Disturbance Compensation in Fuzzy Logic Control of Level in Carbonisation Column for Soda Production

SNEJANA YORDANOVA[1] MILEN SLAVOV[2] GEORGI PROKOPIEV[2]
[1]Faculty of Automation, Technical University of Sofia, Sofia 1000, BULGARIA, sty@tu-sofia.bg
[2]"Solvay Sodi" SA–Devnya, BULGARIA, milen.slavov@solvay.com, georgi.prokopiev@solvay.com

Abstract: - The intelligent approaches emerge as leading techniques in providing of stable and high performance control of industrial plants with nonlinearity, model uncertainty, variables coupling and disturbances. In the present research a novel approach for the design of a nonlinear model-free fuzzy logic controller (FLC) with two inputs – the system error and the main measurable disturbance and a rule base for disturbance compensation is suggested. It is based on off-line parameter optimisation via genetic algorithms. The approach is applied for the development of a FLC for the control of the level of ammonia brine solution in a carbonisation column with compensation of the changes in the inflow pressure. The control algorithm is implemented in a general purpose industrial programmable logic controller in "Solvay Sodi" SA – Devnya, Bulgaria. The FLC system with disturbance compensation outperforms in an increased dynamic accuracy the FLC with the system error as a single input even when linear feedforward disturbance compensation is added. The performance of all systems is assessed from the real time control and the simulations based on a derived TSK plant model.

Key-Words: - Disturbance compensation, Level control, Mamdani fuzzy logic control, Programmable logic controller, Real time experimentation, TSK plant model

Received: October 28, 2019. Revised: March 2, 2020. Accepted: March 16, 2020. Published: March 31, 2020.

1 Introduction

The growing complexity of the modern industrial plants due to intensification of processes and market, environmental and energy consumption considerations as well as the increased performance demands for their control impose the wide replacement or complementing of the classical control approaches by intelligent techniques. The model-free fuzzy logic controllers (FLC) [1, 2] and the based on Takagi-Sugeno-Kang (TSK) plant model fuzzy parallel distributed compensation (PDC) [3, 4] enable an unified design of various nonlinear controllers that ensure stable, high performance, energy-efficient and robust plant control. The TSK plant model, the FLC and the PDC parameters are tuned by the help of off-line optimisation based mainly on genetic algorithms (GA) and experimental or simulation data [5, 6, 7].

The control of the level of the ammonia brine solution in a carbonisation column (CCl) is especially important for ensuring of the quality of the soda ash produced [8]. This is a difficult task for the linear controllers for the following reasons. The plant is nonlinear - the linear plant models for operation at various references and modes - operation or washing, have different parameters. The reference for the level, however, changes as it depends on the solution produced and its distribution among several operating in parallel columns [9]. The plant is also multivariable - the level in one CCl is coupled with the levels in all columns via the common source of feeding of all CCl with ammonia brine solution. The change of the control action in any of the columns affects not only the flow rate of the inlet solution to this CCl but also the flow pressure P in the common supply and hence the flow rates of the inlet solution in all other columns. The result is oscillations in level, control action and inlet flow pressure of all CCl. The plant is subjected also to other disturbances that originate mainly from the counterflow of the gases used in the chemical reaction and the release of the sodium bicarbonate crystals suspension by the control valve at the bottom of the CCl.

FLC and fuzzy gain schedulers are developed for level control in boilers, nuclear generators, tanks, etc. [6, 10, 11]. They are tested via simulations [12] or in real time control [13, 14, 15]. Only a few are implemented in low-cost programmable logic controllers (PLC) and microcontrollers [13, 16]. The real time experiments, however, are for the control of plant models in a laboratory environment free of industrial disturbances and measurement noise.

A TSK plant model-based PDC for the control of the level in a CCl in "Solvay Sodi" SA in the town of Devnya, Bulgaria is developed in [9]. It is programmed in the existing industrial general purpose PLC [17] which has no FLC support facilities. The PLC-PDC is in regular real time operation for over 3 years. In comparison to the previous optimized linear PI control system the PLC-PDC system has a greater dynamic accuracy and a reduced control variance which saves lifetime to the expensive final control elements. The PDC implementation to all CCl requires a lot of design effort mainly related with the derivation of the necessary TSK plant models. To escape from the TSK modelling, a simple model-free single input-single output (SISO) FLC is suggested, programmed in the same PLC and used in real time level control in [18]. The PLC-FLC system outperforms the PLC-PDC system in the simpler algorithm, the expert-based design and the reduced more than twice system error and settling time. The real time industrial experiments outline the importance of reduction of the impact of the measurement noise and the industrial disturbances.

Hence, the aim of the present research is to develop a Mamdani model-free FLC with compensation of the main measurable disturbance and to apply it for the PLC real time level control in a carbonisation column. The FLC should comply with the requirements for easy design and programming for real time control in the existing general purpose PLC. The FLC development is based on the widely used in the engineering practice MATLAB™ Fuzzy Logic Toolbox and GA [19, 20].

The further organization of the paper is the following. The design of the FLC with compensation of the main measurable disturbance for the control of level in a carbonisation column is presented in Section 2. In Section 3 the tuning of the parameters via GA optimisation and simulations is explained. The experiments from simulations and real time control for three investigated systems – with SISO FLC as a basis, with SISO FLC with added linear feedforward disturbance compensation and with the designed FLC with disturbance compensation, are described in Section 4. There different performance indicators are assessed and compared. Section 5 contains conclusions and a vision for future research.

