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INTELLIGENT CONTROL OF COMPLEX COMBUSTION PROCESSES *

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Abstract. *In this paper intelligent control approaches for complex combustion processes have been considered. Successful applications of computational intelligence for advanced modelling, identification and control of thermal plants are presented. Specifically, neuro-fuzzy modelling of fluidized bed combustion process, and also intelligent process control based on developed models have been considered. Also, we have presented a novel control scheme for an industrial hard-coal combustion process in a power plant based on reinforcement-learning in combination with neural networks. These intelligent control approaches are aimed at complying with ever stricter requirements for environmental protection while maximizing the efficiency factor simultaneously keeping other process parameters within predefined limits.*

Key words: *Intelligent Control, Combustion Processes, Fuzzy Systems, Neural Networks, Reinforcement Learning, Genetic Algorithms*

1. INTRODUCTION

Large-scale combustion power plants are monitored by and operated via process control systems, which solve problems of visualization, alarm indications and the application of low-level control-components. It is commonly known that the performance of such complex processes can be significantly improved through a higher control level realized by manual control actions of an experienced operator. As automated solutions for this high level control are very complicated, intelligent control solutions represent natural candidates for these tasks [3][4]. Very important are harmful flue gas emissions such as nitrogen oxides, sulphur oxides and carbon monoxide, which are result of the complex

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burning phenomena occuring in power plants. During the past decades, environmental concerns and emission taxation policies 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. Since the immediate objective of a power plant is the production of energy, the obvious plant operator goal is to maximize the efficiency factor. Simultaneously, both the system-constraints and great requirements for environmental protection limit the workspace. Because of time varying plant properties caused by pollution, fair wear and tear, changing coal qualities, etc., a control system is sought, which autonomously tries to minimize a predefined cost function.

Intelligent control solutions proposed in the first part of this paper regard fluidized bed combustion (FBC) process, and are based on the hybrid soft computing modeling approach [13][16]. Modelling is realised through the implementation of fuzzy systems using artificial neural networks (ANN), which provides for a trainable neuro-fuzzy structure. The learning methods of ANNs enable neuro-fuzzy systems to learn from data sets, and due to the massive parallelism of the ANNs efficient real-time processing and graceful degradation of performance in the case of damage are provided. The fuzzy set theory also enables NF systems to deal with the ambiguous or ill-defined data effectively and to present the learned information in an understandable form. 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 combustion processes makes application of conventional modeling and advanced control strategies difficult [17]. Using both expert knowledge and experimental data models of the FBC sulphur-dioxide emission are constructed and then trained. Both static and dynamic models are considered, as well as their usage for control purposes.

Reinforcement learning (RL) can be also be proposed to efficiently solve control problems for complex combustion processes. The main idea of RL consists in using experiences obtained through interaction with the environment (here combustion process) to progressively learn an optimal value function. This value function predicts the best long-term outcome an agent can receive from a given state when it applies a specific action and follows the optimal policy thereafter [1]. The agent can use a RL-algorithm such as Sutton's TD(λ) algorithm [1], or Watkin's Q-learning algorithm [2] to improve the long-term estimate of the value function associated with the current state and the selected action. Neural function approximators are useful because they can generalize the expected return of state-action pairs the agent actually experiences to other regions of the state-action-space. Thus, in the second part of the paper we have presented a new control scheme for an industrial hard-coal combustion process in a power plant based on reinforcement-learning in combination with neural networks.

2. COMPUTATIONAL INTELLIGENCE MODELLING AND INTELLIGENT CONTROL OF FLUIDIZED BED COMBUSTION PROCESS

In fluidized bed combustion (FBC), besides fuel, the combustion chamber 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 [22]. In fact, possibility to reduce emissions is 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 function are required. With that and other aims concerning control of FBC plant in mind [18][16], models for the SO_2 emissions based on the computational intelligence techniques are considered.

Two primary tasks of fuzzy modeling are structure identification and parameter adjustment [10][11][12]. The former determines I/O space partition, rule antecedent and consequent variables, the number of fuzzy 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 of a well-known quick subtractive clustering technique developed by Yager/Filev and modified by Chiu [11]. To deal with the problem of parameter adjustment, efficient neuro-fuzzy scheme known as an ANFIS (Adaptive network-based fuzzy inference systems) [9] can be used. ANFIS represents TSK fuzzy model 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.

