Energy Efficient Fuzzy Logic Control of Indoor Air-Conditioning in Real Time

SNEJANA YORDANOVA
Faculty of Automation
Technical University of Sofia
8 Kliment Ohridski Blvd., Sofia 1000
BULGARIA
sty@tu-sofia.bg

Abstract: - The indoor human comfort, working efficiency and health are dependent on the control of the quality of air in a heating-ventilation and air-conditioning (HVAC) system. The aim of present paper is to improve this control considering the most important variables – the air temperature, relative humidity and concentration of carbon dioxide by applying fuzzy logic and genetic algorithms (GAs) for compensation of the variables coupling and the plant nonlinearity by energy efficient control. Two fuzzy logic controllers (FLCs) are designed, one of which two-variable based on a derived modified two-variable Takagi-Sugeno-Kang (TSK) plant model. GAs off-line parameter optimization is applied in the TSK modelling and the FLCs tuning. The FLCs are programmed in MATLAB^{TM} and in an industrial programmable logic controller and applied for the real time control of the variables of a laboratory HVAC system. The short settling time and the lack of overshoot in the transient responses of the controlled variables are an evidence for the high accuracy reached and the economic control.

Key-Words: - Energy efficiency, Fuzzy logic controllers, Genetic algorithms, HVAC, Real time control, TSK modelling, Two-variable plant

1 Introduction and State-of-the-Arts

The quality of life is dependent on the air of the working environment people breath [1, 2]. Modern heating-ventilation and air-conditioning (HVAC) systems are designed to ensure indoor climate comfort. The main variables controlled are the air temperature and humidity [1-10]. Less attention is paid to the control of the air composition [2]. The air is a mixture of oxygen, nitrogen, carbon dioxide (CO_2), carbon monoxide, dust particles, smoke and other components of various concentrations. The increased concentrations of toxic gases and the decreased concentration of oxygen may reduce the working efficiency of the occupants of the rooms in schools, small enterprises, etc. and even endanger their health. The proper air composition is usually maintained by constant or periodic ventilation with fresh air [1, 2] without accounting for the changes in the number of the people in the premise, their activity or the operation of the industrial equipment which is energy consuming. Besides, the periodic or continuous ventilation influences the air humidity and temperature thus causing extra heat losses. The plant is multivariable and nonlinear and the separate control of the variables is often difficult and energy inefficient. Half of the energy consumed in buildings is related with the operation of the HVAC system. Therefore the proper control in HVAC has a great potential for energy savings [1-4]. In order to ensure the human comfort in the working environment at low expenses intelligent control approaches based on fuzzy logic (FL) are applied [5-12]. Without the need of a plant model they enable more accurate control, system robustness to plant uncertainties and disturbances, and reduced energy consumption compared to classical control techniques [11]. In [13] two FL controllers (FLCs) are implemented – one for the control of both the air temperature and humidity, and one for the concentrations of carbon dioxide (CCD), carbon monoxide and dust particles. In [14] an energy efficient algorithm controls three variables – the air temperature, humidity and CCD, switching off the control when the variables are within the desired range. In [15, 16] genetic algorithms (GAs) are applied to minimize the number of fuzzy rules and optimize the membership functions (MFs) of the FLC for simultaneous control of the same three variables. In [17] a two-variable FLC for air temperature and humidity is designed accounting for the coupling between the variables, and a two-variable FLC supervisor is developed to auto-tune the main FLC scaling factors in order to ensure energy efficiency. The system is tested for a laboratory HVAC in real time control. In [18] two structures for CCD FL control are designed and their performances and energy efficiency compared in real time control. The aspects of energy efficiency are often discussed separately and not connected with the control [2, 3]. Most of the suggested FL and GAs-based HVAC control approaches are tested only in simulations and also do not consider energy efficiency.

The aim of the present investigation is the development of a general FL and GAs-based approach for real time control of the air temperature, humidity and CCD in premises accounting for the coupling among the variables and the requirement for energy efficiency and using a laboratory HVAC system and the facilities of MATLAB^{TM} [19-22] and a programmable logic controller (PLC) SIEMENS SIMATIC S300 [23].

The paper is further organized as follows. Section 2 describes the plant – a laboratory HVAC system and the derivation of plant models based on GAs and experimental data. In Section 3 FLCs are designed using expert knowledge and GAs parameter optimization. The suggested fitness functions include minimization of both the system error and the energy consumption for the control and are computed by simulation based on the derived plant models. The MATLAB^{TM} and the PLC implementation of the FLCs for real time control, the recorded transient responses for the air temperature, relative humidity and CCD and the assessment of the control systems performance and energy efficiency are presented in Section 4. The novelty in the presented results and the future research are highlighted in Section 5.

