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Parameter Optimisation of Type 1 and Interval Type 2 Fuzzy Logic Controllers for Performance Improvement of Industrial Control System

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Abstract: The fuzzy logic controllers (FLC) gain popularity in ensuring stable and high-performance control of nonlinear industrial plants with no reliable model, where the traditional controllers fail. Their standard expert-based design and simple algorithms that meet the demands for fast execution and economical use of computational resources ease their implementation into programmable logic controllers for wide industrial real-time control applications. This research presents a novel approach to enhancing the performance of FLC systems by compensating for the subjectivity inherent in expert-based design through optimization of the parameters of type-1 (T1) and interval type-2 (IT2) PID FLC membership functions (MF) using genetic algorithms. The approach is demonstrated for controlling the solution level in a carbonization column for soda ash production. Simulations reveal that optimization improves the system performance, measured by a newly introduced overall performance indicator for dynamic accuracy, robustness, and control smoothness, by 48% for the T1 FLC system and 30% for the IT2 FLC system.

Index Terms: Fuzzy Logic Level Control, Design of Type 1 and Interval Type 2 FLC, Genetic Algorithms, Parameter Optimisation, Simulation.

1. Introduction and State-of-the-arts

The demands for high performance of the control of industrial plants on one side and the plants nonlinearity and model uncertainty on the other side determine the need for intelligent approaches to modelling and control. Fuzzy logic controllers (FLC) offer a perspective solution which based on expert knowledge ensures stable and high performance control. The FLC is simple both as algorithm and as design which makes it suitable for programming into programmable logic controllers (PLC) and use in real time control applications. The most widely distributed is the PID FLC with a two-input (2I) fuzzy unit (FU) - the system error e and its derivative $\dot{e}$, and a PI post-processing [1-6]. Its rule base is easily constructed from the requirement to reduce the FU inputs finally reaching zero thus assisting the controlled variable to settle at its reference. The type 1 (T1) FU is expert-defined by standard orthogonal input MF. The output MF are singletons which determines weighted average defuzzyfication ensuring in this way an economical utilization of the PLC resources (memory and execution time) for the FU presentation and its crisp output computation. Fuzzy logic is also successfully applied for deriving of nonlinear Takagi-Sugeno-Kang (TSK) plant models from experimental data [6].

Interval type 2 (IT2) FU is introduced to deal with the plant changes and the expert subjectivity in defining of the MF parameters [4, 7, 8]. The footprint of uncertainty (FoU) is expected to provide robustness and uncertainty handling to the FLC but only after selecting suitable bounds of FoU. The interval MF uncertainty is determined by two MF – lower (LMF) and upper (UMF). Thus, each measured FU input matches two defined MF to degrees Lμ and Uμ in the range [0, 1] which make an interval number μ= (Lμ, Uμ) with lower Lμ and upper Uμ MF bounds. The FoU enables reduction of the MF used and hence of the number of fuzzy rules. It can also serve as an extra tuning parameter for improving of the system performance and robustness. The defuzzyfication is preceded by type-reduction. The IT2 FU are more complex as design and algorithm for engineering applications, and the improvement of the system performance is relatively small. Optimisation of the FoU is expected to increase this improvement.

T1 FLC are developed for a great number of industrial applications - robots, drones, cars, heating, ventilation and air-conditioning, temperature, dryers, wastewater treatment, cement industry, liquid level in various installations - boilers, nuclear generators, carbonisation columns (CCl) for soda ash production, etc. [6, 9-13]. Level is an essential variable in which control is important for the balance of the material and the energy flows or for keeping the optimal functioning of processes. Most of the FLC systems are implemented as real time laboratory tests, hardware-in-the-loop simulations and low-cost automation often using plant models. FLC for level control are developed for PLC in [5,14, 15].

IT2 FLC are designed for robust control in case of plant variations, random noise and disturbances of tank level, inverted pendulum, DC motor and a single joint manipulator in [4, 7, 8, 16, 17]. The systems are studied by simulations or hardware-in-the-loop simulations via FLC implementation in low-cost microcontrollers using plant models.

The design of T1 and IT2 FLC based on subjective expert knowledge and experience, gained usually by trial-and-error experimentation, can be improved using objective optimisation approaches. Genetic algorithms (GA) are the most often used to optimise the parameters of the TSK plant model or of the FLC, mainly the pre- and post-processing parameters and the singletons or gains in the conclusion of a Sugeno FLC [18, 19]. GA are preferred for their advantages as gradient free algorithms for parallel random search of global extremum of fitness functions of many parameters with no analytical description.

A common drawback of the suggested approaches for the design of FLC is the lack of an objective FLC parameter optimisation procedure for improvement of the closed loop control system performance based on multiple safe and fast off-line simulations with experimental data from the real time control of the industrial plant. Such a procedure steps on the FLC parameters from the empirical design in computing of the necessary initial parameter ranges. It can test various types of FLC and combinations of their parameters and obtain a solution with the most favourable impact on the system performance.

The aim of this paper is to develop an approach for enhancing the performance of the control system by optimizing various parameters of empirically designed T1 and IT2 FLC systems, utilizing data from the operation of an industrial system. The research is based on data from experiments during the PLC real time PI linear control of the level of the solution in a CCl for the production of soda ash in the plant "Solvay Sodi" in the town of Devnya, Bulgaria [20, 21].

The optimization uses GA and is carried out by the help of MATLAB™ and its toolboxes Simulink, Fuzzy Logic and Optimisation [22, 23].

The novelty of the research concludes in the developed approach for enhancement of the performance of a FLC system through FLC parameter optimisation, utilizing the data from the operation of an industrial system and considering the constraints of the industrial implementation. The approach passes through empirical design of T1 and IT2 FLC, TSK modelling and validation of the plant for different loads – nominal and heaviest, accepted for varied, design and validation of the necessary simulation models, optimisation of various FLC parameters, investigations of the designed systems via simulation, assessment of performance improvements and rating of the designed FLC control systems.

The further organization of the paper is the following. Section 2 includes results from the empirical design of T1 and IT2 FLC systems in previous research. The design of the system optimisation model based on genetic algorithms is described in Section 3. Section 4 is devoted to the simulation investigations of the T1 and IT2 FLC systems with various optimised parameters and the assessment of their performance and the improvements achieved. Section 5 contains a conclusion and a vision for future research.

2. Preliminary Investigation

The plant output $y(t)$ to be controlled is the level H, $y(t)=H(t)$, %, of the solution in a CCl for soda ash production. Its inputs are the control action $u(t)$ that changes the flowrate of the precarbonised solution feeding of the CCl, and the main disturbance – the change of the pressure $\Delta P(t)$ in the solution supply pipe which is the common feed of several operating in parallel CCl. The produced soda crystals are in result of a complex reversible exothermic chemical reaction between gases with different concentrations of carbon dioxide CO_2 supplied from the bottom and the middle of the column in counterflow to the precarbonised solution. The plant is inclined to oscillations and changes its parameters for CCl operation and washing modes, different operation points and loads. The parallel operation with other CCl with common solution supply has also an impact on its characteristics. Therefore, the plant is difficult to model and hence controlled by classical means achieving the demanded high system performance standards. As a result, fuzzy logic controllers with a simple for PLC implementation structure are designed to tackle plant nonlinearity and model uncertainty using empirical approach in ensuring system stability and robustness [6, 20].

The designed type-1 (T1) and the interval type-2 (IT2) PID FLC have a common basic structure, presented in Fig.1. The measured level H_m, $y_m=H_m$, is filtered from noise by an exponential filter with transfer function $W_f(s)$. The two-input fuzzy unit (2I FU) has normalised in the range [-1, 1] inputs – the system error $e=H_r-H$ and the derivative of level $(-dH)=(-dy)$ which for constant reference H_r, $y_r=H_r$, is equivalent to the commonly used derivative of error $\dot{e}$, $(-dy)=\dot{e}$, but changes smoothly at step reference changes. The derivative dy is computed by a noise insensitive differentiator

$W_d(s)=K_d.T_d.s.(T_ds+1)^{-1}$ with $T_d=(2\div10)\Delta t$ for a sampling period $\Delta t=1$s. For simplification reasons the superscripts 'n' for 'normalised' are further saved. The error normalisation gain K_e is computed based on the maximal expected error, here $K_e=1/|e|_{max}=0.1$.

