Comparison of Modeling Approaches for Prediction of Cleaning Efficiency of the Electromagnetic Filtration Process

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***Abstract*─** The present study aims at applying different methods for predicting the cleaning efficiency of the electromagnetic filtration process (ψ) in the mixtures of water and corrosion particles (rust) of low concentrations. In our study, artificial neural network (ANN), multivariable least square regression (MLSR), and mechanistic modelling approaches were applied and compared for prediction of the cleaning efficiency for the electromagnetic filtration process. The results clearly show that the use of ANN led to more accurate results than the mechanistic filtration and MLSR models. Therefore, it is expected that this study can be a contribution to the cleaning efficiency.

***Index Terms*─** ANN, electromagnetic filtration, MLSR.

I. INTRODUCTION

Some of the known impurities in water used in the industry are mostly Feand its various compounds. In water, high concentrations of ferrous compounds cause serious problems. The ferrous compounds that accumulated in pipeline by separating on the capture surface over time to cause water pollution. Ferrous compounds result in undesirable color and turbidity.It causes to plug and the shrinkage of cross-section by accumulation inside the pipe.It is stained on the clothes and porcelain.The waters with high ferrous concentration are undesirable in various areas such as paper, leather, textile, plastic, and food industries because it leads to vary color and taste of productions.

Magnetic ferrous compounds are Fe_3O_4 andγ-Fe_2O_3. These are called also as corrosive productions. Especially, magnetite (Fe_3O_4) is a basic compound of corrosive productions. In the water and wastewaters, there are low concentrations and micron-sized dispersed particles, showing various magnetic characteristics. Various separation methods can be applied such as membrane filtration, coagulation, ion ex-changer, and precipitation. They depend on the characteristics of the solids and the ratio of the solid/liquid in the suspension. However, if the particle concentration is around 10^{-3}-10^{-5} g/kg and their sizes are lower than 1 μm, the conventional methods cannot be applied for a required separation degree. In the waters, it can be easily separated from magnetic particles using electromagnetic filters and from non-magnetic particles using other effective methods in order to use them in the plants.

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Electromagnetic filtration is a rather simple and quite environment-friendly separation process, as it does not require any chemical or biological reagents and heavy conditions such as high temperature or pressure. Also, these filters can be simply set up and cleaned. Owing to the advantages, electromagnetic filtration is anuseful separation technique employed to separate micron and submicron magnetic particles from the carrier medium with high efficiency.For this reason, electromagnetic filters have used for the separation of heavy metal ions, phosphates, corrosion products, such as the rusts in mining, glass, ceramic, oil, power, and nuclear power generation industries [1-7].The matrix of the electromagnetic filter is composed of the magnetic packed beds, easily magnetized within an external magnetic field. The packing elements are usually balls, steel wools, metal rods, and wires. The high gradient fields are locally formed around these packing elements with an effect of the magnetic field. When liquids or gases are passing through the filter elements in the external magnetic field, the magnetic particles contained are exposed to strong sedimentation forces and most of them accumulate in the granular media of the filter elements, there it appears high gradient magnetic fields at local zones which are called capture-sections of the filter. Purification of a liquid or a gas is accomplished by passing the suspension and holding the micron sized magnetic dispersed particles in the capture-sections of the filter [1, 3, 8-13]. As magnetic filters can withstand high temperatures, corrosive and radioactive mediums, mechanical and hydro dynamical effects, these packed beds can be effectively used in the separation processes of many industrial brunches.

The electromagnetic filtration efficiency depends on several factors such as hydrodynamic, magnetic, rheological, and geometrical parameters of the system and physicochemical properties of a medium. The electromagnetic filtration efficiency is thus a multi-variable stochastic function [1-4, 14, 15]. In order to suggest a general theory for this process, effects of all these parameters must be known.

For predicting effects of the parameters such as the external magnetic field strength, diameter of the filter elements, filter length, viscosity of the suspension and the filtration velocity on the cleaning efficiency (ψ), one approach could be the identification of an input-output relationship between the involved variables based on the experimental measurements. From this perspective, artificial neural networks (ANNs) are powerful tools having the abilities to recognize underlying complex relationships from input–output data only [16].

