Proceedings of International Conference on Heat Exchanger Fouling and Cleaning - 2013 (Peer-reviewed)
June 09 - 14, 2013, Budapest, Hungary
Editors: M.R. Malayeri, H. Müller-Steinhagen and A.P. Watkinson
Published online
www.heatexchanger-fouling.com

PREDICTION OF FOULING IN EGR COOLERS WITH RADIAL BASIS FUNCTION NEURAL NETWORKS

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ABSTRACT
In the present study, radial basis functions are utilized to predict the deposit formation of soot particles in EGR (exhaust gas recirculation) coolers. The data bank for training the network contains a wide range of experimental data, i.e. inlet gas temperature of 250 and 400°C, inlet gas velocity of 10-120 m/s, coolant temperature of 25 and 80°C, and the inlet concentration of soot particles is 75-360 mg/m³. The comparison between the experimental data and predicted results showed a qualitatively consistent model, which is able to predict fouling resistance with good accuracy.

INTRODUCTION
In diesel-driven vehicles, NOx emissions can efficiently be suppressed by using exhaust gas recirculation (EGR) coolers. EGR basically functions by recirculating a portion of the exhaust gas back to the combustion chamber. As the formation of NOx is profoundly dependent upon the combustion temperature then the EGR flow contains lower oxygen, higher heat capacity which in tandem both tend to lower temperature resulting in reduced NOx formation.

As the exhaust gas is cooled when passes through an EGR cooler; the soot particles tend to deposit onto the cooled surfaces. The existence of the fouling layer on the cooler walls leads to an apparent performance degradation of the EGR cooler (Abd-Elhady et al., 2011). Therefore, it is indispensable to study the mechanisms of fouling process. Nevertheless the study of the underlying mechanisms of fouling is too complex and requires in depth knowledge of the physical and chemical properties of bulk gas and fouling layer and the corresponding changes during the course of deposition process. Common methods for the prediction of fouling are generally based on various operating conditions of the cooler and the physical properties of exhaust gas and the deposit layer.

Artificial neural networks, such as back-propagation and radial basis function networks have proven to be powerful function approximators (Poggio and Girosi, 1990). The main advantage of neural networks is to handle complex nonlinear systems without considering the detailed knowledge of underlying mechanisms. The absence of a process-based internal structure is a liability for the neural network when it faces noisy data. For more complicated systems it is not simple to describe the underlying mechanism with above-mentioned parameters of fouled EGR coolers. This is because the mechanisms of deposit formation cannot be easily related to operating conditions with poorly understood interaction which produces nonlinearities in the model of the system.

Previous studies focused on parametric modeling of deposit formation in EGR coolers with numerous assumptions to ease modeling of the phenomena (Warey et al., 2012; Abarham et al., 2010; Hoard et al., 2008). When more than one mechanism is involved in formation of the fouling layer, then these models are not applicable. No attempt is made to make use of non-parametric methods for simulating fouling in EGR coolers through already being successfully applied for other processes (Malayeri and Müller-Steinhagen, 2003; Malayeri and Müller-Steinhagen, 2001).

The principal objective of this study is to analyze the conditions that influence the deposit formation in EGR coolers. The second aim is to correlate the experimental data by the use of a radial basis function neural network (RBFNN). Finally, the network results have to be compared qualitatively with available experimental data.

PROBLEM STATEMENT
Among various mechanisms, thermophoresis is dominant for deposition of nano-sized particles under non-isothermal operating conditions (Abd-Elhady et al., 2011; Epstein 1997). It is the net motion of particles due to the presence of temperature gradient in the flow stream which can be expressed as (Whitmore and Meisen, 1977):

$$V_{th} = -K_{th} \nu_m \frac{\nabla T}{T_m} \tag{1}$$

The mean gas temperature in Eq. (1) can be determined by solving energy conservation equations along the cooler which is prone to the deposit formation. The temperature gradient, the main factor in calculating the thermophoretic force, is also (Abarham et al., 2009):

$$\nabla T = \frac{T_m - T_w}{\delta} \tag{2}$$

and the thickness of laminar sub-layer is $\delta = 5\nu/u^*$ (Abarham et al., 2009).

In addition to these equations, several assumptions are usually made in order to facilitate the modeling of fouled EGR coolers i.e.:

- The flow is assumed to be fully-developed turbulent flow.
- The thermo-physical properties of gas at inlet section remain constant.
- The radial variations of gas properties along the cooler are neglected.
- The physical properties of soot particles in the gas stream do not interfere with those of gas due to the small mass fraction of soot particles compared to air.

