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Modelling and analysis of electrostatic precipitator (ESP) in combustion process

Abstract. *The paper discusses modelling and analysis of electrostatic precipitator (ESP) used in industrial combustion processes. The main emphasis was put on numerical dependencies and physiochemical properties for effective combustion system control.*

Streszczenie. *W artykule omówiono modelowanie i analizę elektrofiltru (ESP) stosowanego w procesach spalania w przemyśle. Główny nacisk położono na zależności i właściwości fizykochemiczne w celu efektywnego sterowania układem spalania. (**Modelowanie i analiza elektrofiltru w procesie spalania**).*

Keywords: electrostatic precipitator, combustion, diagnosis.
Słowa kluczowe: filtr elektrostatyczny, proces spalania, diagnostyka.

Introduction

Coal is still the main fuel used in electricity generation around the world. Solid fuels, such as coal, often contain impurities such as nitrogen and sulphur that can increase pollutant emissions significantly.

There are new combustion techniques developed, such as reburning, air staging and flue-gas recirculation on one hand, but on the other hand the effectiveness of used electrostatic precipitators (ESP) decides on final emission.

Fossil fuel depletion forces the use of renewable fuels, such as biomass neither less in the existing coal-fired power stations, biomass is milled and burned simultaneously with coal. However, low-emission combustion techniques as well as biomass co-combustion have negative side effects both on emissions and combustion installations by increased corrosion, boiler slagging.

To minimize those effects, a proper combustion monitoring system needs to be applied. The way in which a pulverized fuel is burned largely depends on the degree of its granularity, among other parameters. Coal particles of between 5 and 400 µm in diameter are burned together in a swirling turbulent flame. Biomass burning stabilization is even more

The commonly applied, low-emission techniques of pulverized coal combustion use recirculation vortexes that lengthen the paths of the coal grains passing through the flame to minimize generation of thermal oxides of nitrogen (NOx) [1, 2].

In order to make combustion of pulverized coal more efficient and clean, it is necessary to measure its key parameters and associate them with electrostatic precipitator (ESP) outputs.

The paper discusses effectiveness analysis of electrostatic precipitator (ESP) used in industrial combustion processes. The main emphasis was put on numerical dependencies and physiochemical properties connected with fly ash granulation and composition.

The aim of ESP diagnosis in combustion process

An electrostatic precipitator (ESP) is a filtration device that removes fine particles e.g. dust and smoke, from a flowing gas using the force of an induced electrostatic charge minimally impeding the flow of gases through the unit.

The most basic precipitator contains a row of thin vertical wires, and followed by a stack of large flat metal plates oriented vertically, with the plates typically spaced about 1 cm to 18 cm apart, depending on the application. The air or gas stream flows horizontally through the spaces between the wires, and then passes through the stack of plates.

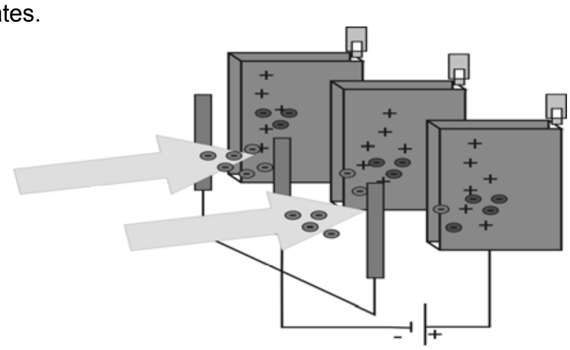

Fig.1. Conceptual diagram of an electrostatic precipitator

A negative voltage (thousands of volts) is applied between wire and plate. If the applied voltage is high enough, an electric corona discharge ionizes the gas around the electrodes. Negative ions flow to the plates and charge the gas-flow particles.

The ionized particles, following the negative electric field created by the power supply, move to the grounded plates. Particles build up on the collection plates and form a layer. The layer does not collapse, thanks to electrostatic pressure (due to layer resistivity, electric field, and current flowing in the collected layer).

