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ADVANCED EVOLUTIONARY OPTIMIZATION FOR INTELLIGENT MODELING AND CONTROL OF FBC PROCESS

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Abstract. *In this paper, the computationally intelligent modeling approach for fluidized bed combustion process is considered, as well as intelligent process control based on developed models and soft computing methodologies. Applied genetic optimization and fuzzy modeling approach are combined with proposed intelligent control strategies. Efficient fuzzy nonlinear FBC process modeling by combining several linearized models is presented, as well as fuzzy and conventional process control systems optimized by real coded genetic algorithms. The obtained results indicate that the computationally intelligent approach can be successfully applied for modeling and control of such a complex fluidized bed combustion process.*

Key Words: *Computational Intelligence, Fluidized Bed Combustion, Fuzzy Systems, Real Coded Genetic Algorithms*

1. INTRODUCTION

In fluidized bed combustion (FBC), the combustion chamber contains, besides fuel, a quantity of particles of inert material such as sand or ash. The combustion air entering from below lifts the mixed material keeping it in constant movement and forming a turbulent bed which behaves like a boiling fluid. This essential feature is the basis for many excellent properties of the FBC technology but it also makes the process highly complex [1][2][3].

Harmful flue gas emissions, such as nitrogen oxides, sulphur oxides and carbon monoxide, are the result of the complex burning phenomena and the individual construction of the plant in question. In the past years, environmental concerns and resulting emission taxation procedures have made their minimization a profitable task. In addition to the development in the plant construction and flue gas cleaners, efficient control of the process operating conditions is also an important and cost-effective way to affect these emis-

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sions. In fact, the possibilities to reduce emissions are one of the main features of FBC technology.

Conventional control process models linearized around different operational points are combined by means of a fuzzy supervisory model, which extends the model usability for a wide range of plant working regimes. The suggested fuzzy model, based on TSK fuzzy reasoning, makes smooth interpolation of singular linear models and therefore overcomes rigid restrictions of the linear model.

Finally, genetic optimization is considered for obtaining usable conventional and fuzzy controllers for regulation of the main FBC plant operational loops. Conventional PID controller and alternative fuzzy PD controller design approaches are considered, where controller parameters are optimized by real coded genetic algorithms. Quick response and small overshoot of a closed loop system is of great importance having in mind energy efficiency, flue gas emission and plant safety.

Soft computing modeling and control approach considered in this paper present extensions of the results that the authors obtained in [4][5][6][7] in a field of neuro-fuzzy-genetic modeling and control of FBC process and flue gas emission. Other authors in [8][9] considered binary coded genetic optimization and genetic learning automata for conventional and fuzzy control based on a neuro-fuzzy model of combustion process. Aside from fuzzy-relation models of flue gas emission and wiener logical models of FBC process, genealogical decision trees for multivariable control were also considered in Refs. [10][11][12].

The usage of fuzzy logic and of the genetic algorithms methodologies applied in this paper is justified, since complexity of the FBC process makes application of conventional modeling and control strategies difficult.

2. FLUIDIZED BED COMBUSTION

In fluidized bed combustion [1] the combustion chamber contains a quantity of finely divided particles such as sand or ash. The combustion air entering from below lifts these particles until they form a turbulent bed, which behaves like a boiling fluid. The fuel is added to the bed and the mixed material is kept in constant movement by the combustion air. The heat released as the material burns maintains the bed temperature, and the turbulence keeps the temperature uniform through the bed. The heat capacity of the solid bed particles gives the system thermal stability, which makes variations in fuel properties less critical than with many other combustion systems [3]. Schematic representation of laboratory experimental FBC plant is shown in Fig. 1.

Normal operating temperature of the bed is between $750 \div 950°C$. At this relatively low temperature the ash and moist fuels do not melt or sinter. Fuel properties like ash content, particle size and moisture are of less importance. Generally, the fluidized bed combustor is distinguished by low operating temperatures ($\sim 1100K$), high excess air levels (~6%), intermediate particle sizes ($1 \div 3$mm), long residence times (several minutes) and vigorous particle motion that dominates heat transfer and reaction processes.