The 3x3 2I FU has three standard orthogonal membership functions (MF) for each of the inputs:

$$\text{MFe} =[\text{Ne Ze Pe}],\ \text{Ne}= [-1\ -1\ -0.5\ 0],\ \text{Ze}= [-0.5\ 0\ 0.5],\ \text{Pe}= [0\ 0.5\ 1\ 1] \tag{1}$$

$$\text{MFdy}=[\text{Ndy Zdy Pdy}],\ \text{Ndy}=[-1\ -1\ -0.3\ 0],\ \text{Zdy}=[-0.3\ 0\ 0.3],\ \text{Pdy}=[0\ 0.3\ 1\ 1]$$

The MF of the output are singletons:

$$S_o=[\text{NGo NSo No Zo Po PSo PGo}]=[-1\ -0.4\ -0.1\ 0\ 0.1\ 0.4\ 1] \tag{2}$$

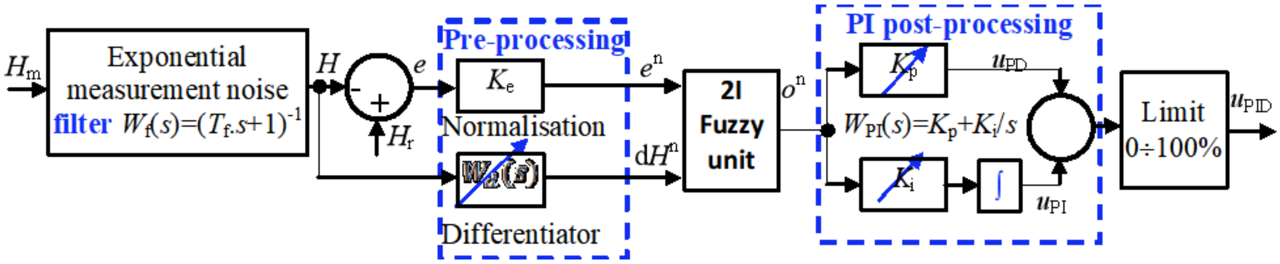

Fig.1. Block diagram of PID FLC

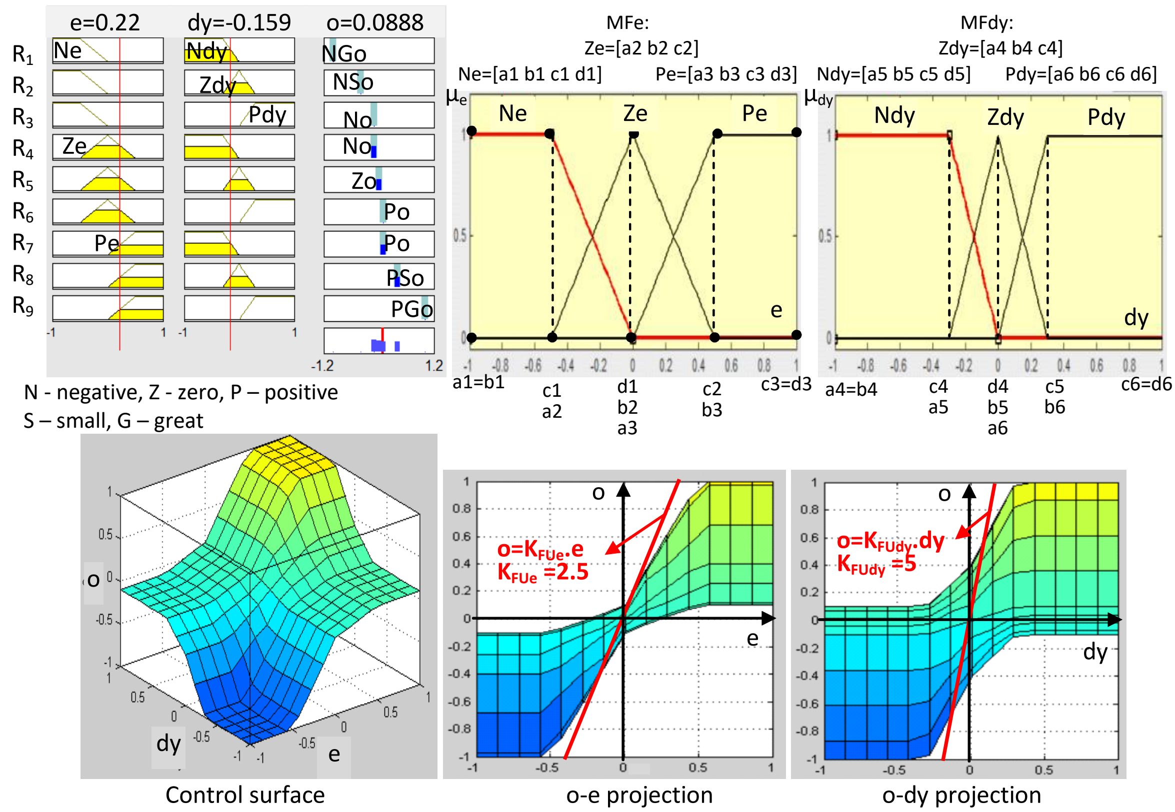

Fig.2. 2I FU membership functions, soft fuzzy rules R_i, control surface and o-e and o-dy projections

The MF, the fuzzy rules and the control curve are shown in Fig.2. The designations are N for negative, Z – for zero, P – for positive, S – for small and G- for great. These empirically designed input MF define the basic 2I FU of the T1 PID FLC and in most cases - the lower MF (LMF) of the IT2 PID FLC. The upper MF (UMF) are computed for a given deviation of selected parameters of the LMF, e.g. for LMF LNe=[a=-1, b=-1, c, d] the UMF is UNe=[a=-1, b=-1, c+Δc, d+Δd].

The normalised in the range [-1, 1] output o of the 2I FU is a nonlinear function of the inputs e and dy, o=Y(e, dy), that can be assumed to describe a nonlinear PD algorithm $o(e,dy)$. The PI post-processing $W_{PI}(s)=K_p+K_i/s$ of $o(e, dy)$ ensures a nonlinear PID algorithm built of nonlinear PD and PI components $u_{PID}(e, dy)=u_{PD}(e, dy)+u_{PI}(e, dy)$, where $u_{PD}(e, dy)=K_p.o(e, dy)$ and $u_{PI}(e, dy)= K_i.\int o(e, dy)dt$.

The PID FLC tuning parameters $q_{FLC}=[K_p\ K_i\ K_d]$ are computed after linearisation of the designed 2I FU based on the highest gain $K_{FU}=\max(K_{FUe}, K_{FUdy})$ of the lines $o=K_{FUe}.e$ and $o=K_{FUdy}.dy$ in the corresponding o-e and o-dy control surface projections which bound from above in a sector the greatest part of the projection as shown in Fig.2. Then the linearised PID controller's parameters $q_{linFLC}=[K_p^*\ K_i^*\ K_d^*]$ with $K_p^*=K_e.K_{FUe}.K_p+K_d.K_{FLCdy}.K_i$, $K_i^*=K_e.K_{FLCe}.K_i$, $K_d^*=K_d.K_{FUdy}.K_p$ are tuned using an engineering approach [24]:

$$K_p^*=A.\ T_{min}/(K_{max}.\tau_{max}),\ T_i^*=B.\tau_{max}\ (K_i^*=K_p^*/T_i^*),\ T_d^*=C.\tau_{max}\ (K_d^*=K_p^*.T_d^*) \tag{3}$$

where K_{max}=2.2 and τ_{max}=30s are the greatest gain and time delay respectively and T_{min}=53s is the smallest time constant of the expert assessed parameters of the ZN plant models $P_i(s)=K_i.(T_is+1)^{-1}$ for all operation points and loads that have the heaviest impact on the closed loop system stability. The factors A=0.3÷1, B=0.9÷3 and C=0.4÷1 are selected to ensure the desired system performance.

