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COMPUTATIONAL INTELLIGENCE MODELING AND CONTROL OF FLUE GAS EMISSION IN FBC PROCESS

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Abstract. *In this paper computationally intelligent modelling approach for fluidized bed combustion process has been considered, and also intelligent process control based on developed models. Applied adaptive neuro-fuzzy model structure provides for efficient combining of available expert knowledge with existing experimental data. On the basis of qualitative information on the desulphurization process models of the SO_2 emission in fluidized bed combustion have been developed, which have been optimally tuned with measured data. Obtained results indicate that such approach can be successfully applied for economical and efficient reduction of SO_2 in FBC by estimation of optimal process parameters and by design of intelligent control systems on the basis of defined emission model.*

1. INTRODUCTION

In fluidized bed combustion (FBC), combustion chamber besides fuel contains a quantity of particles of inert material such as sand or ash. The combustion air entering from below lifts 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 [17].

Harmful flue gas emissions such as nitrogen oxides, sulphur oxides and carbon monoxide, are result of the complex burning phenomena and the individual construction of the plant in question. During the past years, environmental concerns and resulting emission taxation procedures have made their minimization a profitable task. In addition to the developments in the plant construction and flue gas cleaners, also the process operating conditions are an important and cost-effective way to affect these emissions. In fact, possibility to reduce emissions are one of the main features of FBC technology. But to be able to optimize the plant operation, models for the variables of the overall cost

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function are required. With that and other aims concerning control of FBC plant in mind [13][10], in this study models for the SO_2 emissions based on the computational intelligence techniques are considered.

Hybrid soft computing modeling approach [6][10] applied in this paper is based on the implementation of fuzzy systems using artificial neural networks, which provides for trainable neuro-fuzzy structure that can benefit from both qualitative and quantitative available information. Neuro-fuzzy systems combine the theory of artificial neural networks and fuzzy systems. The learning methods of ANNs enable these systems to learn from given training data sets, and due to the massive parallelism of the ANNs real-time processing of larger data sets and graceful degradation of performance in the case of damage are provided. The fuzzy set theory also enables the NF systems to deal with the ambiguous or ill-defined data effectively and to present the learned information in a more human understandable form. In this study fuzzy clustering and evolutionary computing are also applied for model structure determination and optimization. Combining numerical and linguistic information into model is the key-strategy obtained by such hybrid approach, since complexity of the FBC process makes application of conventional modeling and advanced control strategies difficult [12][11].

Using mentioned hybrid fuzzy modeling approach, models of the fluidized bed sulphur-dioxide emission are constructed and then trained, using both expert knowledge and experimental data. Both static and dynamic models are considered, as well as their usage for control purposes.

Fuzzy modeling is one of the most significant areas of application of computational intelligence approaches. Important category of fuzzy system models is based on the Takagi–Sugeno–Kang (TSK) method of reasoning proposed by Sugeno and his coworkers [3]. These models are based on a rule structure that has fuzzy antecedent and functional consequent parts, thereby qualifying them as mixed fuzzy and nonfuzzy models. TSK fuzzy models have the ability to represent not only qualitative knowledge, but quantitative information as well. TSK fuzzy models also allow relatively easy application of powerful learning techniques for their identification from data. Furthermore, all fuzzy systems are nonlinear mappings and are proven to be nonlinear universal function approximators [4], a property they share with neural networks (NN's). This property qualifies them as excellent candidates for identification and control of nonlinear dynamical systems.

Two primary tasks of fuzzy modeling are structure identification and parameter adjustment [2][3][4]. The former determines I/O space partition, rule antecedent (i.e., premise) and consequent variables, the number of IF–THEN rules, and the number and initial positions of membership functions. The latter identifies a feasible set of parameters under the given structure. The problem of structure identification can be tackled by use a well-known quick subtractive clustering technique developed by Yager/Filev and modified by Chiu [3]. It uses an exponential potential function to rank and select most representative cluster centers from plant I/O data. These cluster centers are then used to generate an initial TSK fuzzy model.

