Journal of Automation and Control, 2014, Vol. 2, No. 3, 79-85
Available online at http://pubs.sciepub.com/automation/2/3/3

DOI:10.12691/automation-2-3-3

Design and Tuning of Parallel Distributed Compensation-based Fuzzy Logic Controller for Temperature

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Received October 31, 2014; Revised November 08, 2014; Accepted November 11, 2014

Abstract The parallel distributed compensation (PDC) gains popularity in designing of simple fuzzy logic controllers (FLCs) for nonlinear plants taking advantage of the well-developed linear control theory. The established design approaches suffer difficulties in derivation of standard TSK plant models for processes characterized by time delays, model uncertainties, nonlinearities, inertia, etc., needed for the PDC design. The standard PDC structure is also unfit for parameter optimization and embedding in programmable logic controllers which ensures a broad industrial application. The aim of the investigation is to develop an approach for the design and tuning of a modified process PI PDC-FLC and an on-line fuzzy logic supervisor via off-line GA optimization techniques in order to ensure closed loop stability, robustness, desired performance and energy efficiency. The approach is developed on the example of air temperature control in a laboratory dryer using MATLAB™. Simulations and real time control shows a decreased settling time and increased system robustness and energy efficiency compared to linear PI control.

Keywords: *fuzzy logic supervisor, genetic algorithms, process parallel distributed compensation, temperature real time control, tsk models*

Cite This Article: Snejana Yordanova, and Yavor Sivchev, "Design and Tuning of Parallel Distributed Compensation-based Fuzzy Logic Controller for Temperature." *Journal of Automation and Control*, vol. 2, no. 3 (2014): 79-85. doi: 10.12691/automation-2-3-3.

1. Introduction

The parallel distributed compensation (PDC) gains popularity in designing of simple fuzzy logic controllers (FLCs) for nonlinear plants taking advantage of the well-developed linear control theory [1,2]. The nonlinear plant is represented by a TSK plant model with local linear plant models in the conclusions of the fuzzy rules, each described by a state vector x_{nx1}, an output vector y_{mx1}, an input control vector u_{dx1} and the corresponding matrices A_{nxn}, B_{nxd}, C_{mxn} and D_{mxn}:

If z_1 is Lz_1 **And** … **And** z_n is Lz_n

Then $\dot{x}(t) = Ax(t) + Bu(t)$ **And** $y(t)=Cx(t)+Du(t)$.

The premise variables z with linguistic values Lz recognize the sub-domain for the corresponding local linear plant model. The overall nonlinear plant output is obtained as a fuzzy blending of individual rules (local plants) outputs via the fuzzy inference and defuzzification mechanisms.

According to the principle of PDC a linear controller (state feedback, dynamic compensator, PID, internal model controller, Smith predictor, etc. [2,3,4]) is designed for each local linear plant to ensure stability, robustness and desired performance of the local linear closed loop system using methods from the linear control theory thus compensating a corresponding conclusion in the rules of TSK plant model. The PDC-FLC rules have the same premise as in the TSK plant model and conclusions with the state space descriptions of the linear controllers, for local state feedback the rules take the form:

If z_1 is Lz_1 **And** … **And** z_n is Lz_n **Then** u=-Fx.

The final nonlinear control is a fuzzy blending of the individual rules control actions. The global nonlinear system stability is studied mainly by the help of Lyapunov methods and linear matrix inequalities (LMIs) numerical technique [1,2,3,4,5]. The stability conditions and the corresponding LMIs have been already derived for a great number of TSK-PDC systems in which various system peculiarities such as plant uncertainties, time-delays, signal constraints, constraints on system performance, etc. and conservatism reduction techniques are considered [2,6-10].