2.1 ANFIS Systems and Subtractive Clustering Technique

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

Rule i: If X is A_i and Y is B_i then $f_i = p_i x + q_i y + r_i$, $i = 1,2$.

Fig. 1 illustrates the fuzzy reasoning and the corresponding ANFIS architecture, respectively. 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 premise parameter set (defining membership functions).

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

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

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

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

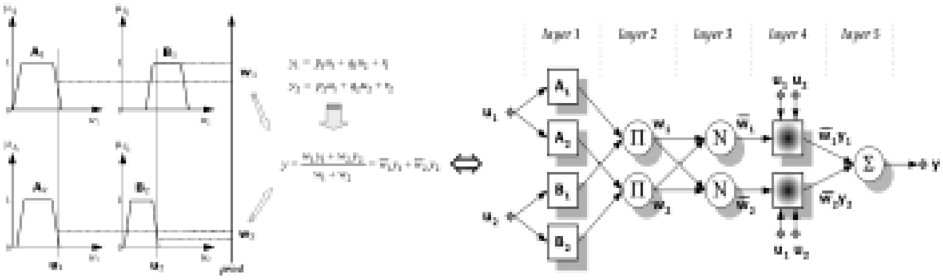


Fig. 1. First-order TSK fuzzy model and corresponding ANFIS architecture

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 consequent parameter set.

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

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

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

1) BP/GD which calculates error signals 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

$$\mathbf{AX} = \mathbf{B} \ , \tag{6}$$

where $\mathbf{X}$ is an unknown vector whose elements are the consequent parameters. An LSE of $\mathbf{X}$, namely $\mathbf{X}^*$, is sought to minimize the squared error $\|\mathbf{AX}-\mathbf{B}\|^2$. Sequential formulas are employed to compute the LSE of $\mathbf{X}$. For given fixed values of premise parameters, the estimated consequent parameters are known to be globally optimal.

The subtractive clustering of I/O data produces a set of cluster centers, acting as prototypical data points describing a characteristic modes of the system and therefore can be considered as nucleuses of a fuzzy rules. 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 $\{x_1, x_2, ..., x_n\}$ in an M-dimensional space is considered, measure of the potential of data point can be defined as

$$P_i = \sum_{j=1}^{n} \exp\left(-\alpha \left\| x_i - x_j \right\|^2 \right), \quad \alpha = 4 / r_a^2 \ . \tag{7}$$

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 and the potential of each data point is revised [11].

2.2 Fludized Bed Combustion (FBC) Process and SO_2 Emission

Normal operating temperature of the fludized bed is between 750÷950^{0}C. At this relatively low temperature ash and moist fuels do not melt or sinter. Fuel properties like ash content, particle size and moisture are of less importance. Generally, FBC 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 an important advantage of FBC. Harmful gaseous emissions are converted to solid material that is eliminated from bed, and there are also possibilities for its later usage. 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. 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.

2.3 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.

