MULTI AGENT SIMULATION IN INFERENCE EVALUATION OF STEAM BOILER EMISSION

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ABSTRACT

A multi agent based prediction monitoring system has been developed. The proposed multi agent system combines two types of autonomous agents – primitive and intelligent agents. Multi modeling techniques to predict the immeasurable gas components and following aggregation, simulation and successive optimization are used. The presented approach is a combination of Predictive Emission Monitoring System (PEMS) and Continuous Emission Monitoring System (CEMS) in order to improve the reliability of the developed monitoring system by generating replacement data in a case of sensor failure.

INTRODUCTION

The problem of clean air and waste gas emissions are now an object of governmental regulation in most of the countries. Ecological monitoring became a wide market and field of extensive R&D. The investment load is particularly heavy for the East European countries, where the scale of environmental protection until a relatively short time ago was out of the national proprieties. Thus the strategy of emission monitoring still represents an actual challenge for investment and research (Gimonez et al.; Hadjiski and Boshnakov 2004).

The Continuous Emission Monitoring Systems (CEMS) is well known conventional design (Eberhard 1995). It can monitor flue gas emissions continuously on the base of direct measurements. However it has the disadvantages of the high installation and maintenance cost. There is a strategic need to develop alternative systems with an acceptable and competitive cost (Eberhard 1995; Ghien et al. 2003; Gimonez et al.; Hadjiski and Boshnakov 2004). The concept of a Predictive Emission Monitoring System (PEMS) (Eberhard 1995; Gimonez et al.) is to use the operating parameters of the stationary emission source in order to predict emissions through mathematical model. The main difference between CEMS and PEMS is that the PEMS does not need actual pollutant monitoring analyzers. Before commercial operation several auditing tests must be conducted on both CEMS and PEMS to be certified. Recently several states in the USA have accepted the PEMS as a primary or alternative monitoring system. In the near future the same kind of regulations should be adopted in EC (Gimonez et al.). The main problem for PEMS is to build adequate model in order to pass the accuracy (RATA) test.

The goal of this study is to set up a PEMS in a coal – fired steam boiler by using Multi Agent System (MAS) approach (Wooldridge 2004). Our MAS realization combines two types of autonomous agents – (i) primitive agents, which can only communicate each other and perform direct algorithmic calculations or routine data performance and (ii) intelligent agents, which in addition are able to learn, to make decision, to be adaptive, to do simulation and optimization. The next peculiarity of our approach is that in contrast to the established unimodel realizations (Ghien et al. 2003; Gimonez et al.) we use multi model predicting of immeasurable gas components and following aggregation, simulation and successive optimization. The third feature is the combination of PEMS and CEMS in order to improve the reliability of the monitoring system by generating replacement data in a case of sensor failure.

The selected platform for multi agent architecture realization is JADE (www.jadeworld.com). The agent's software is written in Java. This ensures accordance with all FIPA specifications (www.fipa.org).

COST ORIENTED DESIGN OF EMISSION MONITORING SYSTEM

According to the recent world experience (Ghien et al. 2003) installation and maintenance cost of PEMS are at least two times less than the corresponding expense for CEMS. In the case under consideration in this paper multiple sources must be covered by integrated monitoring system. Following the best practices in the USA and Europe it is preferable to use PEMS not only for emission monitoring but in the future re-engendering as a base for a tool to optimize combustion process (Gimonez et al.; Hadjiski and Boshnakov 2004). Thus the adopted configuration consists of minimal number of gas analyzers with multiplexing of

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compulsory measurement points. As a result in admissible in conformity with regulations a sample time problem appears. Mathematical models must generate the insufficient report data. In this approach a small part of the data is received from direct measurements by CEMS, and the rest – thought PEMS. The cost analysis shows a big advantage of the proposed combined system mainly due to the reduction of analyzers and operational savings.