To deal with the problem of parameter adjustment, efficient neuro-fuzzy scheme known as an ANFIS [1] can be used. ANFIS represents an initial TSK model obtained from the structure identification phase as generalized feedforward neural network, and trains it with plant I/O data, thereby adjusting the parameters of the antecedent membership functions as well as those of the functional consequents. ANFIS employs a hybrid learning scheme that combines a well known BP/GD algorithm for adjusting the parameters of rule antecedents, with a recursive least-squares estimation (RLSE) algorithm for adjusting the parameters of the functional consequents.

2. ADAPTIVE NETWORK-BASED FUZZY INFERENCE SYSTEMS (ANFIS)

This section summarizes the basic architecture and the hybrid learning algorithm of ANFIS [1], as well as MMC clustering technique for initial neuro-fuzzy model structure determination [3].

2.1 ANFIS structure

Consider a first-order TSK fuzzy inference system that consists of two rules

Rule 1: If X is A_1 and Y is B_1 then $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If X is A_2 and Y is B_2 then $f_2 = p_2 x + q_2 y + r_2$

If f_1 and f_2 are constants instead of linear equations, we have a zero-order TSK fuzzy model. Figures 1(a) and (b) illustrate the fuzzy reasoning mechanism and the corresponding ANFIS architecture, respectively.

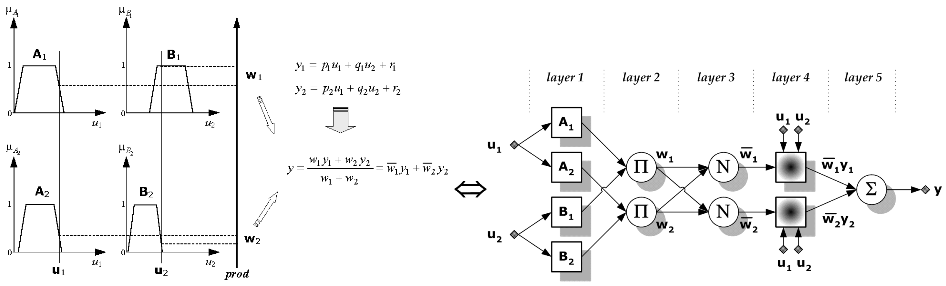

Fig. 1. (a) First-order TSK fuzzy model using trapezoidal membership functions and (b) corresponding ANFIS architecture.

Node functions in the same layer of ANFIS are of the same function family, as described below. Note that O_i^j denotes the output of the i^{th} node in layer j.

Layer 1: Each node in this layer generates membership grades of a linguistic label. For instance, the node function of i^{th} node might be

$$O_i^1 = m_{A_i}(x) = \max\left[\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right] \tag{1}$$

where x is the input to node i; A_i is the linguistic label (small, large, etc.) associated with this node; and $\{a, b, c, d\}$ is the parameter set that changes the shape of the trapezoidal membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: Each node in this layer calculates the firing strength of each rule via multiplication

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \qquad i = 1,2 \tag{02}$$

Layer 3: The i^{th} node of this layer calculates the ratio of the i^{th} rule's firing strength to the sum of all rules firing strength

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{3}$$

Layer 4: Node i in this layer has the following node function:

$$O_i^1 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{4}$$

where w_i is the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals overall output

$$O_i^3 = \textit{overall output} = \sum_i \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i}\,. \tag{5}$$

2.2 The hybrid BP/RLSE learning algorithm

The hybrid learning algorithm of ANFIS consists of two alternating parts:

1) BP/GD which calculates error signals (defined as the derivative of the squared error with respect to each node output) recursively from the output layer backward to the input nodes, and

2) the RLSE method, which finds a feasible set of consequent parameters. We observe that, given fixed values of premise parameters, the overall output can be expressed as a linear combination of the consequent parameters

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2 = (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + (\overline{w}_2) r_2\,. \tag{06}$$