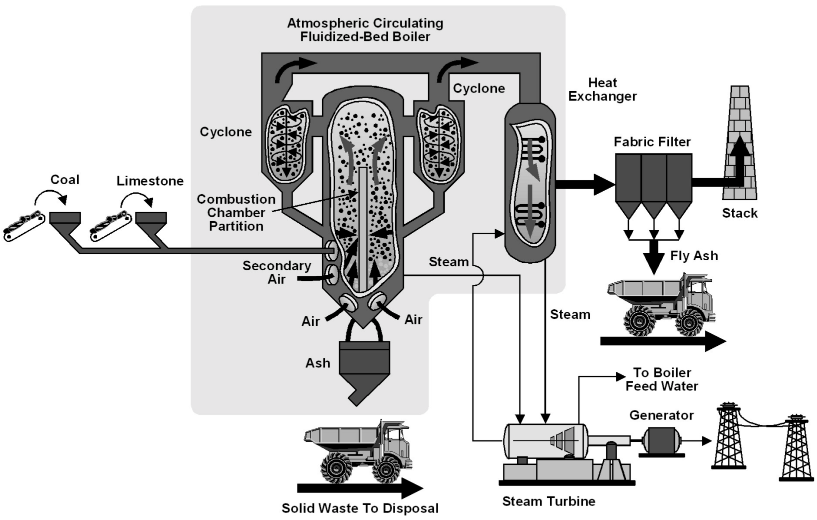


Fig. 2. Schematic representation of one of the FB plants used for experiments

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 desulphurization is improved when more limestone is added in the combustion bed than theoretically needed. 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 is wast. Besides the basic model version with two inputs, another approach with two additional inputs, excess air ratio λ and fluidization velocity v_0, has also been tested. Excess air does not influence desulphurization process directly, but it has indirect positive effect. When fluidization velocity increases, time of contact of SO_2 and limestone particles decreases, so desulphurization is lowered.

Experimental data used in this study originate from several previous researches concerning FBC, conducted at the Thermal engineering department of the Mechanical Engineering faculty in Niš [19][20][21]. Schematic representation of one industrial plant with FB used in this experiments is shown in Fig. 2.

2.4 Methodology and Obtained Results

Several versions of the ANFIS model structures, have been considered. First, versions with two (*Ca*/*S*, θ) and four inputs (*Ca*/*S*, θ, λ, v_0) were tested, while model output was percent of SO_2 removal from flue gas, denoted as η_{SO2} in all considered cases. One realized approach with three inputs is shown in Fig 3.

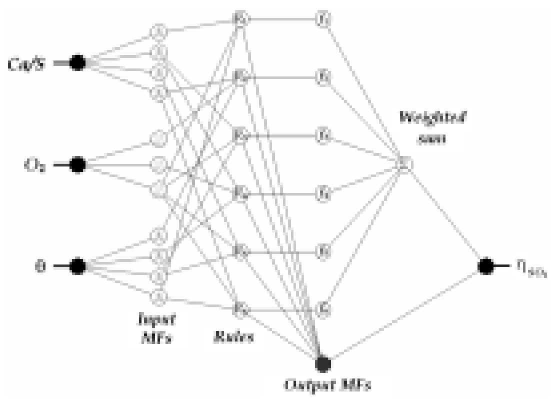


Fig. 3. ANFIS network with 3 inputs and 6 rules

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. Partitioning based on expert process knowledge and on fuzzy subtractive clustering have both been considered.

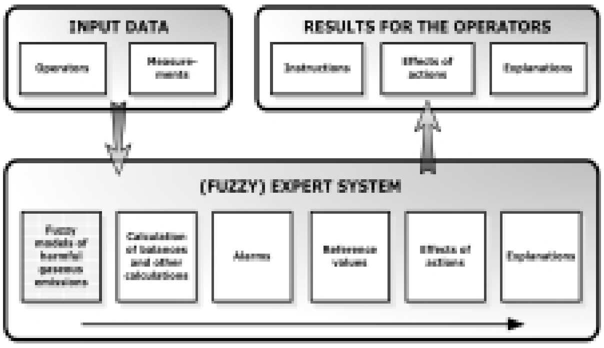
Also, interpretability of the obtained results was issue of interest. Beside the fact that qualitative knowledge about the process was used along with available numerical data thanks to applied NF modeling approach, obtained results after training could also be transformed into understandable information. Multicriteria optimization of the obtained models by applying genetic algorithms with real coding [15] in order to achieve increased accuracy and/or interpretability of the models has also been tested.

Developed models 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.

2.5 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, developed models can be integrated in an expert system [14], 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. It can be used not only in plant operation, but also for training. Its structure is shown in Fig. 4.



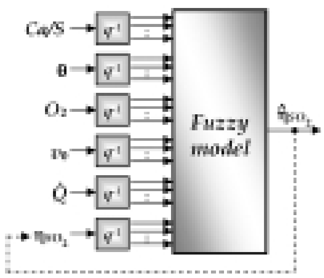


Fig. 4. Expert system for monitoring emissions in FBC boiler plant

Fig. 5. Dynamic fuzzy model of the SO_2 emission with FBC

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.

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 a potentially feasible concept. For dynamic modelling of the emission widely used strategy of external dynamics has been applied. This concept allows for an efficient application of fuzzy models of dynamic systems in advanced control systems. Fig. 5 shows the extension of the basic idea of static modelling to a dynamic version of a model.

