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MODELLING OF THE FILTER-ADSORBER TYPE AIR CLEANER BY USING NEURAL NETWORK

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Miomir Raos[1], Ljiljana Živković[1], Amelija Đorđević[1], Branislav Todorović[2]

[1]Faculty of Occupational Safety, University of Niš, Serbia
[2]Faculty of Science and Mathematics, University of Niš, Serbia

Abstract. *It is well known that most air purifying methods imply the passing of air flow, as a pollutant carrier, through a control unit which retains impurities.*
Properties of the air control unit and the purifying process itself therefore differ depending on the nature of present impurities, as well as on flow-thermal properties of air as the carrier of those impurities. For the assumed conditions, in terms of production of a pollution source and presence of different polluting substances in the form of dust, aerosols, gas, vapor in the exhaust gas, etc., an integrated gas purifier has been designed and tested, comprising a module for purification of mechanical impurities and a module for purification of gaseous impurities.
The purifier is compact and has a universal application while simultaneously retaining several different pollutants. These requirements were met through application of the filtration and adsorption methods. On the formed experimental line with an adequate system of acquisition, filter-adsorber type gas cleaners in the function of flow-thermal parameters of gas mixture were tested simultaneously. Experimental data were used for training the radial basis function neural network, which was then used to model properties of the process and gas cleaner.

Keywords: *flow-thermal parameters, air purification, modelling, neural network*

EXPERIMENT DETAILS

Essence of experimental work is the formation of an original examination line, and the testing of interaction of integrated air cleaner, which contains a filter for mechanical impurities and an adsorption filter, with respect to mechanical and gaseous test contaminants, and air as the carrying gas.

The module of mechanical purifier consists of the panel industrial filter, internal labels 109.122.73/20, designed for the purpose of experiments by a domestic manufacturer of filter products "Frad", Aleksinac.

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Dimensions of the filter partition are 600x600 [mm], and the fill consists of filter paper with specific load of 120 [gr/m^2], with gas flow > 750 (l/m^{2}s], with pressure drop down to 200 [Pa], manufactured by NEENAH GESSNER, Germany, with nominal fineness of filtering F= 13,5 19[μm].

The module of gas pollutants air cleaner contains an adsorption active coal (charcoal) fill in the form of cassette groups with 12 cartridges. The pelletted active coal with granulations of 4[mm] was manufactured by an American corporation CALGON CARBON (and their European branch Chemviron Carbon).

Adsorption filter size depends on the necessary capacity of adsorption and spacial properties of air cleaner, as well as on hydrodynamic and exploitative conditions.

The acquisition system consists of sensors and transmitters of physical non-electric quantities, a device for measuring, processing, and acquiring data, a personal computer, and a source of direct electrical current which supplies power to transmitters.

- ***M1,*** inlet air velocity in the intake canal, in front of the first filter unit, (primary air canal)
- ***M2,*** temperature and relative humidity of inlet air, in front of the first filter unit, (primary air canal)
- ***M3,*** differential pressure streams of air in inlet and outlet canals of the first filter unit (primary and secondary air canal)
- ***M4,*** temperature and relative humidity of air in the outlet canal of the first filter unit, (secondary air canal)
- ***M5,*** concentration of gaseous chemical pollutants (probational measure point), in the outlet canal of the first filter unit, (secondary air canal)
- ***M6,*** differential pressure of air flow in inlet and outlet canals of the second filter unit, (secondary and tertiary air canal)
- ***M7,*** concentration of gaseous chemical pollutants in the outlet canals of the second filter unit, (tertiary air canal)
- ***M8,*** temperature and relative humidity of air in the outlet canal of the second filter unit, (tertiary air canal)
- ***M9***, temperature in the room

Position of measuring points on the examination line is represented in Fig. 1.

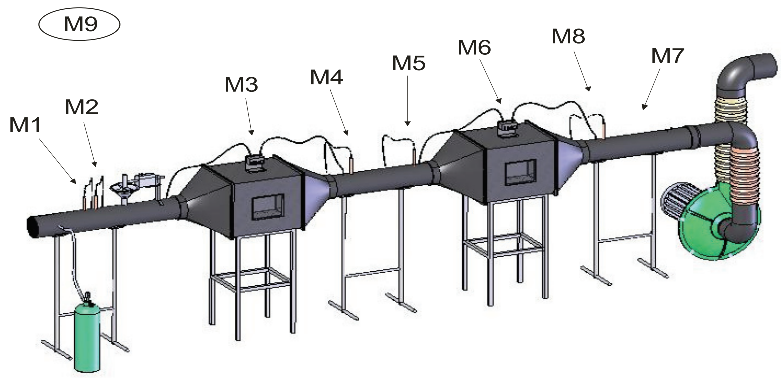

Fig. 1. Appearance of experimental set up with measuring points

Modelling with a Neural RBF network – Neural network learning algorithm

The radial basis function neural network was used, with n^Ientrances, n^H hidden neurons, and n^0 outlet neurons. The outlet of the ‘Ith' in exit layer is defined as:

