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EVALUATION OF ELECTROMAGNETIC FILTRATION EFFICIENCY USING LEAST SQUARES SUPPORT VECTOR MODEL

Mehmet YUCEER[*], Zehra YILDIZ[**], Teymuraz ABBASOV[***]

[*] Department of Chemical Engineering, Faculty of Engineering, Inonu University, Turkey
[**] Department of Bioengineering, Engineering and Natural Science Faculty, Adana Science and Technology University, Turkey, zyildiz@adanabtu.edu.tr
[***] Department of Electrical and Electronical Engineering, Faculty of Engineering, Inonu University, Turkey

Abstract. The present study aims to apply a least squares support vector model (LS–SVM) for predicting cleaning efficiency of an electromagnetic filtration process, also called quality factor, in order to remove corrosion particles (rust) of low concentrations from water media. For this purpose, three statistical parameters: correlation coefficient, root mean squared error and mean absolute percentage error were calculated for evaluating the performance of the LS–SVM model. It was found that the developed LS–SVM can be used to predict the effectiveness of electromagnetic filtration process.

Keywords: *electromagnetic filtration, disperse systems, support vector machine*

Introduction

Water is an important process fluid used for industrial applications. Re-use of disposed water by cleaning a dispersed particle contaminant, thus improving the water quality, has become an important topic in many applications. Natural water may contain a wide range of impurities, mostly arising from weathering of rocks and soils. The most fundamental issue concerning the impurities in an aquatic environment is distinction between dissolved and particulate forms. Substances that are relatively insoluble in water may exist as small particles, which remain suspended in water for long periods. Such impurities in water are undesirable and must be removed, as in water and effluent treatments, or they may be valuable materials that need to be recovered, as in mineral processing or biotechnology. Essentially, particulates can be removed from water by various separation methods such as sedimentation, flotation, membrane filtration, coagulation, adsorption, oxidation, ion exchange, and

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precipitation depending on the characteristics of the solids in a medium (Abbasov, 2002; Gregory, 2006). In order to remove ferrous particles from water, many methods such as membrane filtration, coagulation, adsorption, oxidation, ion exchange, and precipitation can be used. Using the classical methods for separating these particles typically provides low cleaning efficiencies, but some method can be accepted because of low cost and productivity, and lack of broad areas of use. The most common particle impurities in water are the iron(II) and iron(III) compounds such as Fe_3O_4, γ-Fe_2O_3 and Fe_2O_3. Since oxides of iron (Fe^{+2}) can be easily removed magnetically, electromagnetic filtration process (EMF) is frequently used to separate these compounds from water. On the other hand, the performance of the EMF methods strongly depends on the percentage of magnetite or other kind of magnetic species. The EMF involves passing a suspension through filter matrices elements such as steel balls, steel wools, metal wires, and rods. Such filter matrices are composed of magnetic packed beds that can be magnetized easily by an external magnetic field. Local high gradient fields are formed around these packing elements through the effect of the low external magnetic field (such as 0.05 T). Purification of liquid or gas is then achieved by passing either suspension or the colloidal systems and holding from the micron to nano sized magnetic impurities in these areas. The most important characteristic of the magnetic filters that makes them more useful compared to conventional filters was separation of micron/submicron particles from the carrier medium with a very high efficiency.

The electromagnetic filtration process (EMF) is preferred than the others as it does not require any reagents or extreme conditions such as high temperature or pressure. Also, these filters can be easily cleaned and the process is more economical. For this reason, the EMF is competently used for separation of heavy metal ions, phosphates, corrosion products, such as the rusts in mining, glass, ceramic, oil, power and nuclear power generation industries (Oberteuffer, 1974; Sandulyak, 1988; Abbasov, 2002; Yildiz et al., 2010; 2011).