3. Control Scheme for Combustion Processes Using Reiforcement Learning Based on Neural Networks

Based on motivation stated in section 1, another intelligent control approach for complex combustion processes can be considered. Namely, reinforcement-learning (RL) [5] based control scheme, which allows an autonomous exploration of the state-action space of the combustion process, while predefined quality factors have to be optimized.

This approach efficiently addresses the inherent problem of many other control approaches - limited portability to other plants, due to different process parameters. RL is much more flexible, portable and can also adapt to changing plant properties. This main advantage of RL implies a minor drawback, because during the exploration phase the system has to perform many different control actions, of course also suboptimal ones.

3.1 The Plant

The power plant "Tiefstack" that was used for experiments is owned by the "Hamburgische Elektrizaetswerke" (HEW) and is situated in the south of Hamburg. The subsystem to be controlled consists of 6 burners aligned in 2 columns at 3 levels having a maximal output of 252MW (Fig. 6). The burners at each level are supplied with coal by one coal mill. Although the distribution of coal should be equal for each of the 2 burners, due to varying dynamics or pollution this equilibrium is shifted to the benefit of one burner. The exact amount of inlet coal can not be measured for each burner separately.

To get more burner specific information about the distribution of coal and air inside the combustion chamber or about the flames, we observe each of the 6 flames by a special color camera system, and use these data to control the process. Fig. 7 depicts the extraction of visual features describing the combustion process. In order to reduce the large set of flame-describing features, we analyzed the correlation of the visual features and several important process data, for instance the NO_x and O_2 emissions and the waste gas temperature. It was found that already the mean intensities in the R-Band of the RGB-images of the flames (F_{00}^{RMB11}... F_{00}^{RMB32}) entail very detailed information about the distribution of coal and temperature inside the combustion chamber.

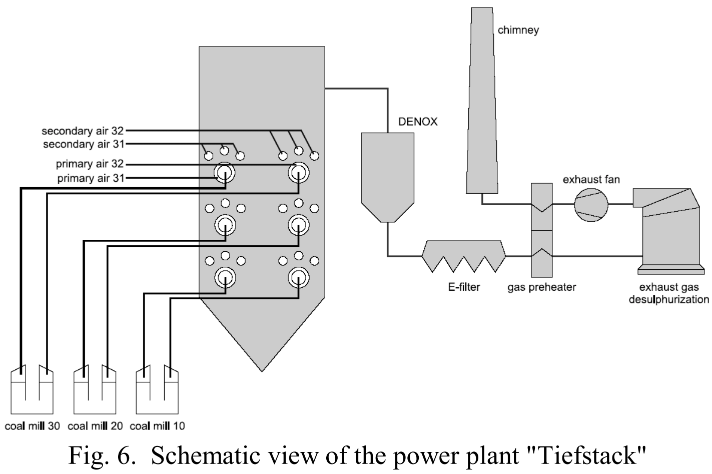


Fig. 6. Schematic view of the power plant "Tiefstack"

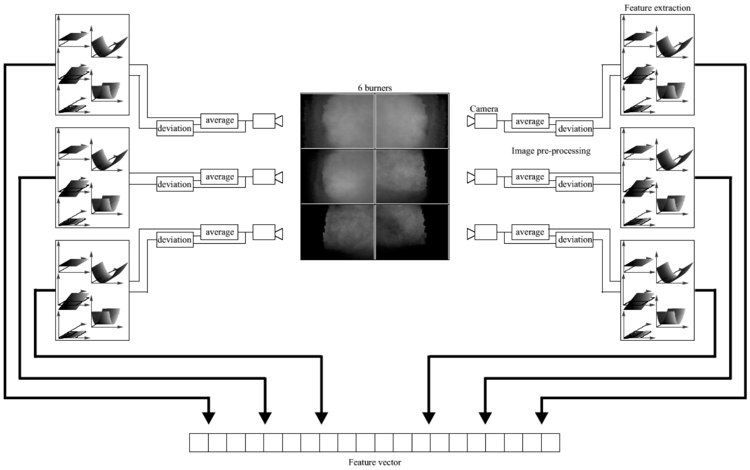


Fig. 7. Extraction of visual features describing combustion process very closely

The plant operator defined the goal of the controller as follows. First, we have to satisfy several limitations at all times to guarantee the safety precautions:

- steam temperature > 540°C,
- waste gas temperature > 340°C,
- NO_x concentration in waste gas < 1200 mg/m^3,
- unused carbon < 5%,
- 0_2 > 3%.