Equation (06) can be recast as a matrix equation

$$\mathbf{AX} = \mathbf{B}\,, \tag{07}$$

where **X** is an unknown vector whose elements are the consequent parameters. An LSE of **X**, namely $\mathbf{X}^*$, is sought to minimize the squared error $\|\mathbf{AX} - \mathbf{B}\|^2$. Sequential formulas are employed to compute the LSE of **X**. Specifically, let the i^{th} row vector of matrix **A** defined in (07) be a_i^T and the i^{th} element of **B** be b_i^T. Then

$$\mathbf{X}_{i+1} = \mathbf{X}_i + \mathbf{S}_{i+1} a_{i+1} (b_{i+1}^T - a_{i+1}^T \mathbf{X}_i),$$
$$\mathbf{S}_{i+1} = \mathbf{S}_i - \frac{\mathbf{S}_i a_{i+1} a_{i+1}^T \mathbf{S}_i}{1 + a_{i+1}^T \mathbf{S}_i a_{i+1}}, \quad i = 0, 1, \ldots, P-1 \tag{08}$$

where $\mathbf{S}_i$ is often called the covariance matrix and the least-squares estimate $\mathbf{X}^*$ is equal to $\mathbf{X}_p$. The initial conditions to bootstrap (08) are $\mathbf{X}_0 = 0$ and $\mathbf{S}_0 = \gamma\mathbf{I}$, where γ is a positive large number and $\mathbf{I}$ is the identity matrix of dimensions $M \times M$, where M is the number of consequent parameters. For given fixed values of premise parameters, the estimated consequent parameters are known to be globally optimal.

2.3 MMC clustering

The purpose of clustering is to distill natural groupings of data from a large data set, producing a concise representation of a system's behavior. The clustering of I/O data produces a set of cluster centers, and each cluster center acts as a prototypical data point that describes a characteristic mode of the system, and can be considered as the nucleus of a fuzzy if-then rule. In that way partitioning of the inputs and determination of the initial minimal rule base for ANFIS can be performed.

Namely, if a collection of n-normalized data points $\{x_1, x_2, \ldots, x_n\}$ in an M-dimensional space is considered, measure of the potential of data point can be defined as

$$P_i = \sum_{j=1}^{n} \exp(-\alpha \| x_i - x_j \|^2), \quad \alpha = 4 / r_a^2 . \tag{09}$$

The constant r_a is effectively the radius defining a neighborhood. After the potential of every data point has been computed, the data point with the highest potential is selected as the first cluster center. If x_1^* is the first cluster center with potential P_1^*, the potential of each data point is revised by the formula

$$P_i \leftarrow P_i - P_i^* \exp(-\beta \| x_i - x_j \|^2), \quad \beta = 4 / r_b^2 , \tag{10}$$

where r_b is positive constant, larger than r_a in order to avoid high density of the cluster centers (usually $r_b = 1.5 r_a$) [3].

3. FLUDIZED BED COMBUSTION (FBC) PROCESS AND SO_2 EMISSION

In fluidized bed combustion [17][5] 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.

The normal operating temperature of the bed is between 750÷950^{0}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 (~1100 K), high excess air levels (~30%), intermediate particle sizes (1÷3 *mm*), long residence times (several minutes) and vigorous particle motion that dominates heat transfer and reaction processes.

Sulphur-dioxide removal from flue gas during the combustion process is possible by adding limestone in bed, which is considered to be one of the most important advantages of FBC. Harmful gaseous emissions are converted to solid material, which is eliminated from combustion bed, and there are also possibilities for its later usage. Degree of binding of sulphur is dependent on many parameters, where most important are: combustion temperature, molar ratio Ca/S, bed height, fluidization velocity, excess air ratio, primary/secondary air ratio, characteristics of limestone, size of particles of limestone, heating velocity, etc.