$$\hat{y}_l = a_{l0} + \sum_{i=1}^{n^H} a_{li}\phi_i(u; m_i, \sigma_i) \tag{1.1}$$

and the outlet of the ‘Ith' hidden neuron is defined as:

$$\phi_i(u; m_i, \sigma_i) = \exp\left\{-\sum_{j=1}^{n^I}\left(\frac{u_j - m_{ij}}{\sigma_{ij}}\right)^2\right\} \tag{1.2}$$

were u is the instant input, a_{l0} is the threshold of the "lth" outlet neuron, a_{li} is the weight between "I" hidden and "l" outlet neuron ; $m_i = [m_{i1},...,m_{in^I}]^T$ and $\sigma_i = [\sigma_{i1},...,\sigma_{in^I}]^T$ are the center and width of the activation function of "I" hidden neuron, respectively.

Adaptation of parameters and structure of the RBF (Radial Basis Function) network goes on in the iterative procedure of passages through a given set of training samples. Off-line algorithms of structure adaptations: K-means and "orthogonal leas squares" provide networks with a large number of neurons because adaptive parameters are the only outlet weights. Katayama et al. combined Maximum Absolute Error method (MAE) for the adaptation of structures and gradient descent for the adaptation of RBF parameters. Their method is extended by application of "Resilient Back Propagation (RPROP") algorithm for parameter adaptation.

The learning algorithm comprises the following processes:

Parameter adjustment for a given set of hidden neurons,

Adaptation of network architecture for the addition of new neurons

The learning task can be formulated as follows. If Λ for inlet/outlet samples of data are given and also a preset model error $\varepsilon > 0$, which has to be satisfied, we need to find the minimal number of hidden neurons n^H and optimal parameter values a_{ki}, m_{ij}, σ_{ij}, $l = 1,...,n^0$, $i = 1,...,n^H$, $j = 1,...,n^I$, so that the following inequation is satisfied:

$$E = \frac{1}{2}\sum_{\lambda=1}^{\Lambda}\sum_{l=1}^{n^O}(y_l^\lambda - f_l(u^\lambda))^2 < \varepsilon \tag{1.3}$$

where E is the criterion function which needs to be minimized, u^λ is the λ^{th} inlet sample, y_l^λ is the lth component of the λ^{th} target outlet and $f_l(u^\lambda)$ is the lth component of RBF network outlet obtained for λ^{th} inlet u^λ. In RPROP, the parameter adaptation method is based on gradient sign $\partial E/\partial a_{li}$, $\partial E/\partial m_{ij}$, $\partial E/\partial \sigma_{ij}$, $l = 1,...,n^0$ $i = 1,...,n^H$, $j = 1,...,n^I$. Let p be any adaptive RBF network parameter. Adaptation of parameter P is defined by the following iterative procedure:

$$\begin{aligned} p(n+1) &= p(n) + \Delta p(n) \\ \Delta p(n) &= -\mathrm{sgn}\big(\partial E(n)/\partial p(n)\big)\cdot \Delta(n) \end{aligned} \tag{1.4}$$

where:

$$\mathrm{sgn}\,(x) = \begin{cases} 1 & if\ x > 0 \\ -1 & if\ x < 0 \\ 0 & else \end{cases} \tag{1.5}$$

and $\Delta(n)$ is a local value of parameter shift in step n. Every parameter has its own change value which is obtained based on:

$$\Delta(n)=\begin{cases}\Delta(n-1)\cdot\eta_{+} & \text{if } \partial E(n)/\partial p(n)\cdot\partial E(n-1)/\partial p(n-1)>0\\ \Delta(n-1)\cdot\eta_{-} & \text{if } \partial E(n)/\partial p(n)\cdot\partial E(n-1)/\partial p(n-1)<0\\ \Delta(n-1) & \text{else}\end{cases} \quad (1.6)$$

When the error reaches the minimum during the process of adaptation for the given number of hidden neurons, i.e. radial basis functions, algorithm generates new basis functions. They are generated so that the centre of the function is located in the point of inlet space for which the maximal amount of absolute error (difference between a desired response and the response received from the RBF network with current structure) is obtained.