In addition, the control system has to minimize both the NO_x emissions and the air consumption in order to increase the efficiency factor. To fulfil the defined goals the plant operator gave us direct access to the controls depicted in Table 1 (also Fig. 8).

Table 1. Control variables

Control variable	**Meaning**
primary air trim at levels 10, 20, 30	air-distribution between left/right burner on the specified level
primary/secondary air trim for all burners	distribution between primary/secondary air at one burner
air amount at levels 10, 20, 30	overall air amount on the specified level

The 12 controls (Fig. 8) only influence the air amount and the distribution of air between 6 burners, but neither amount nor distribution of inlet hard-coal.

3.2 Architecture

The main feature of RL is its self exploration of the outcomes of control actions with respect to a predefined goal. Based on a sensory description of the current process situation, the RL-systcm selects an appropriate control action, performs it, observes its consequences and acquires a reward (Fig. 9). The task of the architecture is to obtain a utility-value for all experienced state-action-pairs, which is defined by the reward and the discounted value of the new state. So called classical Q-learning has been used because of very promising experiences on robot-navigation tasks [6][7].

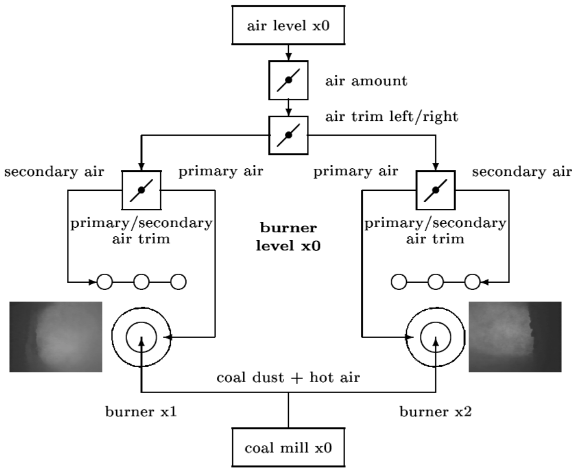


Fig. 8. Combustion chamber with coal and air supply for one of three burner-levels

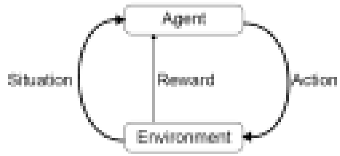


Fig. 9. Interaction between RL-system and the process

During the exploration phase the RL-system has to perform all control actions in all process situations. However, due to the tremendous action space (12 independent control variables) in combination with the very large process situation space a full exploration of all state-action-pairs would last a very long time and is therefore not applicable.

3.3 Problem decomposition

We designed several agents, each observing only a relevant subset of the situation space and using only a subset of the available controls, as it is shown in Fig. 10.

Thus, AGENTL10, AGENTL20, and AGENTL30, observe only the intensity-ratios of the left and right flame on all levels and control the air distribution at their corresponding burner level (3 control variables each). AGENTO$_2$ observes the intensities of all flames and the global ratio of inlet air and coal (λ). This Agent controls the total amount of air consumption for each burner level (3 control variables). The introduction of a scheduling of the 4 agents at this point is very important, since the reinforcement-approach assumes, that each agent is able to observe directly the consequences of its own actions. If two agents would perform their actions together, the consequences of their actions (e.g. NO_x concentration) would interfere and the resulting cross-talk between the agents would prevent a correct acquisition of the real outcomes of the respective actions. Hence, we defined that all 4 agents operate sequentially in time intervals of 10 minutes, which is presented in Fig. 11.

3.4 Neural Function Approximator

Each of these 4 agents is realized by a neural function approximator. A simple approach to this state-action function approximator is the one that combines a neural vector quantization technique (Neural Gas [8]) for optimal clustering of the high-dimensional continuous input space [7] with a subsequent associative memory, to estimate the values of the assigned actions (Fig. 12).