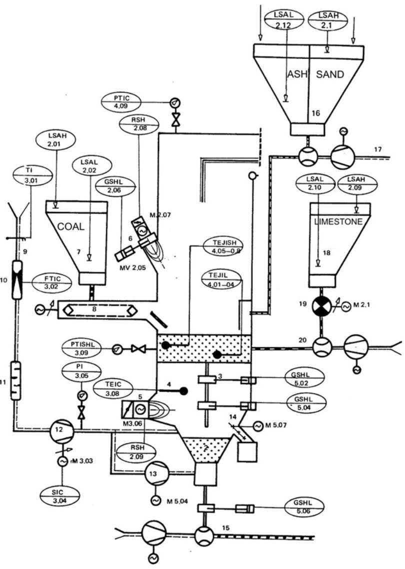

Fig. 1 Schematic representation of laboratory experimental FBC plant

3. OVERVIEW OF REAL CODED GENETIC ALGORITHMS

The Genetic Algorithm (GA) is used to solve difficult engineering problems that are complex and difficult to solve by the conventional optimization methods. GA maintains and manipulates a population of solutions and implements a survival of the fittest strategy in their search for better solutions. The fittest individuals of any population tend to reproduce and survive to the next generation thus improving successive generations. The inferior individuals can also survive and reproduce.

Implementation of the GA requires the determination of six fundamental issues: chromosome representation, selection function, the genetic operators, initialization, termination and evaluation function.

Chromosome representation scheme determines how the problem is structured in the GA and also determines the genetic operators that are used. Each individual or chromosome is made up of a sequence of genes. Various types of representations of an individual or chromosome are: binary digits, floating point numbers, integers, real values, matrices, etc. Real-coded representation is more efficient in terms of CPU time and offers higher precision with more consistent results [13]. The use of real-parameter makes it possible to use large domains (even unknown domains) for variables. Generally natural representations are more efficient and produce better solutions.

To produce successive generations, the selection of individuals plays a very significant role in a genetic algorithm. The selection function determines which of the individuals will survive and move on to the next generation. A probabilistic selection is performed based upon the individual's fitness so that the superior individuals have better chances to be selected. There are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament, normal geometric, elitist models and ranking methods.

The basic search mechanism of the GA is provided by the genetic operators. There are two basic types of operators: crossover and mutation. These operators are used to produce new solutions based on the existing solutions in the population. Crossover takes two individuals to be parents and produces two new individuals while mutation alters one individual to produce a single new solution.

An initial population is needed to start the genetic algorithm procedure. The initial population can be randomly generated or can be taken from other methods.

The GA moves from generation to generation until a stopping criterion is met. The stopping criterion could be maximum number of generations (as in this study), population convergence criteria, and lack of improvement in the best solution over a specified number of generations or target value for the objective function. Evaluation functions or objective functions of many forms can be used in a GA so that the function can map the population into a partially ordered set.

The computational flowchart of the real coded genetic algorithm (RCGA) optimization process employed in the present study is shown in Fig. 2.