It is believed [5][17] that there are two basic reactions that take part during sulphur binding and those are calcination and sulphatization:

$$CaCO_3 = CaO + CO_2 \quad \text{and} \quad CaO + SO_2 + \frac{1}{2}O_2 = CaSO_4 \tag{11}$$

During insertion in bed, limestone particle is heated and on higher temperatures calcination process takes place. During that $CaCO_3$ disassembles to CaO and CO_2 which causes that particles become porous. Sulphur dioxide passes through those pores and reacts with CaO making $CaSO_4$. Because of larger molar volume of $CaSO_4$, previously made pores are blocked which prevents total usage of CaO. As consequence, it is usual that more limestone is added to the combustion chamber than it is theoretically needed.

Consequently, harmful flue gas emissions containing sulphur oxides are a result of the complex burning phenomena and the individual construction of the plant in question. The process operating conditions are an important and cost-effective way to affect these emissions. To be able to optimize the plant operation, neuro-fuzzy models described in previous sections are considered for prediction of the SO_2 emissions based on the values of the most influential (changeable, i.e. adjustable) parameters.

4. Model Inputs/Output and Experimental Training Data

Input signals for SO_2 flue gas content model were selected based on a priori knowledge on the conditions affecting the formation and reduction of sulphur-dioxide in FB combustion process, which are briefly described in the previous section.

First model input is selected to be molar ratio Ca/S. This ratio is in practical operation of FBC experimentally nearoptimaly determined, and is always selected as greater than one since, as it is explained above, desulphurization is improved when more limestone is added in the combustion bed than theoretically needed.

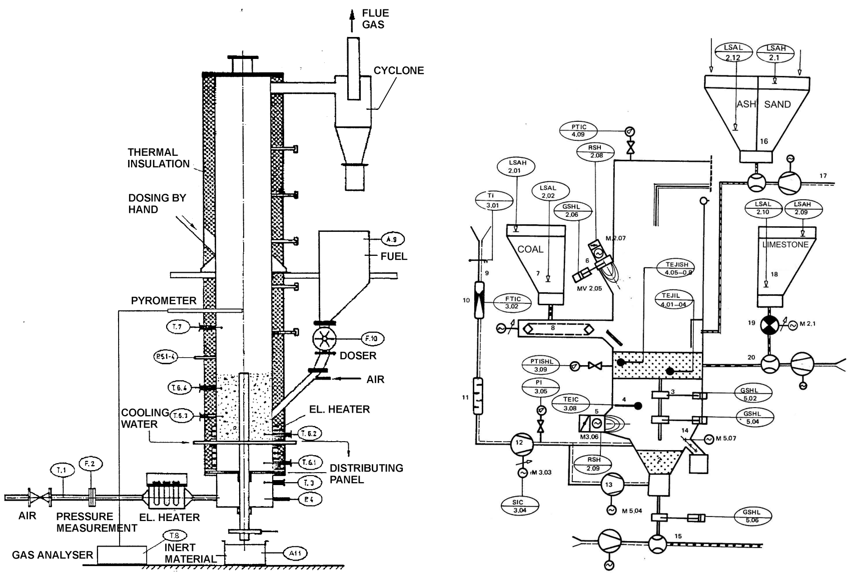

Fig. 2. Schematic representation of laboratory experimental FBs

Second considered model input is bed temperature, denoted as θ. Below optimal temperature porosity of CaO is decreasing since calcination of limestone is substantially smaller. On higher temperatures intense sintering occurs, pores are closed and desulphurization is also decreased. Thus, influence of bed temperature on flue gas SO_2 content is wast.

Besides the basic model version with two inputs, another approach with two additional inputs has also been tested. There, excess air ratio λ is the third (alternative) model input. Excess air does not influence desulphurization process directly, but it has indirect positive effect. Fourth (alternative) model input is selected to be fluidization velocity v_0. When fluidization velocity increases, time of contact of SO_2 and limestone particles decreases, so desulphurization is lowered.

It is assumed that geometrical parameters of the FB plant cannot be changed, as well as fuel type or limestone quality and limestone particle size, so those influential parameters were not considered as possible model inputs. Model output is percent of SO_2 removal from flue gas, denoted as η_{SO2}.