An artificial neural network is an information processing system that imitates the behavior of a human brain by emulating the operations and connectivity of biological neurons [17]. It performs a human–like reasoning, learns the attitude, and stores the relationship of the processes based on a representative data set. In general, the neural networks do not need much of a detailed description or formulation of the underlying process, and thus, appeal to practicing engineers who tend to rely on their own data [16]. Recently, neural networks have been successfully applied to process modelingand control [18-22].

The main aim of this study is to develop a suitable ANN model by considering the feed-forward back propagation learning algorithm in the estimation of the cleaning efficiencyin the system from external magnetic field strength, filter length, diameter of the filter elements, the filtration velocity, and the viscosity of suspension parameters. Moreover, its performance comparison with the mechanistic model that was developed by Abbasov [1], and multivariate least squares regression approach are important.

II. EXPERIMENTAL METHOD

The electromagnetic filter used in the experimental studies is consisting of a non magnetic filter body and the stainless steel balls as the filter elements. As the external magnetizing medium, multipurpose electromagnetic magnetizing equipment (AC/DC, 0-220 V, and 0-10 A) has been used. The experimental studies have been carried out by placing an electromagnetic filter into this equipment, which has a 48 mm diameter. Magnetic field intensity (B) was within the range of 0-0.5 T.

The most important characteristic of the electromagnetic filters that make them more useful and popular compared to classical filters is their ability to separate micron and submicron magnetic particles from the carrier medium with high efficiency.

Experiments were carried for various conditions, such as the filtration velocity of 0.10-0.95 m/s, suspension viscosity of 0.8-10.96 cp, external magnetic field strength of175-279 kA/m, diameter of the filter elements of 4-14 mm, and filter length of 1-10 cm (Table 1).

Table 1: Parameters of the data considered for the present study

Parameters	Min.	Max.	Average	Std. dev.
$H(kA/m)$	175.070	278.521	224.500	40.618
$L(m)$	0.0100	0.1000	0.0908	0.0236
$d(m)$	0.00475	0.014	0.0077	0.0027
$V(m/s)$	0.1000	0.9500	0.1862	0.1398
$\mu(kg/m\cdot s)$	0.00008	0.01096	0.00123	0.00197
ψ	0.1800	0.8300	0.6733	0.1247

H: external magnetic field strength, *L*: filter length, *d*: diameter of the filter elements, V_f: the filtration velocity, μ: viscosity of suspension

In order to prevent the coalescence of the rust particles, a continuous mixing was applied. The filter and balls were washed and dried at the end of each experiment. After determining the total Fe amount by atomic absorption spectroscopy (AAS) analysis, the cleaning efficiency of the filtration process (ψ), was determined using the following equation:

$$\psi = \frac{C_i - C_0}{C_i}\lambda, \tag{1}$$

where, λ, the ferromagnetic fraction of the mixture, C_i and C_0 are the total Fe amount at the inlet and outlet respectively (mg/L).

The total Fe amount at the inlet is constant. A 10 g portion of particles was spread over a permanent magnet and the fraction of particles having magnetic properties was weighed. The procedure was replicated. It was determined that 85% of the corrosion products showed magnetic properties. Thus, it was determined that the magnetic fraction of the mixture (λ), was 0.85.

III. MODELLING PROCEDURE

A. Artificial neural network (ANN)model

By using the experimental observations as the input data set to identify the effects of operating parameters on the cleaning efficiency, an artificial neural network (ANN) model was created. A three-layered feed forward and a back propagation algorithm with 5 neurons in the first layer, 4 neurons in the interim layer and 1 neuron in the last layer were chosen. The network had one input layer, one hidden layer and one output layer as shown in Fig. 1. The first layer has five hyperbolic tangent sigmoid neurons, the second layer has four logarithmic sigmoid neurons, and the last layer has one linear neuron. In the course of training, which was based on the Levenberg-Marquardt method, the number of hidden layers, the number of neurons in the hidden layer, training accuracy, and the number of iterations were determined by using the trial and error method.