The separation efficiency and performance of the electromagnetic filters depend on several factors such magnetic, hydrodynamic and geometrical parameters of the system. The geometric parameters are the diameter of ball, filter length, size of the captured particles, hydrodynamic parameters are the filtration and suspension viscosities and the magnetic parameters are the magnetic permeability, and diameter of the ball andexternal magnetic field strength. It is obvious that the separation efficiency of the electromagnetic filter depends on these parameters. For this reason, a modelling study was performed to quantify how these parameters can affect the separation performance of electromagnetic filters for water contaminated with the rust particles. In this study, a least squares support vector model (LS-SVM) was used for prediction of the EMF quality factor using five input variables, namely: filtration velocity, external magnetic field strength, diameter of the filter elements, filter length and suspension viscosity. The results of the developed LS-SVM model are compared with the results obtained from a previous study by Yildiz et al. (2011). In the previous study, the 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 showed that the use of ANN leads to more accurate results than the mechanistic filtration and MLSR models. In this work, the proposed model can be used to predict the quality factor within a smaller value (2.9%) of the mean absolute percentage error.

Experimental method

The filter used in these experimental studies was consisted of a non-magnetic filter body and stainless steel balls as filter elements. An electromagnet was used as an external magnetizing medium. The experimental studies were carried out by placing the filter into this equipment, which is about 0.05 m in diameter. The magnetic field intensity was within the range of 0-0.50 T. A scanning electron microscope (SEM) analysis was necessarily made in order to determine the mean particle sizes of rust particles that form the suspension. From the measurements taken from eleven different points of sample, the mean particle size for the dry rust samples were verified. As a result of the SEM analysis (Fig. 1), the particle sizes vary between 0.2-2 μm. In this work, the mean particle size was taken as 1 μm.

The X-ray analysis was necessarily made in order to determine the magnetic properties of the rust particles that form the suspension. The X-ray diffraction of particles (Fig. 2) revealed that a corroded material is a composition of ferromagnetic ($CoMn_2O_4$, $Co_2Mn_3O_8$, $CoCrO_4$), ferrimagnetic (Fe_3O_4, γ-Fe_2O_3), and paramagnetic (FeO, α-Fe_2O_3, Cr_2O_5) compounds. This composition of rust particles used in this study is similar to that of corrosion particles occurring during various industrial processes.

The experiments were carried out under various conditions for different filtration (range 0.10-0.95 m/s) and suspension (range 0.8-10.96 cP) viscosities, external magnetic field strength (range 175-279 kA/m), diameter of the balls (range 4-11 mm), and filter length (range 0.01-0.10 m).

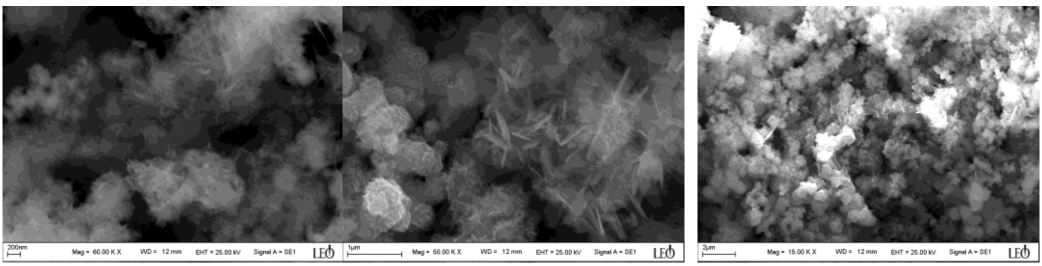

Fig. 1. SEM photos of rust particles

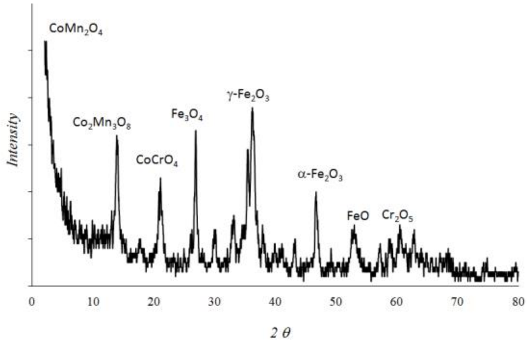

Fig. 2. X-ray diffraction of rust particles

The suspension to be filtered was prepared by the mixing tap water and rust particles. The amount of Fe was determined using an atomic absorption spectrometer (AAS). The magnetic filtration efficiency (Ψ) was determined according to the following formula:

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

where λ is a magnetic fraction of a mixture, $C_i$and C_0 are the total amount of Fe (ppm) at the inlet and outlet, respectively. The total amount of Fe at the inlet was held constant. A 10 g sample of the rust particles was spread over a permanent magnet and a fraction of particles having ferromagnetic properties was weighed. It was found that 85% of the corrosion products exhibited good magnetic properties ($\lambda = 0.85$). The solid/liquid ratio of the suspension used in the experiments was kept as 0.050 g/dm^3. The experiments were carried out at room temperature (23 ±1 °C). In order to prevent agglomeration of rust particles, a continuous mixing was applied. Statistical parameters of the experimental setups are given in Table 1, where H is the external magnetic field strength, L filter length, d diameter of the filter elements, V_f filtration velocity and μ viscosity of suspension.

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

Parameters	Min.	Max.	Average	Standard deviation σ
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_f (m/s)	0.1000	0.9500	0.1862	0.1398
$\mu \left(\frac{\mathrm{kg}}{\mathrm{m \cdot s}}\right)$	0.00008	0.01096	0.00123	0.00197
Ψ	0.1800	0.8300	0.6733	0.1247

In this work the modeling procedure was provided by the support vector model (SVM). The SVM is a machine learning technique which is based on the statistical learning theory and structural risk minimization principle. The SVM was introduced by Vapnik (1998) and is an efficient technique for the problems characterized by small samples, nonlinearity, high dimension, or local minima (Suykens and Vandewalle, 1999). The SVM uses a based quadratic programming (QP) optimization to identify model parameters, while avoiding local minima, and have an advantage over other regression methods (Li et al., 2007). SVM shows the outstanding performance since it can lead to global models that are often unique by embodying structural risk of minimization principle as developed by Vapnik (1998). Furthermore, sparse solutions can be found. However, building the SVM model is computationally difficult because it involves a solution of a nonlinear optimization problem. A modified version of SVM, called the least square support vector model (LS-SVM) was proposed by Suykens and Vandewalle (1999). This model results in a set of linear equations instead of quadratic optimization problem as in original SVM. Further details of the LS-SVM algorithm can be found in the literature (Suykens and Vandewalle, 1999; Suykens et al., 2002). The schematic diagram of the LS-SVM model is shown in Fig. 3, where x_1, x_2, ..., x_n and y are input and output variables, respectively.

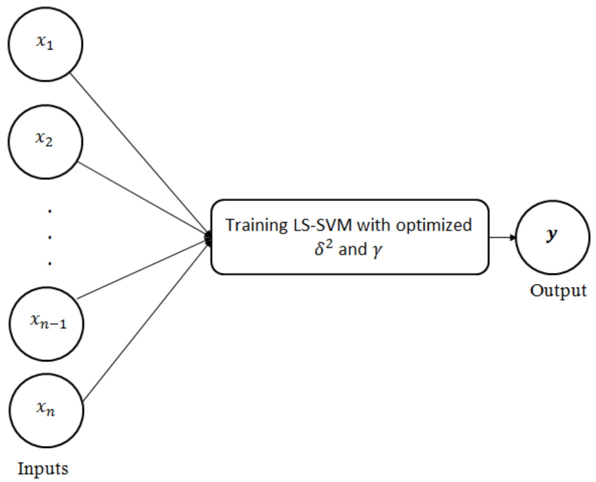

Fig. 3. Schematic diagram of LS-SVM model

In this work, the original 53 data points was divided into training and test sets. The 38 patterns were used for the training set and the remaining 15 for the test set. All data were normalized to be between 0.1–0.9 using Eq. (2) in order to increase the model accuracy and prevent any parameter from dominating the output values (Pyle ,1999):

$$x_{scaled} = 0.8\left(\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right) + 0.1\,. \tag{2}$$