However, these assumptions can only be applied to a limited number of idealized fouling models which always include uncertainties/inaccuracies that influence their objective functions. This could be because of the non-linearity in the fouling phenomena, unsteady-state with high fluctuation characteristics of fouling process, and lack of understanding of underlying mechanisms (Müller-Steinhagen, 2011). Accordingly, implementing a model which can handle all these assumptions and results in reliable outputs will be time-consuming and not easy to achieve.

The utilization of neural networks is an alternative to handle such problems with considerably better accuracy than parametric models (Malayeri and Müller-Steinhagen, 2003). This can be done by using radial basis function neural networks (RBFNN) as a universal approximator within the range of experimental results. For doing so, the dominant parameters that affect the formation of fouling should be considered. These parameters will be served as inputs of the network and mainly are:

- Inlet gas temperature (T_{in}): It increases the mean temperature of bulk gas thus the temperature gradient as stated in Eqs (1) and (2) which in turn leads to higher soot particle deposition velocity.
- Inlet gas velocity (U_{in}): It increases the shear stress on the cooler wall and so does the friction velocity which tends to reduce the thickness of laminar sub-layer resulting in removal of particles (Mirsadraee, 2011).
- Coolant temperature (T_C): A coolant with a very low temperature leads to faster buildup of fouling layer due to a direct increase of temperature gradient between the wall and bulk gas.
- Inlet soot concentration (C_{in}): A higher amount of soot concentration of smaller sizes indicates that more particles are exposed to thermophoresis thus a thicker fouling layer would be built up.

In addition, the geometrical properties of cooler surface including the surface roughness and geometry (rectangular or circular) and flow pattern (laminar or turbulence) affect the soot particle deposition. Nevertheless, as the geometry of the EGR cooler was similar over the range of attempted experiments in this study, its impact on fouling was ignored. As for the particle size which affects the deposition due to influence on thermophoresis, in the present study, was kept constant with an average value of 130 nm. Accordingly we did not consider it as an input to the network. Instead, the inlet gas temperature and velocity, coolant temperature and inlet soot concentration will be used as inputs for the attempted neural networks, and the values of fouling resistance during the course of operation will serve as output.

UTILIZED EXPERIMENTAL RESULTS

A detailed explanation of the test rig and analysis of the experimental results can be found elsewhere (Abd-Elhady et al., 2011).

Selected Experimental Data and Discussions

In this study, two models were made, first model is for a portion of data-bank including nine sets of experiments, each consists of 240 data points which were used to train and generalize the associated neural network. The operating conditions of above-mentioned experiments are listed in Table 1. The data points are divided into two groups. In training phase, 75% of data points are used and the rest in the generalization phase. The inputs of the RBFNN are the normalized parameters of the EGR cooler as stated in Table 1 by dividing by their maximum value and the output of the RBFNN is the normalized fouling resistance that is again divided by its maximum value which may or may not reach the correspondent asymptotic value.

Table 1 Operating Conditions of Experimental Data.

Test Nr.	U_{in} (m/s)	T_{in} $(°C)$	C_{in} $(\mathrm{mg/m^3})$	T_C $(°C)$
1	30	400	105	80
2	30	400	100	80
3	10	400	360	80
4	30	250	100	25
5	30	250	100	25
6	30	250	100	25
7	30	250	100	25
8	30	250	75	25
9	30	250	138	25

The second model includes three experimental data sets that are identical and only the inlet gas velocity changes. Here the inlet velocity of gas varies from 30 to 120 m/s, and the gas inlet temperature (400°C), inlet soot concentration (100 mg/m³) and coolant temperature (80°C) remained constant. The architecture and training methods for the RBFNN is described in the following section.

RADIAL BASIS FUNCTION NEURAL NETWORKS (RBFNNs)

The state approximation of a process based on the measured data has an exact solution only when the plant and the measurement data are linear. In contrast many applications are nonlinear in nature. Neural networks learn the nature of a process by experiencing and obtaining available information from the process. Poggio and Girosi (1990) stated that the ability of learning in a neural network is related to its ability of approximation. However, it should be noted that the process in which all the signals are undoubtedly stochastic make them to be superimposed by some sort of noises. Hence, the strength of neural networks lies in their ability to make sense out of complex, noisy, or nonlinear data.