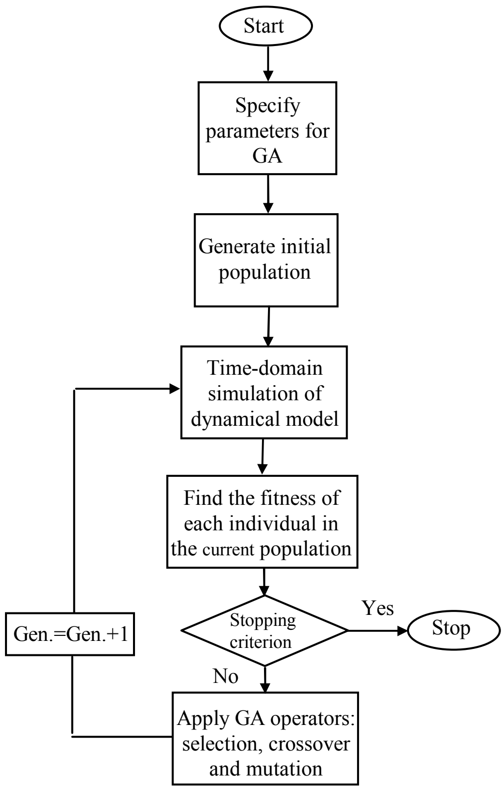

Fig. 2 Flowchart of genetic algorithm

4. SUPERVISORY FUZZY MODEL

Nonlinear mathematical models of FBC process are developed in [14], as well as simple mathematical models [11][12] based on mass and energy transfer. Combustion model inputs are fuel flow Q_c [kg/s], primary air flow F_p and secondary air flow F_s [Nm^3/s]. Measurable system outputs are flue gas oxygen content, bed temperature T_B [K] and freeboard temperature T_F [K].

In this paper, a computational intelligence model based on fuzzy adaptation mechanism is suggested. The suggested fuzzy model intelligently interpolates linear models that are the result of the Lyapunov linearization around several characteristic operating points, in the form:

$$\begin{aligned} \frac{d\mathbf{x}^i(t)}{dt} &= \mathbf{A}_i\mathbf{x}(t) + \mathbf{B}_i\mathbf{u}(t); \\ \mathbf{y}(t) &= \mathbf{C}_i\mathbf{x}^i(t). \end{aligned} \tag{1}$$

The idea is to overcome rigid restrictions of the linear model, where the model is only valid near the operating point. If the parameters of a fuzzy model are optimally set, such restrictions can be exceeded and the fuzzy supervisory model can give correct output for an arbitrary operating point. This approach allows the usage of linear models from [11][12] and optimization of models explained in [4][5][6][7].

Fuzzy model inputs are real system inputs, as well as some measurable state variables, and in the FBC process fuzzy supervisor these variables are flue gas oxygen content C_F, and bed and freeboard temperatures T_B and T_F, that are measured in a real system. Other fuzzy supervisor inputs are outputs of linear systems y_i that are intelligently superpositioned by the fuzzy supervisor in order to generate fuzzy model output y.

Since the suggested fuzzy model is used as an interpolating supervisor of several differently adapted linear models, the Takagi-Sugeno-Kang (TSK) fuzzy reasoning was used [15], with linear dependencies in the consequential part of fuzzy rules, and free members equal to zero. For realization where the number of models is m, and where the models are linearized around m operating points, whose outputs are y^1, y^2,… y^m, implemented k-fuzzy rule is:

$$R_s^k\text{: if } \mathbf{y}=\mathbf{L}\mathbf{y}^k \text{ then } \hat{\mathbf{y}} = a_{k1}\mathbf{y}^1 + a_{k2}\mathbf{y}^2 + \ldots + a_{km}\mathbf{y}^m.$$

All parameters a_{k1}, a_{k2}, … a_{km} of the fuzzy rule, apart from one, are equal to zero, and that other parameter is equal to one. Every fuzzy rule defines one linear model for appropriate inputs defined in the if- part of the fuzzy rule. In this way, the linear model is optimally chosen for each characteristic operating point.

This fuzzy model can activate more than one fuzzy rule for every state of fuzzy supervisor input y, but activation levels are different. Therefore, it is obvious that suggested realization makes smooth interpolation of singular linear models.

Fuzzy supervisor gives the optimal state of model output for the operating points that are not included in m optimally adjusted linear models. A scheme of fuzzy supervisor based on nonlinear model linearized around 4 characteristic operating points is shown in Fig. 3.