The PID FLC parameters $q_{FLC}=[K_p=80\%,\ K_i=0.012,\ K_d=0.014]$ are computed from their relationship with the parameters of the linearised PID controller q_{linFLC} after accepting a maximal possible proportional gain $K_p=K_{pmax}=80\%$ for $o\in[-1, 1]$ and $u_{PID}\in[0, 100]\%$ to ensure the closed loop system high robustness and dynamic accuracy [20, 21].

The empirically designed PID FLC serves as a basic controller which parameters are further subjected to optimisation using off-line GA and simulations with experimental data.

3. T1 and IT2 FLC Parameter Optimisation-based Approach

The general off-line GA parameter optimisation model is presented in Fig.3. The dynamic system represented by a simulation model can be a controller, a plant, a closed loop control system or some part of it. It has a known structure with parameters q_j in the vector $q=[q_j]$, j=1÷M, to be optimised. The optimal values of the parameters q searched within given ranges minimise of an accepted fitness (cost) function F, e.g. a function of the modelling error or of the closed loop control system error. In GA the parameters are coded and arranged in an array to form a chromosome or an individual, here the vector q.

To start the optimisation L chromosomes q_i^o, i=1÷L are randomly generated to constitute the initial population of the zero generation, where the population size L is input data for the GA. For each individual from the population (a combination of values for the system parameters) the system is simulated for given inputs x_{exp}. The fitness function F is evaluated based on the necessary system output variables from simulation y_{sim} and input-output data from experiments on the physical system (x_{exp}, y_{exps}), where y_{exps} is the pre-processed data to filter noise and collinearity and to reduce the sample size. The data recorded from experiments should cover the whole system operation range and be rich in magnitudes and frequencies in order to enable modelling of the real system nonlinearity. Then they are split into data used for modelling and data for model validation.

The individuals in the population are rated according to their fitness function values. New offspring is produced via mating, genes (bits for binary coded parameters values or parameter values) crossover and mutation using different approaches. The most popular are the roulette mating of parents, the single point crossover (exchange of genes) and the random mutation in one gene. The system with the offspring chromosomes is simulated and the fitness function evaluated. The offspring is accepted in the next generation if its fitness function is better than that of the 'parents'. A small random number of elite individuals can directly pass into the new generation without mating, crossover and mutation. The mutation is small not to deform the inherited features from the parents in the process of improving of each new generation but also is useful when the initial population consists of low rated individuals. It helps escaping trapping in a local extremum which is one of the drawbacks of the gradient optimisation algorithms. When the next generation is completed the process is repeated till the end condition is met. The accepted end condition is an input to GA and can be either a reached given number of generations GN or a reached desired low value F_f of F for which $F<F_f$. The system with the optimal parameters q^{opt} is further tested for satisfaction of an alternative criterion Fs, e.g. the maximal absolute value of the modelling error $|e_m|_{max}<\varepsilon$ or the control system error $|e|_{max}<\varepsilon$ at some time instant t_o to be below a given threshold ε. For fulfilled criterion Fs the system with the optimal parameters q^{opt} is validated by simulation for the assigned for model validation different input data. The optimisation ends when the validation is successful, i.e. the simulated system output satisfies an accepted criterion for closeness to the experimental results or for reaching desired performance. If either the criterion Fs is not satisfied, or the validation is not successful the procedure starts from the beginning with new input for GA or from a new random generation of the initial population. The validated model of the dynamic system is reliable and can be used in the further investigations.

Here the following problems are solved by GA parameter optimisation:

- PI controller simulation modelling from input-output experimental data of the PLC-PI from the real time control of the level solution in a CCl;
- TSK plant modelling using available experimental data for the plant input-output from the PLC-PI real time CCl solution level control;
- Optimisation of different groups of parameters of designed T1 and IT2 PID FLC to improve closed loop control system performance.

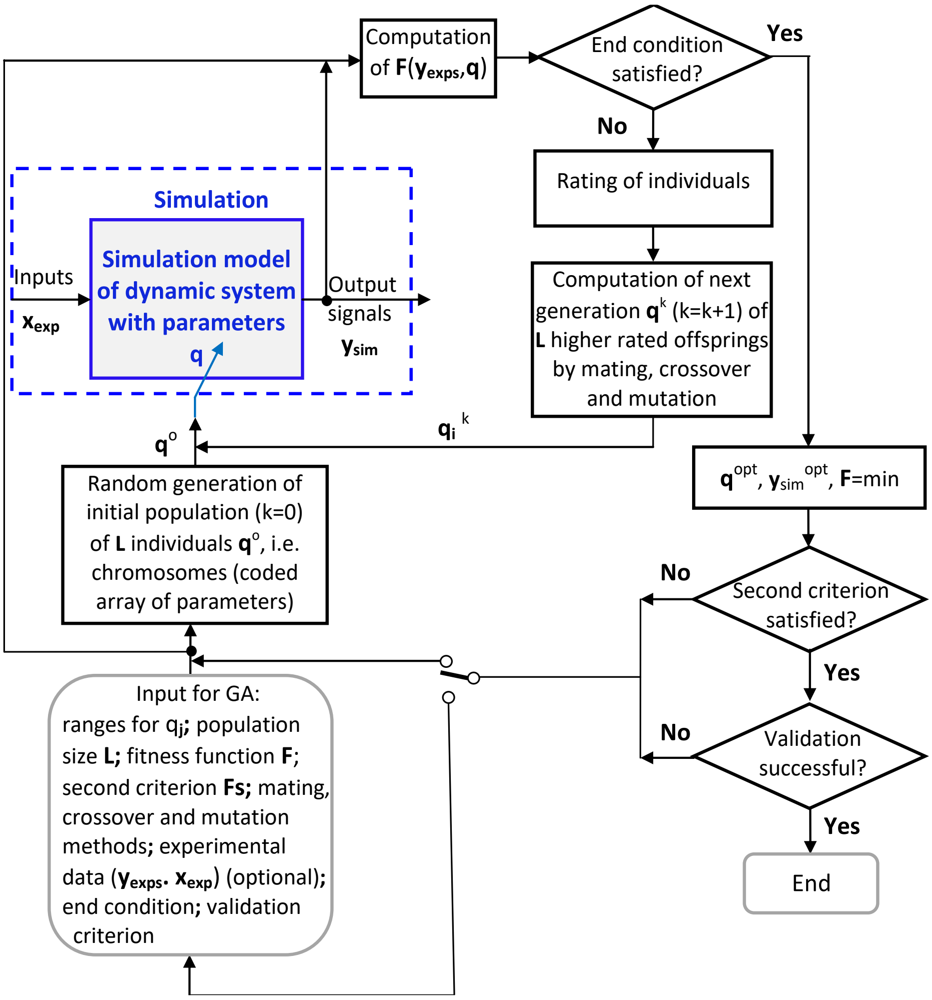

Fig.3. General off-line GA parameter optimisation model

The GA use the default L, decimal encoding of the optimising parameters, roulette mating, GN=20, a single point crossover, mutation in one point, initial lower and upper bounds for each optimised parameter around the empirically tuned values.