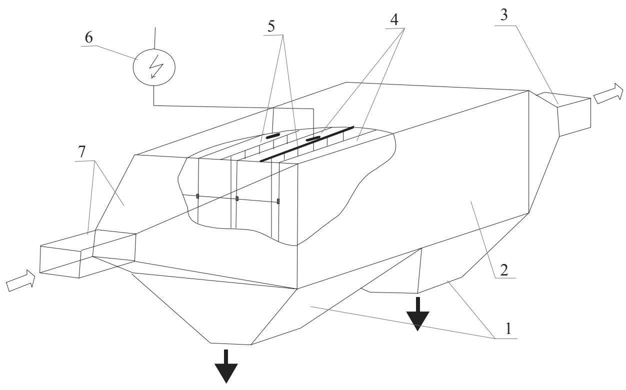

Fig.2. Scheme of horizontal, two stage electrostatic precipitator (ESP): 1 - bulk hopper, 2 - participator chamber, 3 - confusor and outlet channels , 4 - collecting electrodes system, 5 - corona electrode system, 6 - high voltage supply.

Efficiency of precipitation

An electrostatic precipitator (ESP) separates fine particles from a flue gas by charging the particles and driving them toward the collecting plate using electrostatic forces.

To describe the phenomena occurring in electrostatic precipitators - the Deutsch theory is used. His model is also used for the analysis and design of electrostatic precipitators work. The basic equation describing the precipitator performance was introduced by White, and then modified by Matts and Oehnfeldt [3].

For example, typical equation should be as:

$$\begin{aligned} \eta(d) &= 1-\exp\left\{-w_t(d)\cdot\frac{L}{h\cdot v}\right\} \\ \eta(d)_c &= \sum_{d_{\min}}^{d_{\max}} k(d)\eta(d) \qquad (1) \\ \eta_c &= 1-\exp\left\{-w_{ef}\cdot\frac{L}{h\cdot v}\right\} \end{aligned}$$

where: $\eta(d)$ - Interval precipitator performance for grain diameter d , $w_t(d)$ - Theoretical velocity of dust grains with a diameter d , L - the length of the electric field, h - distance between electrodes of different lengths.

Electrostatic body forces can produce a secondary gas flow, well known as *electric wind* or *corona wind* in an ESP.

Yamamoto and Velkoff [4], Kallio and Stock [5] solved governing equations for the fluid flow and the electric field to investigate the particulate-free secondary flow interaction between those fields.

Charged dust particles migrate to the collecting plate due to Coulomb forces, but are also under the influence of momentum interaction with the gas flow in terms of aerodynamic drag. The motion of charged particles suspended in the gas stream has been studied by Watanabe [4] and Meroth et al. [7].

Heavily loaded particles generate high particle charge density, and it can change the electric potential and the ion charge density distribution. Cristina and Feliziani [8] included the particle space charge effect in the calculation of the electric field and the current density distribution. They solved the electrical equations only, and perfect turbulent dispersion of particles was assumed to express particle concentration as a simple function of the distance from the inlet of the ESP. They employed the saturation charge formula to determine the particle charge. Since particles are getting charged by the local electric field through the whole drift motion, the saturation charge would represent only a rough estimation of the particle space charge. Meroth et al. [7] showed that the charge development of particles through their trajectories is much different from the saturation value, especially for small particles.

Physical modelling

In most works regarding ESP modelling physical approach dominates. Electrically induced turbulent flows have very wide spectra of physically important length and time scales.

The gas flow is governed by the time-averaged conservation equations of mass and momentum.