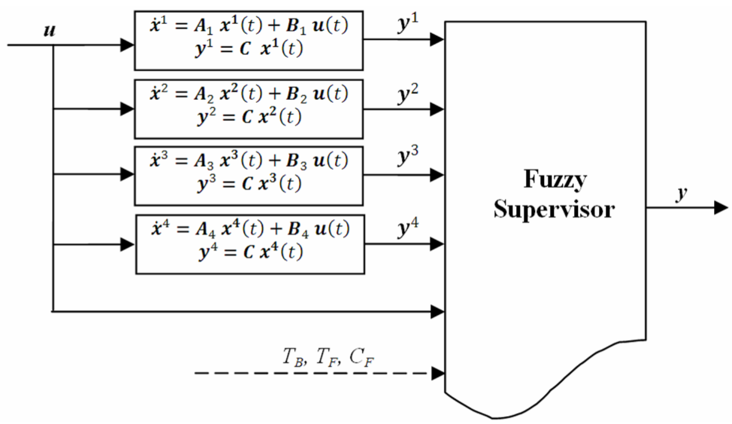

Fig. 3 Fuzzy model

The proposed fuzzy model represents an extension of the results that authors have achieved in [11][12] in a field of FBC process modeling with control tasks in mind, but their models have limited usage due to linearization.

5. INTELLIGENT CONTROL OF FBC

The role of the combustion process is to produce the required heat energy for steam generation at the possible highest combustion efficiency. The efficiency depends on the completeness of burning and the waste heat taken away in the flue gas by the excess air flow. The higher the burning rate and the smaller the waste heat, the higher the efficiency. However, excess air is required for ensuring complete burning. The O_2 content of the flue gas is directly related to the amount of excess air. The aim of the combustion control, from the efficiency point of view, is to keep the O_2 content around 3-6 % [10]. In multi-fuel fired fluidized bed power plants, this is a difficult task due to the inhomogeneous properties of the fuel.

The combustion model, based on the linear model developed in [11][12] and the fuzzy supervisor model developed in this paper, calculates combustion power (P_{comb}) and flue gas components (C_F), including the oxygen content, from the fuel flow, primary airflow F_p, and secondary airflow F_s.

The oxygen and combustion power controller consists of two parallel PID controllers. The error signal from the oxygen content drives the PID controller of the fuel flow signal, while the combustion power is controlled by the primary airflow.

The structure of the PID controller is:

$$\frac{U}{E}(s) = K_P + \frac{1}{s}K_I + sK_D. \tag{2}$$

The reference signals for the fuel flow, primary airflow F_p and secondary airflow F_s signals are calculated by the linearization model as a function of the reference of the combustion power. System is linearized and normalized near operating point $\overline{Q}_C$ =2.6[*kg/sec*], $\overline{F}_P$ =3.1[Nm^3/s], $\overline{F}_S$ = 8.4[Nm^3/s], $\overline{W}_C$ =165[*kg*], $\overline{C}_B$ =0.042, $\overline{C}_F$ =0.031, $\overline{T}_B$ =749[°*C*], $\overline{T}_F$ =650[°*C*], $\overline{P}$ =21.1[*MW*].

The real coded GAs were used for numerical calculation of optimal PID controller gains $\Theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6] = [K_{p1}, K_{i1}, K_{d1}, K_{p2}, K_{i2}, K_{d2}]$, as shown in Fig. 4 for one PID controller.

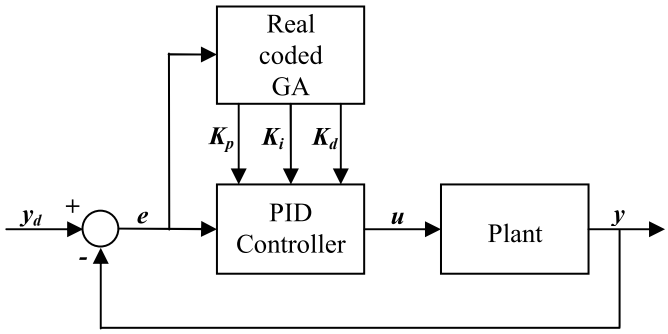

Fig. 4 RCGA for optimal PID controller parameter detection

In the implemented algorithm a small population of 20 individuals, an elitism of 2 individuals was used, the initial population was Θ=[0, 0, 0, 0, 0, 0], the initial range was [0,50]. A scattered crossover function was performed, creating a random binary vector and then selecting the genes where the vector was a 1 from the first parent, and the genes where the vector was a 0 from the second parent, and combines the genes to form a child. All the members were subjected to mutation except for the elite. The mutation operator was adaptive feasible. The individuals were randomly selected by the Roulette method. The fitness function is:

$$f(\theta) = k \cdot \sum_{1}^{M} \frac{|y_{O2} - \hat{y}_{O2}|}{\hat{y}_{O2}} + \sum_{1}^{M} \frac{|y_P - \hat{y}_P|}{\hat{y}_P}, \tag{3}$$

where k is a weight factor. In our case k=2 to emphasize the importance of oxygen content which is directly related to the flue gas emissions, combustion quality and energy efficiency.