The PI controller simulation model of the PLC-PI is necessary for the GA supported TSK plant modelling in a closed loop control system. Its parameters are computed in a GA optimisation using recorded PLC-PI input-output experimental data (e_{exp}, u_{exps}) during the PLC-PI real time level control. Thus, the dynamic system in Fig.3 is a Simulink PID block with parameters $q_{PI}=[K_{p\,PI}\ K_{i\,PI}\ K_{d\,PI}=0]$, input $x_{exp}=e_{exp}$ and output $y_{sim}=u_{PI}$. The fitness function to be minimised is the mean squared modelling error (MSME) $F=\Sigma(u_{PI}-u_{exps})^2/N$, where N is the sample size. The PLC-PI system is subjected to the intrinsic industrial disturbance - the change of the pressure ΔP in the solution supply pipe, and different reference changes in the sequence H_r=50-60-50-40-50,% that cover the whole operation range of the plant. The computed optimal values of the parameters of the PI simulation model are $q_{PI}^{opt}=[K_{p\,PI}^{opt}=10,\ K_{i\,PI}=0.003]$.

The TSK plant model is necessary for the simulation of the closed loop systems with T1 and IT2 PID FLC for generated by GA parameters. The data from the simulation enables the computation of the corresponding fitness function. Thus, various accepted groups of PID FLC parameters are optimised.

The expert determined TSK plant model structure is presented in Fig.4. It assumes 3 linearisation zones – below the norm Z1, norm Z2 and above the norm Z3 accounting for the most often used references H_r= [40 50 60]. The zones are identified by the current measured value for the level H_k which is an input to the static nonlinear Sugeno model. The zones are defined by standard orthogonal input MF Z1= [0 0 40 50], Z2= [40 50 60], Z3= [50 60 100 100]. The Sugeno model outputs o_j, j=1÷3, map the degrees of belonging μ_j of the current level to all linearisation zones, $o_j=\mu_j$. This is achieved by a specific rule base of three fuzzy rules R_j – one for a zone. The premise of R_j compares H_k with Zj and computes the degree of matching μ_j. The conclusion of R_j assigns singleton at 1 only to the j-th output $o_j^j=1$, and 0 to the other two outputs. So, the conclusions in the three rules are $o_1^1=o_2^2=o_3^3=1$ and $o_1^2=o_1^3=o_2^1=o_2^3=o_3^1=o_3^2=0$. Thus, for some H_k and obtained $\mu_1=0.3$, $\mu_2=0.7$, $\mu_3=0$ ($\Sigma\mu_j=1$ for orthogonal MF Z1, Z2, Z3) the final defuzzyfied using weighted average outputs are $o_1=(\mu_1\ o_1^1+\mu_2\ o_1^2+\mu_3\ o_1^3)/\Sigma\mu_j$=0,3.1+0,7.0+0.0=0.3=$\mu_1$, o_2=0.7=μ_2, o_3=0=μ_3.

The dynamic part of the TSK plant model consists of local for each linearisation zone linear plant models that operate in parallel with common input u. The local plant models are described by expert defined linear operator, here the time lags $P_j(s)=K_j/(T_j.\ s+1)$. The Sugeno model outputs that present the degrees of matching of the measured H_k to all defined linearisation zones, serve for scaling of the outputs y_j of the local plant models. The defuzzyfied output $y=(\Sigma\mu_j\, y_j)/(\Sigma\mu_j)$, $\Sigma\mu_j=1$, is further processed by the time lag $P_4(s)=1/(T_4.\, s+1)$ in order to increase the inertia of the TSK plant model. Thus, the output y_j of the local plant with the highest match of H_k to its zone MF has the greatest contribution to the TSK plant model output $H_{TSK\,k}$.

The unknown TSK plant model parameters $q_{TSK}=[K_1, T_1, K_2, T_2, K_3, T_3, T_4, H(0)]$ including the initial level $H(0)$, are computed via offline GA parameter optimisation. The necessary experimental data from the real time PLC-PI control of the solution level in the CCl are the reference H_{rexp} and the smoothed measured level H_{exps}. The simulation model in Fig.3 is of the closed loop system consisting of the PI controller that models the PLC-PI, and the TSK plant model from Fig.4. Its input is the reference $x_{exp}=H_{rexp}$ and the output is $y_{sim}=H_{TSK}$.

The system is simulated with the computed by GA parameters of the TSK plant model from the expert defined ranges. The accepted fitness function **F** minimised is the MSME $\mathbf{F}=\sum_{k=1}^{N}(H_{expsk}-H_{TSKk})^2/N$ or the relative MSME $\mathrm{F}=\sum_{k=1}^{N}[(\mathrm{H_{expsk}}\text{-}\mathrm{H_{TSKk}})/\mathrm{H_{rexpk}}]^2/\mathrm{N}$. The optimisation end condition is the reaching of a desired number of generations **GN**=20 since the desired model accuracy cannot be estimated. The second criterion $\mathbf{max}[|H_{exps}(t_o)\text{-}H_{TSK}(t_o)|]<\varepsilon$ is also a validation criterion.

The parameters of two TSK plant models are computed from two types of experimental data recorded for different CCl loads: $q_{TSK}=[K_1=0.85, T_1=218\text{s}; K_2=1, T_2=6.4\text{s}; K_3=1.15, T_3=86.5\text{s}; T_4=740\text{s}, H(0)=50]$ and $q_{TSKv}=[K_1=0.11, T_1=73\text{s}; K_2=0.26, T_2=350\text{s}; K_3=0.51, T_3=98\text{s}; T_4=150\text{s}, H(0)=33]$.

The two TSK plant models are successfully validated based on the experimental data for validation. The TSK model describes the nominal plant and TSKv – the varied plant, which further is used to assess the designed PID FLC systems' robustness.

The GA optimisation is applied to different groups of T1 and IT2 PID FLC FU parameters to improve the performance of the closed loop system for the control of the output of the nominal TSK plant model with respect to the performance of the system with the empirically tuned basic PID FLC and to reduce the subjectivity of the empirical design. The rest of the parameters are basic.

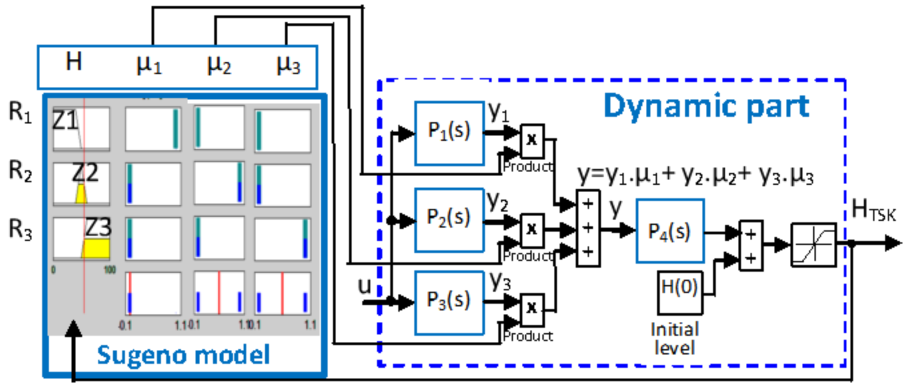

Fig.4. TSK plant model

The groups of parameters to be optimised are:

- 4 parameters of the output MF the singletons $q_S=[p1\ p2\ p3\ p4]$ from S=[-1 p1 p2 0 p3 p4 1] - the most often tuned for the great effect on the closed loop control system performance.
- 12 parameters from the input T1 MF and IT2 LMF description – trapezoidal [a b c d] and triangle [a b c], q_{MF}=[c1 d1; a2 0 c2; a3 b3; c4 d4; a5 c5; a6 b6] that correspond to: MFe=[Ne; Ze; Pe]=[-1 -1 c1 d1; a2 0 c2; a3 b3 1 1] and MFdy=[Ndy; Zdy; Pdy]=[-1 -1 c4 d4; a5 0 c5; a6 b6 1 1];
- 12 deviations of the parameters of the LMF that form the UMF, applied in case of IT2 PID FLC q_Δ=[Δc1 Δd1; Δa2 Δc2; Δa3 Δb3; Δc4 Δd4; Δa5 Δc5; Δa6 Δb6].