Though attractive the PDC-FLC systems design and performance depends on the local linear plant models and the plant dynamics partitioning which are approximate, use average estimations and change with the operation conditions and time. This makes necessary the optimization of tuning of the controllers' parameters. Two basic intelligent techniques in improving system performance are widely spread in industrial applications because of their simplicity and effectiveness - fuzzy logic supervisors (FLSs) for on-line auto-tuning and off-line optimization by genetic algorithms (GAs) [11-29]. The FLS tunes in a nonlinear manner usually the FLC gains introducing adaptive resolution [11] and keeping desired accepted performance indices. Most companies develop extensions for fuzzy assisted auto-tuning - FLSs that minimize the overshoot and undershoot in a shortest time [12,13,14,15] applied mainly to linear controllers. The GAs as a random derivative-free search technique for multi-objective global optimization [16,17] of a non-analytically defined multimodal function of many variables (parameters), are used to tune both linear controllers and FLCs and also their auto-tuning FLS in order to improve different system performance and energy efficiency indices [18]. The GA optimization are not fit for on-line application as it interferes the plant operation, is slow - a great number of experiments are required, inaccurate because of the many disturbances from the industrial environment, restricted by the system stability and parameter constraints. The off-line GA optimization is based on an accurate plant model, an accepted fitness function and a sample of experiments/simulations used in its evaluation.

The two intelligent techniques complement to improve linear controllers [19,20,21] and ordinary FLCs of Mamdani and Sugeno type [11,18,22,23,24,25] which dominate in industrial applications. Lately few applications on PDC-FLCs [23,26,27,28,29] appeared in literature:

- particle swarm optimization - PSO (another similar to GA optimization technique) of tuning of PDC-FLC for load frequency control in interconnected power systems based on fuzzy model of the plant uncertainty [26];

- PSO of tuning of the membership functions (MFs) of the PDC-FLC for a constantly stirred tank reactor – a plant with a time delay in the state variables [27];

- performance-oriented PDC-FLS [28,29] with state feedback gains for each of the linearized local plants computed as fuzzy blending of several gains, which are FLS tuned from accepted performance criteria, with application to a flexible joint robot [28] and an inverted pendulum [29] - the improvements are tested in simulation and conclude in faster system response despite the restrictions on the control;

- simple two-input FLS design in real time auto-tuning of the output scaling factor of a PI PDC-FLC – the FLS inputs are performances easily estimated from on-line measurements $-y/y_r$ (relative with respect to reference y_r plant output y) and magnitude of system error $|e|$, with application to temperature control [23].

The main deficiencies of the few existing approaches for PDC-FLC design are: 1) complex and obscure derivation of the required TSK plant model from identification data for processes with inertia, time delay and model uncertainties – most approaches are developed for mechatronic systems (robots, inverted pendulum, etc.) or plants with no time delay (tank level, frequency in power system, etc.) which facilitates the plant dynamics partitioning based on existing nonlinear plant model; 2) intuitive and application oriented design; 3) lack of tuning or difficult and improper tuning that results in control oscillations responsible for problems with the valve and the energy efficiency; 4) lack of GA and FLS based tuning design methodology for selection of performance indices and of corresponding tuning parameters that best influence them; 5) control algorithms demanding high computational effort, unfit for embedding in programmable logic controllers (PLC) and real time implementations.

The aim of the present investigation is to develop an approach for the design and tuning of a modified process PDC-FLC and a fuzzy logic supervisor via GA optimization techniques in order to ensure closed loop stability and robustness, desired performance and energy efficiency. The approach will be developed on the example of air temperature control in a laboratory dryer. The design and tuning procedure should be easy to apply using MATLAB™ facilities [30,31] and the obtained PDC-FLC-FLS has to be simple in structure for industrial completion in PLCs and real time operation [32,33].

The research is organized as follows. Experimental study of the plant and derivation of its TSK plant model based on a suggested Sugeno-dynamic structure with GA optimized parameters is presented in Section 2. In Section 3 a PID-Sugeno FLC structure is developed for a PDC-FLC and a GA optimization is applied to tune the PDC-FLC parameters. The design and the GA tuning of the FLS is described in Section 4. Simulation and real time experiments are explained in Section 5. The analysis of the main results, the future work and the conclusions is included in Section 6.

2. Experimental Investigations and TSK Modeling of the Plant

The aim of this section is to obtain and validate a TSK model of the plant on the basis of experimental data. It is needed for determination of the structure of the PDC-FLC and in the off-line GA based optimization of the PDC-FLC parameters and later of the designed FLS parameters via closed loop system simulations.