Predicting the change of air cleaner parameters by using neural network

Data for training the radial basis function (RBF) neural network have been taken from experiments. As the input data in the neural network, the following data were considered, in different models: temperature and velocity, relative humidity and flow, velocity and concentration, and as the output data: differential pressure or the output concentration in the filter partition, i.e. the adsorber filter.

The data obtained during the experiment, or the "tripartite data" – velocity, temperature, and differential pressure – are used for training the neural network.

After the training period, the neural network was asked to predict values of differential pressure for those temperature and velocity values which had not been available as measured data during the experiment.

Fig. 2 shows data based on which neural network training activity was conducted.

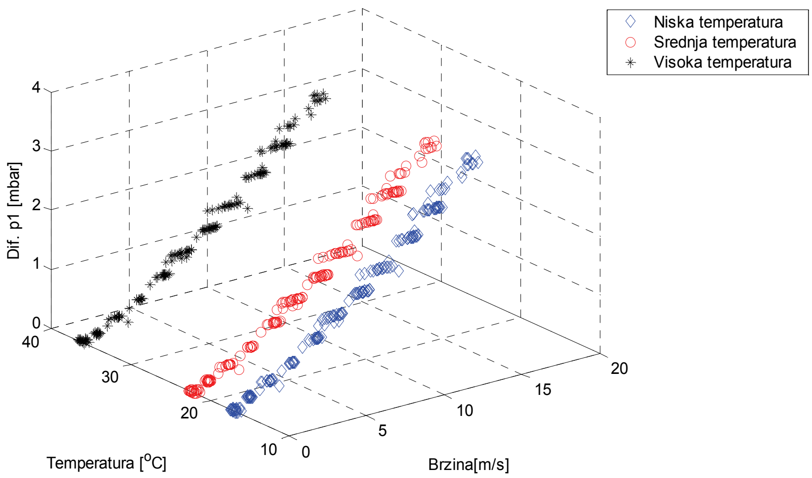

Fig. 2. Three sets of temperature data as a basis for Neural network training and prediction

Neural network prediction essentially represents the law of behavior of differential pressure depending on the temperature, the relative humidity, and the velocity of gas mixture (flow rate).

The similar applies to the prediction of inlet and outlet concentrations of test gases and vapors with respect to changes in temperature, relative humidity, and velocity of gas mixture (flow) through adsorber layers.

Results of the prediction, illustrated by functional dependence of the differential pressure of mechanical impurities filter on temperature, relative humidity, and (gas flow) velocity, which neural network has "learned" based on given measuring data, are shown in figures 3 and 4.

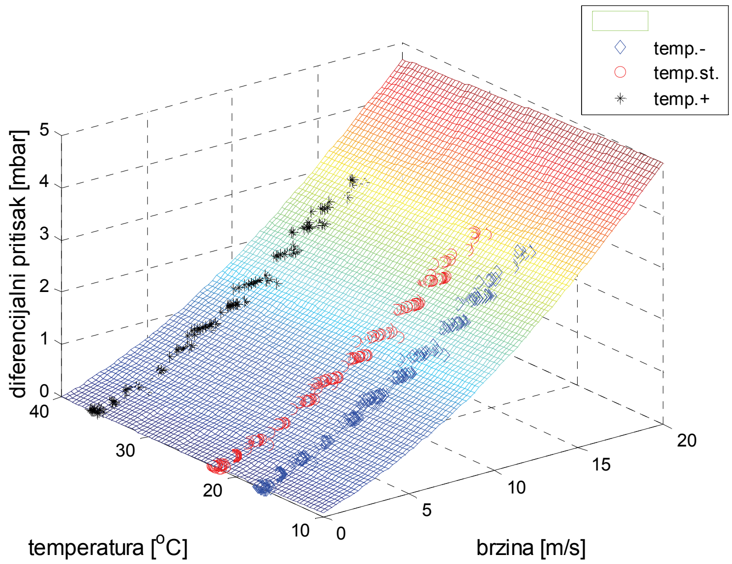

Fig. 3. Prediction of differential pressure on F20 mechanical impurities filter in function of temperature and velocity (flow rate) of gas mixture

