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PREDICTION OF SCALE REMOVAL WEIGHT DEPOSITED ON SURFACE OF HEAT EXCHANGER USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT: - Scale is a term generally used in industry refers to any deposit on equipment surface. Usually the deposition of scale is undesirable because it is uncontrolled and a build-up of scale on metal surfaces may act as insulation causing decreased efficiency. So removal of scale has gained special attention in the last few years due to its significance, when predicting removal scale weight. However, the complexity and variability makes it hard to model its effects. This study evaluates the usefulness of Artificial Neural Networks (ANN) to predict the scale removal weight as a function of several of their properties which have been related in previous studies i.e. time, concentration of organic acid salts, Temperature, density, viscosity. Results showed that neural networks are a powerful tool and that the validity of the results is closely linked to the amount of data available and the experience and knowledge that accompany the analysis. The structure of ANN models is [5-18-1] the best because reach MSE 0.001 with AARE%, S.D%, and R (0.12, 0.46, 0.9) respectively. The training of network use MATLAB program.
Keywords: Back propagation networks, Training network, Heat exchanger piping system

1- INTRODUCTION

Scale deposition in the industrial equipment may occur by any, or all of four mechanisms: crystallization scaling deposition of particulate matter, corrosion with subsequent transfer of corrosion products, and microbiological growth. These processes do not occur in insulation, and it is frequently the interaction between them that result in the worst scaling problems [1]

Problems involved with use of water are caused by the dissolved constituents namely solids. Chemical reaction sometimes occurs between some constituents dissolved in water produce insoluble compounds. These insoluble compounds deposited by the water are called scale, Perfect water for industrial use is one which will not deposit any scale-forming substances, will not corrode metal of appurtenance, and will result in neither priming nor foaming. Because of its dissolving ability, water can leach significant concentrations of mineral matter as well as other materials with which it comes in contact [2]

Besides reducing efficiency, deposits can increase fuel consumption, another added cost. Also increased downtime, loss of production and all the other costly consequences of deposits are part of the scale problem [3].

There are three general options for scale removal

1. Mechanical methods.
2. Chemical methods.
3. Combinations chemical/mechanical methods.

The relative advantage of chemical vs. mechanical cleaning vary from job to job, depending on the nature of the deposited, type of equipment, materials of construction, design factors, and others [4].

Cleaning by chemicals is probably the most widely adopted procedure. It has been used to some extent for many years. Recently, chemical cleaning process has been greatly improved and is now widely employed throughout the world. Mechanical methods still find wide acceptance and relatively satisfactory in some cases, but these are unsuitable or ineffective for cleaning complex plant equipment, many parts of which are inaccessible [5]

The deposition of solid within operating equipment results in an accumulation of sludge or in the production of scale Equipment free of scale operates more efficiently and economically. The deposits in the form of scale are highly objectionable, since they are poor conductors of heat, cause reduced efficiency, induce corrosion, and are often responsible for burned tubes and plates. Also, the scale problem can cause more frequent turnarounds, emergency shutdowns and many other factors. Casts can also be increased by the need for more frequent cleaning and added pumping requirements. Avoiding such deposits is not simple because there are so many kinds. Also, of the numerous deposit control techniques available only certain ones apply to any given system. Many years ago, it was learn that the addition to equipment water of certain organic substances greatly reduced the formation of scale and deposits [6]

Scale can be controlled in two ways;

1. By removal of ions or suspended solid before water is used.
2. By leaving in, the dissolved and suspended solids and treating the water chemically and mechanically in order to prevent or control deposit formation.