2 Design of a Mamdani Model-free FLC with Disturbance Compensation

The FLC with disturbance compensation is based and compared with the designed in [18] nonlinear PI SISO FLC for the control of the level $H(t)$ in a CCl.

The PI SISO FLC consists of a fuzzy unit (FU) and a PI post-processing. Input to the FU is the normalised in [-1, 1] by the help of a normalisation gain K_e system error $e^n(t)=K_e.e(t)$, where for a given reference H_r the system error is $e(t)=H_r\text{-}H(t)$. Five membership functions (MF) are expert defined for e^n – three triangle and two trapezoidal on both ends of the normalised universe of discourse. They are described by different linear equations for the different ranges for e^n in order to be economically represented in the industrial PLC with no FLC support facilities. Five singletons are selected for the output MF of the FU in order to facilitate the defuzzyfication. The tuning of the PI parameters K_p and T_i is based on expert knowledge about the plant, heuristic considerations and robust performance criterion [4].

The FLC with disturbance compensation is shown in Fig.1. The measured level H as the plant output to be controlled and the inflow pressure P as the main measurable disturbance are filtered from noise by the exponential noise filters, represented with the transfer functions $W_f(s)=(T_fs+1)^{-1}$, T_f=0.2min (12s) for H and $W_{f1}(s)=(T_{f1}s+1)^{-1}$, T_{f1}=1min (60s) for P. The FU is a two-input single-output (2ISO). Its first input is the normalised in the range [-1, 1] system error $e^n=K_e.e$. The second FU input is the normalised in the range [-1, 1] inflow

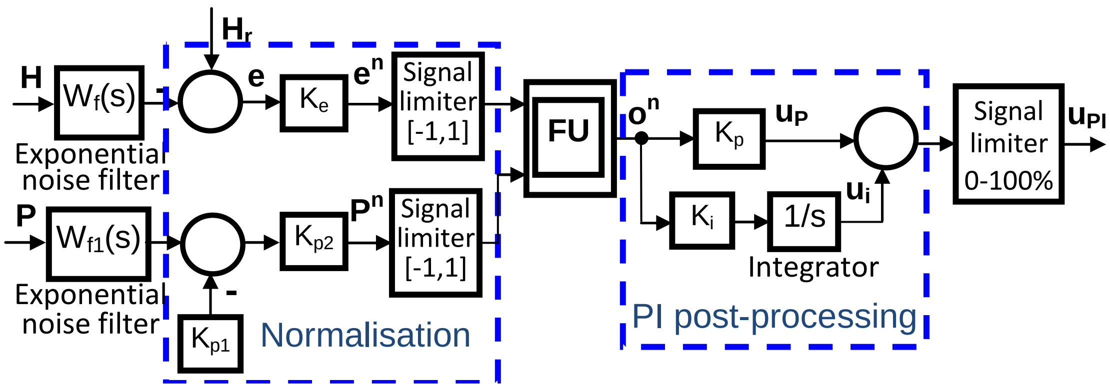
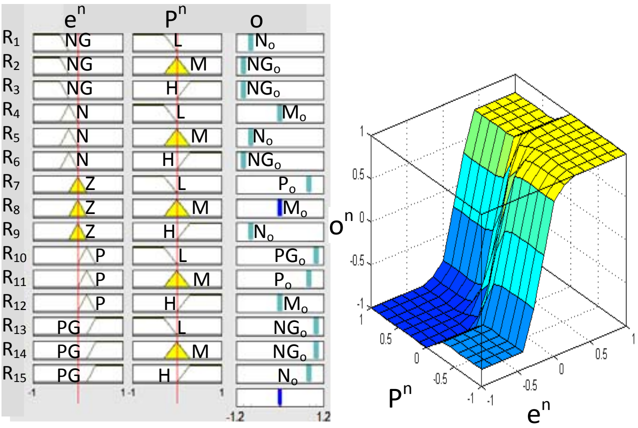


Fig. 1. 2ISO FLC with disturbance compensatio



Negative N, Zero Z , Positive P, great G, Low L, Mean/Medium M, High H, "o" for output

Fig. 2. FU of 2ISO FLC with disturbance compensation

pressure P^n, computed as normalised deviation of the measured pressure after the exponential noise filter P from its mean value P_{mean} $P^n=K_{p2}.(P-K_{p1})$, where $K_{p1}=P_{mean}=1.38$. The triangle and trapezoidal membership functions (MF) of the inputs– five for e^n and three for P^n, and the five singletons MF for the output o^n are standard orthogonal expert defined as shown in the fuzzy rules in Fig.2a).

The fuzzy rules $\mathbf{R}_i$ are derived as a modification of the standard rule base for FU with inputs the system error and rate of error by considering the impact of pressure on the desired FU output. The output in each fuzzy rule of the standard rule base is defined to ensure a proper action on the valve, i.e. on the flow rate of the inlet solution that can move the error and the rate of error in the next time moment closer to their norms, i.e. zero terms. In the new rule base with P^n as a second input to the FU this logic is preserved for pressures of the solution at the supply about the mean value P_{mean}, i.e. for $P^n\approx 0$. The low pressure $P<P_{mean}$ ($P^n<0$) reduces the inlet solution flow rate for the same position of the valve. In order to keep the desired flow rate the FU output should be greater than in the standard rule base. By analogy the high pressure $P>P_{mean}$ ($P^n<0$) requires a decreased FU output with respect to the standard rule base. For example, in Fig. 2a) for e^n=NG and input $_2{}^n$=L in R_1 the FU output in the standard rule base, i.e. for input$_2{}^n=\dot{e}^n$, is o^n=NG$_o$ – a great decrease of the control action. For the new fuzzy rules with input$_2{}^n=P^n$ the FU output is o^n=N$_o$ – a decrease of the control action, because the low pressure P^n = L at the column input assists the decreasing of the inlet solution flow rate and hence the effect is equivalent to a great decrease of the control action.