For steady, isothermal flow they have the following forms:

Conservation of mass and conservation of momentum:

$$\begin{aligned} &\frac{\partial}{\partial x_k}(\rho u_k)=0 \qquad (2) \\ &\frac{\partial}{\partial x_k}\left(\rho u_i u_k-(\mu+\mu_t)\frac{\partial u_i}{\partial x_k}\right)=-\frac{\partial \rho}{\partial x_i}+f_{Di}+\rho_{ion}E_i \end{aligned}$$

where ρ and ρ_{ion} are the mass density of the gas and the ion charge density, u is the time-averaged gas velocity, f_D represents the momentum source associated with the aerodynamic drag, and E is the strength of the electric field. Turbulent viscosity μ_t is calculated from the solution of the conservation equations of turbulence kinetic energy and turbulence dissipation rate in the RNG $k-\varepsilon$ model (Yakhot and Orszag [3,9]).

In the two-layer model, the flow domain is divided into a viscosity-affected region and a fully turbulent region. The one-equation model of Wolfshtein [3] is used in the viscosity-affected near-wall region whereas the RNG $k-\varepsilon$ model is employed in the fully turbulent region.

The particulate two-phase flow is described basically in two ways, namely the Lagrangian and the Eulerian methods. The Lagrangian approach treats the fluid phase as a continuum and calculates the trajectory of a discrete single particle from the balance of forces acting on the particle. The Eulerian approach treats the particulate phase as a continuum as well as the gas phase. The conservation equations of mass and momentum are solved for both phases. Both approaches have their advantages and disadvantages (Durst et al. [3, 10]).

In most cases [3-10] turbulent fluid flow in an ESP is modelled by the commercial CFD package (using finite volume method for the time-averaged Navier-Stokes equations closed by the RNG turbulence model) and the ion charge density and the electric field are obtained from the numerical solution of a Poisson equation for the electric potential and the current continuity equation by using a finite volume method [3, 11].

Despite this fact, for further analysis purposes we have considered time series modelling based on real power plant measured data.

The input signals we considered: summary plant thermal power, exhaust pressure before ESP (both left and right side), input exhaust temperature (both left and right side). System states are based on temperature – resistivity (voltage and current) relation considered in four ESP fields and hopping frequency. Outputs were: output dust concentration, exhaust pressure behind ESP and output exhaust temperature (considered in both left and right ESP side).

The data set was prepared regarding data quality and divided into several subsets for model identification and validation. We used Matlab Identification Toolbox software. Regarding to multivariable plant, the achieved model was identified using state space and nonlinear model structures.

Practically, the MSE is typical performance function used in training. The best results in model accuracy were achieved for the nonlinear autoregressive exogenous model (NARX) is a nonlinear autoregressive model with exogenous inputs. It means that the model relates the current value of a time series where it is possible to explain or predict to both: past values of the same series and current and past values.

The typical equation should be as:

$$y_t = F(y_{t-1}, y_{t-1}, y_{t-2}, ..., u_t, u_{t-1}, u_{t-2}, ...) + \varepsilon_t\ , \qquad (3)$$

where y is the variable of interest, and u is the externally determined variable. In this scheme, information about u helps predict y , as do previous values of y itself. The ε is the error term (sometimes called noise).

Such models are not only important for the forecasting of time series but also generally for the control of the dynamical system. This is a powerful class of models which are well suited for modelling nonlinear systems and specially time series. One principal application of NARX dynamic neural networks is in control systems.

There are some important qualities about NARX networks with gradient-descending learning gradient algorithm. The first one is more effective learning in NARX networks than in other neural network (the gradient descent is better in NARX). Also these networks converge much faster and generalize better than other networks [12 - 15].

The empirical studies have shown that in case gradient-descent learning algorithms, sometimes it is difficult to learn simple temporal behaviour with long time dependencies [14]. It proved that for gradient-based training algorithms for systems with long time dependencies, the information about the gradient contribution m steps in the past vanishes for large m. This effect is referred to as the problem of *vanishing gradients*, which partially explains why gradient descent algorithms are not very suitable to estimate systems and signals with long time dependencies. For instance, common recurrent neural networks encounter problems when learning information with long time dependencies, a problem in the prediction of nonlinear and no stationary signals. The vanishing gradients problem makes the learning of long-term dependencies in gradient based training algorithms difficult or even impossible in certain cases [13].