This is an ideal solution of the scale problem, but so far without complete success. In some times it is difficult and expensive to prevent or control the feed water impurities so, periodic cleaning of such fouled equipment could be the proper solution [7]

2. FACTORS INFLUENCING EFFECTIVENSS OF DESCALING PROCESS

There are numerous conditions which require control during the cleaning of any equipment in order to insure effective removal of deposits from the surfaces and a minimum of corrosive attack on the metal. There are number of variables which can alter the effectiveness of the cleaning process

1. Concentration of solution
   Determining the composition of equipment scales will provide for selecting the reagent systems to be tested. The effectiveness of various reagents is usually enhanced with wetting agents; corrosion inhibitor, suspension additives, dispersants, etc. in addition staged treatments with two or more reagent systems may be more effective. The cumulative weight loss increased as the concentration increased.
2. Effect of temperature
   Rising temperature imparts kinetic energy to molecules causing them to move faster and collide more frequently and causing the rate of reaction in general to increase. Such an increase in temperature on a cleaning job should speed up chemical reactions, thereby decreasing the cleaning time. The cumulative weight loss of scale increased with increasing temperature.
3. Effect of time

The exposure time was an important variable in the descaling process, the weight loss was increased with time but, generally, most of the scale removal was during the first three hours of the descaling process [8].

3. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANNs) are simplified models of central nervous system. The network of highly inter connected neural computing elements that have the ability to respond to input stimuli and learn to adapt to environment [12]. As the term of artificial neural networks implies early work in the field of neural networks centered on modeling the behavior of neurons found in the human brain, engineering systems are considerably less complex than the brain, hence from an engineering view point ANN can be viewed as nonlinear empirical models that are especially useful in representing input-output data. Making predication, classifying data, reorganization patterns, and control process. ANN which will be referred to as a node in this work and is analogous to a single neuron in the human brain. The advantages of using artificial neural network in construct with first principles models or other empirical models [9]

1. ANN can be highly nonlinear.
2. The structure can be more complex and hence more representative than most other empirical models.
3. The structure does not have to be prespecified.
4. Quite flexible models.

a. The back-propagation algorithm

Artificial Neural Networks (ANNs) have been increasingly applied to many problems in transport planning and engineering, and the feed forward network with the error back propagation learning rule, usually called simply Back propagation (Bp), has been the most popular neural network [10].

Back propagation networks are among the most popular and widely used neural networks because they are relatively simple and powerful. Back propagation was one of the first general techniques developed to train multi-layer networks, which does not have many of the inherent limitations of the earlier, single -layer neural nets criticized by Minsky and Papert.These networks use a gradient descent method to minimize the total squared error of the output. A back propagation net is a multilayer, feed forward network that is trained by back propagating the errors using the generalized Delta rule [11]

The input is the input to the hidden layer and the output layer is the output from the immediate previous layer, so it is called feed forward neural network. The number of the input units and the output units are fixed to a problem, but the choice of the number of the hidden units is somehow flexible as shown in Figure (1). Too many hidden units may cause over fitting, but if the number of hidden units is too small, the problem may not converge at all. Usually a large number of training cases may allow more hidden units if the problem requires so [12]

b. Training a Back-Propagation Network

- **Feed forward training of input patterns:** Each input node receives a signal, which is broadcast to all of the hidden units, and each hidden unit computes its activation, which is broadcast to all of the output nodes [13].
- **Back propagation of errors:** Each output node compares its activation with the desired output, and based on this difference, the error is propagated back to all previous nodes [14]
- **Adjustment of weights:** The weights of all links are computed simultaneously based on the errors that were propagated backwards.

The above steps can be shown as follows:

1. Initialize the weights with small, random values.
2. Each input unit broadcasts its value to all of the hidden units.

3. Each hidden unit sums its input signals and applies its activation function to compute its output signal.
4. Each hidden unit sends its signal to the output units.
5. Each output unit sums its input signals and applies its activation function to compute its output signal.

6. Each-output unit updates its weights and bias:

c. Conventional Algorithm

The conventional algorithm used for training a MLFF is the Bp algorithm, which is an iterative gradient algorithm designed to minimize the mean-squared error between the desired output and the actual output for a particular input to the network [15]

Basically, Bp learning consists of two passes through the different layers of the network: a forward pass and backward pass as shown in Figure (1).

