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LOW-RANK FIRED BOILERS MONITORING BY APPLYING HYBRID MODELS

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Abstract. In the paper some practical aspects of hybrid modeling application in power plant monitoring are under consideration. In the case of low-rank lignite firing, a numerous problems arise, due to the lack of measurements of the key process variables such as coal main characteristics – mineral composition, caloricity, moisture; flame characteristics – geometry; space distribution of particles, speeds, chemical contents of gases, temperature, pressure; the properties of coal dust after milling system. Inferred variables and hybrid modeling based monitoring of the hard measurable variables is discussed. In the paper the problems with combination of direct and inferred model's input data are considered. The aggregation of different kind of mathematical models is applied. A number of important cases are presented by applying the inference approach and hybrid modeling: (i) the space position of the flame in combustion chamber, (ii) indirect estimation of the main characteristics of the fired coal, (iii) determination of the admissible control range of the steam boilers. Some of the proposed schemes for monitoring have been applied in 210 MW boilers. The rest of them give promising simulation results and after certain additional engineering will be implemented too.

Key Words. hybrid modeling, inference measurement, low-rank lignite, monitoring, steam boiler

1. INTRODUCTION

In the recent years the monitoring of the powerful steam generators is a subject of more and more researches and applications, made by the leading firms in the field of automation. The above is a result of a set of factors becoming very important in the contemporary conditions of power generation. The systems for full monitoring as well as other construction and technological improvements in the frames of common management of steam generators must assist for:

- Higher competition ability in the conditions of structure changes of energy producing (for example – deregulation);
- Providing timely information for undesired effects as a result of fuel characteristics changes, load deviation or worsening of the technical parameters of the boiler (faults, slag formation, precipitation);
- Improving the information for operational decision making, related with optimization of the current operating conditions;
- More detailed estimation of the steam generators regimes correspondence with the ecological requirements;
- Estimating the life and remaining resource of equipment;

The realization of the above tasks for the steam generators firing low rank lignites is connected with a set of difficulties due to the lack of direct information for lots of parameters of the boiler, like main coal characteristics – calorisity, chemical and mineral content, humidity; coal dust quality after mill – quality of milling, calorisity; parameters of the flame – configuration, position – temperature fields and speed; concentration of coal dust and gases;

compactness of the burners against leaking unorganized air.

Since for the steam generators firing low-rank lignites the most specific are processes of coal milling and burning, this paper considers mainly problems for inference estimation and hybrid modeling of these particular processes.

The modeling of processes which are relatively rare (e.g. slagging) puts complicated problems of estimation of the model's adequacy.

The interest of using combined (hybrid) models is growing in the last few years [1,2,3,4,5,8,9]. This interest is caused by the possibility to use different type of information with different type of models [4]. Introducing the prior information in the models of black box type is considered to be effective because of the improvement of the predicting features of the model in larger area of regimes [5]. Prior knowledge in the form of First Principle Models [1,8], or giving the structure [9] is essential for development of hybrid models using neural networks. Neural networks appear to be convenient for creation of hybrid models by combination of first principle models with linear dynamic models [8].

Different methods for aggregation of separate models are discussed in [1,2]. In [2,3] is shown that applying of fuzzy logic approach is effective for hybrid models development. When developing hybrid models for very complicated plants, Fuzzy Cognitive Maps (FCM) could be useful [3].

Creation of hybrid models imposes to take into account specific features of each case under consideration. That's why, the coordination or aggregation of the separate models is independent complicated problem.

In the following presentation the combining of most common linguistic models, presented by single tones is also considered. For limited and basically qualitative information this possibility could be effective.

In the present research real data for hybrid models are used mainly from 210 MW steam boilers burning low-rank lignites, but a part of the received results (e.g. estimation of coal quantity), could also be transferred on the other boilers firing the same kind of fuel.

2. HYBRID MODELING

From the numerous results, obtained in the area of the hybrid modeling, in this paper only those, related with combining of different type continuous models in the conditions of lack of important measurements are under consideration. The research is addressed to monitoring of complicated processes in the pulverization systems and combustion chamber of low-rank fired boilers.