2 Laboratory HVAC System and Plant Modelling

The developed laboratory HVAC system is shown in Fig. 1. It consists of three sections – heating, humidifying and a test cabin that models the premise, equipped with sensors and transmitters for temperature (T), relative humidity (Rh) and CCD and connected via fans. A balloon is manually set to exhale air rich in CO_2 in order to imitate changes of the CCD in the cabin. The controllers are completed in a MATLAB^{TM}-Simulink model for real time control. Their control actions u_m, m=1÷3, are first subjected to pulse-width modulation (PWM) in the Simulink model. Then the pulses of a proper duty

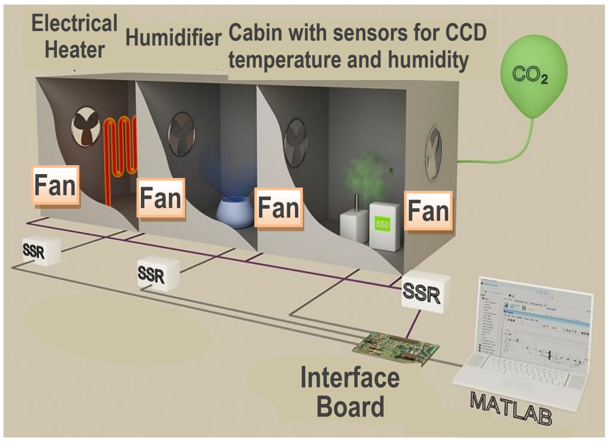


Fig.1. Laboratory HVAC system

ratio are applied via solid state relays (SSRs) to the electrical heater, the humidifier and the fans respectively to ensure the necessary relative duration of their connection to the nets supply according to the preset references for T, Rh and CCD. By the help of the fans fresh air is introduced into the premise for the purposes of cooling, drying and reduction of the CCD via ventilation. The interface board contains Analog-to-Digital Converters (ADCs) for the measured variables and digital outputs (DO) for the pulses. The speed of the fans is limited in order not to cause discomfort by a strong air draft. The developed fuzzy control algorithms are first tested in MATLAB^{TM} real time control and after that they are programmed in an industrial PLC SIEMENS SIMATIC S300 that replaces the computer with the MATLAB^{TM}-Simulink controllers and the interface board.

The plant has three outputs to be controlled - the variables y_1= Rh, %, y_2=T, ^oC and y_3=CCD, ppm. The plant inputs are the control actions - the voltage u_1 to the humidifier for air moistening, the voltage u_2 to the heater for air heating and the voltage u_3 to the fans for ventilation. The first two plant variables are interconnected via their inputs while the third is not connected to the first two as neither the heater nor the humidifier has any impact on the CCD while the impact of the fans for the control of the CCD on T and Rh is negligible. The coupling between Rh and T is explained by the h-X (X- absolute humidity) diagram of Mollier [1], shown in Fig. 2 – an increase of the temperature leads to a decrease in Rh and vice-versa. This relationship is nonlinear. The comfort zone - Rh=40-60, % and T=20-24, ^oC, in Fig. 2 determines the references y_{1r} and y_{2r} for Rh and T respectively. The changes in the CCD are accepted as disturbances to be compensated by relevant changes in the voltage u_3 to the fans.

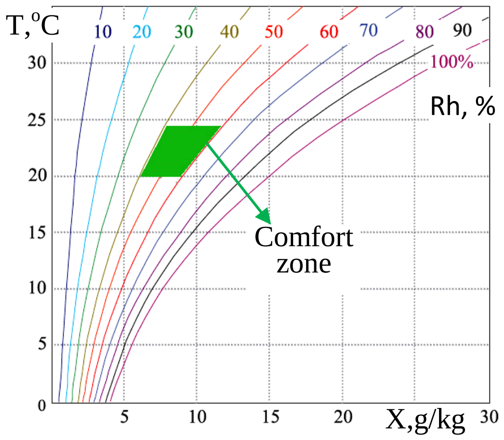


Fig. 2 Relationship between Rh, % and T, °C

The change of u_3, however, influences the air temperature and humidity which has to be compensated by their controllers as a plant uncertainty and disturbance. The usual CCD in the fresh air is 350-450, ppm and the acceptable norm in the cabin is up to 600, ppm. A concentration over 2500, ppm is harmful for the human health.

Since the laboratory HVAC system enables experimentation in real time a plant model can be derived in order to facilitate the design and the optimization of the FLCs.