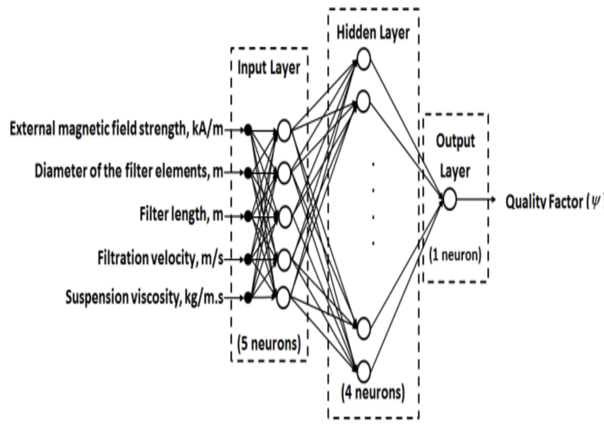

Fig.1.Schematic diagram of ANN model.

The ANN model consists of five input nodes corresponding to

(a) external magnetic field strength
(b) filter length
(c) diameter of the filter elements
(d) the filtration velocity
(e) viscosity of suspension.

The single output was the cleaning efficiency (ψ) in the system.

To develop an ANN model for estimating cleaning efficiency, the data set was partitioned into a training set and a test set. Out of 53 data sets available, 35 were used for training, and the remaining for testing. The performance function was the sum of the squares of the difference between output of ANN and observations of laboratory analysis. Training was preceded for 500 epochs. MATLAB 7.0 [23] software was used for all computations.

B. Multivariable least squares regression (MLSR)

Multivariable regression by the method of least squares is an extension of the least squares simple linear regression model. The multivariate regression methods allow the interrelationship between the response and several independent variables to be evaluated simultaneously. It also allows non-linear relationship between the response variable and the independent variables to be evaluated. The multivariable least squares regression equation is shown in equation (2).

$$y_i = \beta_0 + \beta_1 x_{i,1} + \ldots + \beta_{n-1} x_{i,n-1} + \varepsilon_i, \qquad (2)$$

where y_i is the i^{th} response. $\beta_0, \beta_1, ..., \beta_{n-1}$ are the regression parameters. $x_{i,1}, ..., x_{i,n-1}$ are the i^{th} individual's set of predictors. ε_i is the independent random error associated with the i^{th} response, typically assumed to be distributed N(0,σ). After being built on available data, the model will probably be used for predicting the values taken by the response variable for new data points $\{x\}$ that are not in the original data set (predictive modelling).

C. Model filtration theory

In general, the magnetic filtration theory can become in the basic methods of classic filtrations [24,25]. Besides other forces acting on capturing particles in the pores on magnetic filters (inertia, Archimedes density, drag etc.), the relative magnitudes of magnetic forces are the dominant mechanism in the capturing process. For this reason, the efficiency of magnetic filtration is higher than other filters [1-4]. In general, the efficiency of the magnetic filtration depends on the magnetic, rheological, geometric, and hydrodynamic parameters. On the other hand, physicochemical properties of a medium depend on these parameters determining magnetic filtration efficiency, which is a multi-variable stochastic function.

It faces toomany difficulties in the modelling and optimization of magnetic filtration performance as a variety of parameters affectsthe magnetic filtration process. But the approximation model of the filtration theory that can consider optimization of the change of magnetic filtration efficiency is in the limitation conditions. The detailed theoretical and practical investigations of the magnetic filters are reported in the literature. From the results of these studies, ψ is the cleaning efficiency as follows (equation (3)):

$$\psi = \lambda\left[1 - \exp(-\alpha L)\right]. \qquad (3)$$

where, L is the filter length, λ is the ferromagnetic fraction of the mixture, α is the fraction (coefficient) of the captured particles which depend on the magnetic, hydrodynamic, geometric, and the rheological properties of the filter. By adding the effect of diameter of the filter elements, external magnetic field strength, the filtration velocity, and the viscosity of suspension, the equation (4) can be given

$$\psi = 0.85\left(1 - exp\left\{-A\left[\frac{H^{0.75} L}{\mu d^2 V_f}\right]\right\}\right). \qquad (4)$$

where, A is rational constant, μ is the viscosity of suspension, H is magnetic field strength, d is the diameter of the filter element (stainless steel ball), V_f is the filtration velocity. It is obvious that the separation efficiency of an electromagnetic filter will depend on the operating levels of the relevant variables. In this work, we aimed at the optimization of the external magnetic field, diameter of the filter elements, filter length, and filtration velocity for the separation efficiency of the magnetic particles in the electromagnetic filters.