The computed control surface is nonlinear as shown in Fig.2b):

$$o^n=K_e(e^n, P^n).e^n+ K_P(e^n, P^n).P^n.$$

The post-processing performs a PI (proportional plus integral) algorithm which makes the 2ISO FLC with compensation of the measurable disturbance a nonlinear PI FLC.

The tuning parameters $\mathbf{q}_{FLC}=[K_e\ K_{p2}\ K_p\ K_i]^T$ can be computed from heuristic knowledge about the ranges of the signals, robust stability and robust performance criteria [4] or off-line GA optimisation.

3 GA Optimisation of the Parameters of 2ISO FLC with Disturbance Compensation

The genetic algorithms have found a wide application in FL systems [21]. They perform a gradient-free optimisation by random parallel search of the parameters space for global extremum of an accepted multimodal fitness function of many parameters defined by experimental or simulation data. The GA, inspired by the Darwin theory of evolution of species, produces improved generations by proper mating of individuals, crossover and mutation of their genes. The genes are the system parameters that build a chromosome (an individual and a possible optimal solution). An initial population of chromosomes is randomly generated and each individual rated according to the accepted fitness function. Every next generation is formed from the "better than the parents" off-springs each a result from parents' selection and their genes exchange and mutation. The process is repeated with every new generation till an accepted end condition is met.

The off-line GA optimisation is based on simulations with known system model and available experimental or simulation data. It is preferred because it is precise (free of industrial noise and disturbances), fast and safe for the industrial plant. GA optimisation is applied basically for TSK plant modelling and FLC parameters tuning [6, 7]. In order to ensure mapping of the system nonlinearity and adaptive abilities it is important a correct fitness function to be defined and the data used to be rich in frequencies and magnitudes, i.e. the experiments or simulations to be well-designed to reflect the industrial environment and all system operation conditions. GA tuning of FLC are presented for a heating-ventilation and air conditioning system in [22] and for level in [12].

Here the GA optimisation is first applied to objectively derive a more precise modified TSK plant model than the TSK plant model in [9]. The new TSK plant model recognizes the location of the current operation point with respect to expert defined linearization zones based on two inputs - the control action u and the main disturbance - the inflow pressure P. It captures the plant nonlinearity from the experimental data used. The GA modelling procedure is similar to the used in [4, 9].

The novel 2ISO TSK plant model is depicted in Fig. 3. The Sugeno model is expert designed. It has two inputs - the normalised both in the range [-1, 1] control action u^n and pressure P^n. Three zones of linear operation of the plant are assumed and defined by three for each input standard orthogonal membership functions (MF) in the shape of triangles and trapezoids. The accepted norm is determined to ensure desired flow rate of the inlet solution which corresponds to $P^n=0$ ($P=P_{mean}$) and to the equivalent combinations [($P^n<0$) **and** ($u^n>>0$)] and [($P^n>0$) **and** ($u^n<<0$)] since the decreased P with respect to P_{mean} is compensated by the increased u in preserving the desired inlet solution flow rate and vice versa. The other two zones are defined for combinations of (u^n,P^n) with the effect of a reduction and an increase of the flow rate of the input solution respectively. The outputs are three – one for a linearization zone, with singletons 0 and 1 for the MF. The three fuzzy rules are designed to ensure that each output k, $k=1\div3$, yields the respective MF μ_k of belonging of

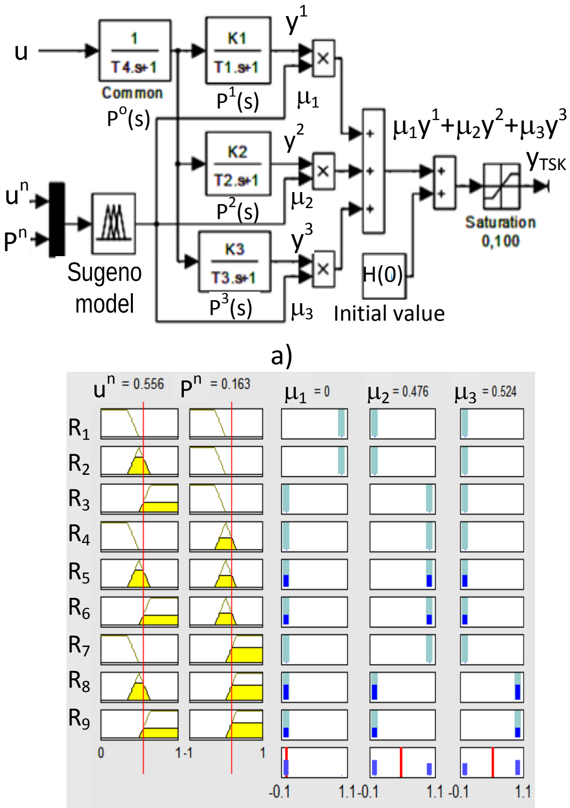


Fig. 3. TSK plant model: a) block diagram; b) Sugeno model fuzzy rules in membership functions