During the forward pass the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule [16]

A MLFF consists of layers of interconnected denoted as the input layer, the hidden layer and the output layer. The number of the input units and the output units are fixed to a problem, but the choice of the number of hidden units is somehow flexible.

Too many hidden units may cause over fitting, but if the number of hidden units is too small, the problem may not converge at all. So the number of neurons in the hidden layer can be varied based on the complexity of the problem and the size of the input information [17]

Two learning factors that significantly affect convergence speed as well as accomplish avoiding local minima, are the learning rate and momentum.The learning rate (η) determines the portion of weight needed to be adjusted. However, the optimum value of η depends on the problem. Even though as small learning rate guarantees a true gradient descent, it slows down the network convergence process. If the chosen value of η is too large for the error value, the search path will oscillate about the ideal path and converges more slowly than a direct descent. The momentum (α) determines the fraction of the previous weight adjustment that is added to current weight adjustment. It accelerates the network convergence process. During the training process, the learning rate and the momentum are adjusted to bring the network out of its local minima, and to accelerate the convergence. The algorithm of the error back-propagation training is given below [18]:
Step1: initialize network weight values.
Step2: sum weighted input and apply activation function to compute output of hidden layer.

$$h_j = f\left[\sum_i X_i w_{ij}\right] \qquad (1)$$

Where
h_j: The actual output of hidden neuron j for input signals X.
X_i: Input signal of input neuron (i).
W_{ij}: Synaptic weights between input neuron hidden neuron j and i.
f: The activation function.
Step3: sum weighted output of hidden layer and apply activation function to compute output of output layer.

$$O_k = f\left[\sum_j h_j W_{jk}\right] \qquad (2)$$

where
O_k: The actual output of output neuron k.

W_{jk}: Synaptic weight between hidden neuron j and output neuron k.

Step4: compute back propagation error.

$$\delta_k = (d_k - O_k) f'\left(\sum_j h_j W_{jk}\right) \qquad (3)$$

where

f' :The derivative of the activation function.

d_k: The desired of output neuron k.

Step5: calculate weight correction term.

$$\Delta W_{jk}(n) = \eta \delta_k h_j + \alpha \Delta W_{jk}(n-1) \qquad (4)$$

Step6: sums delta input for each hidden unit and calculate error term.

$$\delta_j = \sum_k \delta_k W_{jk} f'\left(\sum_i X_i W_{ij}\right) \qquad (5)$$

Step7: calculate weight correction term.

$$\Delta W_{ij}(n) = \eta \delta_j X_i + \alpha \Delta W_{ij}(n-1) \qquad (6)$$

Step8: update weights.

$$W_{jk}(n+1) = W_{jk}(n) + \Delta W_{jk}(n) \qquad (7)$$

$$W_{ij}(n+1) = W_{ij}(n) + \Delta W_{ij}(n) \qquad (8)$$

Step9: repeat step2 for given number of error.

$$MSE = \frac{1}{2p}\left[\sum_p \sum_k (d_k^p - O_k^p)^2\right] \qquad (9)$$

Where

p: The number of patterns in the training set.

Step10: END.

Bp is easy to implement, and has been shown to produce relatively good results in many applications. It is capable of approximating arbitrary non-linear mappings. However, it is noted that two serious disadvantages in the Bp algorithm are the slow rate of convergence, requiring very long training times, and getting stuck in local minima.

The success of Bp methods very much depends on problem specific parameter settings and on the topology of the network (19). So in the next section the quick propagation will be presented.

4. MODELING CORRELATION OF ANN

In the current study, neural networks are used to fit a set of experimental points in order to provide a purely empirical model. The experimental points are called the training cases (or learning cases) and another are called testing cases. They consist of input vectors (values of input variables) associated with the experimental output value. To solve a problem with aback-propagation network, it is shown sample inputs with the desired outputs, while the network learns by adjusting its weights. If it solves the problem, it would have found a set of weights that produce the correct output for every input. This search includes computer simulation, implemented on a Pentium 4 computer using MATLAB**,** version7.