IV. RESULTS AND DISCUSSION

In this study, the proposed models aim to assess the effects of operating parameters on estimating the cleaning efficiency. Thus, these models were created by considering the cleaning efficiency in the mixtures of water and corrosion particles of low concentrations.

For development of the neural network model, the Neural Network Toolbox and MATLAB 7.0 were used. A MATLAB script was written, loaded the data file, trained and validated the network, and saved the model architecture.

The input data was made of the external magnetic field strength, diameter of the filter element, filter length, viscosity of the suspension, and the filtration velocity. The output data was made of the cleaning efficiency. The input data and the output data were normalized and de-normalized before and after the actual application in the network. Thus, the model was trained for input-output behavior of the system.

The neural network (NN) is exported to Simulink environment using the '*gensim*' command after the training is finished. The block diagram in Fig.2 shows the NN in Simulink [23].

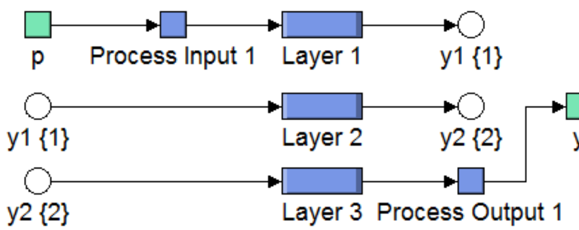

Fig. 2. Three layers of the neural network block diagram.

Figure 3 shows that the block diagram representation of the neural network model for input layer [23].Block diagrams of the neural network model for hidden layer and output layer are shown in Figs. 4 and 5, respectively [23].

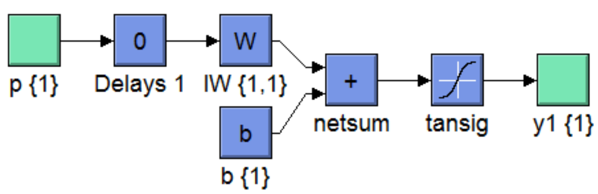

Fig. 3.Input layer simulation.

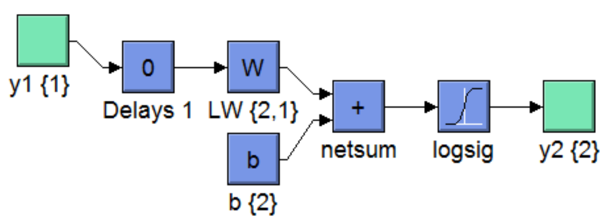

Fig. 4.Hidden layer simulation.

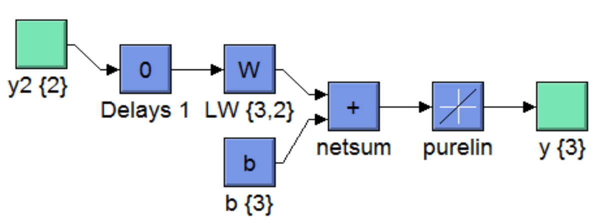

Fig. 5.Output layer simulation.

The transfer functions tansig and logsig used in this study are given in equation (5) and equation (6), respectively.

$$y_i = \frac{2}{1+e^{-2z_i}} - 1, \quad (5)$$

$$y_i = \frac{1}{1+e^{-z_i}}, \quad (6)$$

where z_i is the input of the neuron in the hidden layer and y_i is the output of neuron while calculating z_i, logsig transfer function was calculated a layer's output from its net input [23].

IW, LW, and b are defined as input weight, layer weight, and bias, respectively. In this study, values of IW, LW, and b for NN layers are given in Tables 2, 3, and 4 [23].