the couple (u^n, P^n) to the k-th linearization zone (output$_k$=μ_k). The dynamic part describes by second order time lags the linear dynamic behavior of the plant in the three linearization zones. The nonlinear plant output is a weighted sum of the outputs of the local linear plants $y=\mu_1.y^1+\mu_2.y^2+\mu_3.y^3$. The TSK plant model parameters $\mathbf{q_{TSK}}=[K_1\ T_1\ K_2\ T_2\ K_3\ T_3\ T_4\ H(0)]^T$ are computed via GA parameter optimisation on the basis of experimental data for the plant inputs ($u=u_{exp}$, $P=P_{exp}$) and output y_{exp} from the real time linear PI level control. The minimization of the following fitness function is considered:

$$F=\frac{1}{N}\sum_{i=0}^{N}(y_{expi}-y_{TSKi})^2 \qquad (1)$$

The computed optimal TSK plant model parameters are $\mathbf{q_{TSK}}^{o}=[K_1=-0.35,\ T_1=24s;\ K_2=0.49,\ T_2=80s;\ K_3=0.58,\ T_3=73s;\ T_4=183s;\ H(0)=26]$.

The input data used for the GA parameter optimization is the following:

- the GA parameters - binary coding, population size 20, roulette selection, crossover in a single point, crossover probability 0.8, adaptive mutation, elite 2, rank-based scaling, end condition – 10 generations;
- the fitness function (1);
- the ranges for the unknown parameters;
- the plant inputs and output from the industrial PLC-PI real time level control which are used in the TSK modelling, and from the industrial PLC-PDC real time level control designed in [9] which are used in the model validation.

The derived TSK plant model is successfully validated. Further it is used in the GA optimisation of the parameters of the designed FLC with disturbance compensation and in the simulation of the investigated FLC closed loop systems.

A simulation model of the closed loop system is developed which consists of the suggested in Fig. 1 PI 2ISO FLC with disturbance compensation and the derived 2ISO TSK plant model. It is used for the computation of the fitness function for each chromosome (combination of ordered parameters) in an off-line GA optimisation for tuning of the PI 2ISO FLC parameters $\mathbf{q}_{FLC}=[K_e\ K_{p2}\ K_p\ K_i]^T$. The fitness function introduced integrates two criteria - minimisation of the system dynamic error $\mathbf{F_1}$ and of the control action variance $\mathbf{F_2}$:

$$\mathbf{F=F_1+w.F_2}, \qquad (2)$$

where:

- $\mathbf{F_1}=\frac{1}{N}\sum_{i=1}^{N}e_i^2$ is the mean squared system error;

- $\mathbf{F_2} = \mathbf{D}\left(\frac{u}{H_r}\right)/\mathbf{D}(P)$ is the variance $\mathbf{D}\left(\frac{u}{H_r}\right)$ of the control action u per unit reference H_r relative to the variance $\mathbf{D}(P)$ of the pressure

$$\mathbf{D}\left(\frac{u}{H_r}\right) = \frac{1}{N-1}\sum_{i=1}^{N}\left[\frac{U_i}{H_{ri}} - \mathbf{M}\left(\frac{U}{H_r}\right)\right]^2,$$

$$\mathbf{D}(P) = \frac{1}{N-1}\sum_{i=1}^{N}[P_i - M(P_i)]^2,$$

with $\mathbf{M}\left(\frac{U}{H_r}\right) = \frac{1}{N}\sum_{i=1}^{N}\frac{U_i}{H_{ri}}$ and $\mathbf{M}(P) = \frac{1}{N}\sum_{i=1}^{N}P_i$ the estimates of the mathematical expectations for $\frac{U}{H_r}$ and P respectively.

- w=0.1 is the empirically adjusted weight that ensures the two terms in (2) to be of the same order.

The computed optimal FLC parameters are $\mathbf{q}_{FLC}=[K_e=0.1\ K_{p2}=6\ K_p=53\ K_i=K_p/T_i=0.11\%/s]^T$.

The stability and the robustness of the designed FLC-TSK system are studied on the basis of the derived in [4] FLC system robust stability and robust performance by integrating Popov and Morari criteria [23]. First the nonlinear plant is approximated by a family of linear plants $\mathbf{F}=[P^o(s), l(s)]$. The multiplicative model uncertainty is $l(s)=[P(s)-P^o(s)][P^o(s)]^{-1}$. The linear nominal plant model $P^o(s)=k^o.\exp(-\tau^o.s)(T^o.s+1)^{-1}$ and the worst case varied plant model with respect to the impact on the stability of the closed loop system $P(s)$ with $k=k^o+\Delta k$, $\Delta k>0$, $\tau=\tau^o+\Delta\tau$, $\Delta\tau>0$ and $T=T^o+\Delta T$, $\Delta T<0$ are expert assessed from of the step responses of the TSK plant model [9]. The parameters are $k^o=1$, T^o=500s, τ^o=110s and k=2, T=200s, τ=100s.