SIMULATION BASED DATA RECONCILATION

The inference in PEMS based on the secondary measurements is specific in any particular realization. In our case the preliminary investigations show strong variability depending on: the type of approximation model, the set of input variables for each model, the aggregation approach and parameterization. In the present paper this mixed combinatorial problem has been solved on the base of successful simulation following the next scheme for each inferred gas component:

a) Deriving a cluster of realizations for a given model from the data, varying input sets of secondary measurements.
b) Deriving a set of clusters for three types of data driven models: interpolation-based, regression-based and neural networks-based.
c) Simulation of the gas concentration behavior in 30 minutes intervals based on each already derived model in a form of discrete time series.
d) Aggregation of different models.
e) Selection of the best combination of weighted individual models by optimization.
f) If it's necessary adaptation of the selected hybrid model.

After the computer simulation the adopted multi – model based PEMS must pass the Relative Accuracy Test Audit (RATA) in order to be certified by the authority.

MULTI AGENT ARCHITECTURE

The main reasons to accept multi-agent architecture could be summarized in the following way:

- Variety of sources of information: Decentralized Control Systems (DCS), SCADA, CEMS.
- Different type of information – technological data, status signals.
- Asynchronous data flow.
- Multi-model approach for data reconciliation.
- Computer simulation as a permanent procedure.
- Necessity of intelligent operations – learning, adaptation, reconfiguration.
- Irregular internal data exchange.

The architecture of the Multi-Agent System (MAS) (Figure 1) is structured in four layers: data processing, model-based time series generation, aggregation and data reconciliation, standard processing and reporting. Each layer consists of several autonomous agents. These layers are functional, not hierarchical ones. Two types of agent are accepted:

- Primitive Agents (PA), which accomplish algorithmic calculation and data base formation.
- Intelligent Agents (IA), which undertake intelligent functions like learning, adaptation, decision making.

All autonomous agents correspond to the FIPA specifications (www.fipa.org). The multi agent architecture allows a distributed intelligent system to be realized independently of the space properties of the Thermal Power Plants (TPP).

AGENT FUNCTIONS

MAS consists of thirteen autonomous agent altogether. The agents can communicate bilaterally.

The agents of the data processing layer (A_{11} - Raw data collection agent; A_{12} – Raw data preprocessing agent; A_{13} – Agent for preliminary data base) receive, synchronize, and arrange data from the sensors, make intelligent filtration and verification of the data, analyze the status signals from the preliminary data base.

Agent A_{12} analyses the condition of the whole measurement system – measurement equipment, analyzing equipment, emission source, if the waste treatment station works or not. It forms a message for reliability of the data according to the requirements of the regulations. This agent compares the data of the technological parameters and the status signals and it communicates to agent A_{13} to transfer the processed data.

Agent A_{13} communicates to agents A_{12}, A_{41}, A_{42} for data receiving/sending. It evaluates the completeness of the data, which are necessary for agents A_{21}, A_{22}, and A_{23} performance. Agent A_{13} communicates to agents A_{24} and A_{31} to limit the alternative aggregations in the cases when some of agents A_{21}, A_{22}, or A_{23} cannot generate data because of leak of measured information.

The agents from the data generation layer (A_{21}, A_{22}, A_{23}, A_{24}) realize three different type of models – interpolation (A_{21}), statistical (A_{22}) and neural network (A_{23}) for each predicted gas component – NO_x, SO_2, CO, O_2. Through simulation each model originates a cluster of time series by varying the sets of input variables and model structures.

These agents are intelligent ones – they could learn from current data, adapt/change model structure and parameters, make some decisions.

The generated data for each 30 min test intervals are collected into an intermediate database, which is accomplished by primitive agent A_{24}.