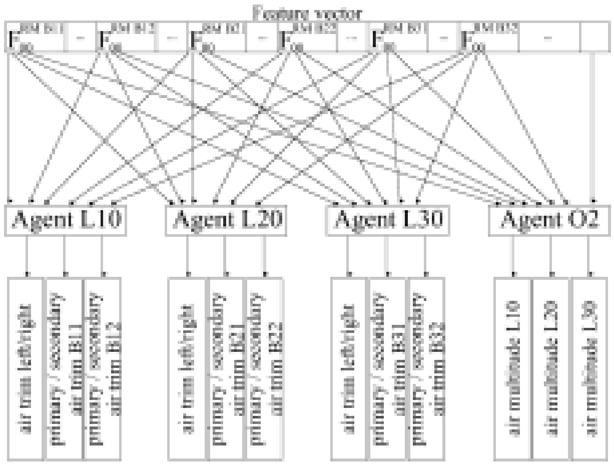


Fig. 10. Decomposition of the control task into 4 agents with their inputs and controls

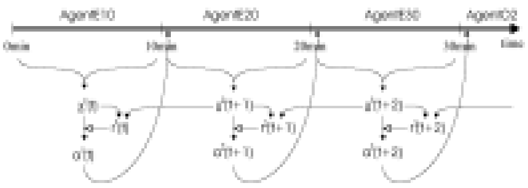


Fig. 11. Applied time scheduling of 4 agents

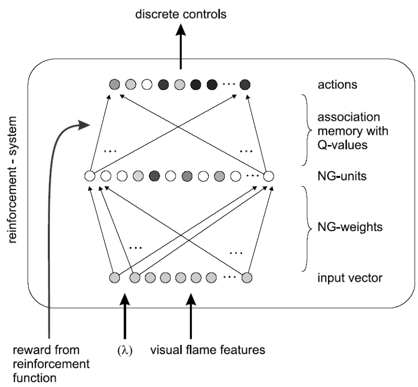


Fig. 12. Neural control architecture for RL of a single agent.

The neural-gas weight $\underline{w}_k(t)$ update rule for the neuron k can be defined as:

$$\Delta \underline{w}_k(t) = \eta^{NG}(t) \cdot e^{-\frac{i(k)}{h(t)}} \cdot [\underline{x}(t) - \underline{w}_k(t)], \tag{8}$$

where $\eta^{NG}(t)$ is a learning rate, $i(k)$ is the index of neuron k in the list sorted by distance to the input $\underline{x}(t)$ and $h(t)$ is the learning radius. Thus, the real-valued process describing input data are mapped onto a low dimensional representation s^t. For action-value approximation Q for state s^t and control action a^t, we utilize the Q-learning [2] variant of RL. The usage of expected future returns discounted by γ in addition to the current reward ensures a policy maximizing long term rewards, thus searching a global maximum:

$$\Delta Q(s^t, a^t) = \eta\{r^t + \gamma V(s^{t+1}) - Q(s^t, a^t)\}, \quad \text{with} \tag{9}$$

$$V(s^{t+1}) = \max_a Q(s^{t+1}, a^{t+1}). \tag{10}$$

For our experiments, we use a discount factor for the value of the subsequent state of γ=0.5, and a Q-learning-rate of η=0.2. The reinforcement r is the result of an agent-specific reinforcement function, which strongly corresponds to the described plant operator objectives. Agents AGENTL10, AGENTL20 and AGENTL30 are rewarded if the NO_x or the O_2 concentrations decrease and punished if they increase:

$$r^{AgentLXX} = \begin{cases} -10.0 : & \textit{any treshold violated} \\ K_{NO_x} \cdot \Delta NO_x + K_{O_2} \cdot \Delta O_2 : & \textit{else} \end{cases} . \tag{11}$$

The reinforcement depends on the O_2 concentration, since these agents can only change the distribution of the air, and a reduction of unused oxygen implies, that this redistribution caused a more complete combustion of the coal. Agent AGENTO2 is also rewarded, if the NO_x concentration or the total amount of used air decreases:

$$r^{AgentO_2} = \begin{cases} -10.0 : & \textit{any treshold violated} \\ K_{NO_x} \cdot \Delta NO_x + K_{air} \cdot \Delta Air : & \textit{else} \end{cases} . \tag{12}$$

Any violation of thresholds for process data, that are defined by safety precautions of the plant, results in a very strong punishment. The terms K_{NOx}, K_{O2} and K_λ allow to balance the importance of the NO_x concentration and the efficiency value.