Next the PI 2ISO FLC is described by an equivalent PI SISO FLC with a control curve from the o^n-e^n projection of the PI 2ISO FLC control surface which is bounded within a sector determined by lines with gains K and r (here K=10, r=1.4) with the exception of a disk around the origin. Finally the linear dynamic part of the SISO FLC consisting of the pre- and the post-processing which in series make a PI component $C_{PI}(s)$, and the linear nominal plant, is stabilised by a local feedback with gain r. The obtained transfer function becomes $P_s(s)=P^o(s).C_{PI}(s).[1+r.P^o(s).C_{PI}(s)]^{-1}$. Thus all requirements for the application of the Popov stability criterion are fulfilled. The designed system is robustly stable since the Nyquist plots of the modified dynamic parts

$$P_m(j\omega)=\mathrm{Real}[P_s(j\omega)]+j\omega.\mathrm{Imaginary}[P_s(j\omega)]$$

for nominal and varied plants, $P_m^o(j\omega)$ and $P_m(j\omega)$ respectively, are located to the right and below the Popov's line through the point $(-1/(K-r), j0)$ for all significant frequencies $\omega\in[0.2\pi/T^o, 20\pi/T^o]$ as seen from Fig.4a). The robust performance curve is computed from the criterion for minimization of the worst system error for some frequency and some

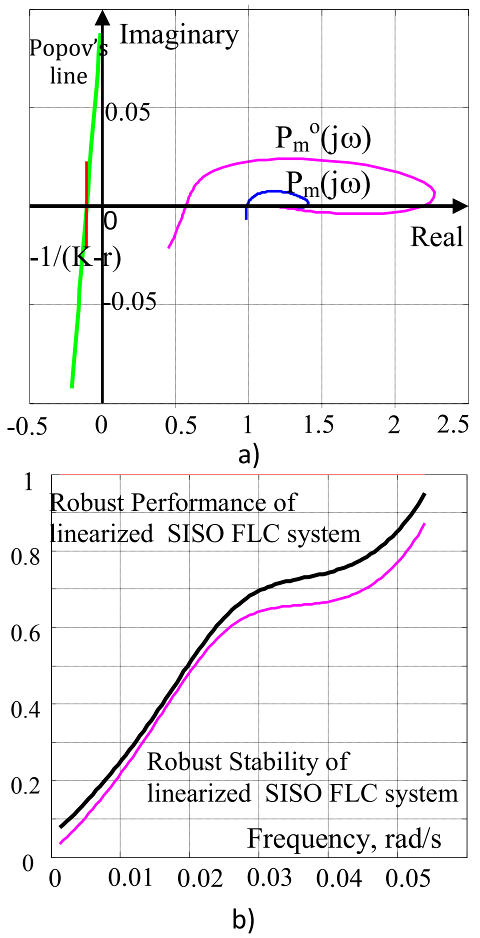


Fig. 4. Robustness of SISO FLC system:
a) Popov robust stability; b) robust stability and robust performance curves for linearized FLC

linear plant model from the family $\mathbf{F}$ after the nonlinear SISO FU of the FLC is linearised. The robust stability and robust performance curves of the system with linearized SISO FLC are depicted in Fig.4b). They are below 1, which shows that the closed loop FLC system is robust. The robust performance criterion is stronger and includes the robust stability condition. That is why its curve in Fig. 4b) lies above the robust stability curve and is closer to 1.

Thus the optimal PI 2ISO FLC tuning parameters ensure also robust system stability and performance.

4 2ISO FLC System Investigation via Simulations and Real Time Level Control

The aim of the investigation of the closed loop system with the designed 2ISO FLC – system 1 (K_e=0.1, K_p=53%, K_{ie}=0.11%/s, K_{p2}=6), is to assess the improvements due to the disturbance compensation in comparison with two SISO FLC

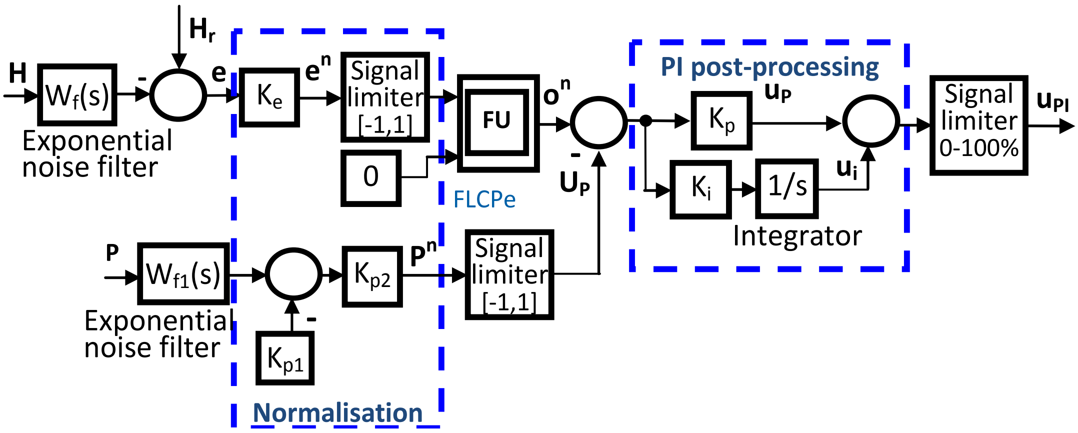


Fig. 5. SISO FLC (K_e=0.1, K_p=80%, K_{ie}=0.75%/s, K_{p2}=0) and SISO FLC with linear feedforward compensation of measurable disturbance (K_e=0.1, K_p=69%, K_i=0.11%/s, K_{p2}=7)

systems, shown in Fig. 5 - system 2 with input the system error without disturbance compensation (K_e=0.1, K_p=80%, K_{ie}=0.75%/s, K_{p2}=0), and system 3 with added linear feedforward measurable disturbance compensation (K_e=0.1, K_p=69%, K_i=0.11%/s, K_{p2}=7). The tuning parameters in all systems are GA optimised using fitness function (2).

The investigation is based on obtained step responses of level for different reference changes and the corresponding control action and pressure first from simulations and then from experiments during the real time level control in industrial environment.

