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THE MODELING OF AIR POLLUTION CONTROL DEVICES USING NEURAL NETWORKS

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Abstract. *The majority of methods for pollutant elimination assume the flow of the polluted gas through the pollution control system. The system is made of various devices which have to be chosen based on the characteristics of the pollutant: aerosol, solid particles, droplets or gaseous. The chosen framework and facilities depend on the type of the pollutant: aerosol, solid particles, droplets or gaseous. There are a number of basic parameters which have to be considered in order to define air pollution control devices. This study represents a modeling of the named parameters which are related to the framework and facilities of air pollution control. In order to set the optimal parameters of a purification device, a deterministic model of the process of purification should be determined. Such a model is often difficult to construct, since physical and chemical characteristics of the source of pollution are not completely known. In this paper we propose a black-box modeling tool based on the application of an artificial neural network.*

Key words: *Air pollution control, modeling, neural network*

1. Introduction

Air pollution, defined as the presence of undesirable materials in the air (solid particles, liquid droplets, gaseous or vapors compounds) in quantities large enough to produce harmful effects: damage human health, vegetation, property or the global environment, occurs in a number of technological processes. Many of these harmful materials enter the atmosphere from natural sources, currently beyond human control. However, the principal sources of these pollutants are human activities.

The largest sources of air pollution are energetic and industrial facilities; however, the influence of small and medium pollution sources must not be ignored. It is our opinion that the starting overview point should be the working place or even a working operation. Therefore, in this paper we consider the point-sources of air pollution because this cumulative influence is not negligible, and what is most important, it is happening in our proximate environment.

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In our opinion, there are three options available to control the air pollution of small and medium sources. Those are: improvement of dispersion, reduction of the emission by technical or technological improvement of the considered process and application of a downstream pollution control device. The best method to control pollution is to avoid it. However, it is not always possible to replace a current process with one which does not cause pollution; therefore, some other methods of control must be considered.

It is a well known fact that the majority of methods for pollutant elimination assume the flow of the polluted gas through the pollution control system. The system is made of various devices which have to be chosen based on the characteristics of the pollutant: aerosol, solid particles, droplets or gaseous. The bearing gas, emission process and changes in the source of the pollution influence the pollution control options as well.

This paper represents a part of a wider study concerning air purification from pollutants originating from small sources. Integrated air pollution control devices consists of two or more air purifying mechanisms whose combination should improve the efficiency with which impurities are collected. Those impurities are heterogeneous and they are present in a limited air stream production with a limited concentration. In order to set the optimal parameters of a purification device, a deterministic model of the process of purification should be determined. Such a model is often difficult to construct, since physical and chemical characteristics of the source of pollution are not completely known. In this paper we propose a black-box modeling tool based on the application of an artificial neural network known as the Radial Basis Function (RBF) network.

2. Problem Definition

Nowadays, it's possible to achieve the complete removal of any polluting substance from any air stream being discharged into the atmosphere. As complete purification is at hand, the cost of purifying an air stream increases drastically, and complete pollution control is too expensive to implement in every air purifying process. In fact, any used method of control increase the cost of the process. However, some of the separated materials are of certain value because they can be utilized in some other industrial processes, thus reducing the overall cost of the pollution elimination. Of course, there are cases where the elimination of the pollutants has to be complete, such as nuclear power plants, biological and chemical research laboratories, disregarding the costs of pollutant elimination.

We have to know every segment of the purifying process, the nature of the source, the pollutant and bearing gas. With all this knowledge we can achieve the best performance of the control units, and on the other hand decrease the costs of purifying. There are many air pollution control devices available for removing contaminants from air. These work on a variety of different principles. Some of the common devices are a settling chamber, the cyclone and inertial collector, filters, electrostatic precipitators, scrubbers, absorbers, combustion chambers, and so on. All of these various control devices have much in common as to their net effect on the air stream that can be described in terms of collection efficiency. Control devices can be used in combination, as a system. The interaction of various control devices of the same type or of different types, with each other and with other elements in the system, can achieve a higher collection efficiency.