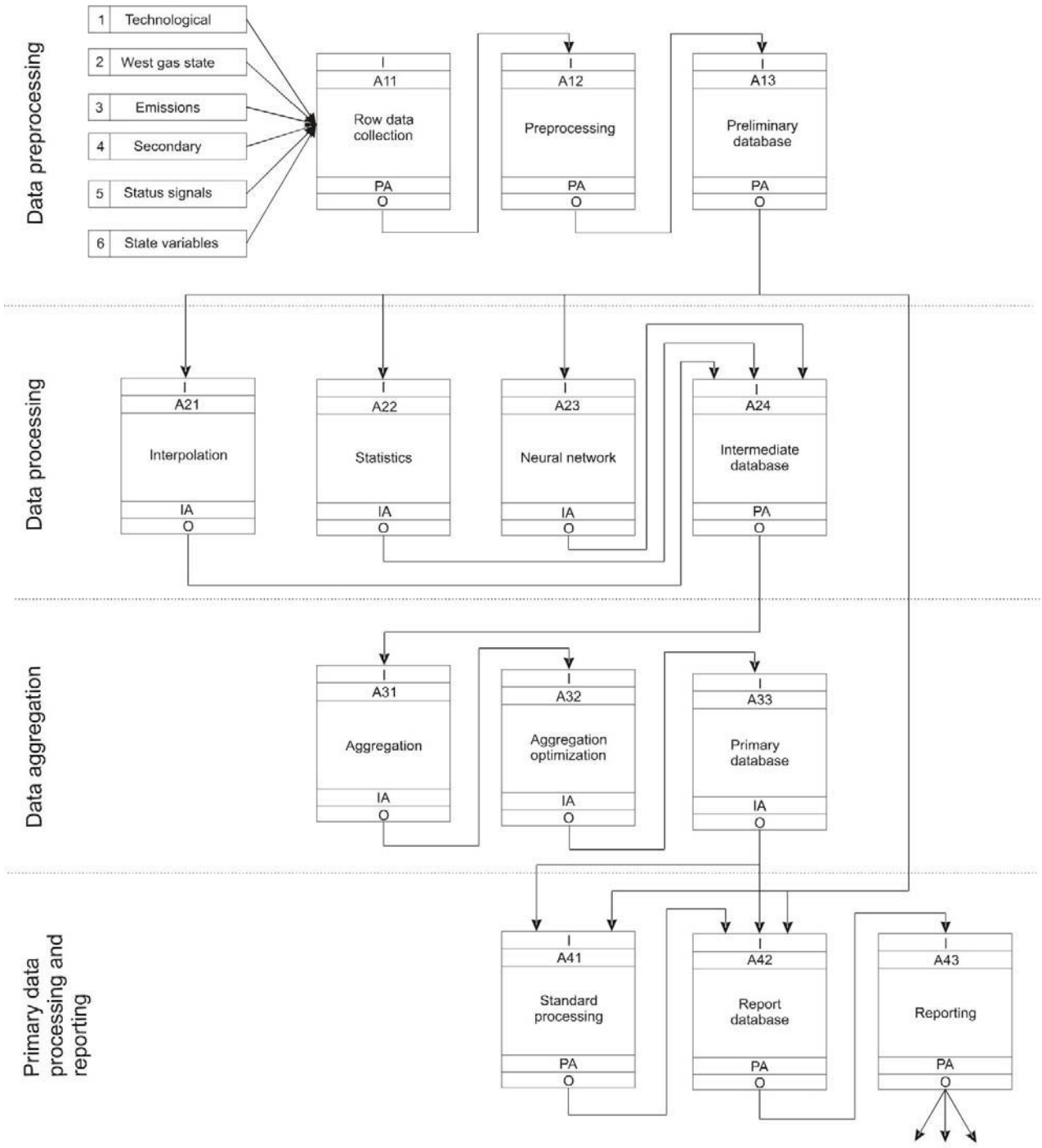

Figure 1: Structure of the multi agent based Predictive Emission Monitoring System

Agent A_{21} receives data from agent A_{13}. The mathematical model uses data from DSC and CEMS. This agent reconstructs the values of the analyzed gas emission parameters during sampling time 2 minutes on the base of interpolation model using the analyses data from CEMS, performed during bigger sampling time. The reconstruction of the missed values of the gas emissions is carried out using combined approach,

including interpolation and mathematical model prediction. The implemented approach possesses ability to evaluate the necessary values of the state parameters and the emissions of the combustion process. During the interpolation function y = f(x) (equation 1) is defined. The interpolation is accomplished using Lagrange polynomial.

$$y = L_0(x)y_0 + L_1(x)y_1 + \ldots + L_n(x)y_n, \qquad (1)$$

where $(x_0, y_0), (x_1, y_1) \ldots (x_n, y_n)$ are the coordinates of points A_i - the direct measurements from CEMS.