For the purpose of derivation of a plant model the plant is decomposed into a two-variable nonlinear plant with respect to the coupled Rh and T for which a nonlinear FL-based Takagi-Sugeno-Kang (TSK) model is suitable [10], and an independent single-input-single-output (SISO) plant with respect to CCD for which a linear Ziegler-Nichols (ZN) is developed [24]. The CCD changes around its norm of 600, ppm. So, in tha small surrounding around 600, ppm, a linear ZN model can be accepted as accurate enough. It is derived after approximation of a step increase of the CCD caused by the help of the balloon. The plant transfer function obtained is $P_{CCD}(s)=70e^{-35s}(45s+1)^{-1}$.

For the TSK modelling of the two-variable plant with outputs y_1 and y_2 the modified transfer matrices-based approach developed in [10] is applied.

Experimental step responses are obtained over the main y_{ii} and the cross y_{ij} , $i, j=1\div2$, $i\neq j$, channels, shown in Fig. 3 - for step changes of u_1 the recorded plant outputs are y_{11} for Rh and y_{21} for T, and for step changes of u_2 the recorded plant outputs are y_{12} for Rh and y_{22} for T. Four identical individual modified TSK models TSK y_{ij} are suggested - one for each channel, with the structure, shown in Fig.4(a). The TSK y_{ij} consists of a Sugeno model

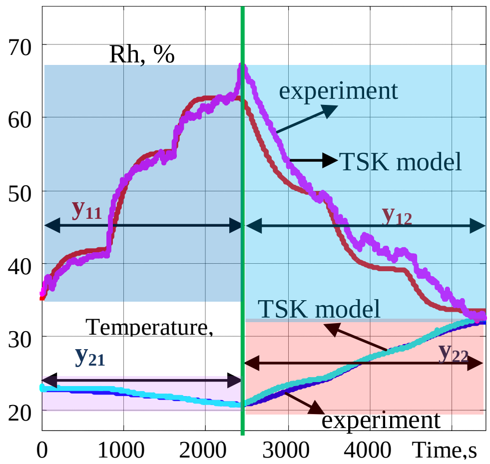


Fig. 3. Step responses of Rh and T for $[u_1, u_2]$=[2, 0; 4, 0; 6, 0; 2, 6; 4, 6; 6, 6], V, changing stepwise at time t_s=[0 800 1600 2400 3400 4400], s

with three Gaussian MFs for the input y_{ij} assuming three operation zones – Small (S), Medium (M) and Big (B) with MFs' parameters the standard deviation 'sigma' and the mean value 'mean' for each, and three outputs mapping the degrees of matching μ_S, μ_M and μ_B of the current value for y_{ij} to the three defined operation zones. The dynamics of each zone is described by linear local plant models based on transfer functions – here a time lag for each zone in series with a time lag common for all zones are accepted. The three local plants work in parallel with input u_j. The output y_{ijTSK} of the channel TSK model is computed as a weighted average of the local plants' outputs:

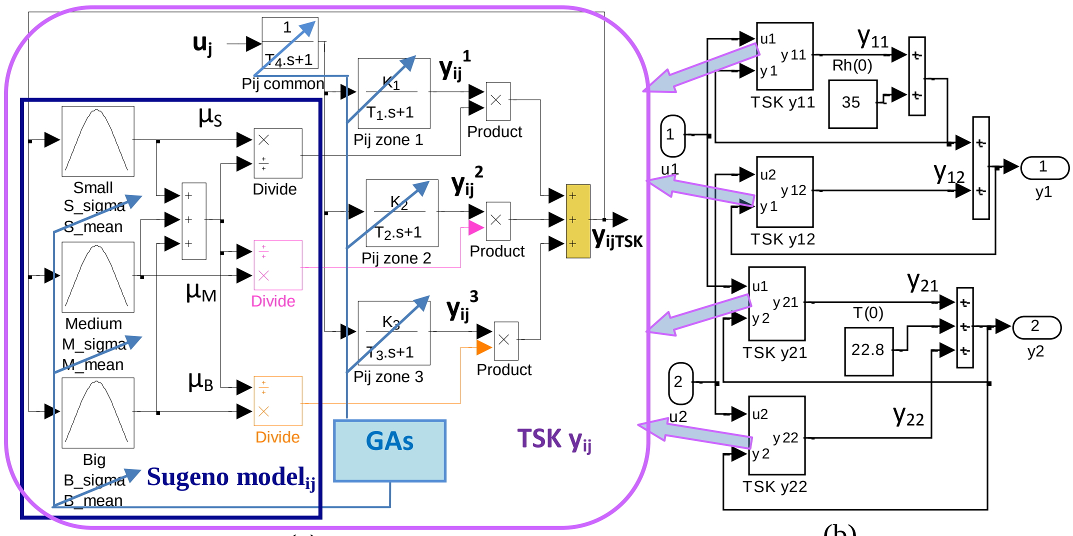
$$y_{TSKij} = (\mu_S\, y_{ij}^1 + \mu_M y_{ij}^2 + \mu_B\, y_{ij}^3)/(\mu_S + \mu_M + \mu_B) \quad (1)$$