The modeling of ANN correlation began with the collection of large data bank following the learning file was made by randomly selecting about 80% of the data base to train the network. The remaining 20% of data is then use to check the generalization capability of the model. The last step is to perform a neural correlation and to validate it statistically. So that the steps of modeling are:-

Collection of Data: The first step in neural network modeling is collection of data. The data is necessary to train the network and to estimate its ability to generalize. In this model about 80 experimental points have been collected for scale removal weight deposited on surfaces of heat exchanger by chemical methods. The data collected for the problem of scale formation in cooling water systems of daura refinery has been chosen to study the effect of chemical method on descaling of such deposits "1".

The data were divided into training and test sets: the neural network was trained on 80% (64) of the data and tested on 20% (16).

Scale removal weight =f (t, c, T, μ, ρ)

a. The Structure of Artificial Neural Network

In this work, a multilayer neural network has been used, as it is effective in finding complex non-linear relationships. It has been reported that multilayer ANN models with only one hidden layer are universal approximates. Hence, a three layer feed forward neural network is chosen as a correlation model. The weighting coefficients of the neural network are calculated using MATLAB programming. Structure of artificial neural network built as:-

1. **Input layer:** A layer of neurons that receive information from external sources and pass this information to the network for processing. These may be either sensory inputs or signals from other systems outside the one being modeled. In this work five input neurons in the layer and there is a set of (64) data points available of the training set.
2. **Hidden layer:** A layer of neurons that receives information from the input layer and processes them in hidden way. It has no direct connections to the outside world (inputs or output). All connections from the hidden layer are to other layers within the system. The number of neuron in the first hidden layer consists of eighteen neurons. Gave best results and was found by trial and error. If the number of neurons in the hidden layer is more, the network becomes complicated. Results probably indicate that, the present problem is not too complex to have a complicated network routing. Hence, the results can be satisfactorily achieved by keeping the number of neurons in hidden layer at a best value with one hidden layer.
3. **Output layer:** A layer of one neuron that receives processed information and sends output signals out of the system.
4. **Bias:** The function of the bias is to provide a threshold for activation of neurons. The bias input is connected to each of hidden neurons in network.

The structure of multi-layer ANN modeling is illustrated in Figure (2)

b. Training of Artificial Neural Network

Training is just the procedure of estimating the values of the weights and establishing the network structures and the algorithm used to do this is called a "learning" algorithm. Learning typically occurs through training or exposure to set of input, output data where the training algorithm iteratively adjusts the connection weights. These connection weights represent the knowledge necessary to solve specific problems (i.e. calculates the coefficients of correlation).

The training phase starts with randomly chosen initial weight values. Then a back-propagation algorithm is applied after each iteration, the weights are modified so that the cumulative error decreases. In back-propagation, the weight changes are proportional to the negative gradient of error. Back-propagation may have an excellent performance, this algorithm is used to calculate the values of the weights the following procedure is then used (called "supervised learning") to determine the values of weights of the network:-

1. For a given ANN architecture, the value of the weights in the network is initialized as small random numbers.
2. The input of the training set is sent to the network and resulting outputs are calculated.
3. The measure of the error between the outputs of the network and the known correct (target) values is calculated.

4. The gradients of the objective function with respect to each of the individual weights are calculated.
5. The weights are changed according to the optimization search direction.
6. The procedure returns to step 2.
7. The iteration terminates when the value of the objective function calculated using the data in the test approaches experimental value. The trial and error to find the best ANN correlation model shown in table 1:-

The structure with [5-18-1] is the best because reach MSE 0.001
With reduced MSE the network is more accurate, because MSE is defined as:-

$$\text{MSE} = \frac{1}{2p}\left[\sum_p \sum_k (d_k^p - o_k^p)^2\right] \qquad (10)$$

Where p: the number of patterns in training set
k=No. of iterations.
d_k^p =The desired output.
o_k^p =The actual output.