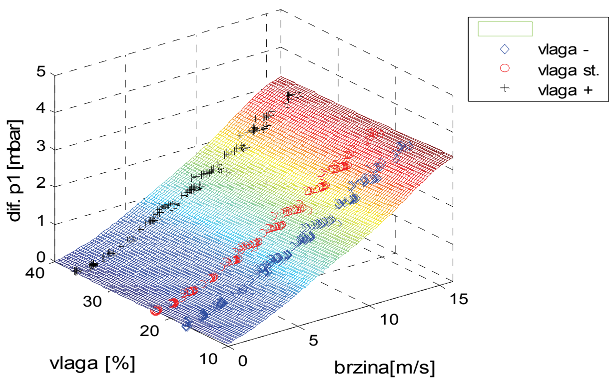

Fig. 4. Prediction of differential pressure on F20 mechanical impurities filter in function of relative humidity and velocity (flow rate) of gas mixture

The previous diagrams show the impact of flow-thermal parameters on the mechanisms for test dust separation on the filter partition. It is obvious that increased temperature of the gas mixture results in density reduction and viscosity increase for the carrying gas (air), which is manifested through small pressure drops on the filter partition and vice versa.

In the event of the increase in the relative humidity of the gas mixture, bigger pressure drops occur on filter partitions and purification is less efficient.

Since the integrated air cleaner comprises a filter for mechanical impurities and an adsorber, figures 5 to 8, show the prediction of inlet and outlet concentrations of acetone vapor used in the experimental phase.

Fig. 5 shows the prediction of inlet concentration of acetone vapor in function of temperature and velocity (flow rate) of gas mixture through the adsorption fill (charcoal).

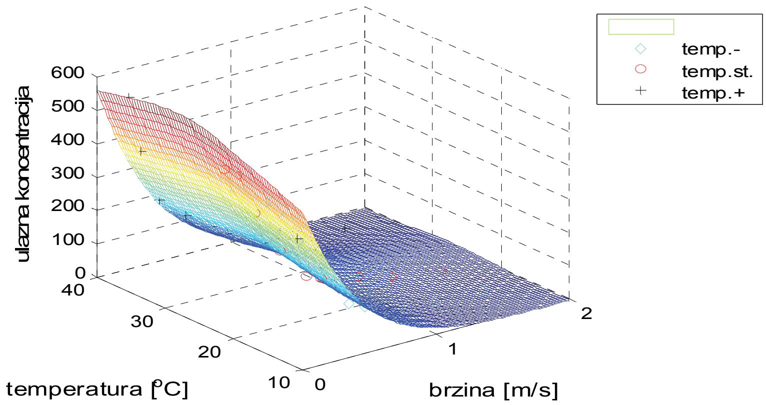

Fig. 5. Prediction of inlet concentration [ppm] of acetone vapor in function of temperature and velocity (flow rate) of gas mixture

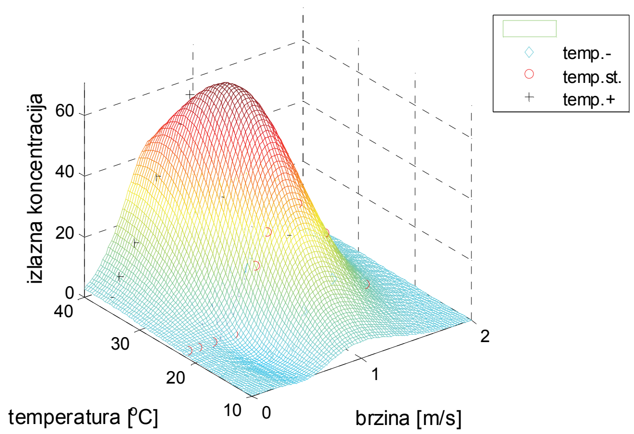

Fig. 6. Prediction of outlet concentration [ppm] of acetone on adsorption filte (charcoal) in function of temperature and velocity (flow rate) of gas mixture

Increased temperatures in the system facilitate the evaporation of acetone, which results in increased concentrations in front of the adsorption filter. As the air flow rate in filter-ventilation system increases, inlet concentrations of acetone become diminished. Fig. 6 shows predictions of outlet concentration of acetone vapor in function of temperature and velocity (flow rate) of gas mixture through the adsorption fill (charcoal).

