho, Uo, Tio, Kdo) for System 3 with K_d and T_i PDC auto-tuning and optimised K_{dj} and $T_{ij}.$

The designation "i" corresponds to T_i auto-tuning while "o" stands for optimised parameters. The systems are compared on the basis of the performance indicators:

1) minimal integrated criteria \mathbf{F}^{opt} and mean squared error $\mathbf{F}_1^{opt};$ 2) overshoot $\sigma, \%$ and settling time $t_s, s;$ 3) peak U_{peak} and settled U_∞ values for the control action and its maximal range $|\Delta U|_{max}$ — estimates for smooth and economical control action.

The assessed from the four step responses performance indicators of the three systems and their mean values are systemised in Table 1. The analysis of the results rates System 3 as the best for the following reasons:

— System 3 has the minimal \mathbf{F}^{opt} and \mathbf{F}_1^{opt} equal with System 1, which is the second low after Sys-

tem 2. This means that System 3 reaches high dynamic accuracy at a control action with small variance, i.e. economical and smooth;

— The three systems have the same U_∞ for a given reference and the greater the reference is — the higher the settled control action is. System 3 has the smallest $U_{peak},$ hence the lowest deviation of U_{peak} from U_∞ and the lowest $|\Delta U|_{max},$ which are indicators for economical and smooth control, i.e. safe for the final control elements valve and pneumatic cylinder;

— System 3 is the best with minimal both σ and t_s and also with the minimal mean values from all step responses for all performance indicators.

5. Conclusion and future research

The contribution and the novelty of the present research are the following.

An approach is developed for the improvement of the performance of a closed loop system with PLC implemented adaptive PID FLC for the control of the level of the solution in an industrial carbonisation column. The adaptive PID FLC consists of a 2ISO PD FLC with parallel integrator of the system error. A PDC auto-tuning mechanism ensures soft blending of the local PD FLC gains and the integrator time-constants which are empirically determined for three expert defined plant operation linearisation zones. The suggested approach is based on off-line GA optimisation of the parameters of the adaptive PID FLC for two adaptation strategies and simulation experiments for assessment of the best strategy.

The off-line GA optimisation is based on system simulation for the computation of the accepted fitness function. Therefore, a system simulation model is developed. It consists of a model of the adaptive PID FLC developed from its PLC implementation

for the real time level control and a TSK plant model. The two models are derived via GA optimisation using data recorded and processed from designed experiments during the real time PLC PID FLC level control with PID FLC empirically determined parameters. The optimal parameters of the adaptive PID FLC result from offline GA minimization using system simulations of a suggested fitness function which integrates requirements for minimal mean squared system error and minimal control variance.

The closed loop PID FLC systems for level control using the two adaptation strategies with empirically determined and optimised PID FLC parameters are investigated by simulations. The system with PDC auto-tuning of only of the integrator time-constant and constant post-processing gain of the PD FLC shows an increased dynamic accuracy compared with the system with the same strategy implemented in the PLC PID FLC with empirically determined parameters for real time level control. The PDC auto-tuning of both the integrator time-constant and the PD FLC gain leads to the best system improvements — the highest dynamic accuracy and the lowest control variance which prolongs the lifetime of the expensive final control elements for the level control in the carbonisation column.

The future research is related with the real time experimentation of the system with the PID FLC with the best adaptive strategy and optimised parameters for the control of the solution level in an operating CCl.

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