The implementation of the SISO and 2ISO FL controllers in the industrial PLC with no FLC support facilities in "Solvay Sodi" SA – Devny a is based on the transformation of the fuzzy rules into ordinary logic conditions and of the MF into piecewise linear functions [18]. The algorithm is the following.

1. The universe of discourse for the normalised system error e^n in Fig.2a) is divided into 6 intervals [-1÷-0.4), [-0.4÷-0.2), [-0.2÷0), [0÷-0.2), [0.2÷0.4) and [0.4÷1] where the five MF are constants 0 or 1 or computed from the corresponding equations that describe lines $\mu^m{}_e=a^m.e^n+b^m$, m=1÷5. In the same way the universe of discourse for the normalised pressure P^n is divided into 4 intervals [-1÷-0.3), [-0.3÷0), [0÷0.3) and [0.3÷1] where the three MF are equal to 0 or 1 or computed from $\mu^l{}_P=c^l.P^n+d^l$, l=1÷3.

2. For each current time moment t_i the level H_i and the pressure P_i are measured and filtered and the normalised system error e_i^n and P_i^n are computed.

3. All MF for e_i^n and P_i^n are computed from the expressions defined for the intervals where the normalised values for e_i^n and P_i^n fall.

4. For all rules R_p, p=1÷15, the degree of activation is computed as w_i^p=**min**($\mu^{mp}{}_e$, $\mu^{lp}{}_P$) where $\mu^{mp}{}_e$ and $\mu^{lp}{}_P$ are respectively the values of the MF for e_i^n and P_i^n in the premise of rule R_p.

5. The singleton K^p in the conclusion in each rule R_p is scaled by the corresponding w_i^p, where according to Fig.2a) $K^2=K^3=K^6$=-1, $K^1=K^5=K^9$=-0.8, $K^4=K^8=K^{12}$=0, $K^7=K^{11}=K^{15}$=0.8, $K^{10}=K^{13}=K^{14}$=1.

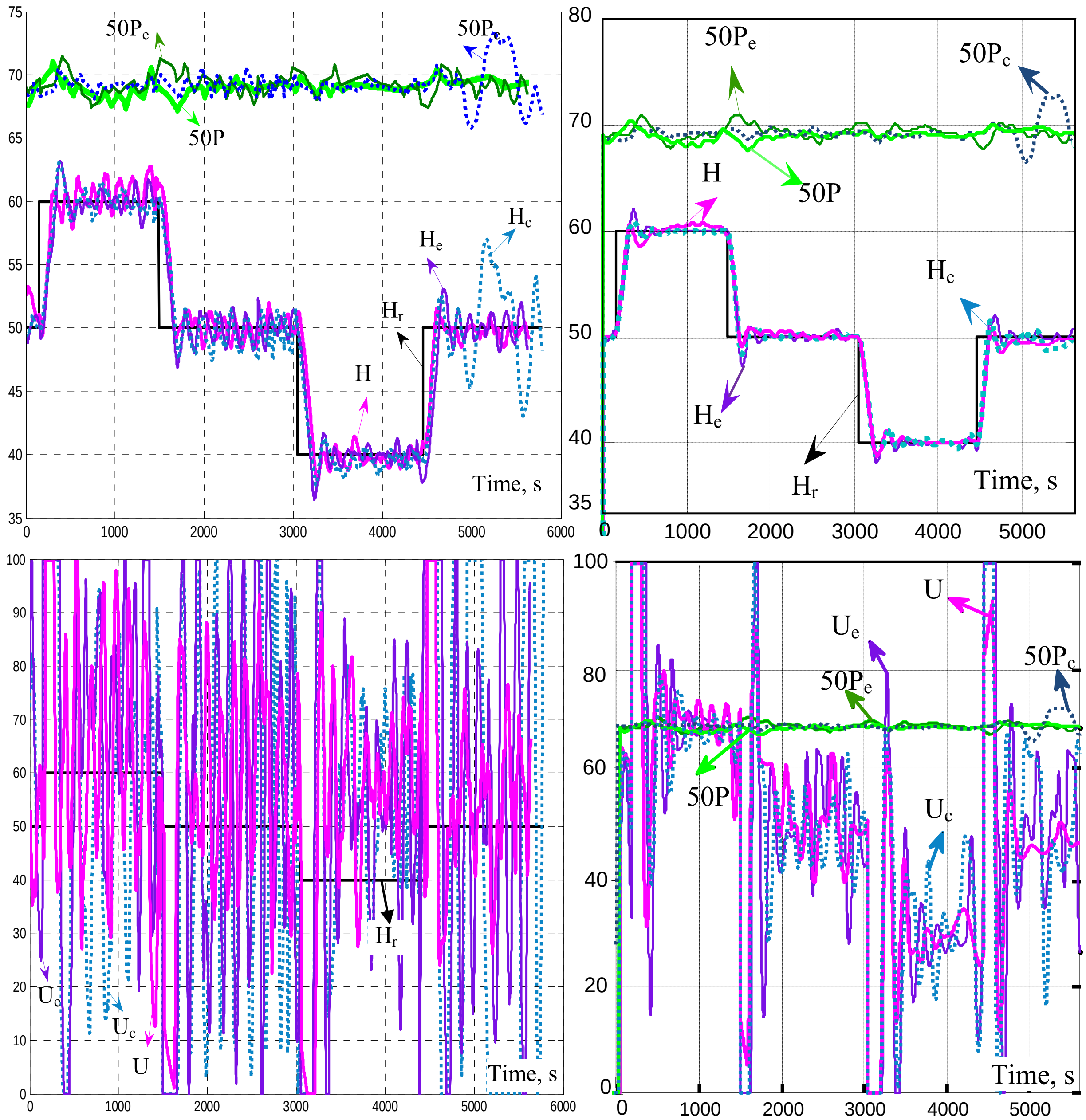
6. The final crisp output o_i^n is computed after a weighted average defuzzyfication:

$$o_i^n = \left(\sum_{p=1}^{15} w_i^p K_i^p\right) / \left(\sum_{p=1}^{15} w_i^p\right).$$