A state space representation of recurrent NARX neural networks can be expressed as [12]:

(4) $$z_k(k+1) = \begin{Bmatrix} \Phi(u(k), z_i(k)) & i = 1 \\ z_i(k) & i = 2,3,\ldots N \end{Bmatrix}$$

where the output $y(k) = z_i(k)$ and $z_i, i = 1,2,\ldots N$, are state variables of recurrent neural network. The recurrent network exhibits forgetting behaviour, if:

(5) $$\lim_{m \to \infty} \frac{\partial z_k(k)}{\partial z_j(k-m)} = 0 \quad \forall k, m \in K, i \in O, j \in I$$

where z is state variable, I denotes the set of input neurons. O denotes the set of output neurons and K denotes the time index set.

Several approaches have been suggested to get around the problem of *vanishing gradient* in training recurrent neural networks. Most of them rest on including embedding memory in neural networks, whereas the others propose improved learning algorithms, such as the extended Kalman filter algorithm, Newton type algorithm or annealing algorithm, etc.

Particularly significant in recurrent NARX and NARMAX neural networks is embedded memory.

This embedded memory can help to speed up propagation of gradient information, and hence help to reduce the effect of vanishing gradient. There are various methods of introducing memory and temporal information into neural networks.

These include creating a spatial representation of temporal pattern, putting time delays into the neurons or their connections, employing recurrent connections, using neurons with activations that sum input over time, etc.

The NARX model for approximation can be implemented in many ways, but the simpler seems to be by using a feedforward neural network with the embedded memory (a first tapped delay line), plus a delayed connexion from the output of the second layer to input (a second tapped delay line).

For learning purposes, a dynamic back-propagation algorithm is required to compute the gradients, which is more computationally intensive than static back-propagation and takes more time. In addition, the error surfaces for dynamic networks can be more complex than those for static networks. Training is more likely to be trapped in local minima [12, 16].

The training process has some difficulties. One is related to the number of parameters, which refers to how many connections or weights are contained in network. Usually, this number is large and there is a real danger of "overtraining" the data and producing a false fit which does not lead to better forecasts. This fact motivates the use of an algorithm including the regularization technique, which involves modifying the performance function for reducing parameters value. The typical performance function used in training is Mean Squared Error, MSE [12].

In our research we applied achieved model into Simulink scheme and tested step responses with maximal amplitudes for appropriate signals. The system response is presented in the figure 3.

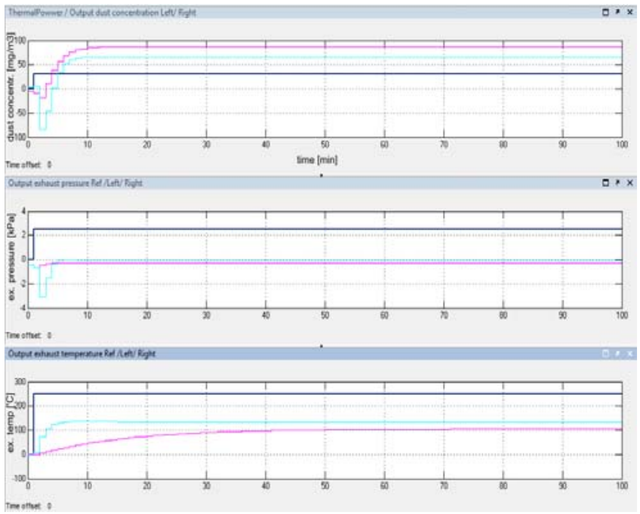

Fig.3. Achieved, linearized model step response

The output dust concentration response, both for left and right side of the ESP model may be treated as inertial second-order member in response to step thermal power input.

For further research ESP resistance in reference to hopping frequency in all four fields was considered presented in fig. 4.