The parameters of each channel TSK model $\mathbf{q}_{ij}$=[K$_1$ K$_2$ K$_3$ T$_1$ T$_2$ T$_3$ S_sigma S_mean M_sigma M_mean B_sigma B_mean] are computed from the requirement to minimize a cost function - the sum of the relative squared modelling error:

$$F_{TSKij} = \sum_{k=1}^{N} E_{kij}^2 / y_{kijex}^2 \rightarrow \min_{\mathbf{q}_{ij}}, \quad (2)$$

where $E_{kij}=y_{kijTSK}-y_{kijex}$ is the difference between the TSK model output y_{kijTSK} for channel 'ij' and the real plant output y_{kijex}, recorded from the experiment, both as step responses to the same inputs u_{kjex} at discrete time t_k, $k=1\div N$. The experimental data are first smoothed to filter measurement noise applying moving average.

GAs are applied for the minimization of (2) since they are suitable for analytically not defined nonlinear multimodal cost (fitness) function of



(a) (b)

Fig. 4. TSK plant model: (a) for an individual channel - TSK y_{ij}; (b) integrated two-variable for the whole plant

Table 1 Parameters of the TSK plant models for the main and cross channels

Parameters	K_1	K_2	K_3	T_1	T_2	T_3	T_4	S_sigma	S_mean	M_sigma	M_mean	B_sigma	B_mean
$q_{11}{}^{o}$; F=3.6	1	0.8	4.8	158	251	21	123	4.5	34	11	18	30	54
$q_{12}{}^{o}$; F=4.5	12.4	0.5	22	432	181	261	306	15.5	58	37.5	87	3.4	54
$q_{21}{}^{o}$; F=5.6	0.81	0.63	0.18	1100	534	371	1027	12.5	16.6	8.4	6.2	7.1	60
$q_{22}{}^{o}$; F=0.25	3.78	0.78	0.75	256	934	506	287	18.2	23.7	14.6	32.9	11.7	7.4

many parameters since they are based on a gradient-free random search algorithm for global extremum [10, 21]. The unknown TSK model parameters known as genes, often binary coded, are arranged in an array comprising a chromosome. Their initial values are assigned randomly from a given range. The fitness function is computed via TSK model simulation. Then in the same way a number of chromosomes (individuals) are obtained to form together a generation, and rated according to their fitness. The next generation is formed imitating the "survival of the fittest" in the evolution process. Mating couples are selected by a roulette approach or other to give birth to an offspring with better fitness function values by exchange of genes in a random way and a mutation in a randomly selected gene(s) or bit(s) in binary coding. Thus the new generation of better individuals continues the "evolution" till an assigned stop condition is met – final number of generations or desired accuracy reached.

The optimal parameters of the individual TSK plant models computed are shown in Table 1. The initial values for the air humidity and temperature are determined from the experimental step responses Rh(0)=35, % and T(0)=22.8,°C. The integrated two-variable TSK plant model is depicted in Fig. 4(b) and its step responses to the same inputs are presented in Fig. 3, where they can be easily compared with the experimental step responses. The accuracy is satisfactory and this gives grounds to use the derived model further for the design via simulations of the two-variable FLC. The Sugeno model with the Gaussian input MFs with tuned optimal parameters can be substituted by a single simple FLC block designed in MATLAB™ Fuzzy logic Toolbox [20].

3 Design of Fuzzy Logic Controllers for Three Variables of HVAC System

The FLC-based closed loop system suggested is depicted in Fig. 5. Three FLCs control the outputs y_m, m =1÷3, in three closed loop systems. FLC_1 and FLC_2 built a two-variable FLC system. FLC_3 system has no reference for CCD as the control is ensured via ventilation with a fresh air with variable CCD – the desired CCD in the room is defined by the input MF for a norm term of FLC_3. The FLCs' inputs are the normalized in the range [-1, 1] system errors $e_i=y_{ir}-y_i$, plant outputs derivatives dy_m/dt, and the normalized y_3 in the range [0, 1]. The normalization is accomplished by the help of the gains K_{ei}, K_{dm} of the differentiators $W_{dm}(s)=K_{dm}.T_{dm}s/(T_{dm}s+1)$ and K_y respectively. The fan for warm humid fresh air in the cabin is switched on by a control action