The data reconstruction of the concentrations is performed as follows:

$$C_i(t_j) = C_i^{int}(t_j) + \Delta C(t_j) \qquad (2)$$

where

$C_i(t_j)$ is the concentration of the i-component for the desired time t_j;

$C_i^{int}(t_j)$ is the evaluated value of the concentration;

$\Delta C_i(t_j)$ is the correction value calculated by the mathematical model using indirect sources of information.

The general mathematical model is defined as

$$\Delta C_i(t_j) = f(B(t_j), V(t_j), O_2(t_j), \ldots) \qquad (3)$$

where the more important sources of indirect information are: $B(t_j)$ - the fuel flow rate; $V(t_j)$ - the air flow rate; $O_2(t_j)$ - the oxygen content in the combustion gases.

A comparison of the experimental values of the nitrogen oxides NO_x concentrations (*) and the corresponding calculated values NO_x obtained from the agent is presented at Figure 2. The relative mean square error is 3.8 %.

Agent A_{21} tunes the mathematical model during decreasing of the prediction accuracy. As well as it sends the calculated parameters values to agent A_{24}, realizing the intermediate data base.

Agent A_{22} realizes statistical model and receives data from agent A_{13}. The model uses data from the DCS to evaluate the gas emissions. Under decreasing the prediction accuracy agent A_{22} tunes the regressive mathematical model. Agent A_{22} sends the calculated parameter values to the agent A_{24}, realizing the intermediate data base.

Agent A_{23} realizing neural network model uses data from the unit DCS. The developed neural network models predict the concentrations of O_2, NO_x and SO_2 in each of the gas outlet ducts A and B.

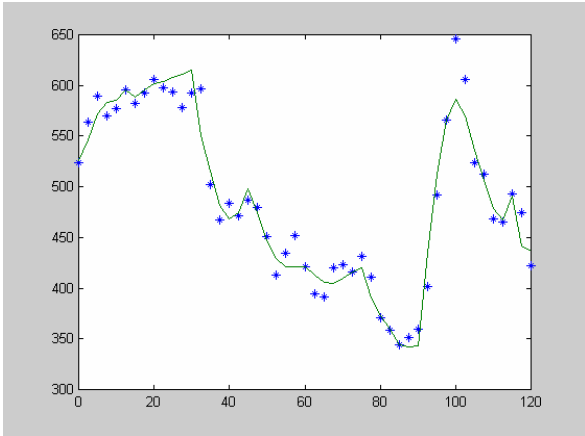

Figure 2: Experimental and calculated values of the NO_x concentrations

The highest prediction accuracy is achieved by using two layers neural networks of Cascade-Forward Backdrop type with sigmoid transfer function in the hidden layer and with linear one in the output layer. The input variables $X_1, X_2, \ldots, X_N$ are anlogous to these ones, used by the statistical model (agent A_{22}). One of the developed neural networks, namely for prediction of the emissions of nitrogen oxides NOx in gas outlet duct A (NO_x^A) is given at Figure 3.

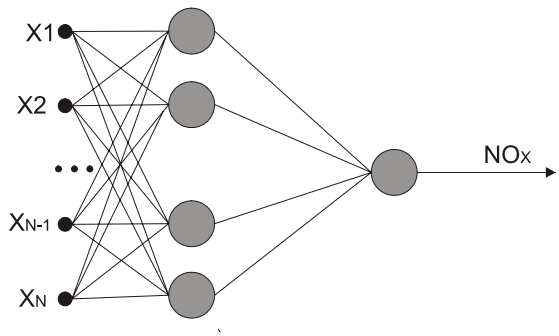

Figure 3: Neural network in Agent A_{23} for each prediction of NO_x

The received simulation results are summarized in Table 1. The mean square errors of the predicted values of the gas concentrations given by agent A_{23} compared to the real experimantal data are presented.

Table 1: Results from agent A_{23} performance

Gas	O_2^A	O_2^B	NO_x^A	NO_x^B	SO_2^A	SO_2^B
Mean Square Error, %	2.71	2.94	6.22	6.99	2.77	3.07

The prediction ablility of agent A_{23} is illustrated at Figure 4.