After 100 generations, the following parameters were calculated: K_{p1}=21.59; K_{i1}=27.60; K_{d1}= 6.66; K_{p2}= 6.37; K_{i2}=0.17; K_{d2}=21.09, and the fitness value was $f(\Theta)$=13.47.

After a slight change of genetic operations, where population consisted of 30 individuals, an elitism of 3 individuals was used and the initial range was [0,20], the optimization results were as follows: K_{p1}=18.55; K_{i1}=19.84; K_{d1}= 13.53; K_{p2}= 5.87; K_{i2}=0.0039; K_{d2}=9.30, and the fitness value was $f(\Theta)$=10.76. RCGA that used initial population Θ=[18.55, 19.84, 13.53, 5.87, 0.0039, 9.30], that was actually a solution of previously done optimization, was even better: K_{p1}=35.89; K_{i1}=40.93; K_{d1}=7.43; K_{p2}= 5.93; K_{i2}=0.0039; K_{d2}=9.05, and the fitness value was $f(\Theta)$=6.84.

Stabilization of system with initial disturbances, where the flue gas oxygen content is 2.1% (ΔC_F=-0.01), and the initial plant power is 23.1[MW] (ΔP=2[MW]) for 360 seconds controlled by PID controllers with optimally adjusted parameters is shown in Fig. 5.

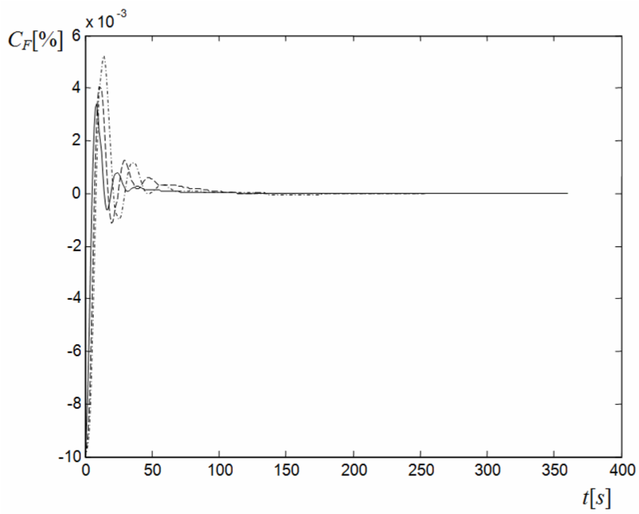

Fig. 5 Stabilization of flue gas oxygen content with PID controller

The closed loop system where PID controller gains were with best/smallest fitness value had the quickest response and the least overshoot. A slower response would increase chances for incomplete combustion that could lead to a major plant failure.

In addition to the conventional PID controller design approach, the fuzzy controller design [15][16] for fluidized bed combustion control was considered in this paper. The fuel and primary air fuzzy controller consisted of two parallel Fuzzy PD controllers. The error signal from the oxygen content and error derivate drove the fuzzy PD controller of the primary airflow, while the combustion power is controlled by the fuel flow error signal and error derivate. The error signal and error derivate for the controllers were normalized and divided in three regions each: low, middle and high. The output MFs of the controllers were constants, which in our case meant six parameters. The first controller output was generated as a result of an interpolation of 3 constant gains based on fuzzy rules.