Here a reduced number of 4 deviations is accepted $q_{\Delta r}=[\Delta e1\ \Delta dy1; \Delta eo\ \Delta dyo]$ to economically describe the UMF on the basis of the LMF, where Δc1=Δb3=Δe1, Δd1=Δa2=Δc2=Δa3=Δeo, Δc4=Δb6=Δdy1, Δd4=Δa5=Δc5=Δa6=Δdyo with $e1=e(\mu_e=1)$, $eo=e(\mu_e=0)$, $dy1=dy(\mu_{dy}=1)$, $dyo=dy(\mu_{dy}=0)$;

- combinations of the parameters of any two groups of parameters.
- all 28 or 20 parameters from the groups.

The fitness function accepted is F=F1+0.1F2, where $F1=[\Sigma_{k=1}^{N}(H_{rexp\,k}\text{-}H_{TSKk})^2]/N$ is the mean squared error (MSE) and $F2=\max[|\max(u_n)\text{-}\min(u_n)|]$, $n=1\div4$, is the maximum for all 4 step responses span of the control action u_n. The minimisation of F increases the control system dynamic accuracy by reducing the MSE F1 and smooths the control action by decreasing its span F2 which reduces the final control elements wear and the energy for control.

The simulation model of the dynamic system is built using Simulink of MATLAB™. In order the GA to access the parameters of the output singletons, the input MF, as well as the deviations, the T1 and the IT2 FU are presented by open blocks for the description of triangular and trapezoidal MF or LMF and UMF. The T1 FU rule base and the inference mechanism perform:

- aggregation of premises with 'min' operator to obtain the degree w_i of activation of each i-th rule applied.
- scaling by w_i of the singletons in the conclusions.
- accumulation by summing up the qualified by w_i rules conclusions and
- computation of the final crisp output by weighted average.

In Fig.5 a developed IT2 FU simulation model is presented. The current normalized error e and derivative dy are compared to the defined by trapezoid or triangle UMF and LMF to obtain the degrees of matching to UMFe= [UNe UZe UPe], LMFe= [LNe LZe LPe], UMFdy= [UNdy UZdy UPdy] and LMFdy= [LNdy LZdy LPdy]. Thus, each couple (LMF, UMF) defines an interval MF. Then the rule base in Fig.2 is built of fuzzy rules R_i, $i=1\div K$, $K=9$, of interval MF, e.g.: R_1: IF (LNe, UNe) AND (LNdy, UNdy) THEN o=NGo (NGo=-1).

The aggregation of the rule premises [(LNe, UNe) AND (LNdy, UNdy)] results in an interval degree of rules activation w_1= (Lw_1, Uw_1) with Lw_1=min (LNe, LNdy) and Uw_1=min (UNe, UNdy), $Lw_1<Uw_1$. Then the output singleton S_1=NGo=-1 is scaled by w_1 to obtain an interval fuzzy qualified output o_1=(Lo_1, Uo_1) with $Lo_1=Lw_1.S_1$ and $Uo_1=Uw_1.S_1$. It is proceeded with the rest of the fuzzy rules with interval MF in the same manner. Finally, the sums $Lw=\Sigma_{i=1}^{9}Lw_i$, $Uw=\Sigma_{i=1}^{9}Uw_i$, $Lo=\Sigma_{i=1}^{9}Lo_i$ and $Uo=\Sigma_{i=1}^{9}Uo_i$ from the nine fuzzy rules are computed. The type of reduction and the weighted average defuzzyfication, not shown in Fig.5, are based on the rules for division of interval numbers. First, 1/Uw and 1/Lw are computed and by multiplication with Uo and Lo all combinations are obtained, [(Uo/Uw)], (Lo/Uw), (Uo/Lw), (Lo/Lw)]. Their minimal and maximal values determine the lower and the upper value of the FU interval output respectively. The final crisp output is computed as a mean value that is bound in the range [-1, 1]: o={max[(Uo/Uw)], (Lo/Uw), (Uo/Lw), (Lo/Lw)] +min[(Uo/Uw)], (Lo/Uw), (Uo/Lw), (Lo/Lw)]}/2.

The necessary simulation model of the closed loop system includes the control of the TSK plant model from Fig.4 by the PID FLC from Fig.1 based on the developed in Fig.5 T1 or IT2 2IFU model and the pre- and post-processing components.

4. Simulation Investigations of Designed T1 and IT2 Control Systems

The investigation of the PID FLC systems is based on the simulation of the responses for step reference changes in the sequence H_r=50-60-50-40-50, %. All PID FLC have the same FU rule base and the empirically designed parameters $\mathbf{q}_{FLC}$. Some groups of FU parameters are GA optimised from the requirement to improve the performance of the simulated closed loop system for the control of the nominal TSK plant model by minimisation of the fitness function F. The rest of the FU parameters are kept to their empirical basic values from Fig.2. The optimised PID FLC control systems are also studied via simulation for the control of the varied TSK plant model to assess their robustness, i.e. capability to tackle plant changes. The systems investigated with their FU parameters are the following.

A. T1 PID FLC Systems

- System 1 with the basic empirically designed parameters of the FU singletons S_o and input MF MFe and MFdy from Fig. 2.
- System 2 with basic MFe and MFdy and GA optimised output singletons of the FU from Fig. 2 S^{opt2}= [-1 -0.7 -0.53 0 0.7 0.9 1].
- System 3 with basic S_o and optimised parameters of the input MF of the FU MFe^{opt3}= [-1 -1 -0.83 0; -0.31 0 0.27; 0 0.66 1 1], $MFdy^{opt3}$= [-1 -1 -0.69 0; -0.44 0 0.52; 0 0.65 1 1].
- System 4 with optimised parameters of both the FU singletons and the input MF MFe^{opt4}= [-1 -1 -0.64 0.12; -0.72 0 0.3; -0.26 0.73 1 1], $MFdy^{opt4}$= [-1 -1 -0.69 0.095; -0.57 0 0.9; 0.26 0.51 1 1], S^{opt4}= [-1 -0.8 -0.66 0 0.89 0.92 1].

The control surfaces of the systems are seen in Fig. 6. The step responses with respect to level H, and control action U of the four systems for the control of the nominal and the varied TSK plant models are presented in Fig.7. The systems are rated according to the assessed from the step responses performance indicators, presented in Table 1:

- F and F1.
- maximal overshoot σ_{max}, %, and settling time t_{smax}, s, from all four reference step responses of the system.
- maximal absolute deviation max|H-H_v|, %, between the levels of the corresponding systems with nominal $H(t)$ and varied plant $H_v(t)$ as a measure for robustness (the system is more robust for smaller deviations).
- maximal control action span $\max_j$(Uspan), Uspan=|U_{max}-U_{min}|, from all system step responses.
- The relative indicators are computed with respect to the corresponding maximal indicator for some system. The sum of all relative indicators for each system is accepted as an overall (general) indicator which as dimensionless

enables the rating of the systems. In bold are the best (the smallest) values, in bold and italic are the second best and underlined – the worst.