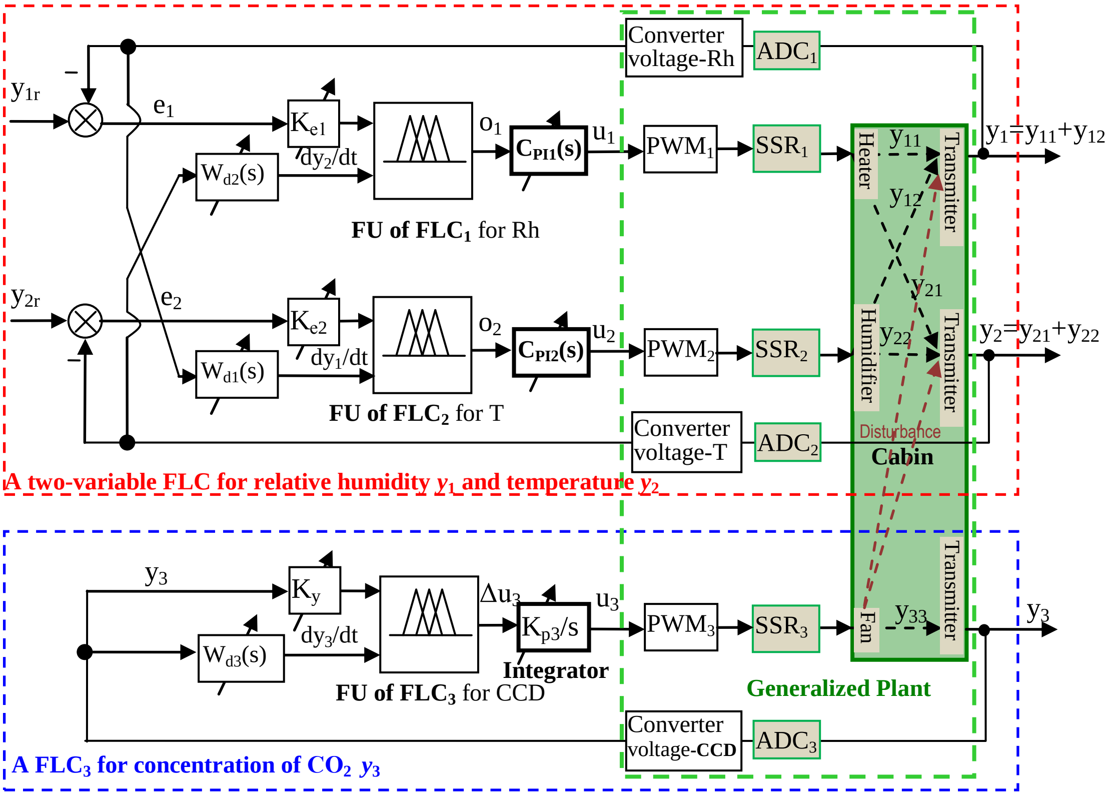


Fig. 5. FL control of humidity, temperature and CCD in a laboratory HVAC system

produced by any of the three controllers. The measured values for y_m are converted from voltages in the range [2, 10], V of the corresponding transmitter to the corresponding physical variable – y_1=0÷100, %, y_2=-30÷70, ^{o}C, y_3=300÷900, ppm. Then the system errors e_i and the derivatives of the plant outputs dy_j/dt are computed. The scaled errors and derivatives for y_1 and y_2 are passed to the identical fuzzy units (FUs) of FLC$_1$ and FLC$_2$ with identical rule bases. The post-processing for the two-variable FLC is performed by two linear PI controllers with transfer functions $C_{PIi}(s)=K_{pi}/(1+1/T_{ii}s)$. The inputs to FLC$_3$ are the normalized y_3 and derivative dy_3/dt. The post-processing for FLC$_3$ is an integrator. The gains K_{pm} include denormalization of the FUs' outputs and ensure control action for the PWM in the linear range [0, 10], V. The FUs of FLC$_{1,2}$ and FLC$_3$ are determined by standard MFs and rules, shown in Fig. 6, where the nonlinear control surfaces are presented as well. The MFs of the FUs' outputs o_i and Δu_3 are singletons in order to enable the programming of FLC$_{1,2,3}$ on PLC SIEMENS SIMATIC S300 [23] for experiments in real time control of Rh, T and CCD. The differentiators' time constants T_{dm} are computed from T_{dm}=(5÷10).Δt on the basis of the accepted sample period Δt=0.1T_{min},s, where T_{min} is the minimal time constant of the plant over the three channels of input control u_m – output variable y_m according to the expert assessment of the dynamics of the plant. The computed in this way T_{dm} ensures a derivative dy_m/dt close to the ideal but smooth with filtered noise and also nonzero for a significant time interval so that the FUs can sense it in computing of the control action. The integral action time is determined by applying an engineering approach of tuning of PI controllers in a SISO system [24] for minimal overshoot and settling time where T_i=B.T_{max} with T_{max} - the dominating plant time constant and B=0.3÷3. Considering the highest time constants of all local plants (zones 1÷3) in the main and the cross channel for a given output, highlighted in Table 1, it is established that T_{max1}=432 for Rh and T_{max2}=1100 for T. So, for B=0.3 it is computed T_{i1}=B.T_{max1}≈100,s and T_{i2}=B.T_{max2}≈400, s.