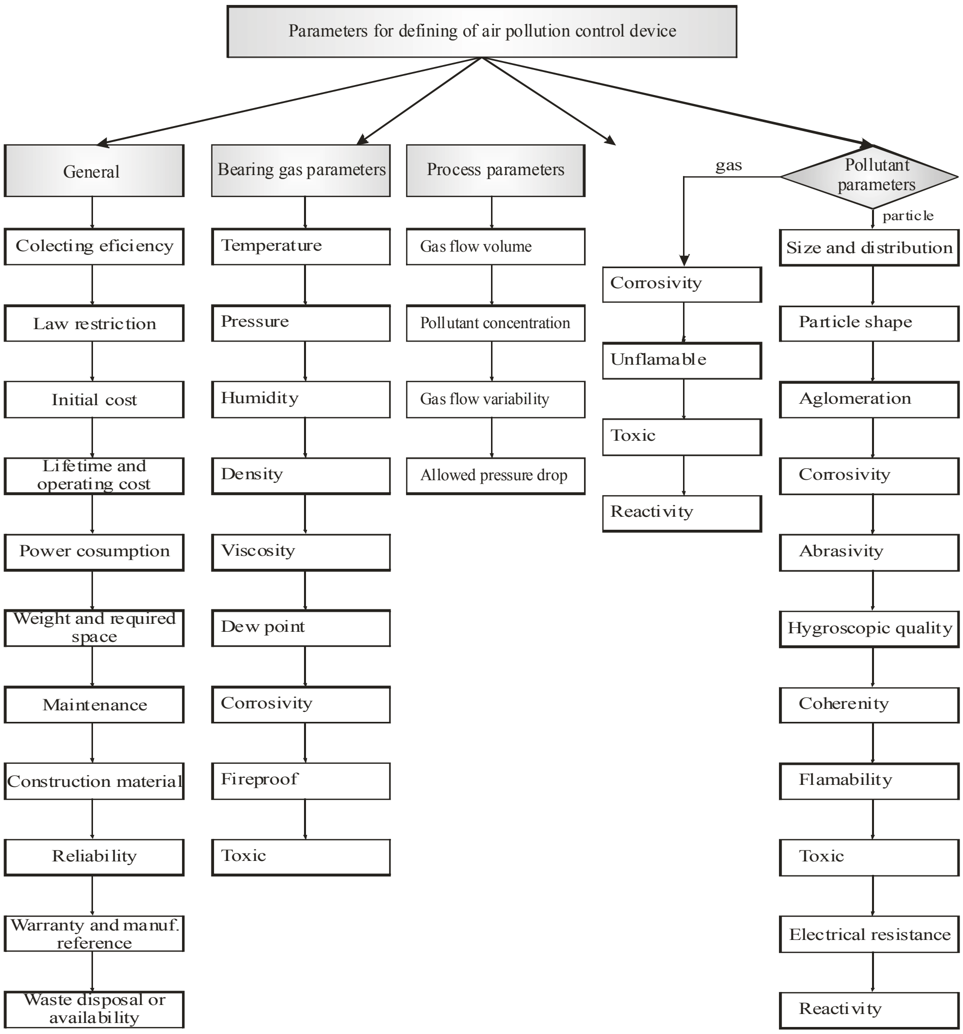

Fig. 1. Parameters related to the framework and facilities of air pollution control

We must be able to identify which pollutants are present in a given air stream. Moreover, we must also be able to determine many other particulate properties of the present pollutants such as: size distribution, concentration, and various physical properties and so on. Also we have to define different physical properties of the bearing gas, usually air, such as: temperature, humidity, air flow velocity and so on.

The basic parameters which have to be considered in order to define air pollution control devices have been given in figure 1. These parameters relate to the framework and facilities of air pollution control.