Figure (3) illustrates the number of epochs with MSE for scale removal weight
Learning rate: - the main purpose of the learning rate is to speed up the rate at which the network learns. This is also accomplished by multiplying the learning rate by the change in weight factor from the previous iteration in order to determine the new weight factors.
Momentum coefficient: - the momentum coefficient is a parameter of what has been termed “gradient learning “in gradient learning we use the momentum coefficient to allow the network to avoid settling in local minima of error. The momentum coefficient is used to determine new weight factors by multiplying by the change in the weight factor that was produced in last iteration.

The choice of transfer function is based on the function of the network being used. The tan-sigmoid function is appropriate for most types of network, especially prediction problems.

The learning process includes the procedure when the data from the input neurons is propagated through the network via the interconnections. Each neuron in a layer is connected to every neuron in adjacent layers. A scalar weight is associated with each interconnection.

Neurons in the hidden layers receive weighted inputs from each of the neurons in the previous layer and they sum the weighted inputs to the neuron and then pass the resulting summation through a non-linear activation function (tan sigmoid function).

Artificial neural networks learn patterns for this can be equated to determining the proper values of the connection strengths (i.e. the weight matrices $\mathrm{W}_{\mathrm{h}_1}$ and w_o illustrated in Figure (2) that allow all the nodes to achieve the correct state of activation for a given pattern of inputs. The matrix, bias, and vector, given eq. (11), (12), and (13) illustrate the result of coefficient weights for ANN correlation for this case where w_h is the matrix containing the weight vectors for the nodes in the hidden layer and w_o is the vector containing the weight for the nodes in the output layer.

$$w_{h1} = \begin{pmatrix} -0.0184 & -0.1073 & 0.5126 & -2.8466 & -0.5764 \\ -0.3403 & -0.3041 & -0.4980 & 1.0961 & 3.5550 \\ -0.0559 & 0.0428 & 0.2025 & -3.5426 & 4.1195 \\ -0.2341 & -0.1640 & 1.6933 & -1.3292 & -3.0071 \\ 0.0064 & 0.8807 & -0.1386 & -8.0502 & -3.1748 \\ -0.0178 & -1.6148 & 0.4377 & 8.9206 & 12.1174 \\ -2.5176 & -7.5643 & 0.9476 & -3.1745 & 24.2873 \\ 0.5808 & 0.1872 & 0.1320 & -2.1190 & 2.4756 \\ -0.0004 & 0.0081 & -0.0364 & 1.0411 & -0.2882 \\ 0.0634 & 0.1496 & 0.1996 & -0.4681 & -2.8220 \\ -19.8520 & 6.4670 & 1.3028 & 6.6262 & -27.0678 \\ 0.0504 & 1.9213 & -0.5447 & -31.8105 & 0.0228 \\ -0.0862 & 0.4223 & 0.7488 & -6.4481 & -18.3982 \\ -9.9503 & 2.4110 & 3.6973 & 3.8349 & 4.8884 \\ -0.0030 & 0.1310 & 0.0549 & -10.9477 & 0.9241 \\ 0.1178 & -1.3946 & -1.6326 & 2.7115 & 56.1982 \\ 0.2450 & -0.5403 & -0.5122 & 0.3478 & -2.7624 \\ 0.6972 & -0.0202 & -0.0712 & -70.8102 & -2.3831 \end{pmatrix} \quad \textbf{(11)}$$

$$b= \begin{pmatrix} 2.5455 \\ 0.0985 \\ 4.0055 \\ 2.8372 \\ 1.7492 \\ -2.9740 \\ 1.0015 \\ 2.8323 \\ 1.2631 \\ 5.1446 \\ 14.6053 \\ 37.2468 \\ -0.2790 \\ 0.8253 \\ 5.7122 \end{pmatrix} \quad \textbf{(12)}$$

$$w_o = [6.2035 \;\; -5.2416 \;\; 5.6336 \;\; 4.8458 \;\; 43.0927 \;\; 15.5753 \;\; -1.0319 \;\; 5.3191 \;\; -118.4881 \;\; 5.0495 \;\; -0.1037 \;\; 9.5193 \;\; -11.3962 \;\; 0.2802 \;\; -81.3394 \;\; -9.1290 \;\; -4.8906 \;\; 0.9500] \quad \textbf{(13)}$$