The rest of the FLCs' tuning parameters $\mathbf{q}_{FLC1,2}$=[K_{ei}, K_{dj}, K_{pi}] and $\mathbf{q}_{FLC3}$=[K_y, K_{d3}, K_{p3}] are computed using off-line GAs minimization of the following cost (fitness) functions respectively:

$$\mathbf{F}_{\mathbf{FLC1,2}} = \sum_{i=1}^{2}\left(\sum_{k=1}^{N}\left(|e_{ki}|/\mathrm{D}_{ei} + u_{ki}/\mathrm{D}_u\right)\right) \to \min_{\mathbf{q}_{\mathbf{FLC1,2}}} \quad (3)$$

$$\mathbf{F}_{\mathbf{FLC3}} = \sum_{k=1}^{N}\left(|e_{k3}|/\mathrm{D}_{e3} + u_{k3}/\mathrm{D}_u\right) \to \min_{\mathbf{q}_{\mathbf{FLC3}}}, \quad (4)$$

where $\mathrm{D}_u = 8$ is the span of the control u_m, $\mathrm{D}_{e1} = 5,\%$; $\mathrm{D}_{e2} = 2,^o\mathrm{C}$; $\mathrm{D}_{e3} = 300,\mathrm{ppm}$ are the spans of the system errors e_m (e_{k3}=600-y_{k3}), i.e. the maximal absolute change of the errors with respect to Rh, T and CCD respectively. The errors e_{km} and the control actions u_{km} are computed via simulations of the two-variable and the SISO FLC systems in Fig. 5 in a MATLAB™- Simulink model [19] using the derived two- variable TSK plant model for Rh and T and the ZN SISO model for CCD instead of the real plant. The fitness functions combine two criteria to ensure good system performance and energy efficiency of the control – one related with the system error reduction, and another linked to the minimization of the control effort used.

The optimal tuning parameters computed are: $\mathbf{q}_{FLC1,2}$=[K_{e1}=0.3, K_{d2}=1.9, K_{p1}=1.8; K_{e2}=0.8, K_{d1}=2.6, K_{p2}=1.3]; $\mathbf{q}_{FLC3}$=[K_y=1/600, K_{d3}=0.02 , K_{p3}=0.2].

4 Real Time Fuzzy Logic Control of Air Humidity, Temperature and Carbon Dioxide Concentration

The designed FLCs are implemented in a Simulink model for real time control of Rh, T and CCD in the laboratory HVAC in Fig. 1. The Simulink model follows the block diagram in Fig. 3 where Simulink blocks for connecting the model to the interface board are added - 'Analog Input' (drivers) for reading of the measured values for the variables from the ADC and 'Digital Output' (drivers) for passing the PWM pulses to the DO for control of the SSR [22]. The step responses to reference changes of Rh and T from real time control are presented in Fig. 7 together with the process of compensation of the increased CCD by the FLC$_3$ control of the ventilation. The coupling effect between Rh and T is reduced and observed only in y_2 for t=0÷1000,s when the reference for Rh y_{1r} is stepwise changed by 5%. The changes in y_{2r} are well compensated in y_1 and the changes in CCD (y_3) are compensated both in y_1 and y_2. The main channels reference step responses y_{1r} - y_1, y_{2r} – y_2 and the disturbance rejection in y_3 have short settling times – t_{s1}=400,s, t_{s2}=900,s and t_{s3}=1200,s. The step responses have no overshoot – an evidence for energy efficient economic control.

The control algorithm in Fig. 5 is programmed in a PLC SIEMENS SIMATIC S300 using also SIEMENS SIMATIC WINCC and Fuzzy Control [23]. The analog signals from the transmitters for humidity and temperature in the range [2, 10], V are converted by the PLC ADC to integer numbers in the range [6400, 32767]. So, the conversion of the ADC output to values of the physical variable requires scaling - for the air relative humidity 6400=0%; 32767=100% and for the temperature 6400=-30°C; 32767=70°C. After the scaling an exponential filter filters the measurement noise. Then the algorithm follows the diagram in Fig. 5. The PWM is connected to the digital outputs of the PLC that control the SSRs for the humidifier, the electrical heater and the fans.