Experimental data used in this paper originate from several previous researches concerning FBC, conducted at the Thermal engineering department of the Mechanical Engineering faculty in Niš [14][15][16]. For example, some data sets used in these experiments were measured from a laboratory FBC plant, of circular cross section with 120 *mm* diameter, 1500 *mm* height and 20 *kW* power (Fig. 2a). During experiments oil shales were used as fuel. Signals were measured with a frequency of 1 Hz, and the process was operated changing the values of parameters.

A sample of obtained measurement data is shown in Fig 3. Concentration of SO_2 was directly measured and then recalculated as percent of SO_2 removal from flue gas, which was used as training data for model output.

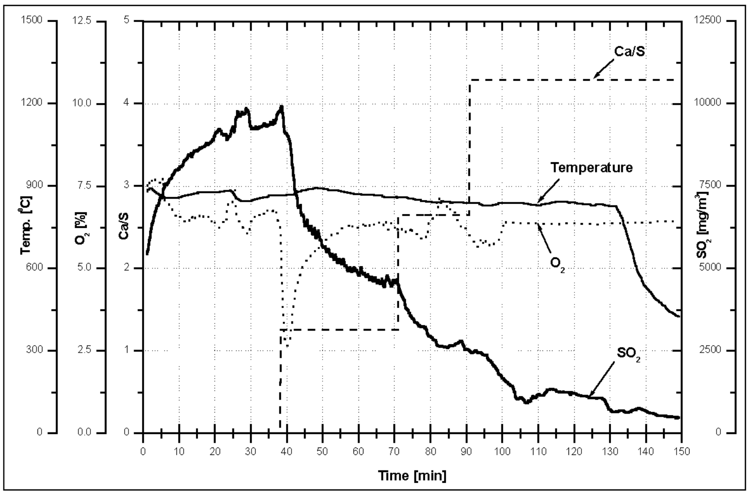

Fig 3. A set of experimental data used for training of neuro-fuzzy model

5. Methodology and Obtained Results

Several versions of the ANFIS model structures, such as described in section 2, were considered. First, versions with two (*Ca*/*S*, θ) and four inputs (*Ca*/*S*, θ, λ, v_0) were tested, while model output was η_{SO2} in all considered cases. One realized approach with four inputs is shown in Fig 4.

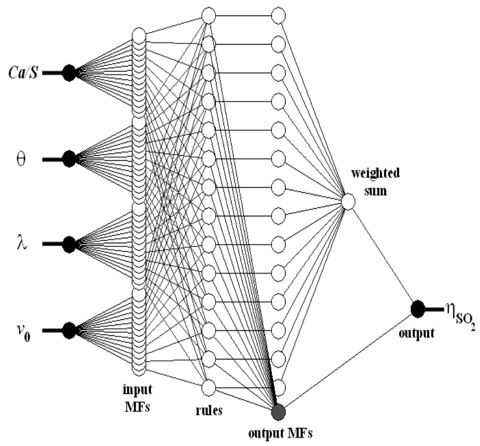

Fig. 4. ANFIS network with 4 inputs and 14 rules

Partitioning of input spaces, i.e. selection of number of primary fuzzy sets for each input variable is nontrivial task, along with determination of type of membership functions to be used. Increase of number of primary fuzzy sets leads to exponential growth of number of parameters that need to be adapted during training, and also decreases interpretability of the obtained result. Two approaches were considered: first, partitioning based on expert process knowledge, and second based on fuzzy subtractive clustering. As mentioned in the introduction, it is a fast, one pass algorithm for estimating the number of clusters and the cluster centers in the set of data [3]. This methodology was combined with Gaussian membership functions.