Data acquisition necessary for the monitoring is carried out in accordance with the scheme shown in Fig.1

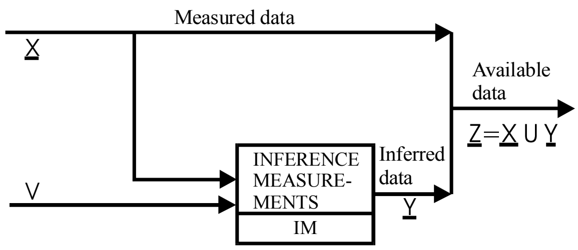


Fig. 1 Available variables formation

On the base of measurable input variables **X** and possible additional linguistic or other quality information **V**, inferred variable **Y** are formed. These could be presented in explicit form:

$$\boldsymbol{Y}=f(\boldsymbol{X},\boldsymbol{V}) \qquad (1)$$

or in implicit form:

$$F(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{V})=0 \qquad (2)$$

The denotations $f(.)$ and $F(.)$ have the sense of operators, which in a particular case can be of function type. The available data $\boldsymbol{Z}$ are union of measured and inferred data:

$$\boldsymbol{Z}=\boldsymbol{X} \cup \boldsymbol{Y} \qquad (3)$$

Inference measurements and hybrid modeling are carried out in accordance with a unified generalized scheme shown in Fig.2.
In this scheme the following operators are included:

1. Selectors S_{xx}, which take into account the condition that the different operators for information processing $H_{xx}(.)$ use different quantity and/or quality information Z_{xx}.

2. Functional operators H_{xx}(s) are of explicit or implicit type by analogy with (1) and (2). For implicit functional operators of type (2) iterative procedures for minimization of the differences are used:

$$\Delta_{xx}(k+1)=U_{xx}(k+1)-H_{xx}(\boldsymbol{U}(k), \boldsymbol{Z}_{xx}, U_{xx}) \qquad (4)$$

where k is the number of iteration step.

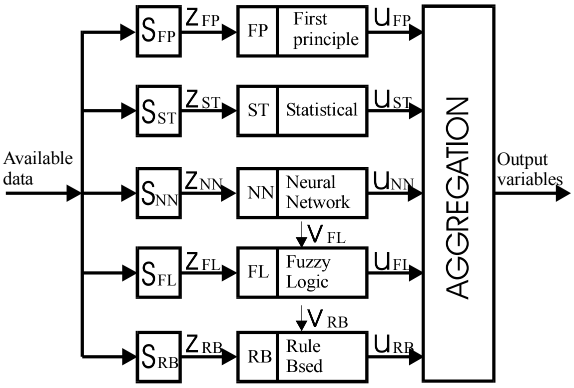


Fig. 2. Generalized scheme of hybrid modeling

Functional operators $H_{xx}(.)$ can be mathematical models and/or calculation procedures of different type: First Principles (FP), Statistics (ST), Neural Networks (NN), Fuzzy Logic (FL) and Rule Based (RB).

3. Aggregation procedure, which incorporates the all partial model/inferred measured outputs U_{xx} in a hybrid output $\boldsymbol{U}$.

$$\boldsymbol{U}=L(U_{xx}) \qquad (5)$$

Aggregation methods defined by operator $L(.)$ are discussed in [3].

The common procedure for inference measurements from Fig. 2 usually is considerably simplified either by the size of the input information and by the number and complexity of the functional operators $H_{xx}(.)$ and $L(.)$. It has to be noted that the generalized procedure from Fig. 2 allows developing the hybrid model to juxtapose unified components using available input data as well as to aggregate the separate models.

Using the scheme form Fig. 2, it is possible to create complicated multifunctional technological constraints.
Below some important cases of application of the above discussed approach to low rank fired steam generators are considered.

3. FLAME POSITION ESTIMATION

Flame position is an important characteristic of the combustion as well as hydrodynamic processes in furnace chamber. Because of the low caloricity of the low-rank coal, its often-changing composition and combustion characteristics, the processes of combustion are closely connected with the functioning of the pulverizing system. The boilers considered in this paper have eight tangential burners, which determine the flame position (Fig. 3). The flame could move in horizontal plane because of wrong operations namely not coordinated work of the burners in exploitation (normally 5-7) or due to emergency situations. The temperature maximum in the chamber could have an axial displacement as well. These cause a set of harmful effects: uneven thermal load of the furnace chamber walls, changes in the ratio of radiation to convection heat exchange; increasing the water flow for the atemperators; increasing the boiler thermal looses because of the higher temperature of the flue gases. In some cases a slag formation occurs in the upper part of the furnace chamber. Because of that, the center flame positioning is of vital importance for effective and safety boiler exploitation. The flame position monitoring allows estimating the changes in the work of the mill fans due to wearing out or air leakage increasing. The problem with the flame position is related with the visualization of the temperature field in important intersections (Fig. 3b).