When the prediction accuracy decreases agent A_{23} tunes the neaural network model. Agent A_{23} sends the calculated parameters value to agent A_{24}, realizing the intermediate data base.

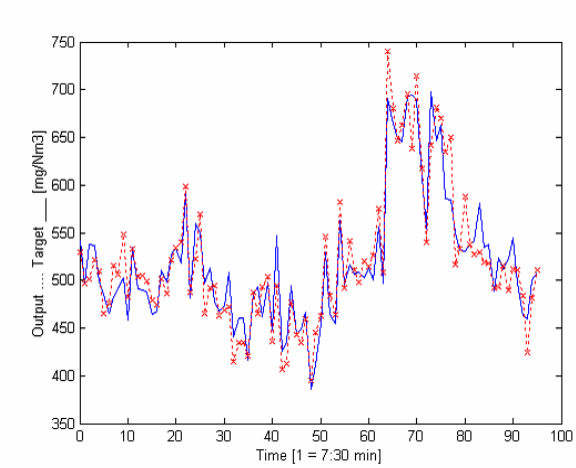

Figure 4: Results from Agent A_{23} performance

Agent A_{24}, realizing the intermediate data base communicates to agents A_{21}, A_{22} and A_{23} to receive data and to agent A_{31} to send the required data. It forms rules for possible aggregation in agent A_{31}.

The aggregation layer consists of three agents: two intelligent (A_{31}, A_{32}) and one primitive (A_{33}). The agent A_{31} aggregates different time series by weighted blending with weights, given from the optimizing agent A_{32}.

Agent A_{31} defines the aggregation method and the initial settings of the aggregation procedure. It communitates to agents A_{24} and A_{32}. Agent A_{31} forms time series at given optimization stage.

Agent A_{32} is carrying out the aggregation optimization. It calculates the difference between the predicted values by the autonomous agents A_{21}, A_{22} and A_{23} and the current aggregated predictive model M(κ). Agent A_{32} defines the mean square errors of the prediction and the parameter varying in the aggregation procedure in the next step (κ+1). It stores the necessary data for evaluation of the permanent parameters, which do not vary at each step. Agent A_{32} stops the optimization process and forms the optimal prediction set, which contains primary data for the given 30 minutes interval. This agent communicates to agents A_{31} and A_{33}.

The best resulting time series are collected as reconciliated data in the agent for primary database A_{33}.

The agents from fourth layer make standard processing on primary data (A_{41}) according to the regulations; form the complete report database (A_{42}) and provide all the requested reports (A_{43}). All of them are primitive agents.

MULTI AGENT SYSTEM SOFTWARE PLATFORM

After comparative analysis of variety of MAS platforms like JADE, ZEUS, Grasshopper etc., Jade (Java Agent DEvelopment framework) was accepted for first realization of MAS based environmental monitoring system. JADE is open source software to develop agent-based application in compliance with the FIPA (Foundation for Intelligent Physical Agents) specifications that provide the normative framework within developed agents can exist, operate and communicate. In JADE agents are implemented as one thread per agent. JADE is based on the Java language and supports scheduling of cooperative behaviors and structuring complex tasks as aggregation of simpler ones. JADE allows remote management, monitoring and controlling the status of agents.

APPLICATION

Described above Multi Agent System (MAS) was developed for the purposes of ecological monitoring of waste flue gases from coal-fired steam boilers in Thermal Power Plants. A cost oriented system was commissioned as a combination of Continuous Emission Monitoring System (CEMS) and Predictive Emission Monitoring System (PEMS). The carried out simulation tests with NO_x and SO_2 concentration have shown high accuracy of the Predictive Emission Monitoring System (PEMS), with a standard deviation according a special direct measurements lying in the interval 3 – 7 %.

CONCLUSIONS

The computer simulation is suitable approach for building a Predictive Emission Monitoring Systems (PEMS) for coal-fired steam boiler. The combination of direct and secondary measurements provides acceptable initial and maintenance costs. The multi agent part of the project is now in development phase based on Jade concept, mentioned above and it will be incorporated in the existing DCS before the end of the year.

ACKNOLEDGMENTS

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