The step responses of the three systems with respect to level H and control action U are presented in Fig. 6a) from real time control and in Fig. 6b) from simulation, where P is the real time system disturbance. By H, U and P are denoted the variables of the 2ISO FLC (system 1), by H_e, U_e and P_e – of the SISO FLC (system 2) and by H_c, U_c and P_c – of the SISO FLC with the linear feedforward disturbance compensation (system 3).

The analysis of the graphs shows that the simulation results are close to the recorded from real time control of level. The rating of the three investigated systems is predicted correctly in the simulations which are carried out before the real time control is applied. From the simulation system 1 with PI 2ISO FLC with disturbance compensation is the best with the least overshoot, settling time and control action variance. Next is system 3 with the PI SISO FLC with linear disturbance compensation and the last is system 2 with the ordinary PI SISO FLC.

The comparison of the performance of the three systems assessed from the step responses during the real time level control is based on the following performance indicators:



a) b)

Fig. 6. Step responses with respect to level (up) and control action (down) for the investigated systems: a) from real time control; b) from simulation

- the system mean squared error $\mathbf{F_1}$ from (2) – a smaller $\mathbf{F_1}$ means a higher dynamic accuracy;

- the mean of squared error relative to the disturbance $\mathbf{F_3} = \frac{1}{N}\sum_{i=1}^{N}(e_i^2/P_i)$ - this estimate of the dynamic accuracy considers the level of disturbance (changes of P with respect to P_{mean}) during the real time experiments performed in different industrial environment for the three systems, $\mathbf{F_3}$ can be small when the system error is not very small but the deviation of the pressure P from P_{mean} is high (high level of disturbance) for the specific experiment;

- the variance of the control action $\mathbf{F_2}$ from (2) – a smaller $\mathbf{F_2}$ means a higher energy efficiency and a longer lifetime of the final control elements;

- the sum of the control action needed for a unit reference relative to the maximal control action U_{max}=100% $\mathbf{F_4} = \frac{1}{100}\sum_{i=1}^{N}\frac{U_i}{H_{ri}}$ – a smaller $\mathbf{F_4}$ means a more economical control for the respective references.

The assessed performance indicators of the three systems are systemised in Table 1. The best (the smallest) values are dark highlighted and the worst (the highest) are given in bold. From there it is

Table 1 Performance indicators of investigated systems from real time control

N=5626	System 1	System 2	System 3
F_1	7.29	7.42	**8.5**
F_3	5.27	5.36	**6.14**
F_2	1494	**1672**	889
F_4	**64.4**	64	56.6

evident that sy stem 1 with the 2ISO FLC with disturbance compensation has the great est dynamic accuracy while system 3 with SISO FLC with linear disturbance compensation has the most economical control with the s mallest variance at the expense of the lowest dynamic accuracy.

4 Conclusion and Future Research

The novelty and the main contribut ions of th e present research can be summarised as follows.

A FLC wi th compensation of the main measurable disturbance for the control of level in a carbonisation column in the soda production plant in Bulgaria is developed. The FLC has two inputs – the system error and the measured pressure at the solution supply which is considered as the main disturbance. A specifi c fuzzy rule base is derived that accounts for the im pact of the ch ange of the pressure on the level.

A FLC parameter tuning procedure is developed based on an off-line GA parameter optimisation. It uses simulations to com pute a suggested two-criterion fitness function for increased sy stem dynamic accuracy and reduced control action variance.

A new modified TSK plant model with two inputs - the control action and the pressure as the measurable plant inputs, i s derived and validated from experimental data for the sake of sy stem simulations. It is built on a Sugeno model that computes the degrees of matching of the current operation point to the heuristically determined three operation zones and loca l transfer functions based dynamic models which p arameters are determ ined via GA optim isation. The TSK plant m odel performs soft blendin g of the out puts of the local linear plants.

The designed FLC with disturbance compensation is implemented in the general purpose industrial PLC of the existing Experion digital control system [17] in “Solvay Sodi” SA – Devnya, Bulgaria using ordinary logics expressions. It is further used in the real time level control.

Simulation and real tim e experiments show that the designed FLC sy stem outperforms the existing SISO system and the SISO system with added linear feedforward disturbance compensation in improved dynamic accuracy due to the good nonlinear disturbance compensation.

The future research will focus on further improvement of the sy stem performance by considering the rate of er ror in the desi gn of a FLC with disturbance compensation.

Funding and declaration of interest

This research did not receive any specific grant from funding agencies in the p ublic, commercial, or not-for-profit sectors.

The authors declare that they have no conflict of interests of any kind and consent this final version of the m anuscript to be s ubmitted for publication. The manuscript is an original unpublis hed research work and is not under consideration for publication elsewhere.

References:

[1] Driankov D., Hellendoorn H., Reinfrank M., *An Introduction to Fuzzy Control*, Springer-Verlag, New York, 1993.

[2] Jantzen J., *Foundations of Fuzzy Control*, New York: John Wiley and Sons, 2007. DOI:10.1002/9780470061176.