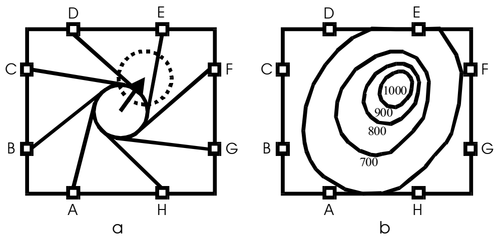


Fig. 3. The flame configuration in the furnace chamber

The structure scheme of hybrid modeling of the flame status in the furnace chamber is shown in Fig.4.

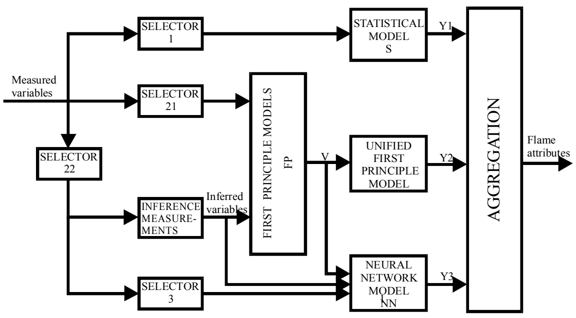


Fig. 4. Scheme of hybrid modeling of the pulverizing system and flame cinfiguration

It includes aggregation of three different models – statistical (ST), first principle (FP) and neural network based (NN).

3.1. Statistical Model

The only inputs of the statistical model are the inlet temperatures of the drying shaft of each pulverizing system t^i_{dg} $(i=1,\ 8)$ and steam flow D_s. Regression equations for the temperature field in the plane of drying shaft entrance are used.

3.2. First Principle Model (FP)

This is a complex model, in which the separate models of each pulverizing system *(i=1, 8)* are incorporated.

The scheme of FP_i model of the i^{th} pulverization system is presented in Fig.5.

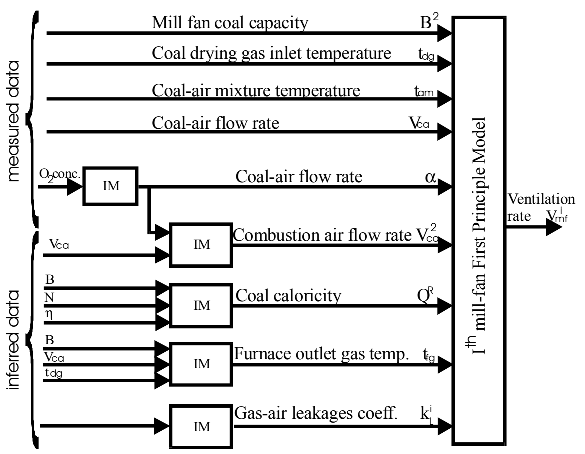


Fig.5. Separate mill-fan first principle model with directly measured and inferred input data.

In accordance with Fig.1, applying Inference Measurements (IN) a variety of input variables are formed. Some of IM operators are of FP type (IM_1, IM_2 and IM_4), but the rest are hybrid ones using NN and FL operators [1, 2]. Mass and heat balance equations are used to derive FP models for each mill-fan system on the base of the full available input data **Z**. As a result the ventilation rates V_{mf} of processing mill-fans are estimated. Geometric approach combined with rule base procedure is used to find the current position of the flame center. (Fig.3a.)

The information used in FP_i models is larger than it is utilized in ST model. FP model gives the information mainly according the geometry of the flame in the plane of the burners, while ST model estimates 2D temperature field, e.g. each of them gives different information for the flame in different space locations. The aggregation of the ST and FP models is accomplished by linear combination of the two outputs and weight's optimization [1].

Some results of the hybrid modeling of the flame configuration are presented below.

3.3. Neural Network Based Model

In order to supplement the above model, a NN based model is now in preparation. It is well known that neural networks can approximate large classes of non-linear systems to a desired degree of accuracy [2,9]. Using this property, NN model is developed in the following sequence:

1. A full 3-D FP model of the combustion process in the furnace chamber using difference elements method is developed [7]. As input data for the model measured data and inferred data from mill-fan FP model are used.
2. A lot of offline simulations are carried out in order to supply the synthetic data for NN learning. These data are now in preparation.
3. A Multy Layer Perception (MLP) type neural network is learned by Back Propagation (BP) method using obtained database in order to model particular intersections into the combustion chamber. In this way the extremely time consuming numerical 3-D model will be replaced by a very fast NN model, which approximates the only desired parts of the complete model.