The plant is the air temperature y in a laboratory dryer [2,18,23] which is controlled by changing the voltage u to a Pulse-Width Modulator (PWM) thus varying the duty ratio of switching of an electrical heater and a fan. The dryer is equipped with industrial sensors, transmitters, solid state relay, fan, electrical heater and interfacing board to a computer with analog-to-digital converter and digital outputs. The controller, the PWM, the graph recorders and the noise filters are accomplished as software in the Simulink model.

Six experimental step responses of the temperature y in various operation points to equal in magnitude step changes of u are depicted in Figure 1. One of the input steps is reverse in order to estimate the plant dynamic asymmetry to heating and cooling. Each i of the step responses (i=1÷6) is approximated by Ziegler-Nichols (ZN) model $P_i(s)=K_i.e^{-\tau_i s}.(T_i s+1)^{-1}$ and the model parameters – plant gain K_i, time constant T_i and time delay τ_i, are graphically estimated. The ZN model is simple with clear physical meaning and describes most of the industrial processes, also is well studied and widely accepted in engineering practice. Adjacent step responses with similar ZN model parameters can be grouped in j zones. This is a prerequisite in favour of the selection of a PDC-FLC. There can be distinguished three overlapping linearization zones (j=1÷3) as shown in Figure 1 – Zone 1 for y=20÷50°C, Zone 2 for y=40÷57°C and Zone 3 for y=50÷80°C. In each zone a mean ZN model is computed with mean values for the parameters of the ZN models. The TSK plant model consists of three rules – one for each zone. The conclusion in each rule is the state space representation of the mean ZN model for the corresponding zone – time lag with time delay with mean values for the parameters. The premise variable is the temperature $z=y$, which distinguishes the zones and the plant behavior respectively.

Instead of a standard TSK plant model an equivalent Sugeno plant model structure of clear physical nature is developed, shown in Figure 2. It consists of a Sugeno soft switch (Smodel) with input y in the range [20,80] °C partitioned by 3 MFs [S M B] for Small, Medium and Big allocated in the range according to the definition of the three zones in Figure 1. The outputs of the Smodel are singletons that yield specific values of the three MFs of belonging μ_j of the current plant output y to each of the fuzzy zones, defined by S, M and B. The dynamic part is divided into three parallel branches – one dominating for each zone. Each branch consists of two time lags to represent a high order local linear plant. The first time lag in a branch has the physical meaning of the time lag in the ZN model, while the second time lag – the linear term of the Taylor's series expansion of the time delay element in the ZN model $e^{-\tau_i s} \approx (\tau_i s+1)^{-1}$. Input to the plant is u, which is passed to the inputs of the three branches whose outputs are weighted by the corresponding μ_j and then summed to accomplish defuzzification and yield the plant model output. The inertia of the plant is increased by the common time lag - (K=1, T=1) at the plant model output, where the initial condition (initial or ambient air temperature $y(0)=y_{amb}$) in the dryer is added.

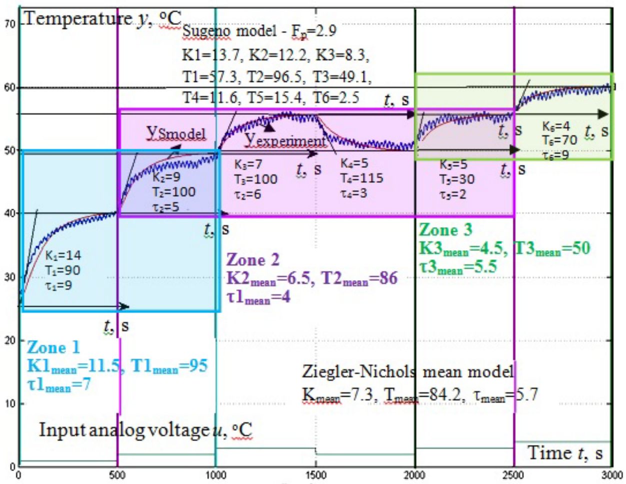


Figure 1. Experimental (blue) and GA optimized Sugeno model (red) plant step responses