Table 2: Weights and bias values for input layer

IW{1,1}					b{1}
-0.0146	-0.1923	0.0820	-0.7444	-0.1297	0.0626
-0.3359	-1.6946	0.3514	-0.9232	0.9588	-1.1541
-0.0231	0.8443	-0.0010	0.2818	-0.9518	-0.1249
0.1286	0.4234	-0.2894	0.1692	-0.4117	-1.5776
0.4185	0.7018	-0.8372	0.2380	-0.4048	1.9692

Table 3: Weights and bias values for hidden layer

LW{2,1}				b{2}
0.3408	-0.4659	0.4341	0.4329	0.0911
-0.7031	1.0237	-0.9640	-0.9616	-0.2155
-0.5071	0.6775	-0.6480	-0.6468	0.1957
0.8026	-0.9064	0.8920	0.8926	0.1947
-0.9699	1.1218	-1.1010	-1.1015	

Table 4: Weights and bias values for output layer

LW{3,2}	b{3}
-1.6987	
2.2956	0.1829
-2.1251	
-2.1241	

The ANN model is summarized in the following equations (7, 8&9) [23];

$$y_1 = tansig\left[IW\{1,1\} * p + b_1\right], \quad (7)$$

$$y_2 = logsig\left[LW\{2,1\} * y_1 + b_2\right], \quad (8)$$

$$y_3 = purelin\left[LW\{3,2\} * y_2 + b_3\right], \quad (9)$$

where y_i are i^{th} output of layers. ANN model output is defined as y_3.

The preliminary results are shown in Fig. 6. The behavior of the network for the test data is shown in the following Fig. 7. As detected from Fig. 7, the network model results are compatible with the observations.

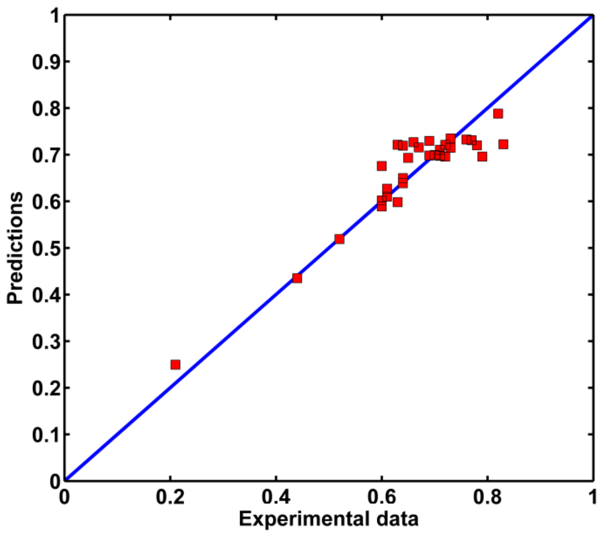

Fig. 6.ANN training results.

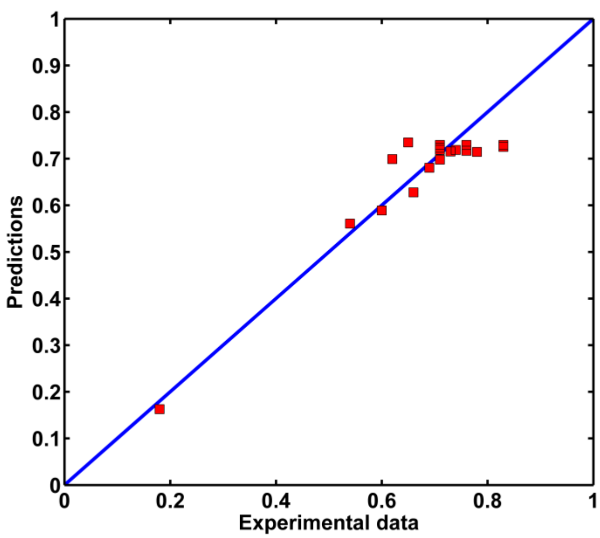

Fig.7. ANN testing results.

The MLSR analysis was performed on the training set, used to develop the neural networks. The regression parameters of the MLSR model are given in Table 5.

Prediction capability of the mechanistic model was performed on the testing data set, used to performance evaluation of the ANN and MLSR. Fig. 9 depicted the results of the mechanistic model.

Table 5: The regression parameters(in equation 2)

i	β_i
0	0.3730
1	0.3131
2	0.0318
3	-0.0022
4	-0.2443
5	-0.0096

The test data set was used to performances of the MLSR equations. The result of MLSR model is shown in Fig. 8.