Among various types of artificial neural networks, RBFNN, where the activation functions are radially symmetric and produce a localized response to the input variables are of great interest. The main features of radial basis function neural networks are their high accuracy and fast training/learning rate. Various types of activation functions exist including Gaussian, (generalized/inverse) multi-quadratic, thin plate spline, cubic, and linear functions.

A RBFNN generally consists of two layers, the hidden layer of neurons that implements a set of radial basis functions and the output layer of neurons which implements a linear summation functions. The transform from the input nodes to the hidden layer is nonlinear and from the hidden layer to the output layer is linear. Radial basis function networks are used as a multidimensional interpolation technique of general mapping of $f: \mathfrak{R}^N \to \mathfrak{R}$. Let the number of input nodes, hidden and output layers be n, m and p respectively. For any input data point (any sample could be a vector) $\mathbf{x} = [x_1\ x_2\ \dots\ x_i\ \dots x_n]$, the output of the RBFNN is then $z(\mathbf{x}) = [z_1(\mathbf{x})\ z_2(\mathbf{x})\ \dots z_k(\mathbf{x})\ \dots\ z_p(\mathbf{x})]$. Therefore, the model of a radial basis function neural network can be written in the form of:

$$z_k(x) = \omega_k + \sum_{j=1}^{m} \omega_{kj} \sum_{i=1}^{n} \left(\varphi_j\left(\|x_i - \lambda_{ji}\|\right) + \lambda_j\right) \qquad (3)$$

where, $\varphi(\|.\|)$ is the non-linear mapping of each neuron in input layer to the hidden layer and the λ_j is the bias value for the class j in the hidden layer, and $\omega_{kj} = [\omega_{k1}\ \dots\ \omega_{k3}]$, for $k = 1, 2, \dots, p$ are the weights of the connection between the hidden layer and kth node in the output layer and the ω_k is the bias value for the class k.

The transfer functions of the hidden nodes are similar to the multivariate Gaussian density function:

$$\varphi\left(\|x_i - \lambda_{ji}\|\right) = \exp\left(-\frac{\|x_i - \lambda_{ji}\|^2}{2\sigma_{ji}^2}\right) \quad \text{for } \mathrm{j} = 1, \dots, \mathrm{m} \qquad (4)$$

where, the notation $\|.\|$ indicates the Euclidean norm of distance, values of λ_{ji} are the center positions of the radial units and is a vector with the maximum number of elements as the input vector $\mathbf{x}$, and σ_{ji} are the widths of RBF units. It should be noted that each RBF unit has a unique center and width, and has a significant effect over a region defined by its defined parameters.

The basic function of an RBF network is as follows. Each input vector $\mathbf{x}$ is passed to the network then shifted in $\mathfrak{R}^{\mathrm{N}}$ space according to centers of the radial basis function in the network. The Euclidean norm is computed for each of these shifted vectors. A schematic architecture of RBFNN with multiple inputs and multiple outputs is shown in Fig. 1.

Now consider the action of the Gaussian basis function on the resulting outputs from the Euclidean distance measures. For data which are far away from the centers, the output from the corresponding basis functions will be small, approaching zero with increasing the distance. On the other hand, for data which are close to the centers, the output from the corresponding basis functions will be larger, approaching one with decreasing the distance. Hence, radial basis function networks are able to model data in a local sense. For each input data vector, one or more radial basis functions provide an individual output.

Neural Network Training

In a RBFNN, three group of parameters need to be chosen to adapt the network for a particular task. These parameters are the size of the hidden layer, center vectors and width parameters and the connecting weights. There are various methods for training the network to choose appropriate centers, weights and width parameters of the radial basis functions. The weights are initiated randomly between 0.1 and 2 and are updated in a way to minimize the mean squared error of overall network versus experimental data. The overall performance of RBFNN is evaluated in terms of mean squared error (MSE) according to the equation below:

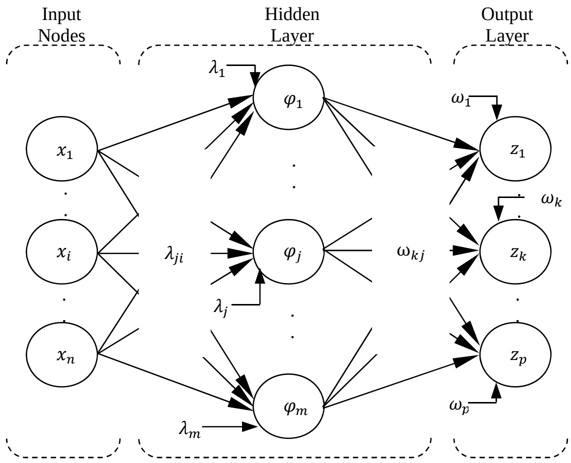

Fig. 1 – Schematic diagram of a RBFNN, x is input node (normalized parameters listed in Table 1.), φ is the activation function of neurons in the hidden layer and z are the output nodes (normalized fouling resistance).

$$MSE = \frac{\sum_{k=1}^{p}(z_k - \hat{z}_k)^2}{p} \qquad (5)$$

where, z_k is the desired output and $\hat{z}_k$ is the actual output of the network, p is the number of components in the analyzed set.

Training Method

The training of the RBFNN is performed in three steps. In the first step; the number of the neurons in the hidden layer is defined, in the second step; the center and width of the basis function are established from the input data. In the third step; the connection weights are adjusted to minimize the error defined in previous section. The training starts by setting the mean squared error of the RBFNN and maximum allowable number of neurons in the hidden layer. The neurons are then added to the hidden layer one by one in order to fulfill the above-mentioned conditions. The inputs and the target matrices are introduced to the network initially, then the primary size of the hidden layer is set to minimum number of the allowable neurons, the network design the widths and centers of the network and return the desired configuration of the network, the MSE of the network is checked for validating the network performance and if the MSE is in a satisfactory range, then the procedure stops, otherwise another neuron is introduced to the network and this iterative procedure continues until the desired MSE or maximum number of neurons is reached, if the maximum number of neurons is achieved without meeting the desired error value of the network, the network must be trained again or one of the pre-trained networks with lowest error would be selected.

In this study the centers of hidden neurons are obtained by method of random sampling of the input data iteratively by increasing the size of center matrix described previously. Once the centers for the basis function are established, the width of the basis function is computed using the normalization method of spread determination where the width is approximated as twice the average difference between consecutive centers (Bishop, 1995). Usually, the width is set between 0.1 and 2.0, in order to obtain an acceptable network performance, the width bigger than 2.0 will results in no effect of input nodes and the network would give same results for all inputs and the widths smaller than 0.1 would result in a very sensitive network to the inputs and leads to increase the hidden layer size. It is important that the widths parameters is large enough the activation function neurons respond to the overlapping margin of the input space, but not too big that all neurons respond in a same manner.

Once the number of neurons in hidden layer, centers and width are determined, then one should also calculate the weights of connections between the input nodes and hidden layer and the hidden layer and the output layer. The well-known pseudo-inverse method is utilized for estimating the weights. Detailed explanation can be found elsewhere (Bishop, 2005).

$$\lambda^T = (\varphi^T \varphi)^{-1} \varphi^T z \qquad (6)$$

where λ is the weight matrix defined previously, z is the desired output of the RBFNN and φ radial basis function in hidden layer. The code was written in MATLAB by the authors.

RESULTS AND DISCUSSIONS

In this study, the first model used 9 sets of experiments with various operating conditions those are attempted for an identical EGR cooler. Each set of data has at least 240 data points that are collected in a sampling interval of one minute. Various operating conditions as a simple 4×9 matrix are fed to the network and the output of the network as a row matrix expressing the fouling resistance is obtained. Therefore the input of the network is a matrix with four rows and 9 columns and the output of the network is a matrix of 9 rows with 240 columns. The hidden layer of the RBF network uses multiple Gaussian functions with various centers and widths which are determined during the training and generalizing steps. Results of implementation of RBF neural networks showed the ease of modeling of the fouling formation in EGR coolers.

The experimental data were compared to the results using a RBFNN with an architecture described in previous section. This section compares the results obtained by the approach on the basis of measured and calculated cooler data. Accordingly, the MSE method, Eq. (5), was used for evaluating the performance of the RBFNN in prediction of the fouling resistance.

Fig. 3 demonstrates the comparison of experimental data and simulation results for various operating conditions mentioned in Table 1. The presented experimental points were obtained during 4 hours period of continuous run and are shown in a normalized form to readily compare the performance of RBFNN for various operating conditions. The input data are normalized by dividing to the maximum value of the parameter, normalizing will also facilitate the utilization of activation function of hidden layer with steep exponential trends which otherwise leads to malfunctioning of the model. The RBFNN illustrates a very good agreement of the obtained data.