5. SIMULATION RESULTS

The network architecture used for prediction scale removal weight deposited on surface of heat exchange in figure(2) consist of five inputs neurons corresponding to the state variables of the system, with hidden neurons and one output neuron. All neurons in each layer were fully connected to the neurons in an adjacent layer. The prediction of ANN correlation result is plotted in Figure (4) compares the predicted of scale removal weight with experimental for training set.

6. TEST OF THE PROPOSED ANN

The purely empirical model was tested on data that were not used to train the neural network and yielded very accurate predictions. Having completed the successful training, another data set was employed to test the network prediction scale removal weight. We made use of the same model to generate (16) new data values.

The result of prediction is plotted with experiment value as shown in Figure (5).

7. STATISTICAL ANALYSIS

Statistical analysis based on the test data is calculated to validate the accuracy of the output for pervious correlation model based on ANN. The structure for each model should give the best output prediction, which is checked by using statistical analysis. The statistical analysis of prediction is based on the following criteria:-

1. The AARE (Average Absolute Relative Error) should be minimum

$$AARE = \frac{1}{N}\sum_{1}^{N}\left|\frac{x_{prediction} - x_{\exp erimental}}{x_{\exp erimental}}\right| \qquad (14)$$

Where N=Number of data points.
x=Corrosion rate.

2. The standard deviation should be minimum.

$$S.D = \sqrt{\sum_{1}^{N} \frac{[\left|(x_{prediction} - x_{\exp erimental} / x_{\exp erimental}\right| - AARE]^2}{N-1}} \tag{15}$$

3. The correlation coefficient R between input and output should be around unity.

$$R = \frac{\sum_{i=1}^{N}(x_{\exp erimental\,(i)} - \bar{x}_{\exp erimental})(x_{prediction\,(i)} - \bar{x}_{prediction})}{\sqrt{\sum_{i=1}^{N}(x_{\exp erimental} - \bar{x}_{\exp erimental})^2}\sqrt{\sum_{i=1}^{N}(x_{prediction} - \bar{x}_{prediction})^2}} \tag{16}$$

Where $\bar{x}_{\exp erimental}$ =corrosion rate mean of experimental points

$\bar{x}_{prediction}$ =corrosion rate mean for prediction points.

Table (2) illustrated the statistical information of neural networks models for prediction of scale removal weight.

8. CONCLUSIONS:

Artificial neural network (ANN) model can predict the scale removal weight deposited on surface of heat exchanger for wide range of physical properties and operating parameters. It has been demonstrated that the optimal model is a network that predicate scale removal weight with one hidden layer. It is important to mention that over training of ANN with the purpose of achieving low MSE vale could make it exclusive to the data used for its training and development such a network would give error to new predictions of the untrained data and thus, cannot be used for modeling purposes. To avoid such problem, the ANN developed in this work was validated using experimental data values which were not used in the training of the network.

Nomenclature

d_k	The desired of output neuron k
f	The activation function
f'	The derivation of the activation function
h_i	The actual output of hidden neuron j
o_k	The actual output of output neuron k
P	The number of patterns in the training set
V_{ij}	Weight on link from Xi to Zj
W_{ij}	Synaptic weights between input and hidden neurons
W_{jk}	Synaptic weight between hidden and output neuron
x_i	Input signal of input neuron i
Y	Target vector
Y_k	Output unit
Z_i	Hidden unit

Greek Symbols

Symbol	**Definition**
δ_k	The error term
η	The learning rate

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Table (1): network parameters in ANN model

Structure	network Parameters				
	MSE	No.of iteration	Learning rate	Momentum coefficient	Transfer function
[5-12-1]	0.1	1340	0.7	0.9	Tan sigmoid
[5-16-1]	0.01	7654	0.65	0.9	Tan sigmoid
[5-18-1]	0.001	3379	0.9	0.75	Tan sigmoid

Table (2): Gives the statistical information of neural networks models for prediction of scale removal weight.