The figure shows negligible concentrations of acetone vapor behind the adsorption filter at lower temperatures and abstemious flow rates of gas mixture. In contrast, higher temperatures cause the increase in outlet concentrations of acetone vapor. At higher gas mixture velocities through the adsorber, outlet concentrations become equal to the inlet ones, because the time of phase contact decreases, wherein the adsorption process is negligible. Fig. 7 shows the predictions of inlet acetone vapor concentration in function of relative humidity and velocity (flow rate) of gas mixture through the adsorption fill (charcoal).

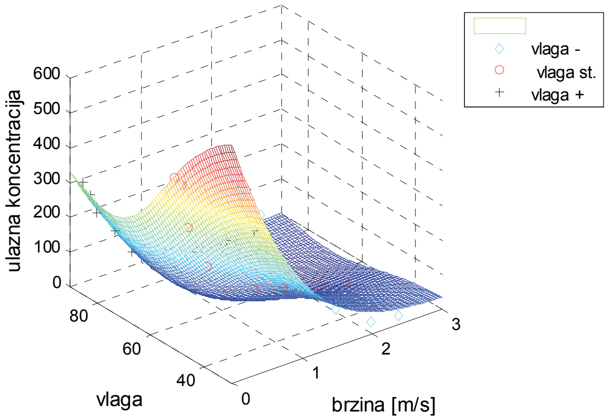

Fig. 7. Prediction of inlet concentration of acetone vaporin function of relative humidity and velocity (flow rate) of gas mixture

From the previous figure, we may notice an increase in inlet acetone vapor concentrations with reduced humidity content in the air. The evaporating of acetone is then more intensive, and the inlet concentrations are larger. With larger gas mixture flows in the filter-ventilation system, inlet concentration drops to the minimum as a consequence of large volume of air flow. Fig. 8 shows the predictions of outlet acetone vapor concentration in function of temperature and velocity (flow rate) of gas mixture through the adsorption fill (charcoal).

Outlet concentrations are a consequence of complex thermodynamic, flow, and diffusion processes in the adsorber. Lower humidity content in the air results in increased inlet concentrations, but also in a good response from desorption filling of the filter. With large flows of gas mixtures, outlet concentrations are similar in value to the inlet ones, because there is no sufficient time for the contact of phases. It is very important to observe the inlet and outlet concentration models simultaneously because they are closely related and can be explained only through their relation to one another. It is important to emphasize the importance of simultaneous observation of predictions of inlet and outlet concentrations of test gases and vapors in function of flow-thermal parameters because it is the only way of getting the full picture of the process in real time. Owing to the decrease in temperature, production of organic solvent vapors also decreases, resulting in

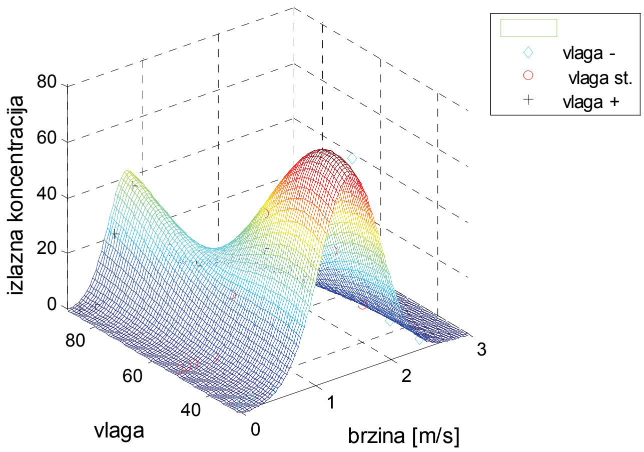

Fig. 8. Prediction of outlet concentration of acetone [ppm] on adsorption filter (charcoal) in function of relative humidity and velocity (flow rate) of gas mixture

the decrease of inlet concentration. An additional decrease of inlet concentration occurs with constant increase of velocities (flow rates) of gas mixtures. i.e. with the ever-growing quantities of air passing through the system. Simultaneously, on the outlet of the adsorber, there are positive responses in terms of removing unwanted compounds for lower temperatures and relatively moderate velocities of gas mixtures. On the other hand, high velocities of gas mixture and higher temperatures result in larger quantities of outlet concentrations, which indicates that the adsorber is not functioning properly. Predictions of adsorber behavior in case of relative humidity change, shows positive behavior in the event of lower relative air humidity and lower (moderate) velocities of gas mixture through the adsorber. In contrast, higher humidity actively participates in the adsorption process and occupies the place of the active chemical compound. In addition, increased air humidity has limited acceptancy for organic compound vapors; therefore, inlet concentrations are reduced. There is obviously specific dual behavior present in the filter-adsorber system, resulting from the opposed natures of filtering and adsorption processes. Generally, what is beneficial for the process of filtration and what facilitates particle separation through the aforementioned mechanisms, is quite the opposite for the process of adsorption, and vice versa. Certainly there are many other aspects of observing this system which can be added between these statements. They refer to many possible reactions of chemical compounds and particles, interactions between particles and air, etc.