The model performance was then assessed by evaluating the scatter between the experimental and predicted results via statistical parameters, that is correlation coefficient (*R*), mean absolute percentage error (MAPE %), and root mean square error (RMSE). The statistical values were determined as follows:

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})\cdot(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\,\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{3}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{|y_i - x_i|}{x_i}\right]\cdot 100 \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{5}$$

where, x_i is an observed value, y_i is a simulated value, N is the number of data points, $\bar{x}$ is the mean value of observations, and $\bar{y}$ is the mean value of simulations.

A higher value of the correlation coefficient and smaller values of MAPE and RMSE would indicate a better performance of the model. All scripts were written in MATLAB using the LS-SVM toolbox (LS-SVMLab1.8, 2013).

Results and discussion

The cleaning efficiency of the electromagnetic filtration process was modeled using the least square support vector machine method. The LS-SVM which was developed using experimental observations as the input, in order to identify the effects of operating parameters on the quality factor. In this study, the optimal output *y* and standard deviation σ values were found to be 165.43 and 0.0059, respectively. The results of the LS-SVM model for the test data are shown in Fig. 4. As can be seen from Fig. 4, the LS-SVM model captures the general trend in the output, and the test results showed that the developed model can accurately predict the quality factor of the electromagnetic filtration EMF process.

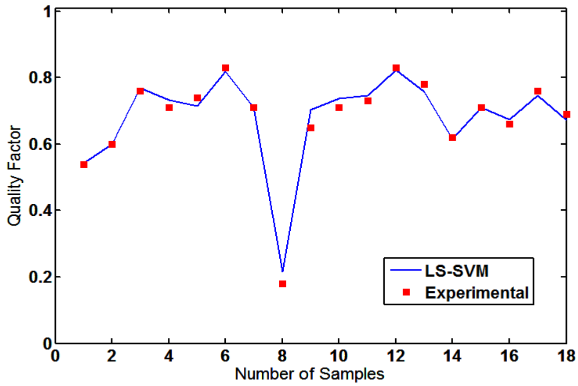

Fig. 4. Experimental values and LS-SVM predictions of quality factor for data

In this work we compared the obtained results with different EMF modeling approaches that were used in our previous work for the same set of compounds (Yildiz et. al., 2011). Table 2 shows the performance evaluation parameters for the LS-SVM model and our previous study. For the a least squares support vector model (LS-SVM), correlation coefficient (*R*), mean absolute percentage error (*MAPE*), and root mean square error (*RMSE*) values were found to be 0.99, 2.98 % and 0.019, respectively.

Table 2. Comparison of different models to predict the cleaning efficiency for EMF process

Test Data			
Model	*R*	*MAPE*, %	*RMSE*
ANN (Yildiz et. al., 2011)	0.94	5.8	0.050
MLSR (Yildiz et. al., 2011)	0.92	12.9	0.077
Abbasov (2002)	0.86	15.3	0.126
LS-SVM	0.99	2.98	0.019

From Table 2 it can be seen that the correlation coefficient given by the LS-SVM model was higher than for other models, and the LS-SVM model gave the lowest MAPE and RMSE values. It means that described in this work model gives the most satisfactory results compared with the results obtained from our previous work. Consequently, the LS-SVM approach currently constitutes a more accurate method for prediction the cleaning efficiency of the EMF process.

Conclusion

In this work, a model based on the least squares support vector model (LS–SVM) was developed for predicting cleaning efficiency of the electromagnetic filtration process. The results based on statistical parameters of experimental data, clearly showed that the LS-SVM had better performance when compared to other approaches and can be used for predicting the cleaning efficiency of the electromagnetic filtration EMF process. The LS-SVM proved to be a powerful and useful tool for predicting cleaning efficiency of electromagnetic filtration process. It means that LS-SVM as a very powerful and useful tool can be used in applications to the quality factor of the EMF process in different settings.

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