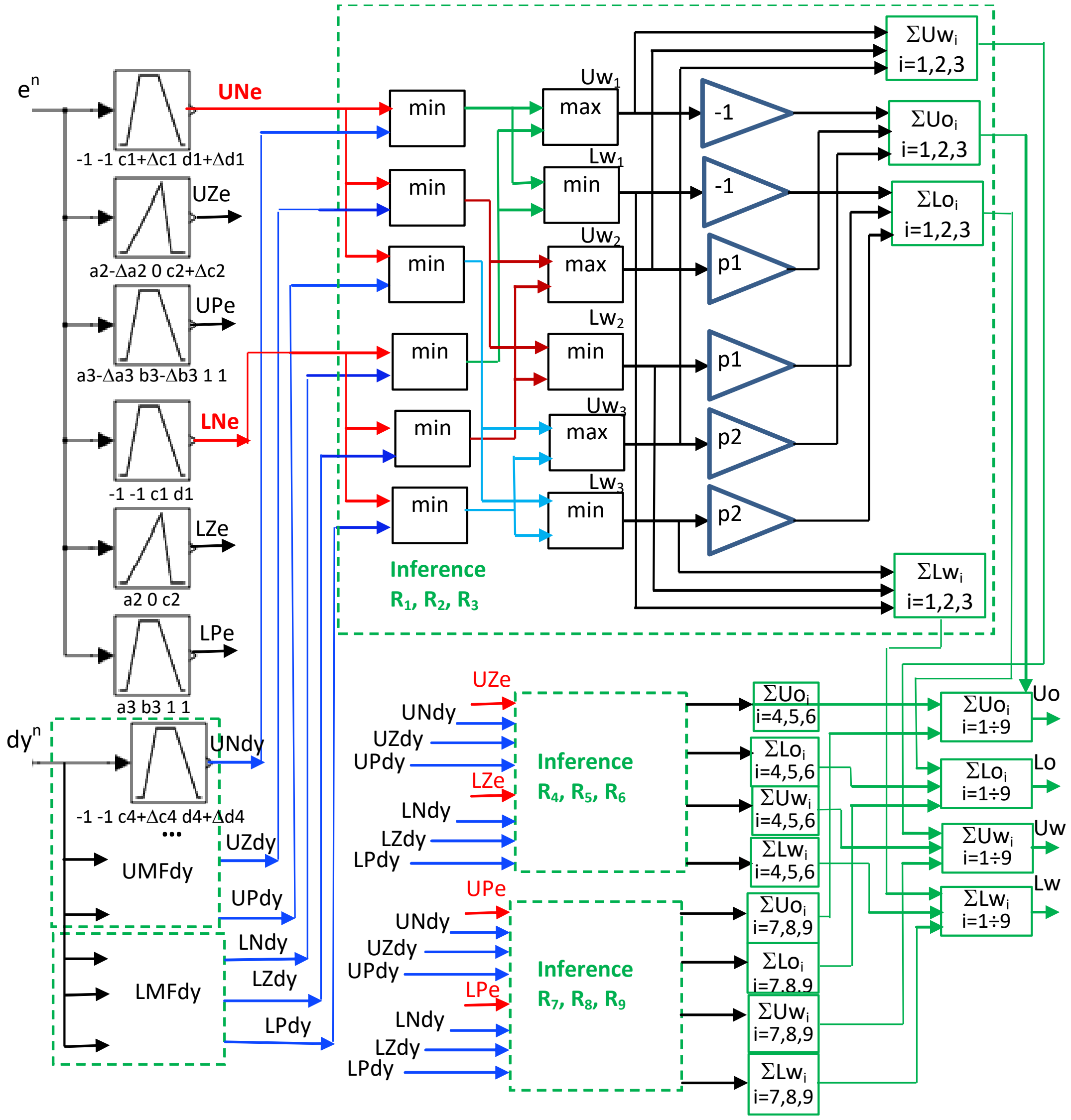

Fig.5. IT2 2I FU simulation optimisation model

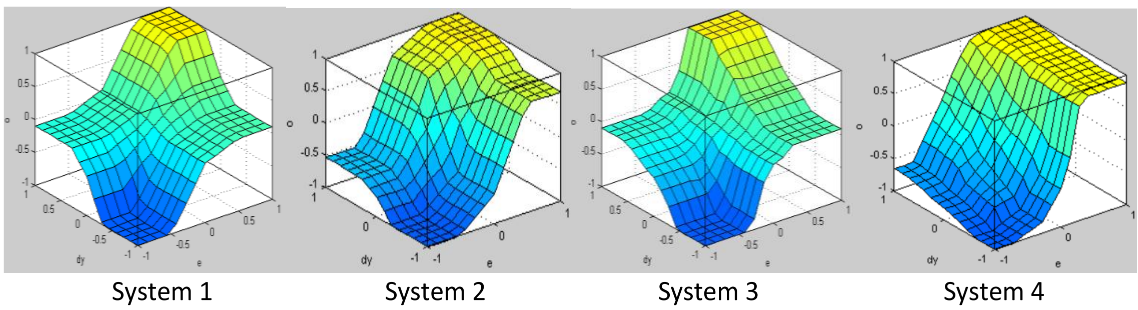

Fig.6. Control surfaces of the investigated T1 PID FLC systems

The best is System 2 with the highest dynamic accuracy expressed in reduced settling time and overshoot at the expense of high control action span. It has also the highest robustness, i.e. the smallest difference between the level and the control action from the control of the nominal plant and the varied plant. Besides, it has the smallest number of parameters to be optimised. The empirically tuned System 1 has the smoothest control action. System 3 is a compromise between dynamic accuracy and smooth control and is selected for further comparison with the IT2 PID FLC control systems.

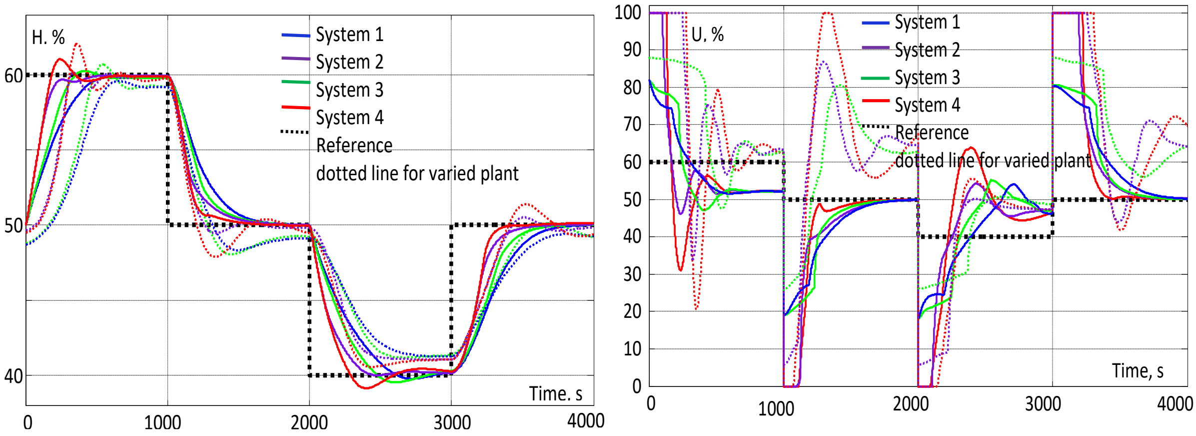

Fig.7. T1 PID FLC systems reference step responses of level H and control action U

Table 1. Performance indicators of investigated T1 PID FLC systems

Indicators (relative)	**Systems T1 PID FLC**				
	System 1 Basic T1	System 2 Opt S	System 3 Opt MF	System 4 Opt all	Maximal
F	23.9 (1)	**14.8 (0.62)**	16.8 (0.7)	***15.9 (0.67)***	23.9
F1 (MSE)	20.6 (1)	***9.4 (0.46)***	13 (0.63)	**8.9 (0.43)**	20.6
σ_{max},%	***3 (0.3)***	**0 (0)**	***4 (0.4)***	10 (1)	10
t_{smax}, s	***800 (0.8)***	**600 (0.6)**	***800 (0.8)***	1000 (1)	1000
max|H-Hv|,%	3 (0.86)	**2 (0.57)**	***2.5 (0.72)***	3.5 (1)	3.5
$\mathbf{max_j}$ Uspan,%	***33 (0.47)***	53 (0.76)	***38 (0.54)***	70 (1)	70
Σ of relative	4.43 (0.87)	**3.01 (0.59)**	***3.79 (0.74)***	5.1 (1)	5.1

B. IT2 PID FLC Systems

- System 5 accepted as the basic IT2 PID FLC system with the empirically defined basic FU output singletons S^o from (2) and LMF from (1), and UMF computed from the LMF with the deviations $q_{\Delta r}{}^o=[\Delta e1=\Delta dy1=0; \Delta eo=\Delta dyo=0.2]$, i.e. the UMF and the LMF have the same parameters for $\mu_e=1$ and $\mu_{dy}=1$, and a direct type-reducer based on interval number arithmetic [20]:

$$UMFe^o=[UNe^o;UZe^o;UPe^o] = [-1\ -1\ (-0.5+\Delta e1)\ (0+\Delta eo);\ (-0.5-\Delta eo)\ 0\ (0.5+\Delta eo);\ (0-\Delta eo)\ (0.5-\Delta e1)\ 1\ 1];$$
$$UMFdy^o= [UNdy^o;\ UZdy^o;\ UPdy^o] = [-1\ -1\ (-0.3+\Delta dy1)\ (0+\Delta dyo);\ (-0.3-\Delta dyo)\ 0\ (0.3+\Delta dyo);\ (0-\Delta dyo)\ (0.3-\Delta dy1)\ 1\ 1].$$

The LMF and the UMF are shown in Fig.8.