The basic parameters which should be measured are temperature, relative humidity, pressure drops and air stream flow, and those represent input. Basic output from a pollution control system is the collecting efficiency obtained from pollutant concentration data.

Modeling of air refinement parameters using a neural network should improve the design of some integrated devices for air pollution control by selecting optimal parameters. In the case of an integrated device, it has to involve various refinement mechanisms in order to achieve an emission rate under the threshold limit values, the best performance possible, a low price, low energy consumption and so on. The results of this study can also be applied in the pollutant control of small sources in the urban area.

3. The Modelling Procedure

Our main goal is to obtain a model of the air pollution control device. We shall assume that there is a nonlinear, non-stationary dependence between the bearing gas parameters (temperature, humidity and pressure), the bearing gas flow volume and the pollutant concentration. The only information about this nonlinear dependence is obtained through the measurements. In order to obtain the approximation of the mapping between the bearing gas parameters and flow on one side, and the pollutant concentration on the other, we shall apply an artificial neural network (Fig. 2) capable of learning unknown nonlinear mappings using only measurement data.

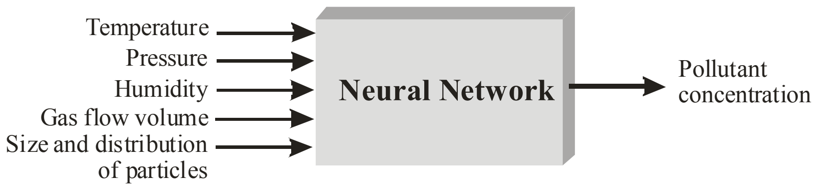

Fig. 2. A neural network as a model of an air pollution control device

As a model of unknown mapping we shall apply the Radial Basis Function (RBF) neural network, well known for its approximation capabilities. Here we propose an algorithm for the sequential learning of the RBF neural network. Both the parameters and the structure adaptation are incorporated into the framework of an extended Kalman filter. Two approaches: construction (growing) and pruning are combined during the adaptation of the RBF network structure. We considered the general problem of modeling some phenomenon using the following statistical model:

$$y_k = h(u_k) + v_k\,,\ k = 1,2,... \tag{1}$$

where u is the vector of independent (input) variables, y is the vector of dependent (output) variables and v is the noise representing the ignorance about the functional relationship between u and y. The goal of the modeling is to find a deterministic nonlinear function $h(\cdot)$. The modeling will be performed based on empirical knowledge, given as the sequence of input/output samples $\{(u_k,y_k),\ k = 1,2,...\}$. We shall consider the adaptation (learning) scenario where at each time step the k input/output data sample (u_k,y_k) is presented to the model. After that, the sample is discarded and cannot be used again for adaptation. The joint input/output data distribution is unknown and varies with time. Such a scenario will be referred to as a sequential adaptation.

Possible changes in input/output data distribution could influence the adaptation of the model. For example, let us consider the mean squared error criterion to estimate the model $\hat{h}$ to approximate the function $h(\cdot)$:

$$J = \int_{-\infty}^{\infty} (y_k - \hat{h}(u_k))^2 p(y_k, u_k) du_k dy_k = \int_{-\infty}^{\infty} (y_k - \hat{h}(u_k))^2 p(y_k / u_k) p(u_k) du_k dy_k \tag{2}$$

From (2) it is obvious that the model $\hat{h}$ depends both on the conditional output probability density function (pdf) $p(y_k/u_k)$ and the input pdf $p(u_k)$. Only for an infinite number of training samples will $\hat{h}$ asymptotically depend solely on $p(y_k/u_k)$ [9]. This means that the model may have to change if either $p(y_k/u_k)$ changes or the learning data is not sampled from a fixed input distribution. Sequential adaptation should maintain the optimal complexity of the model, where the complexity is defined as the number of adaptable parameters.