ANN models	Structure	AARE%	S.D%	R
Case study	[5-18-1]	0.12	0.46	0.9

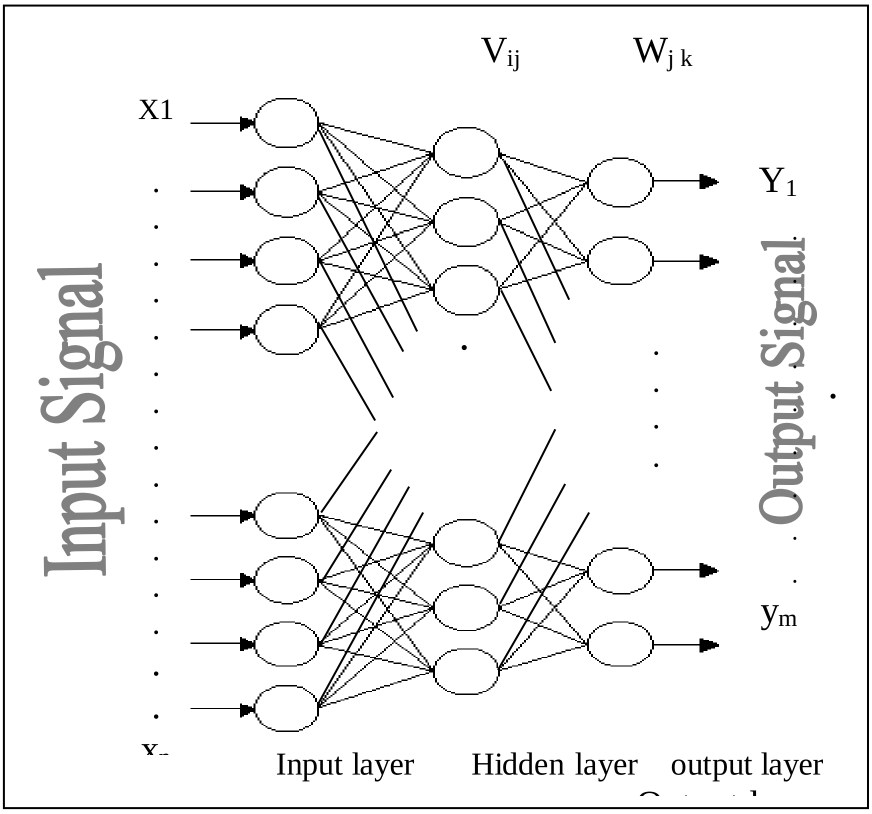

Figure (1): Multi- layer feed forward network (one hidden layer).