A GA algorithm is used to objectively optimize the parameters of the time lag elements in the suggested Smodel structure. The optimal parameters computed are $\mathbf{q_p}$=[K_1=13.71, K_2=12.2, K_3=8.3, T_1=57.3, T_2=96.5, T_3=49.1, T_4=30, T_5=11.6, T_6=15.4, T_7=2.5]. The GA optimization minimizes the integral squared relative error accepted as a fitness function

$$\mathbf{F_p} = \int \left[E(t) / y_e(t) \right]^2 dt, \quad (1)$$

where $E(t)=y_{Smodel}(t)-y_e(t)$ is the difference between the model output $y_{Smodel}(t)$ from simulations and the real plant output from experiments $y_e(t)$ – both as responses to one and the same pattern of input step changes $u(t)$. The GA optimization reaches minimum of $\mathbf{F_p}$=2.9. The pattern of input signal $u(t)$ is selected according to the requirements to be rich in magnitudes and frequencies and to cover the whole range of the input signal, so that the Smodel can learn the real plant nonlinearity. The ready Sugeno plant model is validated comparing its response to the real plant experimental response for input signals, different from the used in modeling. The red line in Figure 1 shows the Smodel responses which are close to the experimental ones in blue from the real time operation of the plant. The parameters of the GA are: population size=20; number of generations=20; elite=2; crossover rate = 0.8 and method – single point; mutation operator –adapt feasible; fitness scaling – rank based; selection – roulette wheel; binary coding.

3. Design and GA Optimization of PID PDC-FLC

When the plants dynamics can be partitioned in a finite number of linear models, a TSK plant model with a small number of rules can be derived to allow a PDC-FLC design. The standard PDC-FLC representation is a single fuzzy block with linear controllers' state space descriptions in the conclusions of the same number of rules with the same premise as in the TSK plant model.

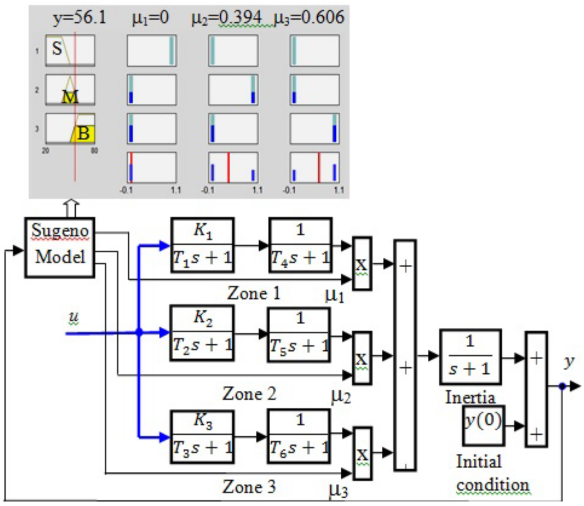


Figure 2. Modified TSK plant model

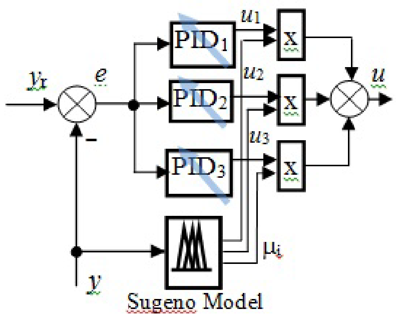


Figure 3. Modified PDC-FLC

Here, first this PDC-FLC is equivalently substituted by a Sugeno-dynamic structure similar to the new plant Sugeno modification of TSK model, shown in Figure 2. The new structure is depicted in Figure 3. It contains the same Sugeno model block used in producing the degrees μ_i of belonging of the current temperature y to each of the three linearization zones, and j PID linear controllers with input the system error e. The controller output u is computed as weighted by μ_j sum of the individual PID controllers' outputs u_j thus performing fuzzy blending and defuzzification.