The strength of the RBFNN laid in the estimation of fouling resistance for various operating conditions where the calculated MSEs for Fig. 2 (a) – (h) indicate the performance of the RBFNN.

The calculated MSEs for Fig. 2 (a) – (h) are 0.0012, 0.002, 0.01, 0.001, 0.001, 0.002, 0.002 and 0.004, respectively. Unlike other processes, the deposit formation is highly complex which exhibit peculiar behavior i.e. fluctuation of experimental data points in Fig. 2 (d) – (g). Nevertheless, RBFNN is capable of handling such data and the estimated value for fouling resistance in these cases is quantitatively comparable. The EGR experimental results contain high fluctuations and the network predictability is particularly poorer in these regions which can be seen in Fig. 2 (c) and (h).

The network is also able to estimate highly fluctuated data, as shown in Fig. 3 separately. In this special case, one set of network centers is exactly located on the operating conditions of this experiment. Then the network estimates the exact solution for fouling resistance where MSE becomes zero. Sudden decrease of fouling resistance would be due to some incidents like partial removal of the fouling layer or change of its physical properties.

The second model considers a RBFNN of the same architecture illustrated in Fig. 1, these experimental data are completely identical and the only parameter that is changed is the inlet velocity of the bulk gas. The results proved the performance of the network. The network can be tuned to cover regions with fluctuations/discontinuities at the expense of more sensitivity and more computing time. The network ability for doing so has already been illustrated in Fig. 3 in which the results are shown in non-normalized form and can be compared quantitatively versus each other and the output of the RBFNN. The network estimated smooth curves that have MSE < 0.005. On the other hand, the network estimates the asymptotic fouling resistance qualitatively. The network ignores small noises or fluctuations of the experimental data and hand in an ideal curve of fouling resistance.

CONCLUSIONS

This paper reports on modeling of fouling resistance in EGR coolers using radial basis function neural networks. The network includes input nodes (operating conditions), hidden layer and output layer (fouling resistance). The operating conditions of the available EGR cooler are fed to the network via input nodes and through passing some weighted radial basis functions appear at the output layer presenting the fouling resistance of the cooler for a wide range of operating conditions. A databank of nine experimental runs is used for training and generalizing the first RBFNN. The second dataset is used for modeling the cooler with same operating conditions but different inlet gas velocities. The network successfully predicted qualitative trends of fouling resistance. The performance of the cooler is evaluated using the mean squared error method.

It is shown that RBFNN is also capable of handling noisy data; however, special care has to be taken for configuring the network structure and selection of training method and generalizing phases.

NOMENCLATURE

$\lVert . \rVert$	Euclidean norm
C_{in}	Inlet concentration of soot particles, mg m^{-3}
K_{th}	Thermophoretic coefficient, –
MSE	Mean Squared Error
RBF	Radial Basis Function
T_C	Coolant temperature, °C
T_i	Gas temperature at the outlet section, °C
T_m	Mean temperature of bulk gas, °C
T_o	Gas temperature at the inlet section, °C
T_w	Wall temperature of cooler, °C
U_{in}	Inlet velocity of bulk gas, m s^{-1}
V_{th}	Thermophoretic deposition velocity, m s^{-1}
$\hat{z}$	Actual network output
∇T	Temperature gradient across the laminar sub-layer, °C m^{-1}
x	Network input
z	Network output

Greek Symbols

δ	Thickness of laminar sub-layer, m
λ	Weights of the networks between the input nodes and the hidden layer known as centers
ν_m	kinematic viscosity of bulk gas at T_m, m^2 s^{-1}
φ	Radial Basis Function
ω	Weights of the network between the hidden layer and the output layer
$\Re$	Domain of Real numbers
∇	Gradient symbol

Subscripts

i	th element of the input nodes
j	th element of the hidden layer
k	th element of the output layer
m	Number of input nodes
n	Number of neurons at the hidden layer
p	Number of neurons at the output layer