3.5 Results

To reduce the exploration time for the plant, we pre-trained our multiagent-approach on past process data. This is a kind of supervised reinforcement learning. The decreasing of cluster error documented the adaptation of the neural gas towards the distribution of process situations in the input space.

In Fig. 13 comparison of the standard conventional control scheme with fixed air distributions used previously and multiagent-reinforcement-system is given. The amount of used air could be reduced significantly by the reinforcement-system. In contrast, both the NO_x and O_2 waste-gas concentrations remained at the same level, but the potential for NO_x and O_2 reduction vanishes with increasing load factors of the power plant. During these experiments the power plant worked with a load of about 90%.

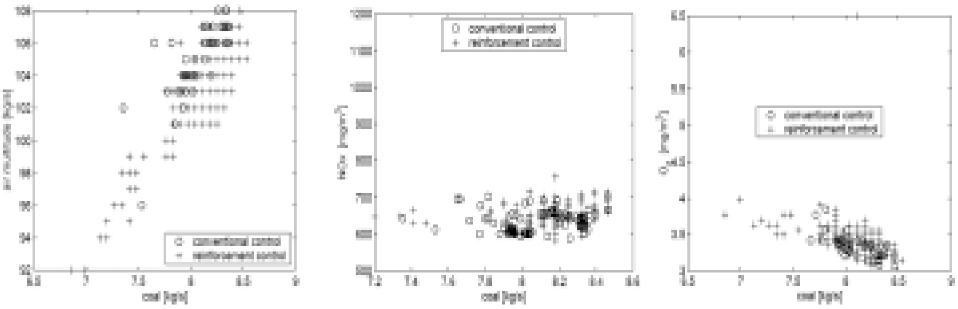


Fig. 13. Comparison of the conventional and reinforcement-based control schemes by for a time period of about 6 days

4. CONCLUSIONS

In this paper we have presented intelligent control solutions for some complex combustion processes. Firstly, modelling problem was studied that originates from the fluidized bed combustion process, specifically models for the flue gas SO_2 content were identified using soft computing models. 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 NF 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 NF 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.

Secondly, we have presented a reinforcement-based multiagent approach based on neural networks to control a complex industrial combustion process. To cope with both the tremendous action and situation space of the power plant, we decomposed the complex system into several agents. The proposed multiagent-reinforcement-system consists of 4 agents, which are realized by relatively simple neural function approxirnators. Neural function approximators are very useful, because they can generalize the expected return of state-action pairs the agent actually experiences to other regions of the state-action-space. Thus, the agent can estimate the expected return of state-action pairs that it has never experienced before.

Our results are very promising, and demonstrate wide applicability of intelligent control to complex burning processes. Nevertheless, the application of computational intelligence to these demanding control problems represents also a great challenge.

REFERENCES

1. Sutton R.S., Learning to predict by the methods of temporal differences, *Machine Learning*, 3:9-44, 1988.
2. Watkins Ch., Dayan P., Q-learning, *Machine Learning* 8, pp. 279-292, 1992.
3. Karray F.O., de Silva C.W., *Learning and Adaptation in Complex Dynamic Systems*, In Jain L.C., de Silva C.W., eds., Intelligent Adaptive Control, pp. 25-40. CRC Press, Boca Raton, London, New York, Washington D.C., 1999.
4. Wu Q.M.J., Stanley K., de Silva C.W., *Neural Control Systems and Applications*, In Jain L.C., C.W. de Silva C.W., eds., Intelligent Adaptive Control, pp. 63-104. CRC Press, Boca Raton, London, New York, Washington D.C., 1999.
5. Sutton R.S., Barto A.G., *Reinforcement Learning: An Introduction*, MIT Press, 1998.
6. Gross H.-M., Boehme H.-J., Stephan V., *Sensory-based Robot Navigation using Self-organizing Networks and Q-learning*, World Congress on Neural Networks 96, San Diego USA, pp. 94-99, 1996.
7. Gross H.-M., Stephan V., Krabbes M., *A Neural Field Approach to Topological Reinforcement Learning in Continuous Action Spaces*, In Proc. WCCI-IJCNN'98, Anchorage, pp. 1992-1997. IEEE Press, 1998.