The modified PDC-FLC shows a simple way for turning linear controllers into nonlinear fuzzy as well as easy embedding of the PDC-FLC into a PLC algorithm for industrial real time operation. Several linear PID controllers are smoothly mixing outputs when y is moving along different linearization zones, characterized by different linear plant models. The fuzzy blending is ensured by a simple Sugeno fuzzy model of j rules with singletons as outputs –available as a fuzzy block in most PLCs [12,13,14,15,32,33]. This modified PDC-FLC facilitates the design – each of the PID controllers is tuned considering the mean linear plant model in the corresponding linearization zone without turning plant and PID controller description into a state space representation. Different tuning criteria and techniques can be selected from the linear control theory – robust stability, robust performance, engineering approaches, pole placement, desired performance indices, etc. In this research it is accepted that the PID block operates as PI algorithm.

The complexity of tuning of a number of linear controllers considering local linear plant model uncertainties can be decreased using a GA based optimization. The parameters to be searched are the parameters of the three PI controllers $\mathbf{q}_{PI}=[K_{p1}, T_{i1}; K_{p2}, T_{i2}; K_{p3}, T_{i3}]$.

The fitness function combines four objectives – minimization of: 1) mean absolute error (MAE) ; 2) mean control effort (MCE); 3) maximal relative output with respect to reference y_r and the range of the step changes in reference D_r - an estimate of the maximal overshoot $\sigma = y/y_r - 1$; 4) relative with respect to D_r maximal deviation y_m from reference y_m:

$$\mathbf{F} = \frac{1}{N}\sum_{k=1}^{N}|e_k| + \frac{1}{N}\sum_{k=1}^{N}u_k + \mathbf{max}\left(\frac{y}{y_r D_r}\right) + \frac{\mathbf{max}(y_m)}{D_r} \to \min_{\mathbf{q}_{PID}}, \quad (2)$$

where N is the total number of samples, collected from the experiment/simulation.

The fitness function is computed using (2) and the recorded values for the corresponding variables from simulation of the closed loop system with an initial set of parameters for the three PI controllers. The initial parameters are taken from the user defined bounds for the parameters, which are determined using some engineering tuning approach. The closed system model used in the simulation with the GA optimizer for tuning of the modified PDC-FLC parameters is shown in Figure 4, where a Limiter bounds the control signal to correspond to the laboratory set-up for operation of the dryer. The GA performs selection, crossover and mutation to build a new generation of offspring thus provides a new set of controller's parameters. After a new simulation the fitness (2) is computed. This cycle continues till the end condition is met – the final number of generations of 20 is reached. The simulation is fast, more realistic, with full control on the experiment, without unplanned noise or disturbances, safe for the plant which ensures the best solution with respect to system stability and gradual parameter changes without restrictions on parameters and signals. It allows considering of various inputs – reference changes and disturbances with different magnitude and frequency that cover the realistic industrial environment impact range. However, a reliable plant model is required for the whole range of operation conditions.

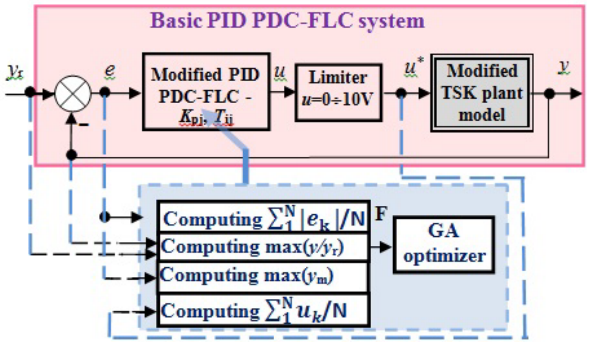


Figure 4. Closed loop system of modified PID PDC-FLC and TSK plant model with GA optimizer

The optimal PI controllers' parameters that minimize (2) in the GA optimization are $\mathbf{q}_{PI}^{opt}=[K_{p1}=0.27, T_{i1}=99s; K_{p2}=0.36, T_{i2}=120s; K_{p3}=0.83, T_{i3}=200s]$. A linear PI controller for comparison is tuned by GA optimization and its optimal parameters are $K_p=0.25$, $T_{i3}=85s$.

The stability of the designed global nonlinear system can be proven using the methodology, developed in [2,5].