- System 6 with MFe^o= ($LMFe^o$, $UMFe^o$), $MFdy^o$= ($LMFdy^o$, $UMFdy^o$) and GA optimised singletons S^{opt6}= [-0.76 -0.28 0.3 0.9].
- System 7 with $LMFe^o$, $LMFdy^o$, S^o and GA optimised $q_{\Delta r}$ $q_{\Delta r}{}^{opt7}$= [$\Delta e1$=0.034 $\Delta y1$=0.29; Δeo=0.002≈0 Δyo=0.29]. Thus $UMFe^{opt7}$=[-1 -1 -0.47 0.002;-0.5 0 0.5; -0.002 0.47 1 1] ≈$LMFe^o$ and $UMFdy^{opt7}$=[-1 -1 -0.01 0.29; 0.59 0 0.59; -0.29 0.01 1 1].
- System 8 with $LMFe^o$, $LMFdy^o$ and GA optimised singletons S and $q_{\Delta r}$: S^{opt8}= [-1 -0.9 -0.49 0 0.66 0.68 1], $q_{\Delta r}{}^{opt8}$= [$\Delta e1$=0.013 $\Delta dy1$=0.12; Δeo=0.18 Δyo=0.14]. Thus $UMFe^{opt8}$=[-1 -1 -0.49 0.18; -0.68 0 0.68; -0.18 0.49 1 1] and $UMFdy^{opt7}$=[-1 -1 -0.18 0.14; 0.-44 0 0.44; -0.14 0.18 1 1].

The LMF and the UMF are shown on Fig.9.

- System 9 with optimised parameters of the singletons, the LMF and $q_{\Delta r}$: S^{opt9}=[-1 -0.59 -0.39 0 0.69 0.72 1], $LMFe^{opt9}$=[-1 -1 -0.74 0.074; -0.56 0 0.67;0.13 0.53 1 1], $LMFdy^{opt9}$=[-1 -1 -0.65 0.16; -0.48 0 0.37;-0.22 0.36 1 1], $q_{\Delta r}{}^{opt9}$=[$\Delta e1$=0.05 $\Delta dy1$=0.29; Δeo=0.063 Δyo=0.25]. Thus $UMFe^{opt9}$=[-1 -1 -0.69 0.14;-0.49 0 0.73;0.07 0.48 1 1] and $UMFdy^{opt9}$=[-1 -1 -0.36 0.41;-0.73 0 0.62;-0.46 0.065 1 1]. The LMF and the UMF are shown on Fig.10.

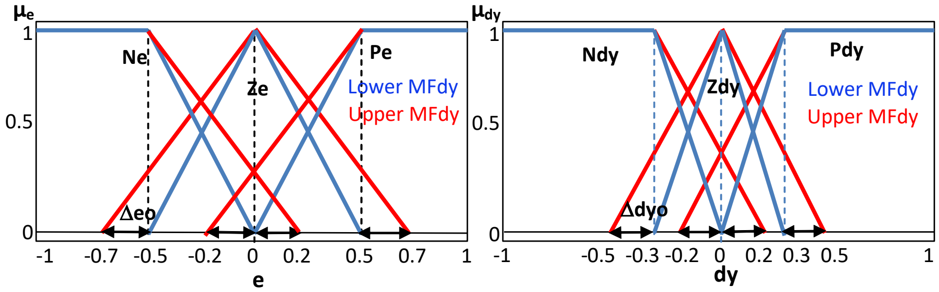

Fig.8. Lower and Upper MF of accepted basic FU of IT2 PID FLC

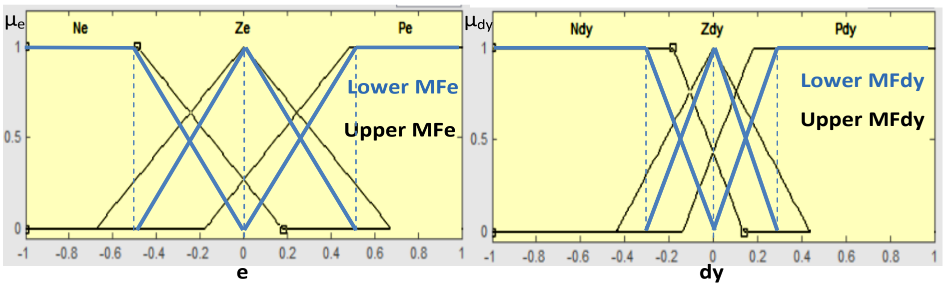

Fig.9. Lower and Upper MF of FU of IT2 PID FLC with GA optimised S and $q_{\Delta r}$.

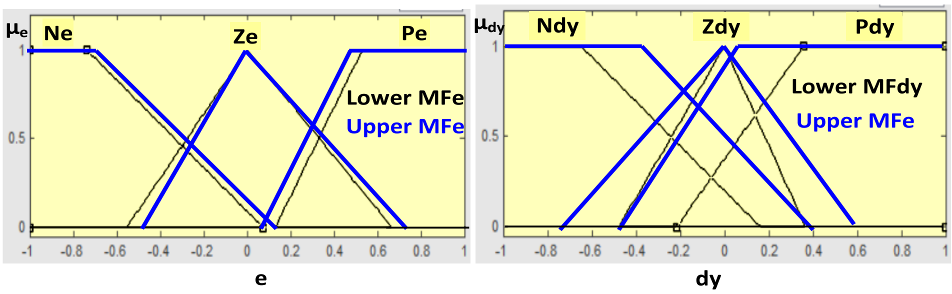

Fig.10. Lower and Upper MF of FU of IT2 PID FLC with GA optimised S, LMF and $q_{\Delta r}$.

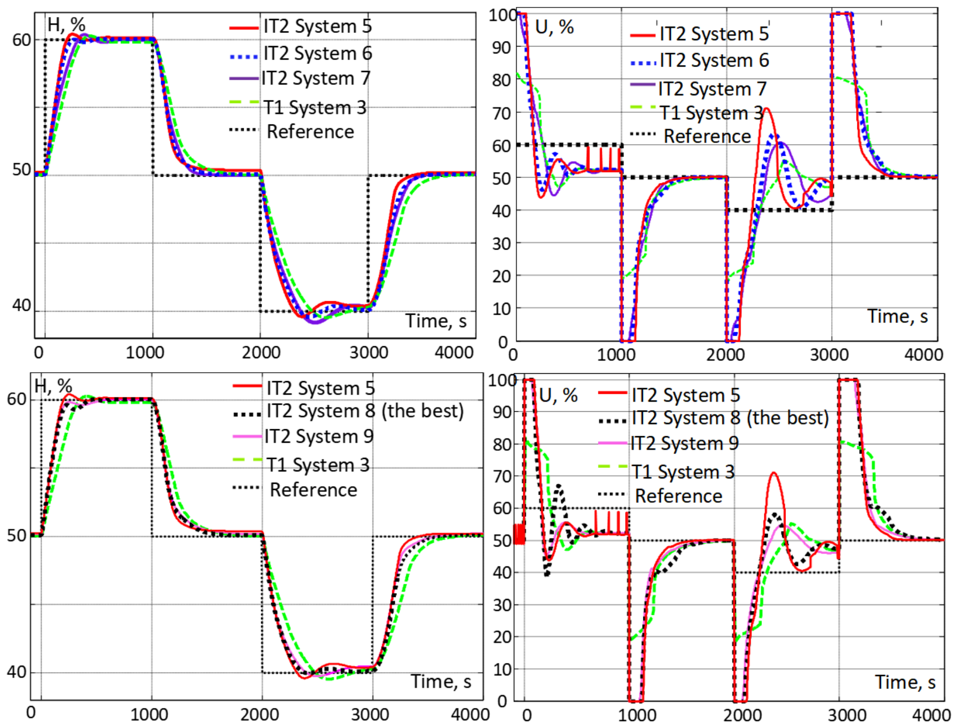

Fig.11. IT2 PID FLC systems reference step responses of level H and control action U for nominal plant

The reference step responses with respect to level and control action of the IT2 PID FLC systems and the best T1 System 3 for the control of the nominal TSK plant model is presented in Fig.11. The robustness of the IT2 PID FLC systems is assessed from the step responses of the level and of the control action from the control of the nominal plant and the varied plant. The step responses of the best T1 and IT2 PID FLC systems are shown on Fig. 12.