Also, interpretability of the obtained results was issue of the significant interest. Beside the fact that qualitative knowledge about the process was used along with available numerical data thanks to applied neuro-fuzzy modeling approach, obtained results after training can also be transformed into easily understandable information. For example in Fig. 5 output surface for fuzzy model with two inputs and modest number of primary fuzzy sets with Gaussian membership functions, after training, is presented. It is obvious that some theoretical knowledge can be confirmed from such results, as the fact that there is optimal bed temperature which provides for maximal SO_2 removal, after which further increase degrades SO_2 removal process, and so on. Also, rules with trained optimal parameters can be arranged in readable form thus providing easily understandable conclusions that were extracted from data by the model [10].

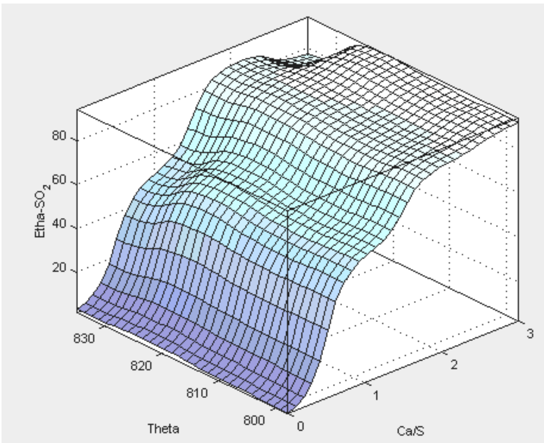

Fig. 5. Output surface for fuzzy model with two inputs and modest number of primary fuzzy sets after training

The possibility to perform multicriteria optimization of the obtained models by applying genetic algorithms in order to achieve increased accuracy and/or interpretability of the models has been also tested. For this purpose genetic algorithms with real coding have been used [9].

6. INTELLIGENT CONTROL OF FBC DESULPHURIZATION

Developed computationally intelligent models are intended to be used as aproximators for determination of optimal process parameters in relation to SO_2 removal from flue gases. Models are to be integrated in FBC boiler's control system at supervisory level, and have the task of estimating parameters for basic control loops. Optimization of emissions demands compromises between different aims, and proposed models provide inputs for the optimization cost function which defines optimal balance between plant's thermal efficiency and emissions.

Beside described usage, following the ideas from [7][8] developed models can be integrated in an expert system, which advises plant operators when limits for NO_x, SO_2, and CO emissions are reached and helps to stabilize burning conditions. Such a system provides easy access to the knowledge concerning emissions and helps operators to act quickly and efficiently, while effects of actions can be clearly seen. Such a system can be used not only in plant operation, but also for training. Its structure is shown in Fig. 6.

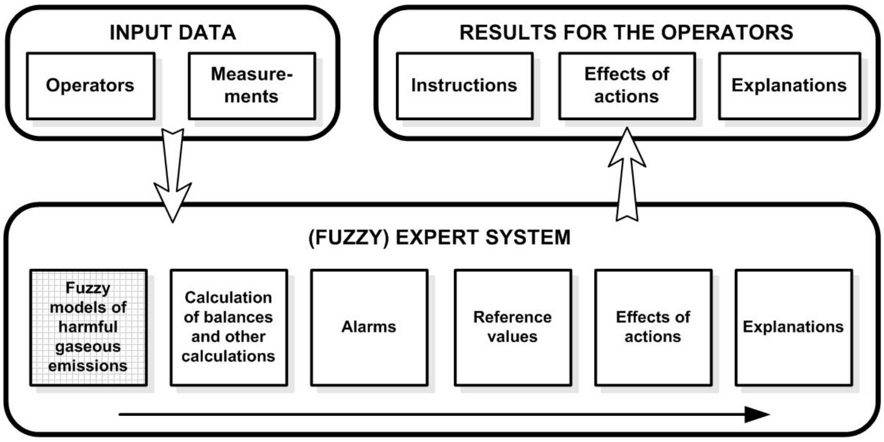

Fig. 6 Expert system for monitoring emissions in FBC boiler plant

The main power of the proposed approach lies in centralized aquisition of all sources of information about the process, whether they origin from the operators' experience, theoretical knowldge about the process or measured data. Expert system can also potentially be based on computational intelligence, i.e. it can also be fuzzy.