Preliminary results received by now are very promising.

4. COAL HEATING VALUE ESTIMATION

The low value and often changing caloricity of the low-rank lignites are the basic disturbance for the power plant unit. The direct measuring of the caloricity is impossible. Because of that the current estimation of the fuel caloricity is of great importance for stable and effective combustion. In Fig. 6 a hybrid scheme for coal heating value estimation is shown.

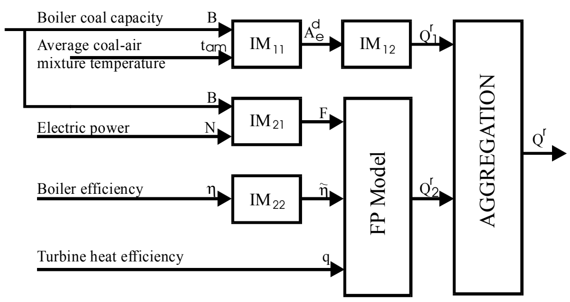


Fig.6. Hybrid model based coal calorisity estimation

Two models are used in this scheme:

1. Statistical model (ST), in which using subsequently regression analysis the values of ash content of a dry mass A_e^d and fuel caloricty of working mass Q_I^r are estimated [11]. This model is suitable only for coal with steady correlation between moisture content W^r and ash content A^d. Also such type of inference measurement is admissible only in a case of steady state boiler regime.
2. First Principle model in which coal heat value is calculated on the base of the relation:

$$Q_I^r(t) = \frac{q(t)}{\eta_B(t)F(t)} \tag{6}$$

where q is the relative turbine heat consumption, η_B is the boiler efficiency and

$$F(t)=\frac{1}{N(t)}\int_0^t \omega_{NB}(\tau)B(t-\tau)d\tau \qquad (7)$$

where F is the relative coal consumption, $N(t)$ – current power demand, B – coal consumption, $\omega_{NB}(\tau)$- impulse transient function of the dynamic chanel “coal-power”.
Equation (7) takes into account dynamical connection between coal supply and power generated as a result. The dynamic characteristic $\omega_{B}(\tau)$ is determined by identification methods[6].

Data for the boiler efficiency η_{B} are received from the DCS, but are filtered by operator IM_{22} to avoid dynamical discrepancies.
Aggregation is accomplished by weighted linear combination of separate models outputs.
Some experimental results of the proposed system are presented below in Table 1.

Table 1.

	W^r	$A^d{}_m$	$A^d{}_e$	ΔA^d	$Q^r{}_m$	$Q^r{}_e$	ΔQ^r
	%	%	%	%	kcal/kg	kcal/kg	%
1	50.2	38.1	38.3	-0.50	1481.6	1457.2	1.65
2	50.7	37.6	38.9	-3.46	1473.4	1439.7	2.28
3	50.0	38.1	37.0	2.88	1490.0	1495.0	-0.34
4	49.8	40.5	40.2	0.74	1409.1	1401.9	0.51
5	49.4	39.9	38.2	4.26	1447.6	1460.1	-0.86
1	53.1	30.4	33.3	-9.80	1627.9	1602.8	1.54
2	51.6	31.9	32.8	-2.82	1645.3	1617.3	1.69
3	54.3	32.9	32.7	0.61	1486.3	1620.2	-9.01
4	51.8	33.5	32.6	2.69	1578.9	1623.1	-2.80
5	51.5	35.0	33.3	4.86	1538.6	1602.8	-4.16

5. ESTIMATION OF ADMISSIBLE BOUNDS OF POWER GENERATION

To know the admissible bounds of variation of power generation is important information when forming the proper scheduling for each unit. When TPP works as deregulated one, this information is also useful for centralized dispatching. In [10] an inference measurement approach is proposed. Corresponding structure scheme is shown in Fig. 7. The leading variables are: the coal-air mixture temperature t_{am}, the number of switched-on mill-fans n and ash content of a dry mass A^d, estimated according the system presented in Fig. 6. The admissible bounds are defined mainly because upper and lower temperature of the mill-fan are explicitly specified at 200°C and 150°C correspondingly. Experimental results of performance of the proposed system are shown below in Fig.9.

6. APPLICATIONS

Some of the above discussed results have been applied in 210 MW boilers firing different kind of lignites.