4. Design and GA Optimization of Fuzzy Logic Supervisor

A further improvement of the closed system performance is possible by connecting a properly designed FLS. The FLS operates on-line in real time and can compensate for signals, difference in plan of experiments and changes of plant parameters which are not included in the sample used by the GA for optimization.

Here it is suggested that the FLS has an input the bounded control u^*_{k-1} in previous time moment t_{k-1} and output u_c which to provide a multiplicative correction of the PDC-FLC output u according to Figure 5. The correction is assumed to vary in the range [0.3, 1.7] not to influence system stability but also for the purpose of its tuning a scaling gain K_u is introduced. The input and output MFs of the FLS fuzzy block and the rules are selected standard and are shown also in Figure 4. The meaning of this embedding of a FLS is to keep a reasonable control action thus ensuring energy efficiency in control. The bigger the control – the longer the period when the dryer and the fan are connected to the nets supply, so the greater the consumed electrical energy for heating. Oscillations with great peaks of control action are not good for the heater durability and reliability, and also show energy inefficiency – too much heating followed by a necessary cooling.

The scaling gain is optimized by GA minimization of the fitness function (2) using a modified simulation model from Figure 4 with the connection of the FLS from Figure 5. Besides, the PDC-FLC parameters remain fixed to their optimal values and the tuning parameter is $\mathbf{q}_{FLS}=[K_u]$. As a result the optimal FLS parameter computed is $K_u=0.71$ and the minimal value for $\mathbf{F}$ reached is $\mathbf{F}=1$.

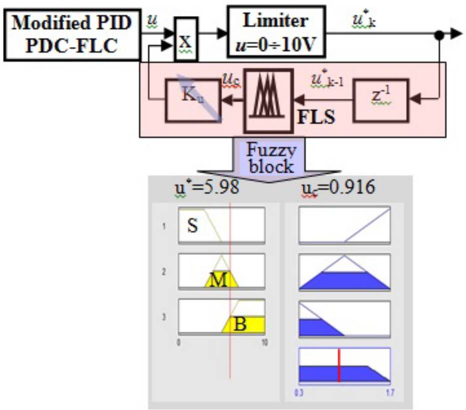


Figure 5. Fuzzy logic supervisor block diagram

5. Simulations and Real Time Control of Temperature in a Laboratory Dryer

The designed PDC-FLC, consisting of a Sugeno model and three local PI linear controllers (PDC-3PI) with GA optimized parameters, and the GA optimized FLS are applied for the control of the air temperature in a laboratory dryer. The plan of the experiments is to prove first in simulations and then in real time control:

- expected improvement of closed loop system performance (settling time and overshoot reduction) and increased robustness to plant model uncertainty - similar step responses in different operation points despite the different plant parameters;

- improvements in the step responses of the system with the PDC-3PI with respect to the system with the linear PI controller, and improvements in the step responses of the system with the PDC-3PI with the FLS with respect to the system without the FLS;

- improvements in the control action $u(t)$ (smooth, without peaks and oscillations) and in the energy efficiency, defined as $EEF = \sum_{k=1}^{N} u_k$;

- closeness between the step responses in simulations and in the real time control;

- preservation of good performance for step inputs different from the used in the GA optimization.