Because of its well-known approximation properties, the Radial Basis Function (RBF) network represents a good foundation for a nonlinear model [2]. The RBF network consists of three layers of neurons. Input neurons only transmit input pattern to the hidden units. The i-th hidden unit response $\phi_i(u_k)$ to an input pattern u_k is given by the radial basis function (often Gaussian),

$$\phi_i(u_k) = \exp\{-\textstyle\sum_{j=1}^{n_I} ((u_{k,j} - m_{ij}) / \sigma_{ij})^2\}, \tag{3}$$

and the l-th output unit response is a linear combination of hidden unit responses:

$$h_l(u_k) = a_{l0} + \textstyle\sum_{i=1}^{n_H} a_{li} \phi_i(u_k), \tag{4}$$

where n_I is the number of input neurons, n_H is the number of neurons in the hidden layer, u denotes the input of the RBF network, a_{l0} denotes bias, a_{li} is the weight of the i-th radial basis function for l-th output, m_i and σ_i are the center and width vector of the i-th basis function respectively.

Nonlinear mapping realized by the RBF network is characterized by its structure (the number of hidden neurons and connections) and parameters (weights, centers and widths). The approximation of a nonlinear function $h(\cdot)$ in (1) is obtained by the sequential adaptation of the RBF network parameters and structure. In order to track changes of input pdf $p(u_k)$ and conditional output pdf $p(y_k/u_k)$, the RBF network parameters and structure are assumed as being time varying.

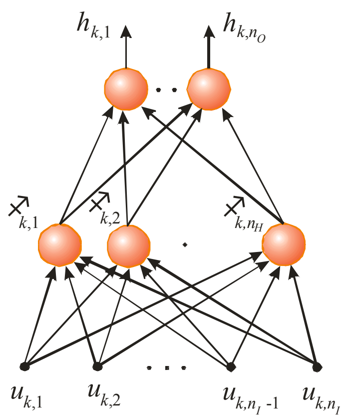

Fig. 3. RBF neural network

Time-varying parameters of the RBF network are sequentially estimated using the EKF. The dynamics of the network parameters and neurons is represented by the state space model. The state equation models time evolution of the n_x-dimensional vector of the RBF network parameters x_k (weights, centers and widths) as the first order Markov process. The measurement (observation) equation describes how the n_y-dimensional measurement (observation) vector y_k depends on RBF network parameters x_k.

$$x_k = x_{k-1} + d_k, \tag{5a}$$

$$y_k = h(u_k, x_k) + v_k. \tag{5b}$$

In (4), u_k represents the n_u-dimensional vector of known inputs, d_k is the n_x-dimensional process noise and v_k is the n_y-dimensional measurement noise. The RBF network approximates the nonlinear mapping $h(\cdot)$.

The conditional pdf of x_k, given a set of the measurements $y_{1:k} = \{y_1, y_2, ..., y_k\}$, is called the posterior and is obtained by applying Bayes rule:

$$p(x_k / y_{1:k}) = \frac{p(y_k / x_k)}{p(y_k / y_{1:k-1})} p(x_k / y_{1:k-1}) \tag{6}$$

where pdf $p(y_k/x_k)$ represents the likelihood, pdf $p(y_k/y_{1:k-1})$ is the evidence, and the prior is given by pdf $p(x_k/y_{1:k-1})$. Process noise and observation noise are assumed to be mutually independent, white, and Gaussian: $d_k \sim N(0,Q_k)$ and $v_k \sim N(0,R_k)$. In order to obtain an analytic solution to (5), the observation equation is linearized around the parameter prediction:

$$y_k = h(\hat{x}_k^-) + H_k(x_k - \hat{x}_k^-) + v_k \tag{7}$$

where $H_k = \nabla_x h(\hat{x}_k^-)^T$ and $\hat{x}_k^-$ is the prediction of x_k given the observations $y_{1:k}$.