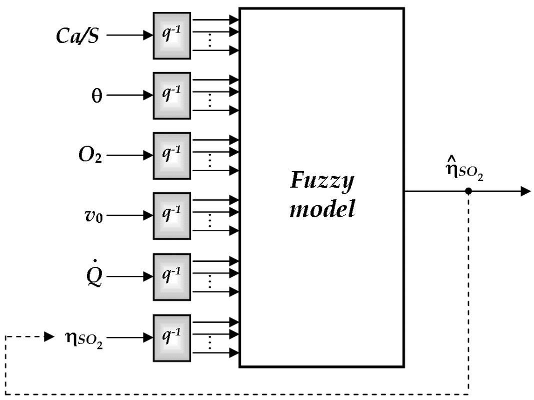

Fig. 7 Dynamic fuzzy model of the SO_2 emission with FBC

Beside proposed static models of the emission of SO_2 in boilers with FBC, identification of dynamic fuzzy models for the sake of application in the framework of adaptive control of FBC process has been considered as potentially feasible concept.

For dynamic modelling of the emission widely used strategy of external dynamics has been applied. This concept allows for the efficient application of fuzzy models that represent static approximators for modeling of dynamic systems, which has application in control systems as its final aim. Term "external dynamics" originates from the fact that nonlinear dynamic model can be divided into two parts: nonlinear static approximator and external bank of delay elements. Fig. 7 shows the extension of the basic idea of static modelling to a dynamic version of a model.

7. CONCLUSIONS

Modeling problem that was studied in the paper originates from the fluidized bed combustion process, specifically models for the flue gas SO_2 content were identified using soft computing models. ANFIS networks were capable of capturing the nonlinearities in process data, the training was efficient and prediction accuracy of the obtained models is good. That goes along with other features, such as interpretability of the models, acquisition of all sources of information on the process, etc.

Concisely recapitulated, triple usage of the developed computationally intelligent models of the emissions in FBC has been proposed for intelligent control of FBC boilers:

- application of static fuzzy models of emissions in order to provide for input values for optimization criteria, on the basis of which reference values for basic control loops are calculated;
- application of static fuzzy models in expert system that has the task of centralized treatment of information on harmful gaseous emissions and also to provide recommendations to plant operators;
- application of dynamic fuzzy models of emission and their inverses for design of control in the framework of adaptive fuzzy control with internal model and fuzzy predictive control.

Based on the studies reported in this paper, some interesting directions for future research can be pointed out. A good initial fuzzy partitioning of the input and output spaces is a strongly nontrivial task, and the possibility of using other fuzzy clustering techniques beside applied subtractive clustering, is also interesting, along with application of available expert knowledge about the process. Also, more efficient learning methods for ANFIS network can possibly be applied, and genetic optimization can be further explored.

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MODELIRANJE I UPRAVLJANJE EMISIJOM DIMNIH GASOVA KOD PROCESA SFS PRIMENOM RAČUNARSKE INTELIGENCIJE

Žarko Ćojbašić, Ljubica Ćojbašić, Vlastimir Nikolić, Nenad Radojković, Mića Vukić

U ovom radu razmatran je neuro-fazi pristup modeliranju procesa sagorevanja u fluidizovanom sloju i inteligentno upravljanje zasnovano na korišćenju razvijenih modela. Primenjena adaptivna neuro-fazi struktura modela omogućuje efikasno kombinovanje dostupnih ekspertskih znanja o procesu sa raspoloživim eksperimentalnim podacima. Na osnovu kvalitativnih informacija o procesu odsumporavanja razvijeni su modeli emisije SO_2 kod sagorevanja u fluidizovanom sloju, koji su zatim optimalno podešeni korišćenjem merenih podataka. Ostvareni rezultati pokazuju da se takav pristup može uspešno primeniti u cilju ekonomične i efikasne redukcije emisije SO_2 kod SFS estimacijom optimalnih parametara procesa, odnosno projektovanjem inteligentnog upravljanja na osnovu definisanih modela emisije.