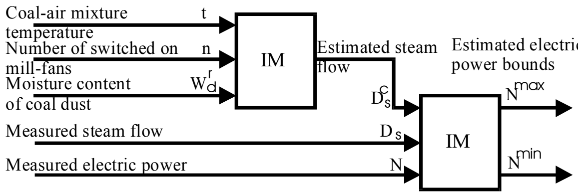
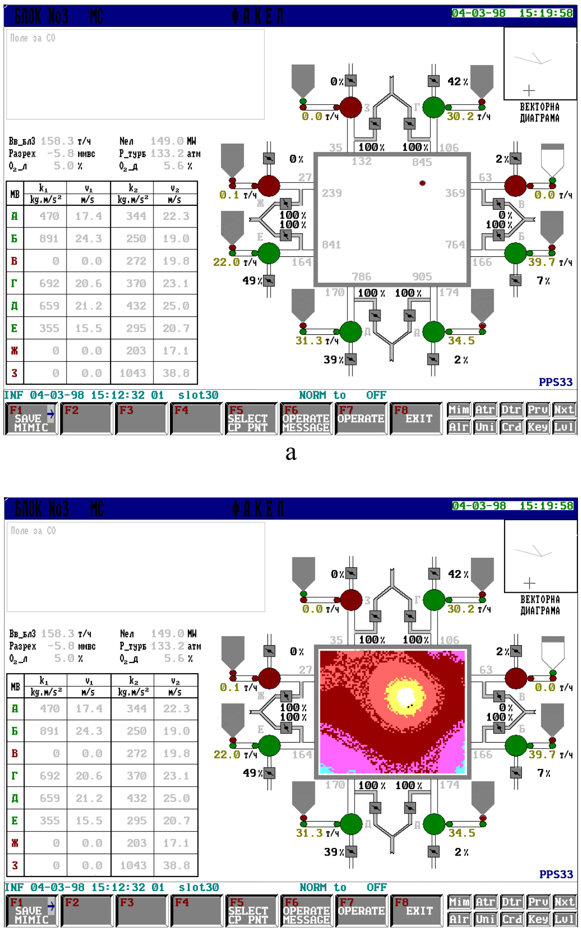


Fig.7. Electric power bounds estimation.

- A hard copies of screens for flame center position and temperature distribution monitoring of 640 t/h boiler in TPP “Bobov dol”, Bulgaria, realized using hybrid models according Fig.5 is shown in Fig.8.



a

b

Fig.8 Display of flame center position.
First principle model (FP) of each mill fan is used as well as a rule based approach to incorporate the separate models into a common pulverization system model. A hybrid model is composed by combination with a statistical (ST) model in which a regressor is derived to transform the filtrated data form the temperatures of furnace gases supplied for coal drying in each mill-fan.

- Some results of hybrid model based system for coal caloricity estimation according Fig. 6 are presented in Table 1 for a 640 t/h boiler from TPP "Maritza East" 2. The accuracy for the calorisity estimation Q_e^l as well as the ash content A^d are completely satisfactory. The average deviations are under 3.5 % and only in separate cases they exceed 6 %.
- In Fig. 9 online estimations of upper and lower bounds of the admissible electric power generation for 210 MW unit from TPP "Maritza East" 2 are shown. The calculation module is realized following the scheme presented in Fig. 7.

7. CONCLUSIONS

Hybrid models for monitoring the processes of dust preparing and combustion of low-rank lignites in drum boilers are effective tool to overcome the lack of direct measurements of a set of key parameters. The combination of direct measured, inferred and linguistic variables allow to be used different type of models for the same process. By relevant aggregation of these models, higher accuracy of non-measurable variables estimation and prediction is achieved in comparison if using corresponding models separately. This fact is due to the different information used and processing in the separate models.

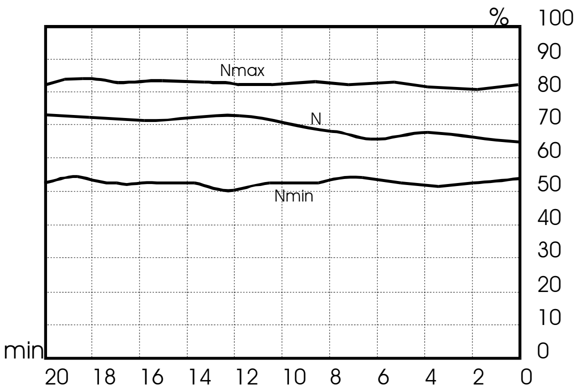


Fig.9. Estimation of upper and lower admissible bounds of the electric power.

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