8. Martinetz T.M., Schulten K., *A "neural gas" network learns topologies*, In Kohonen T., Makisara K., Simula O., Kangas J., eds., Artificial Neural Networks, pp. 397-402., Elsevier Amsterdam, 1991.
9. Jang R.-S., ANFIS: Adaptive Network based Fuzzy Inference Systems, *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 23, No. 3, pp. 665-685, 1993.
10. Chiu S., Fuzzy Model Identification Based on Cluster Estimation, *Journal of Intelligent & Fuzzy Systems*, Vol. 2, No. 3, 1994.
11. Takagi T., Sugeno M., Fuzzy identification of systems and its application to modeling and control, *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, pp. 116–132, 1985.
12. Hellendoorn H., Driankov D., *Fuzzy Model Identification*, Springer-Verlag, Berlin, 1997.
13. Ćojbašić Ž., Ćojbašić Lj., Nikolić V., Fuzzy and neuro-fuzzy systems in problems of process control and modeling: possibilities and some aspects of application, *Journal of Process Technology*, Vol XXV, No. 3, Belgrade, pp. 164-167, 1999.
14. Leppäkoski K., Mononen J., Kortela U., Kovács J., *Integrated optimisation and control system to reduce flue gas emissions*, 4th IFAC/CIGRE Symposium on Power Plants & Power Systems Control 2000, Brussels, Belgium, 2000.
15. Herrera F., Lozano M., Verdegay J. L., Tackling realcoded genetic algorithms: Operators and tools for behavioral analysis, *Artificial Intell.Rev.*, vol. 12, pp. 265–319, 1998.
16. Ćojbašić Ž., *Development of New Intelligent Adaptive Fuzzy and Hybrid Control Systems*, Ph.D. Thesis, University of Niš, Faculty of Mechanical Engineering, Niš, 2002.
17. Ikonen E., Kortela U., Dynamic model for a bubbling fluidized bed coal combustor, *Control Engineering Practice*, 2, pp. 1001-1006., 1994.
18. Karppanen E., *Advanced control of an industrial circulating fluidized bed boiler using fuzzy logic*, doctoral dissertation, Department of Process Engineering, University of Oulu, Finland, 2000.
19. Mitić D., *Model of bed for FBC of solid fuels*, Master thesis, University of Niš, Faculty of Mechanical Engineering, Niš, 1985.
20. Mihajlović E., *Influence of power and design parameters of bed for FBC of solid fuels to the* SO_2 *emission*, Master thesis, University of Niš, Faculty of Mechanical Engineering, Niš, 1995.
21. Minčić G., *Heat exchange between CFC and surfaces in the bed*, Master thesis, University of Niš, Faculty of Mechanical Engineering, Niš, 1995.
22. Oka S., *Fluidized bed combustion – processes and application*, Yugoslav thermal association, Belgrade, 1994.

INTELIGENTNO UPRAVLJANJE SLOŽENIM PROCESIMA SAGOREVANJA

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U radu su razmatrani inteligentni pristupi upravljanju složenim procesima sagorevanja. Razvijene su uspešne primene računarske inteligencije za modeliranje, identifikaciju i upravljanje termoenergetskim postrojenjima. Konkretno, razmatran je neuro-fazi pristup modeliranju procesa sagorevanja u fluidizovanom sloju kao i inteligentno procesno upravljanje na bazi razvijenih modela. Osim toga projektovana je i nova upravljačka šema za industrijski proces sagorevanja uglja u termoelektrani, zasnovana na obučavanju sa osnaživanjem u kombinaciji sa veštačkim neuronskim mrežama. Ovi inteligentni upravljački pristupi su usmereni na zadovoljavanje sve strožijih zahteva u pogledu zaštite okoline uz istovremenu maksimizaciju faktora efikasnosti i uz simultano održavanje drugih parametara procesa u definisanim granicama.

Ključne reči: *inteligentno upravljanje, procesi sagorevanja, fazi sistemi, neuronske mreže, obučavanje sa osnaživanjem, genetski algoritmi*