Consequently the prior, likelihood, evidence and posterior are approximated as Gaussians:

$$p(x_k / y_{1:k-1}) = N(x_k; \hat{x}_k^-, P_k^-) \tag{8}$$

$$p(y_k / x_k) = N(y_k; h(x_k), R_k) \tag{9}$$

$$p(y_k / y_{1:k-1}) = N(y_k; h(\hat{x}_k^-), S_k) \tag{10}$$

$$p(x_k / y_{1:k}) = N(x_k; \hat{x}_k, P_k) \tag{11}$$

The parameter estimate $\hat{x}_k$ can be computed by the maximizing posterior $p(x_k/y_{1:k})$ or equivalently by minimizing the cost function defined as the negative logarithm of the likelihood and prior product [10, 11].

$$J(x_k) = \frac{1}{2}\{\{y_k - \hat{h}(x_k))^T R_k^{-1}(y_k - \hat{h}(x_k)) + (x_k - \hat{x}_k^-)^T (P_k^-)^{-1}(x_k - \hat{x}_k^-)\} \tag{12}$$

The obtained equations, known as extended Kalman filter, can be grouped into two sets: time update and measurement update equations.

Time update equations

Parameter prediction: $\hat{x}_k^- = \hat{x}_{k-1}$ (13a)

Parameter prediction covariance: $P_k^- = P_{k-1} + Q_k$ (13b)

Measurement update equations

Innovation: $e_k = y_k - h(\hat{x}_k^-)$ (14a)

Innovation covariance: $S_k = H_k P_k^- H_k^T + R_k$ (14b)

Kalman gain: $K_k = P_k^- H_k^T S_k^{-1}$ (14c)

Parameter estimate: $\hat{x}_k = \hat{x}_k^- + K_k e_k$ (14d)

Parameter estimation covariance: $P_k = (I - K_k H_k) \cdot P_k^-$ (14e)

In real data applications process noise covariance Q_k and observation noise covariance R_k are not known and have to be estimated. The wrong estimates of Q_k and R_k can cause large estimation errors or even a divergence. Also, due to their influence on the growing and pruning criteria, wrong estimates of Q_k and R_k can stop network growth, or can cause unnecessary growing and pruning. A number of estimation methods for Q_k and R_k are considered in [1] and [6]. We have estimated the process of noise covariance Q_k by applying a heuristic method based on the change in parameter errors [10]. The observation noise covariance R_k was estimated using a covariance-matching technique [6], making innovations e_k consistent with their theoretical covariance S_k.

CONCLUSION

The modeling procedure of an air pollution control system is suggested in the paper, based on an artificial neural network application. It has demonstrated that there are a number of variables we can consider as the input of the air pollution control device. In order to obtain the approximation of the mapping between the bearing gas parameters and flow on one side, and the pollutant concentration on the other, we propose the application of an artificial neural network capable of learning nonlinear mappings using only measurement data.

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MODELIRANJE PREČISTAČA GASOVA PRIMENOM NEURONSKE MREŽE

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Većina metoda za prečišćavanje gasova podrazumeva prolazak gasne struje kroz neki sistem za prečišćavanje. Takav sistem se uglavnom sastoji od ralzicitih uređaja za prečišćvanje. Izabrani sistem i njegove karakteristike zavise o kakvom se zagađenju radi, dali su to aerosoli, čestice, raspršene kapi ili gasovi. Svakako da noseći gas,proces emisije i promene u izvoru zagađenja utiču na izbor sistema za prečišćavanje. Postoji veliki broj parametara koje treba razmotriti u procesu izbora sredstava i sistema kontrole, a ova studija predstavlja njihovo modeliranje. Osnovni zadatak je dobijanje modela nepoznate, vremenski promenljive nelinearne zavisnosti. Predložen je algoritam za sekvencijalnu adaptaciju mreže radijalnih bazisnih funkcija (RBF). Adaptacija parametara i strukture je inkorporirana u sistem proširenog Kalmanovog filtra. Za vreme adaptacije strukture RBF mreže kombinovana su dva prilaza: izgradnja (rast) i uprošćenje.

Ključne reči: *prečišćavanje vazduha, modeliranje, neuronska mereža*