This gives information about important meaning of first and second ESP field as well as compensatory action in the other fields.

Then model was updated about the information of resistance – temperature information, presented in the figure 5.

Only the first field gives representative information so it was used in ESP model.

The research also included a comparison of NARX obtained in Matlab Identification Toolbox with NNARX obtained using Neural Network Toolbox.

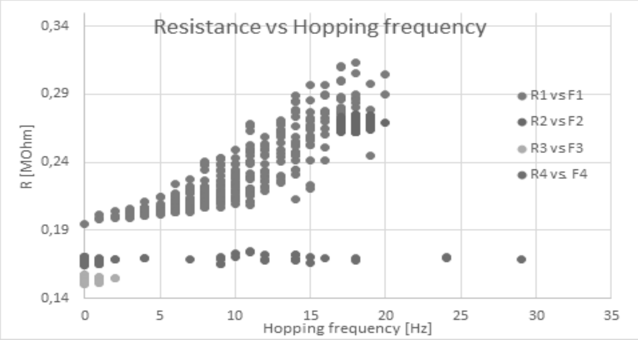

Fig.4. Achieved, linearized model step response

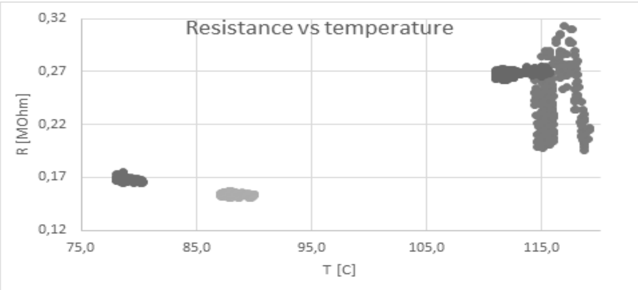

Fig.5. Resistance – temperature relation in considered ESP

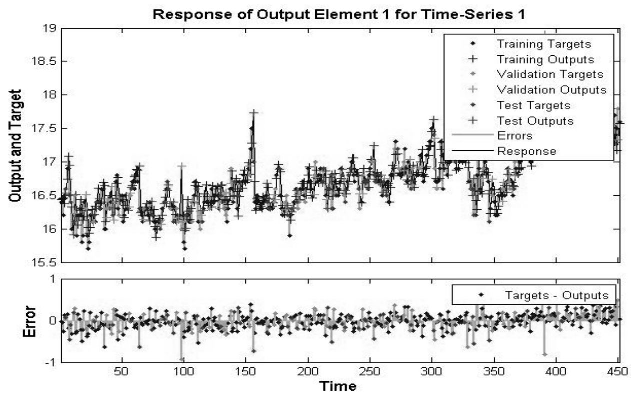

Fig.6. ESP NNARX model response plot

Figure 6 illustrates ESP neural network ANRX model response.

This approach allowed for a more flexible selection of model parameters, including more precise adjustment of the quantity of neurons and hidden layers. It also offered to distinguish nonlinear part from the achieved model.

Conclusions

The aim of the study was the relationship between dust removal efficiency and selected physicochemical parameters from the process for effective combustion system diagnosis and control.

Thus obtained results enabled more efficient process diagnostics (less complex) than computational fluid dynamics (CFD) approach. This offers new opportunities to implement control system with on-line reference model for such a combustion system. It is especially important in biomass co-firing process.

Analysing the electrostatic dust extraction flue gas from the combustion process must take into account the burned fuel parameters and physicochemical properties of the processes in ESP. Fly ash grain composition was neglected in our research.

The simulated results show that NARX networks are often much better at discovering long time – dependences than conventional recurrent neural networks.

An explanation why output delays can help long-term dependences can be found by considering how gradients are calculated using the back-propagation-through-time (BPTT) algorithm.

Ensuring effective dust removal in the combustion process directly affects the emissivity of the process. On the other hand, in an indirect way can contribute to a more effective maintenance of process parameters.

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