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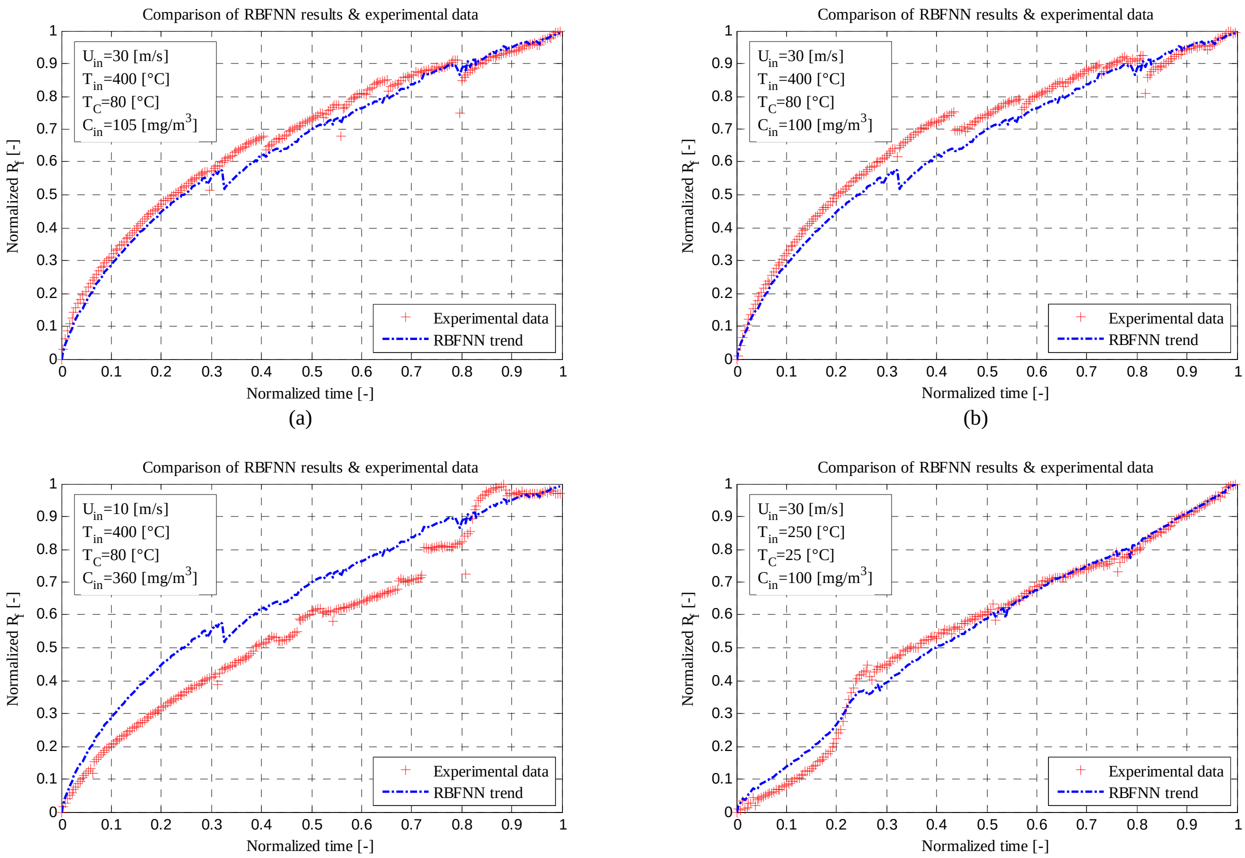
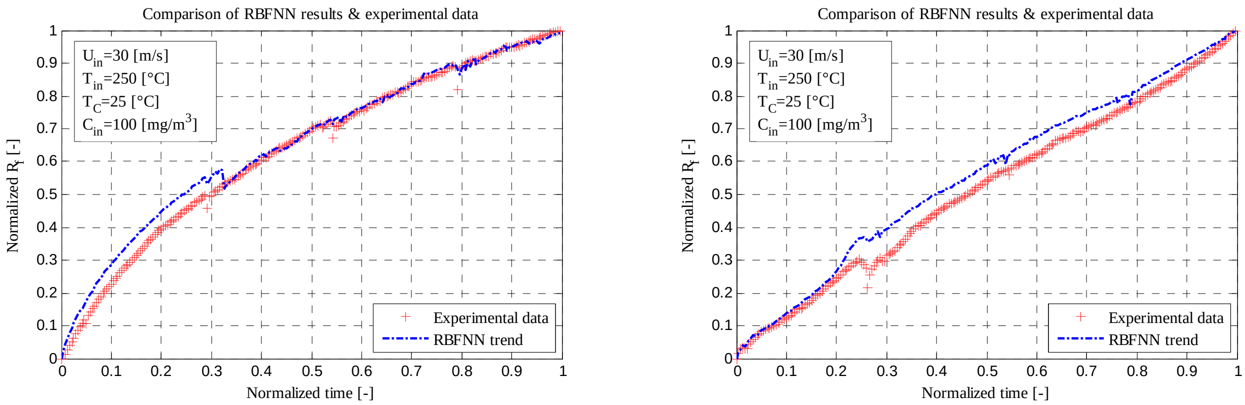
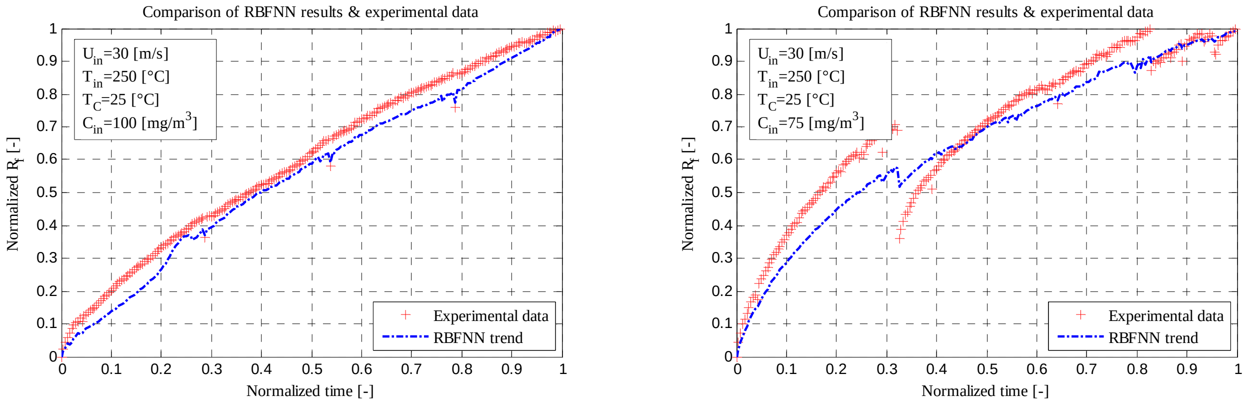