A designed operator panel enables switching among different screens for:

- display of various mnemonic diagrams of the control system
- input of the parameters of the controllers, the filters and the PWM, also the references and the schedule for their change, the bounds and the initial values of the signals and the limits for the anti-wind up for the integration, the sample periods for control and for archiving;
- selection of modes of operation among: programming, manual and automatic control; control only of one variable - Rh, T or CCD; control of two selected variables; control of all the three variables; in manual control plant identification is enabled;
- display of the values and the graphs of the output variables, the references and the control actions;
- start and stop of the real time operation and interruption by an operator for new input or mode selection – at 'start' the initial values for the variables and the control are set equal to their current values, at 'stop' the final values ensure safety closing of the real time operation, e.g. switching off the heater and the humidifier, operation of the fans at high speed for several minutes.

A desired screen can be selected by the help of the functional buttons on each screen.

In Fig. 8 the screenshots of the mnemonic diagram of the two-variable FLC system and the step responses of air humidity and temperature, their references and the control actions are displayed.

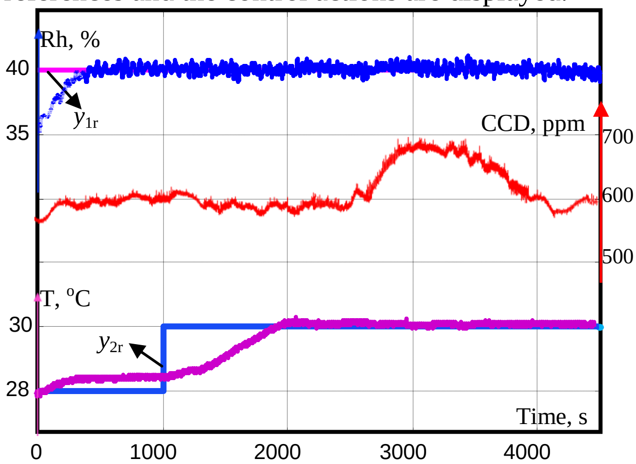


Fig. 7. MATLAB™ real time FL control of Rh, T and CCD of a laboratory HVAC system

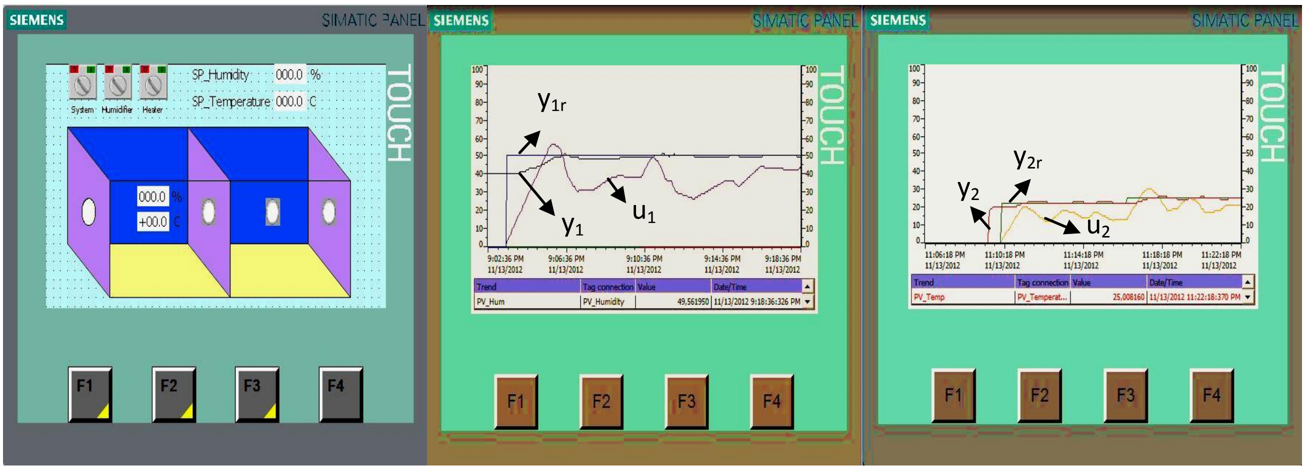


Fig. 8. Screenshots from real time two-variable PLC-FL control of Rh and T of laboratory HVAC

5 Conclusion

The novelty of the research presented in this paper concludes in the following. An approach for the design of FL controllers is developed for the most important variables for the indoor human comfort – the air relative humidity, temperature and CCD, accounting for their coupling. It is based on the application of GAs optimization in both the derivation of a nonlinear two-variable transfer functions based TSK plant model from experimental data and the off-line tuning of the parameters of the FLCs. The tuning criterion is formulated by a suggested fitness function that combines two requirements – for high systems accuracy (minimization of system error), and for minimal energy for control. The FLCs are intended for and used in real time control of the three variables in a laboratory HVAC system. The experimentally recorded transient responses have short settling times and no overshoot – an evidence for good systems performance and economic controls. The FLC algorithms are fast and simple and are easily programmed in a PLC. The PLC-FLC real time control confirms the good systems performances and the economic controls.