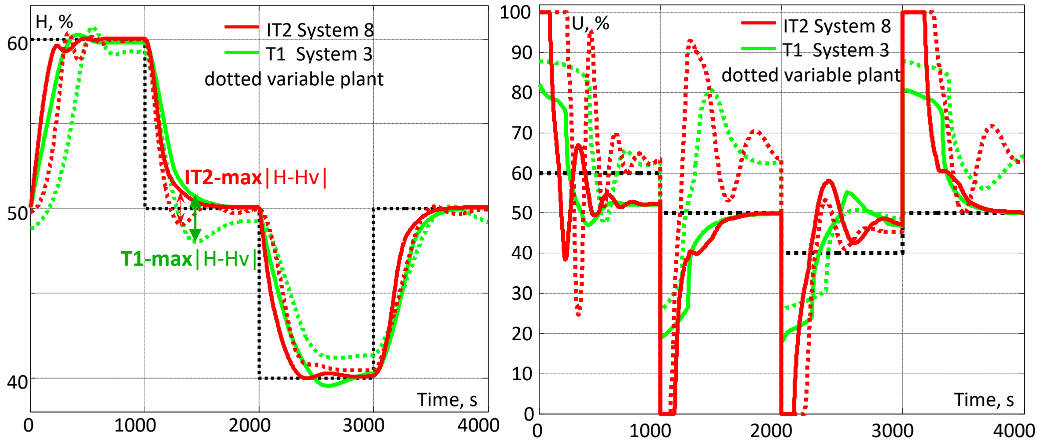

Fig.12. IT2 System 8 and T1 System 3 reference step responses of level H and control action U for nominal and varied plant

The performance indicators of the IT2 PID FLC systems assessed from the systems step responses are presented in Table 2. The analysis of the overall indicators determines that System 8 is the best with respect to the high dynamic accuracy, measured by the smallest overshoot and settling time, and the low MSE. It has also the highest robustness, smooth enough control action and a small number of optimised parameters.

The GA optimisation ensures no single unique solution. The reason is that when restarted with the same input data, it generates randomly a different initial population. Besides, the final values of the tuned parameters depend on the assumed parameter ranges, the accepted fitness function, alternative and validation criteria and the experimental data.

In the present research and for the assumed GA input, the GA optimisation improves the empirically designed T1 PID FLC system performance. The indicators F and F1 are reduced from F=23.9, F1=20.6 of the empirically tuned (basic) T1 FLC to F=14.8, F1=9.4 by optimisation of 4 parameters of the output singletons. Further F and F1 are changed to F=15.6, F1=9.4 using IT2 PID FLC with optimised 4 output singletons and 4 deviations that define the UMF. Notably, optimizing a small number of output singletons yields the most significant performance enhancement. The overall performance indicators for the systems with empirically tuned T1 and IT2 FLC and with the T1 FLC with optimised 4 singletons and IT2 FLC with optimised 4 singletons and 4 deviations are 4.43, 5.05, 3.00, and 3.89, respectively. This identifies the optimised T1 FLC system with the lowest overall indicator values as the best, followed by the optimised IT2 FLC system with twice as many optimisation parameters. The performance improvement due to optimisation for the T1 FLC system is 4.43/3=1.48 (48% improvement) and for the IT2 FLC system – 5.05/3.89=1.3 (30% improvement). No improvements are observed due to the substituting of T1 MF by IT2 MF (0.88 for both the empirically designed and the optimised FLC).

Table 2. Performance indicators of investigated IT2 PID FLC systems

Indicators (relative)	System 3 T1-opt MF	**Systems IT2 PID FLC**					
		System 5 Basic IT2	System 6 Opt S	System 7 Opt UMF	System 8 Opt S,UMF	System 9 Opt all	Maximal
F	16.8 (1)	16.1(0.96)	16 (0.95)	16.1(0.96)	***15.6 (0.93)***	**14.6(0.87)**	16.8
F1 (MSE)	13 (1)	**9 (0.69)**	9.7 (0.75)	10 (0.77)	***9.4 (0.72)***	**9 (0.69)**	13
σ_{max},%	4 (0.4)	5 (0.5)	3 (0.3)	10 (1)	**0 (0)**	***2.5 (0.25)***	10
t_{smax}, s	***800 (0.8)***	900 (0.9)	***800 (0.8)***	1000 (1)	**700 (0.7)**	850(0.85)	1000
max|H-Hv|,%	***2.5 (0.83)***	3 (1)	3 (1)	3 (1)	**2 (0.67)**	3 (1)	3
max$_j$ Uspan,%	**38 (0.54)**	70 (1)	62 (0.89)	60 (0.86)	61 (0.87)	***55 (0.79)***	70
Σ of relative	4.57(0.82)	5.05 (0.9)	4.69 (0.84)	5.59 (1)	**3.89 (0.7)**	***4.45 (0.8)***	5.59

5. Conclusions and Future Research

The main contributions described in the present paper are the following.

A novel approach for improvement of the performance of PID FLC systems for the control of an industrial plant is developed based on off-line optimisation of the parameters of type 1 and interval type 2 FLC. It is demonstrated for the control of the solution level in a CCl for soda ash production. The optimisation incorporates genetic algorithms, simulations and experimental data from the real time PI control of the level. The system simulation model is designed using a derived and validated TSK plant model. Various parameters of the T1 and IT2 input membership functions, output singletons from the fuzzy rules' conclusions and FoU are optimised to find the best solution. The suggested novel fitness function that integrates the MSE as an indicator for system dynamic accuracy and the maximal control action span as a measure for control smoothness is computed from simulations.

The systems with the empirically designed and with the optimised FLC are investigated via simulations for the control of the nominal plant (TSK plant model) and of the varied plant (TSKv plant model), derived from experimental data during the CCl operation at nominal and low load respectively and their robustness is assessed.

The simulations reveal that optimization improves the system performance, measured by a newly introduced overall performance indicator for dynamic accuracy, robustness, and control smoothness, by 48% for the T1 FLC system and 30% for the IT2 FLC system. The introduction of IT2 MF does not lead to system performance improvement both for the empirically designed and the optimised FLC. The T1 PID FLC system with optimised 4 singletons has the best performance followed by the IT2 PID FLC system with optimised 4 singletons and 4 deviations (FoU). The T1 and IT2 FLC system performance is most affected by the optimisation of the singletons. The system performance improvement for the best optimised IT2 FLC can hardly justify the more complex design and algorithm.

The optimisation results are a function of the selected parameters, their initial ranges, the fitness function used, the quality of the data used and the randomly generated initial population.

The developed approach can be extended to improve FLC system performance for controlling a variety of nonlinear plants that are challenging to be modelled using traditional methods. The future research will focus on its application for the optimisation of the parameters the FLC for the control of temperature in a laboratory fruit dryer in order to minimise energy consumption.

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