[3] Tanaka, K., and Wang, H. O., *Fuzzy control systems design and analysis*: *A Linear Matrix Inequality Approach*, New York: John Wile y and Sons, 2001.

[4] Yordanova S., *Methods for Design of Fuzzy Logic Controllers for Robust Process Control*, KING, Sofia, 2011. (in Bulgarian)

[5] Wu C-J, Ko C-N, Fu Y-Y, Tseng C-H., A Genetic-based Design of Auto-tuning Fuzzy PID Controllers, *Int. J. Fuzzy Systems*, 2009, Vol.11, No.1, pp. 49-58.

[6] Yordanova S., Intelligent Approaches to Real Time Level Control, *Int. J. Intell. Sys.and Appl.*, 2015, Vol.7, No.10, pp. 19-27, DOI: 10.3233/IFS-141242.

[7] Yordanova S., Design of Fuzzy Supervisor-based Adaptive Process C ontrol Systems, in: Nakamatsu K. and Koun tchev R. (Eds), *New Approaches in Intelligent Control: Techniques, Methodologies and Applications*, *Book series “Intelligent Systems Reference Library*”, Vol. 107, Springer Int. Publ ., Switzerland, 2016, pp.1-42, DOI: 10.1007/978-3-319-32168-4_1.

[8] Thieme Ch., Sodium Carbonates, in: *Ullmann's Encyclopedia of Industrial Chemistry*, Wiley-

VCH Verlag GmbH & Co. KGaA, Weinheim, Germany, 2012, Vol.33, pp. 299-316. https://onlinelibrary.wiley.com/doi/10.1002/14356007.a24_299.

[9] Yordanova S., Slavov M., Gueorguiev B., Parallel Distributed Compensation for Improvement of Level Control in Carbonisation Column for Soda Production, *Contr. Eng. Practice*, 2018, Vol.71, pp.53-60, DOI:10.1016/j.conengprac.2017.10.003. https://www.aspentech.com/en/products/msc/aspen-infoplus21.

[10] Ahmad S., Ali S., Tabasha R., The Design and Implementation of a Fuzzy Gain-scheduled PID Controller for the Festo MPS PA Compact Workstation Liquid Level Control, *Eng. Sci and Techn, an Int. Journal*, 2019 (on line), DOI:10.1016/j.jestch.2019.05.014.

[11] Kanagasabai N., Jaya N., Fuzzy Gain Scheduling of PID Controller for a MIMO Process, *Int. J. of Comp. Appl.*, 2014, Vol.91, No.10, pp. 13-20, DOI:10.5120/15916-4803.

[12] Mousa H. M., Koutb M. A., El-Araby S. M., Elsayed H. M. A., Design of Optimal Fuzzy Controller for Water Level of U-Tube Steam Generator in Nuclear Power Station, *Journal of American Sci.*, 2011, Vol.7, No.4, pp. 629–637.

[13] Aydogmus Z., A Real-time Robust Fuzzy-based Level Control Using Programmable Logic Controller, *Elektronika ir Elektrotechnika*, 2015, Vol.21, No.1, pp.13-17, DOI:10.5755/j01.eee.21.1.7812.

[14] Shome A., Ashok D., Fuzzy Logic Approach for Boiler Temperature and Water Level Control, *Int. J. of Scientific and Eng. Res.*, 2012, Vol.3, No.6, pp. 1-6.

[15] Tan W., Water Level Control for a Nuclear Steam Generator, *Nuclear Eng. and Design*, 2011, Vol.241, No. 5, pp.1873-1880, DOI:10.1016/j.nucengdes.2010.12.010.

[16] Chabni F., Taleb R., Benbouali A., Bouthiba M.A., The Application of Fuzzy Control in Water Tank Level Using Arduino, *Int. J. of Adv. Comp. Sci. and Appl.*, 2016, Vol.7, No.4, pp.261-265, DOI:10.14569/IJACSA.2016.070432.

[17] *Experion overview,* Honeywell Int. Inc., Release 300.1 May 5, 2006.

[18] Yordanova S., Gueorguiev B., Slavov M., Design and Industrial Implementation of Fuzzy Logic Control of Level in Soda Production, *Eng. Sci. and Techn. an Int. Journal*, 2020, (on-line),ISSN:2215-0986, DOI:10.1016/j.jestch.2019.08.005, https://www.sciencedirect.com/science/article/pii/S2215098619313461?via%3Dihub.

[19] *Fuzzy Logic Toolbox: User's Guide for Use with MATLAB*, TheMathWorks, Inc. Natick, MA, 1998.

[20] *MATLAB – Genetic Algorithm and Direct Search Toolbox. User's Guide*, MathWorks, Inc., 2004.

[21] Fazzolari M., Alcala R., Nojima Y., Ishibuchi H., Herrera F., A Review of the Application of Multiobjective Evolutionary Fuzzy Systems: Current Status and Further Directions, *IEEE Trans. on Fuzzy Syst.*, 2013, Vol.21, No.1, pp.45-65,DOI: 10.1109/TFUZZ.2012.2201338.

[22] Gacto M.J., Alcalá R., Herrera F., A Multi-Objective Evolutionary Algorithm for an Effective Tuning of Fuzzy Logic Controllers in Heating, Ventilating and Air Conditioning Systems, *Appl. Intell.*, 2012, Vol.36, pp.330-347, DOI: 10.1007/s10489-010-0264-x.

[23] Morari M., Zafiriou B., *Robust Process Control*, New Jersey: Prentice Hall, 1989.