CONCLUSION

On the basis of experimental data, the modelling of air cleaner parameters by neural network was conducted, with respect to flow-thermal parameters of gas mixture. The radial basis function neural network was used and data for its training were taken from experiments. In different models, inlet parameters of neural network are represented by temperature and velocity, relative humidity and flow rate, velocity and inlet concentration of test dust and test gases, and outlet parameters by differential pressure on filter partition (adsorber), in other words, outlet concentration of gaseous test substances at the adsorption filter outlet. Experimental data, or "tripartite data" – velocity, temperature, and differential pressure – are used for training the neural network.

In the trainings process, the neural network was given the task to predict outlet values (differential pressure on the mechanical impurities filter, outlet concentration of gaseous test substances) for those values of temperatures, relative humidity, and velocity (flow rates) of gas mixtures, for which experimental testing has not been conducted.

Predictions by neural network basically represent the law of behavior of outlet quantities relative to the inlet ones, obtained by self-learning of neural network and through available experimental data.

Our topic for consideration was the prediction of differential pressure and outlet concentration depending on temperature, relative humidity, and velocity of gas mixture.

REFERENCES

1. M. Riedmiller, Rprop-description and implementation details, Technical Report, University of Kalsruhe, January 1994.
2. M. Riedmiller, H. Braun, A direct adaptive method for faster backpropagation learning: The RPROP algorithm, in H. Ruspini, editor, Proceedings of the IEEE International Conference on Neural Networks (ICNN), San Francisco, USA, 1993, pp. 586-591.
3. M. Raos, Lj. Živkovic, N. Živkovic, B. Todorović, Moddeling of air pollution control devices using neural networks, Facta Universitatis, Series: Workig and Living Environmental Protection, VOL., No, Niš, 2006.
4. EnvirocarbTM, Adsorption capacity, Chemviron Carbon, Application & Service Bulletin, European operations of Calgon Carbon Corporation, Belgium, 2004., Calgon Carbon, Pittsburg, PA, USA, 2004.
5. Isobutylene CAS:115-11-7, Product Identification, Airgas Inc., Randor, PA, USA, 1998.
6. Dwyer Instruments Inc., Engineering and applications handbook, K-20, Michigan City, IN, USA, 2003.

MODELIRANJE KARAKTERISTIKA PREČISTAČA GASOVA TIPA FILTER-ADSORBER NEURONSKOM MREŽOM

Miomir Raos, Ljiljana Živković,
Amelija Đorđević, Branislav Todorović

Poznato je da većina metoda prečišćavanja gasova podrazumeva prolazak struje gasa kao nosioca zagađenja kroz neki prečistač koji vrši zadržavanje nečistoća. Karakteristike prečistača i samog procesa prečišćavanja se zato razlikuju zavisno od vrste i prirode prisutnih nečistoća kao i od strujno termičkih osobina vazduha kao nosioca tih nečistoća. Za predpostavljene uslove, u smislu produkcije izvora emisije, prisustva različitih zagađujućih supstanci u obliku prašine, aerosola, gasova i para u otpadnom gasu, itd., koncipiran je i ispitivan integrisani prečistač gasova koji se sastoji iz modula za prečišćavanje mehaničkih nečistoća i modula za prečišćavanje gasovitih nečistoća. Prečistač je kompaktan, i ima univerzalnu primenu uz istovremeno zadržavanje više različitih zagađujućih materija. Realizacija ovih zahteva ostvarena je primenom metoda filtracije i adsorpcije. Na formiranoj eksperimentalnoj liniji sa odgovarajućim sistemom akvizicije, simultano su izvršena ispitivanja prečistača gasova tipa filter-adsorber u funkciji strujno termičkih parametara gasne smeše. Eksperimentalno dobijeni podaci, iskorišćeni su za obučavanje neuronske mreže radijalnih bazisnih funkcija, kojom je izvršeno modeliranje karakteristika prečistača i procesa.