An optimal fuzzy controller gain values K_{11}, K_{12}, K_{13}, K_{21}, K_{22} and K_{23} were the result of RCGA. In the implemented algorithm a small population of 30 individuals, an elitism of 3 individuals was used, the initial population was Θ=[0, 0, 0, 0, 0, 0], the initial range was [0,50]. A scattered crossover function was performed, the mutation operator was adaptive feasible and the individuals were randomly selected by the Roulette selection. The fitness function was:

$$f(\theta) = k_1 \cdot \sum_{1}^{M} \frac{|y_{O2} - \hat{y}_{O2}|}{\hat{y}_{O2}} + k_2 \cdot \sum_{1}^{M} \frac{|y_P - \hat{y}_P|}{\hat{y}_P}, \tag{4}$$

where k_1 and k_2 were weight factors. In our case k_1=1 and k_2=2, that emphasized the importance of oxygen content which was directly related to the flue gas emissions, combustion quality and energy efficiency. After 200 generations the following parameters were calculated: K_{11}=73.5455; K_{12}=-594.7892; K_{13}=-340.1936; K_{21}=22.7710; K_{22}=8.8464; K_{23}=85.5625, and the fitness value was $f(\Theta)$= 4.02.

Stabilization of closed loop fuzzy controlled system with initial disturbances, where the flue gas oxygen content is 2.1% (ΔC_F=-0.01), and the initial plant power is 23.1[MW] (ΔP=2[MW]) for 360 seconds is shown in Fig. 6.

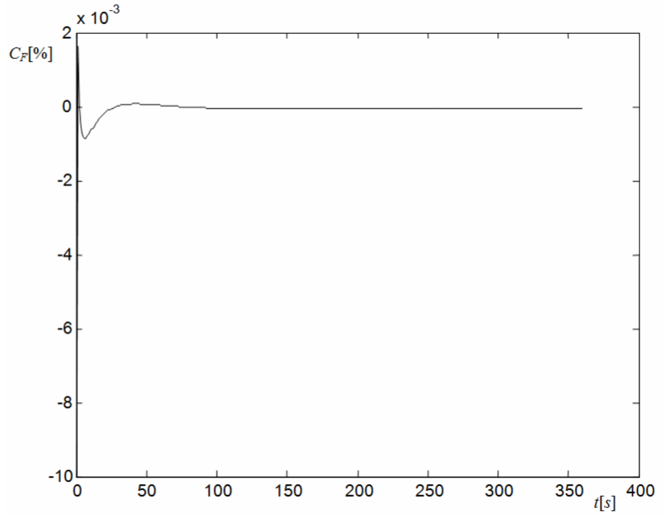

Fig. 6 Stabilization of flue gas oxygen content with fuzzy controller

The closed loop system with two optimally adjusted fuzzy PD controllers had a quick response and small overshoot. Such response is of great importance having in mind energy efficiency, flue gas emission and plant safety.

6. CONCLUSIONS

Modeling and control problem studied in the paper originates from the fluidized bed combustion process, which is highly nonlinear and complex, thus making conventional modeling and control of FBC plants difficult.

The suggested fuzzy supervisor, based on the TSK fuzzy reasoning, gives the optimal state of model output for the operating points that are not included in m optimally adjusted linear models. It makes smooth interpolation of singular linear models and, therefore, overcomes rigid restrictions of linear models. The proposed fuzzy model represents an extension of the results in a field of the FBC process modeling with control tasks in mind.

Stabilization of system with the initial disturbances controlled by PID controllers with optimally adjusted gains as well as controlled by alternative fuzzy PD controllers with optimally adjusted parameters is presented. Real coded genetic algorithms were used for numerical calculation of optimal PID controller gains and fuzzy controller parameters. Both the closed loop systems have a quick response and small overshoot. Such response is of great importance having in mind energy efficiency, flue gas emissions and plant safety. A slower response would increase chances for incomplete combustion that can lead to a major plant failure.