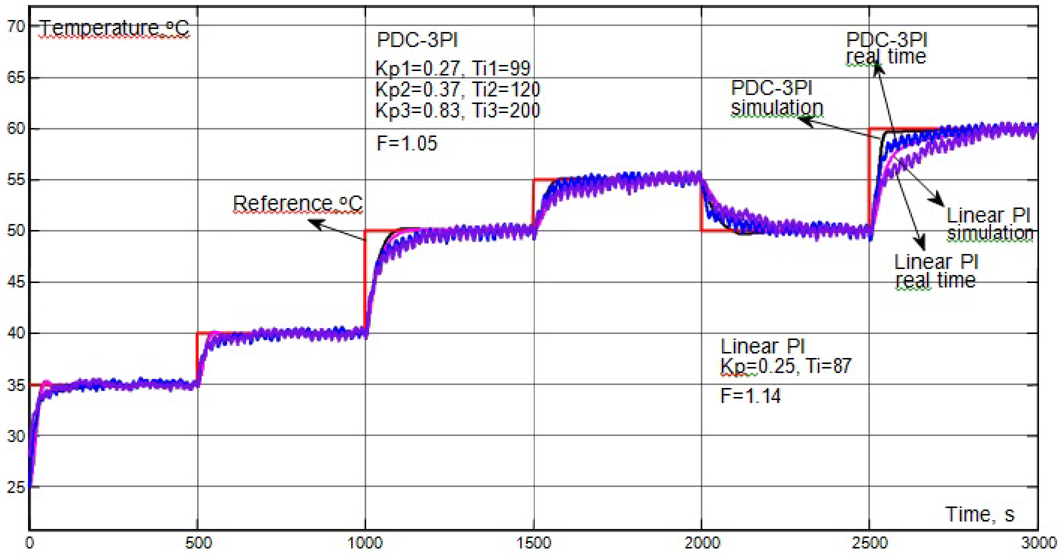


Figure 6. Step responses of systems with PDC-3PI and linear PI controller from simulation and real time control

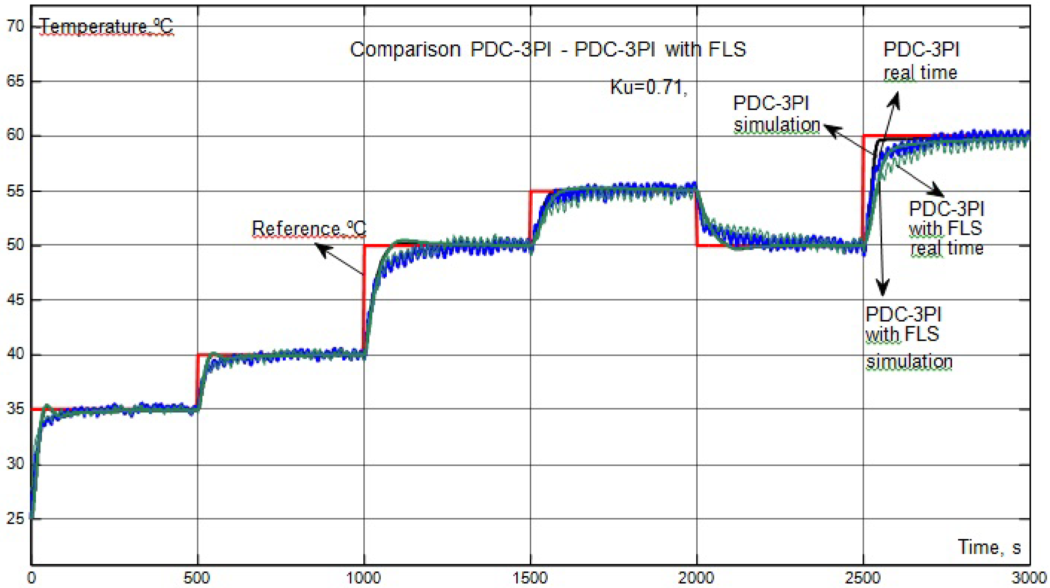


Figure 7. Step responses of systems with PDC-3PI with FLS and without FLS from simulation and real time control

The step responses of temperature in systems with PDC-3PI and linear PI controller from simulation and real time control are depicted in Figure 6. Simulation and real time results are close and lead to the same conclusion:

– the PDC-3PI system shows faster settling for high reference, where the plant has the smallest gain for the whole temperature range, which makes the settling time of all system step responses almost the same - an evidence for high robustness;