The future research will focus on application of the approach to other important with respect to energy savings and difficult to control plants.

References:

[1] *ASHRAE Handbook Fundamentals*, SI Edition, CA, 1989.

[2] *Carbon Dioxide (CO2) HVAC Basics*, Honeywell Inc, 1998.

[3] K.W. Roth, D. Westphalen, J. Dieckmann, S. D. Hamilton, W. Goetzler, Energy Consumption Characteristics of Commercial Building HVAC Systems, *Vol. III: Energy Savings Potential, Report for Building Technologies Program*, Cambridge, MA, 2002.

[4] R. Freire, G. Oliveira, N. Mendes, Predictive Controllers for Thermal Comfort Optimization and Energy savings, *Energy and Buildings*, No.40, 2008, pp. 1353–1365.

[5] M. Gouda, Fuzzy Ventilation Control for Zone Temperature and Relative Humidity, *American Control Conference*, 2005, pp. 507-512.

[6] M. Jaradat, Fuzzy Logic Controller Deployed for Indoor Air Quality Control in Naturally Ventilated Environments, *Journal of Electrical Engineering*, Vol.60, No.1, 2009, pp. 12-17.

[7] J. Jantzen, *Foundations of Fuzzy Control*, John Wiley & Sons Inc., 2007.

[8] L. Reznik, *Fuzzy Controllers*, Newnes, Melbourne, 1997.

[9] D. Driankov, H. Hellendoorn, M. Reinfrank, *An Introduction to Fuzzy Control*, Springer, Berlin, 1993.

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

[11] M. Arima, E.H. Hara, J.D. Katzberg, *A Fuzzy Logic and Rough Sets Controller for HVAC Systems*, N.Y., 1995.

[12] A. Kaur, A. Kaur, Comparison of Mamdani-Type and Sugeno-Type Fuzzy Inference Systems for Air Conditioning System, *Int. Journal of Soft Computing and Engineering*, Vol. 2, No.2, 2012, pp.323-325.

[13] M. Tennakoon, R. Mayorga, E. Shirif, A Comfort Monitoring System and Hazard Detection Unit using Fuzzy Logic, *Environmental Informatics Archives*, Vol.5, 2007, pp.621-630.

[14] W. Batayneh, O. Al-Araidah, K. Batayneh, Fuzzy Logic Approach to Provide Safe and Comfortable Indoor Environment, *Int. Journal*

of Engineering, Science and Technology, Vol.2, No.7, 2010, pp. 65-72.

[15] R. Alcala, G. Casillas, O. Cordon, A. Gonzalez, F. Herrera, *A Genetic Rule Weighting and Selection Process for Fuzzy Control of Heating, Ventilating and Air Conditioning Systems*, Pergamon Press, Inc. Tarrytown, N.Y., 2005.

[16] R. Alcala, J. Casillas, A. Gonzalez, Tuning Fuzzy Logic Controllers for Energy Efficiency Consumption in Buildings, *Proc. of the EUSFLAT-ESTYLF Joint Conference*, Palma de Mallorca, Spain, September 22-25, 1999, pp.103-202.

[17] S. Yordanova, D. Merazchiev, L. Jain, A Two-Variable Fuzzy Control Design with Application to an Air-Conditioning System, *IEEE Trans. on Fuzzy Systems*, Vol.23, No.2, 2015, pp.474-481.

[18] S. Yordanova, D. Merazchiev, V. Mladenov, Fuzzy Control of Carbon Dioxide Concentration in Premises, In: *Recent Advances in Systems Science*. *Proc. 17th Int. Conf. on Systems –CSCC'13*, 16-19 July, 2013, Rhodes Island, Greece, 2013, pp. 269-273.

[19] S. Sivanandam, S. Sumathi, S. Deepa, *Introduction to Fuzzy Logic using MATLAB*, Springer, 2007.

[20] *Fuzzy Logic Toolbox User's Guide for Use with MATLAB*, v.3.0, MathWorks, 1998.

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

[22] *MATLAB – Real-time Workshop. User's Guide*, MathWorks, Inc., 1992.

[23] *SIMATIC S7 Fuzzy Control. User's Manual*, Siemens AG, 2001.

[24] T. Neshkov, S. Yordanova, I. Topalova, *Process Control and Production Automation*, Sofia: TU- Sofia, 2007.