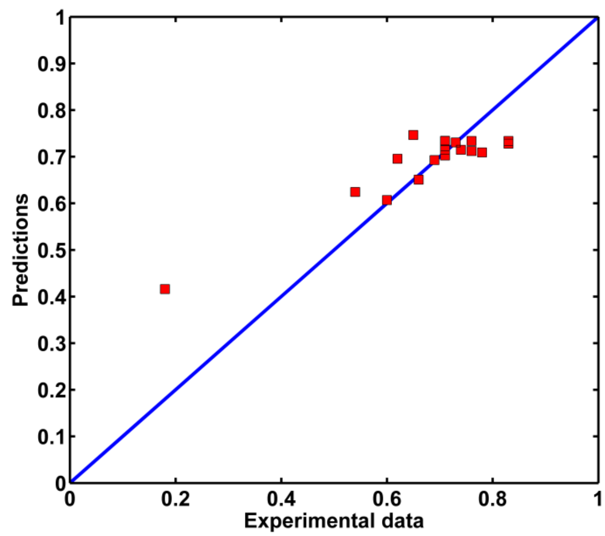

Fig.8.MLSR results for testing data.

Three parameters namely correlation coefficient (R), mean absolute percentage error (MAPE), and root mean square error (RMSE) values were used for the performance evaluation of the models.

A higher value of the correlation coefficient and the smaller values of MAPE and RMSE mean a better performance of the model. Correlation coefficients calculated for training and testing of network were 0.93 and 0.94, respectively. MAPE values were found as 4.67 % and 5.8 %.

The results suggest better performances by the artificial neural network as well as the other two approaches. Moreover, ANN is relatively more accurate than MLSR and the mechanistic model by Abbasov [1] in predicting the cleaning efficiency in the system. The results are tabulated in Table 6.

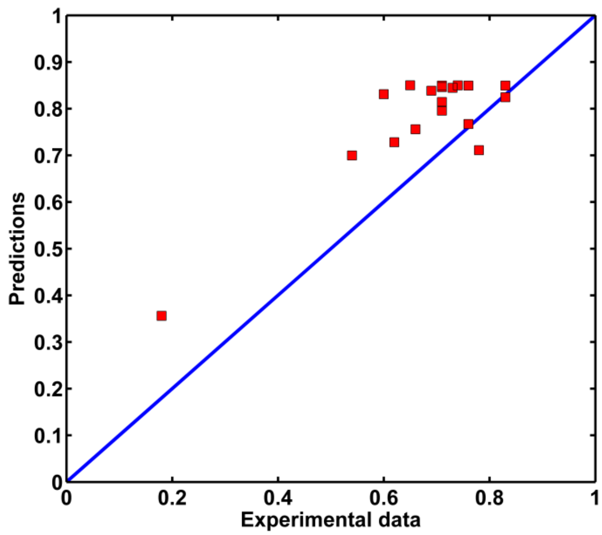

Fig.9.Mechanistic model results for testing data.

Table 6: Performance indexes achieved using ANN, MLSR and Mechanistic model during training and validation periods

	Training data			Test data		
Model	**R**	**MAPE (%)**	**RMSE**	**R**	**MAPE (%)**	**RMSE**
ANN	0.93	4.67	0.042	0.94	5.8	0.050
MLSR	0.74	9.26	0.076	0.92	12.9	0.077
Abbasov[1]	–	–	–	0.86	15.3	0.126

V. CONCLUSIONS

The proposed ANN model predicts the cleaning efficiency (ψ) in the mixtures of water and corrosion particles of low concentrations, when the external magnetic field strength, diameter of the filter elements, filter length, viscosity of the suspension, and the filtration velocity are given. The errors for MLRS (12.9 %) and the mechanistic model (15.3 %) are higher than the error obtained for ANN (5.8 %) as the capability of ANN is more than MLRS and mechanistic model in predicting the quality factor which is a complex and nonlinear process. These results showed that the ANN model is useful for the prediction of cleaning efficiency for electromagnetic filtration process. Estimation of the mechanistic model constants using a powerful optimization techniquecan give better results.

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