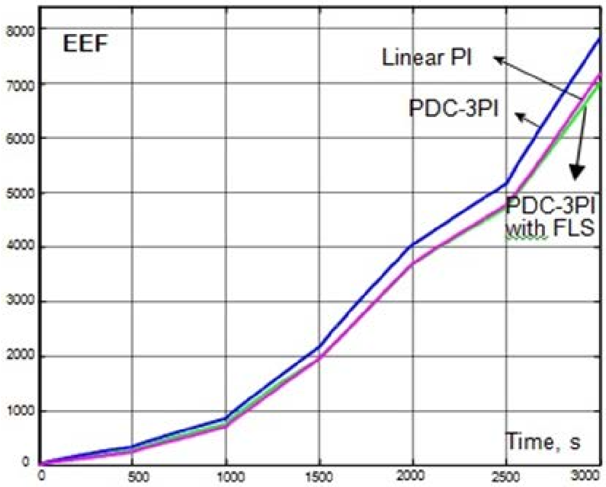
- the settling time of the PI control system step responses differ in the different operation points -increase with the increase of reference, so the this system is less robust to the plant parameter changes with the operation point;

- both systems have very good performance for small references, PDC-3PI system improves performance where the linear PI system is slow at high references.

The step responses of temperature of the PDC-3PI system and the PDC-3PI system with FLS from simulation and real time control are shown in Figure 7. The FLS does not lead to significant improvements in temperature responses since it is designed to reduce control effort and GA optimized to minimize a fitness function that unites several criteria – three related to system performance (MAE, σ, y_m), and one - to the control action (MCE). Both in simulations and in real time the two systems have close settling time – only for the last reference the FLS system has a slower response.

The improvements due to the FLS are observed in Figure 8, where the EEF and the control action take smaller values – the control is more economic and smooth (small peaks and oscillations) and the system more energy efficient.

The GA optimization of the controllers' parameters is carried out for the developed plant model and the accepted fitness function and sample of step responses. The fact that simulation results are close to the obtained in real time control in all previous investigations gives grounds to test the three systems by simulation to a different pattern of step reference changes. The results lead to the same conclusions and this confirms their validity for all possible step inputs in the given range.



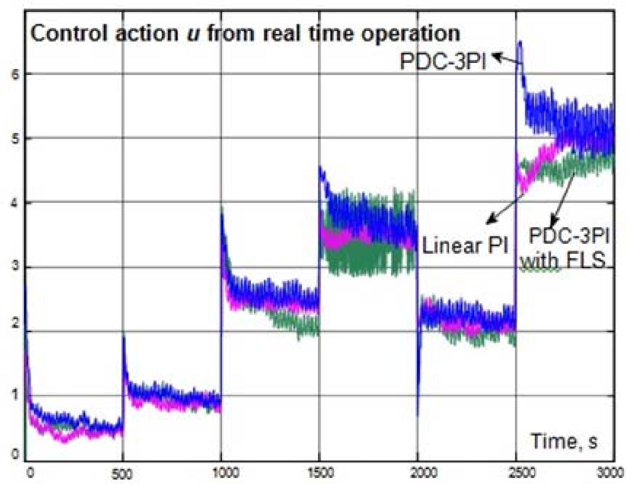


Figure 8. Energy efficiency (up) and control action (down) from real time control with linear PI controller and with PDC-3PI with and without FLS

6. Analysis of Results, Conclusion and Future Work

The main results of the present research can be summarized as follows.

A modification of the PDC design approach is developed and applied for the control of temperature. It concludes in building of a modified TSK plant model from experimental plant step responses in order to obtain a simple model structure of clear physical nature that is fit for easy GA optimization used to objectively and accurately determine the model parameters. The model is validated and further used in off-line GA optimization of different controllers via simulation of the closed loop system. A modified structure of a PDC-FLC is suggested on the basis of the modified TSK plant model for easy design and embedding in industrial PLCs. It consists of the same fuzzy block used in the modified TSK plant model to distinguish the linearization zones and parallel linear standard PI/PID controllers – PDC-PID which parameters are tuned via off-line GA optimization. Then a FLS is designed with GA optimized output scaling factor to reduce the PDC-FLC system control effort and improve system energy efficiency. The approach suggested is applied for the control of the air temperature in a laboratory furnace. The simulations and real time control show improved system performance and robustness with respect to linear PI control system. The implementation for temperature control demonstrates the simple design and tuning technique which together with the simple structure of both the PDC-PID and the FLS aims to facilitate the industrial application of the approach for the control of a great number of other process variables.

The future work will focus on completion of the PDC-FLS on Siemens PLCs and its implementation for the control of other industrial plants.

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