(a) (b) (c) (d)

Fig. 2 – Comparison of simulation results and experimental data for various operating conditions (cont'd)



(e) (f)



(g) (h)

Fig. 2 (cont'd) – Comparison of simulation results and experimental data for various operating conditions

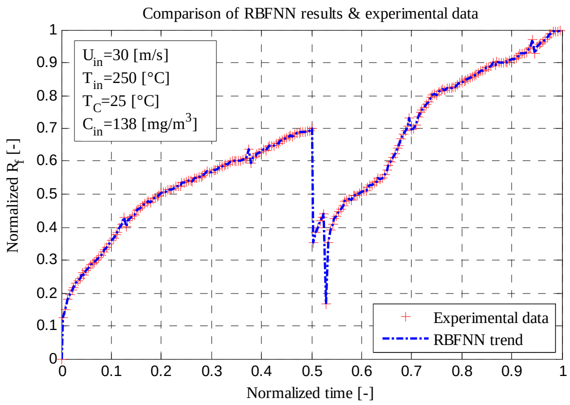


Fig. 3 – Simulation results for highly fluctuated experimental data

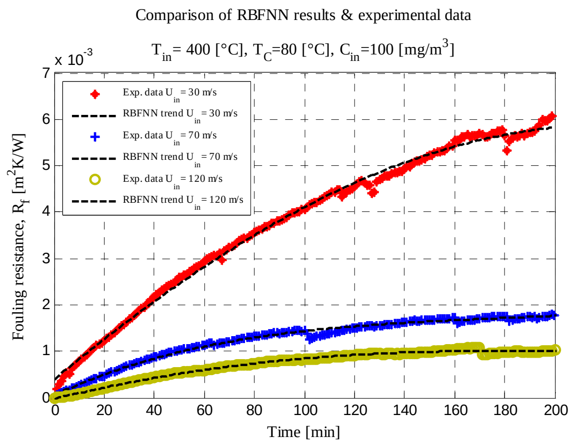


Fig. 4 – Simulation results for second dataset