REFERENCES

1. Oka, S., 2004., *Fluidized Bed Combustion*, Marcel Dekker, New York
2. Ćojbašić, Lj., 1983., *Kinetics of Combustion of Oil Shales in Fluidized bed*, Ph.D. dissertation, Faculty of Mechanical Engineering, University of Niš
3. Janevski, J., Stojanović, B., Stojiljković, M., 2004., *Thermal diffusivity coefficients by air fluidized bed,* Facta Unioversitatis, Mechanical Engineering, Vol.2, No 1, pp. 125 -134
4. Ćirić, I., 2010., *Neuro-fuzzy-genetic modeling and control of combustion process*, Master thesis, University of Niš, Faculty of Mechanical Engineering, Niš
5. Ćojbašić, Ž., Ćojbašić, Lj., Nikolić, V., 1999., *Fuzzy and neuro-fuzzy systems in problems of process control and modeling: possibilities and some aspects of application*, Journal of Process Technology, Beograd, pp. 164-167.
6. Ćojbašić, Ž., 2002., *Development of New Intelligent Adaptive Fuzzy and Hybrid Control Systems*, Ph.D. Thesis, University of Niš, Faculty of Mechanical Engineering, Niš
7. Ćojbašić, Ž., Volker, S., Gross, H. M., Wernstedt, J., 2003., *Intelligent control of complex combustion processes,* Facta Universitatis, Mechanical Engineering, Vol.1, No 1, pp. 1393-1406
8. Hímer, Z., Dévényi, G., Kovács, J., Kortela, U., 2004.,*Control of combustion based on neuro-fuzzy model*, IASTED International Conference on Applied Simulation and Modelling (AMS 2004), Rhodes, Greece, pp. 13-17.
9. Himer, Z., Devenyi, G., Kovacs, J., Kortela, U., 2005., *Advanced fuzzy control of combustion with genetic learning automata*, Proc. IASTED Int. Conf. Applied Simulation and Modelling, Innsbruck, Austria.
10. Ikonen, E., Kovacs, J., 2007., *Learning control of fluidized bed combustion processes for power plants*, In: Kalogirou S. (Ed.), *Artificial Intelligence in Energy and Renewable Energy Systems*, Nova Publishers,
11. Najim, K., Ikonen, E., 2002., *Advanced Process Identification & Control*, Marcel Dekker, New York, USA,
12. Najim, K., Ikonen, E., Del Moral, P., 2006., *Open-loop regulation and tracking control based on a genealogical decision tree*, Neural Computing & Applications 15(3/4), pp. 339-349.
13. Herrera, F., Lozano, M., Verdegay, J. L., 1998., *Tackling real-coded genetic algorithms: Operators and tools for behavioral analysis*, Artificial Intell.Rev., vol. 12, pp. 265–319.
14. Leppäkoski, K., Paloranta, M., Ikonen, E., 2004., *Comparing two nonlinear structures for secondary air process modelling*, Control, Bath, U.K.
15. Takagi, T., Sugeno, M., 1985., *Fuzzy identification of systems and its application to modeling and control*, IEEE Trans. Syst., Man, Cybern., vol. SMC-15, pp. 116–132.
16. Hellendoorn, H., Driankov, D., 1997., *Fuzzy Model Identification*, Springer-Verlag, Berlin.

NAPREDNA EVOLUCIONA OPTIMIZACIJA ZA INTELIGENTNO MODELIRANJE I UPRAVLJANJE PROCESOM SFS

Žarko Ćojbašić, Vlastimir Nikolić, Ivan Ćirić, Sorin Grigorescu

U ovom radu razmatran je pristup modeliranju procesa sagorevanja u fluidizovanom sloju zasnovan na računarskoj inteligenciji, kao i inteligentno upravljanje procesom bazirano na razvijenim modelima i metodama mekog računa. Primenjena genetska optimizacija i fazi pristup modeliranju kombinovani su sa predloženim strategijama inteligentnog upravljanja. Predstavljeno je efikasno fazi nelinearno modeliranje procesa SFS kombinovanjem linearizovanih modela, kao i realno kodirana genetska optimizacija fazi i konvencionalnog sistema upravljanja procesom. Dobijeni rezultati ukazuju da se pristup zasnovan na računarskoj inteligenciji uspešno može primenjivati na ovakav kompleksni proces sagorevanja u fluidizovanom sloju.

Ključne reči: *računarska inteligencija, sagorevanje u fluidizovanom sloju, fazi sistemi, realno kodirani genetski algoritmi*