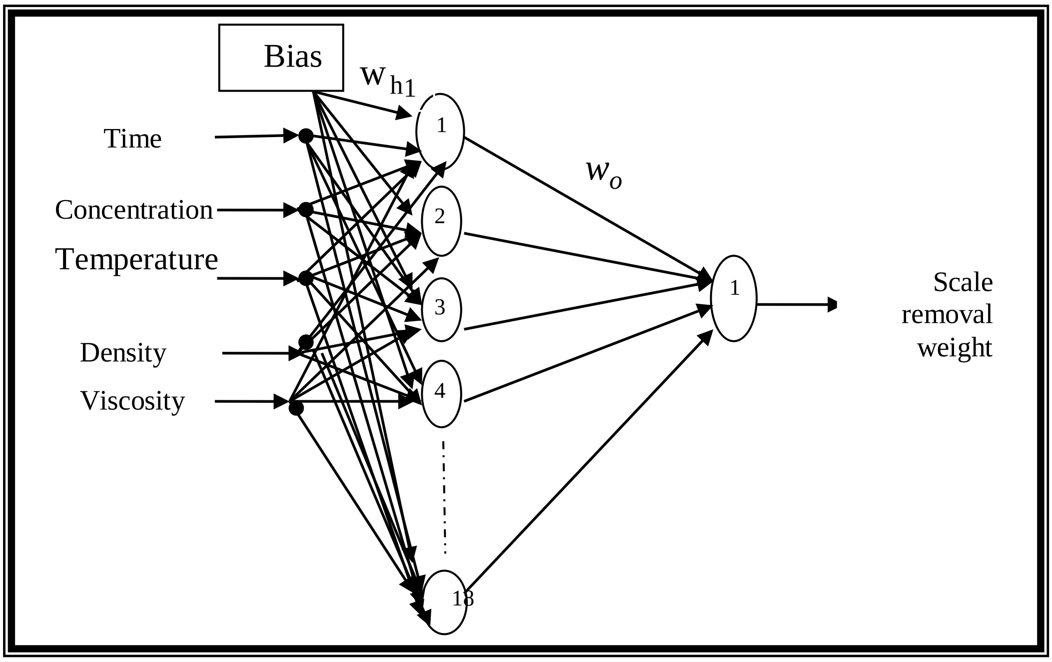

Figure (2): Structure of a layer neural network.

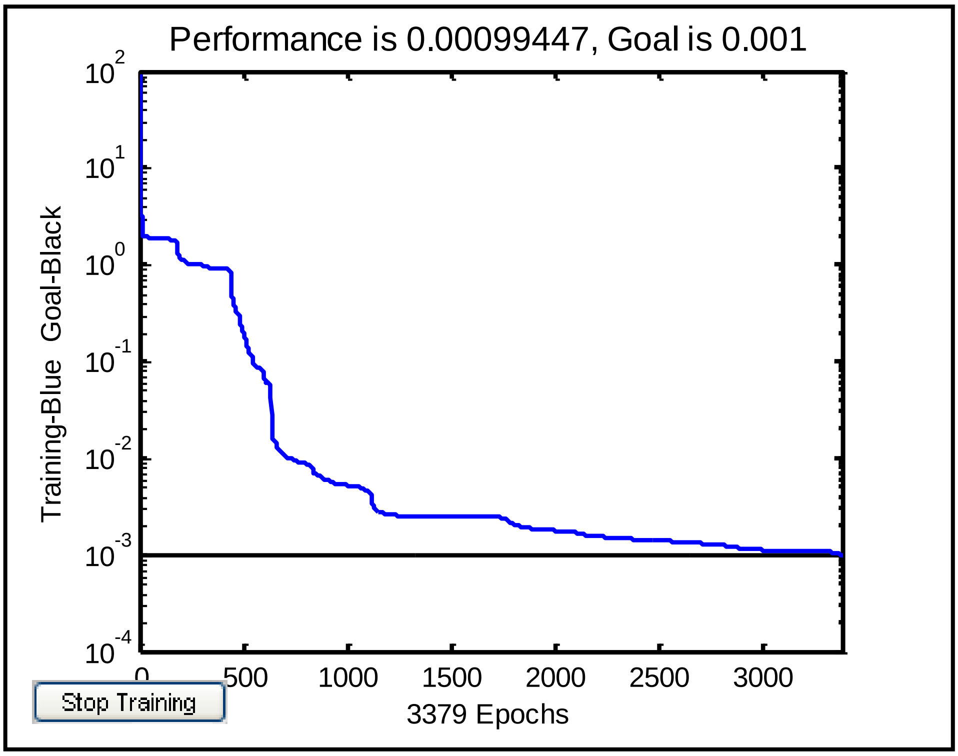

Figure (3): Training MSE with iteration for scale removal weight

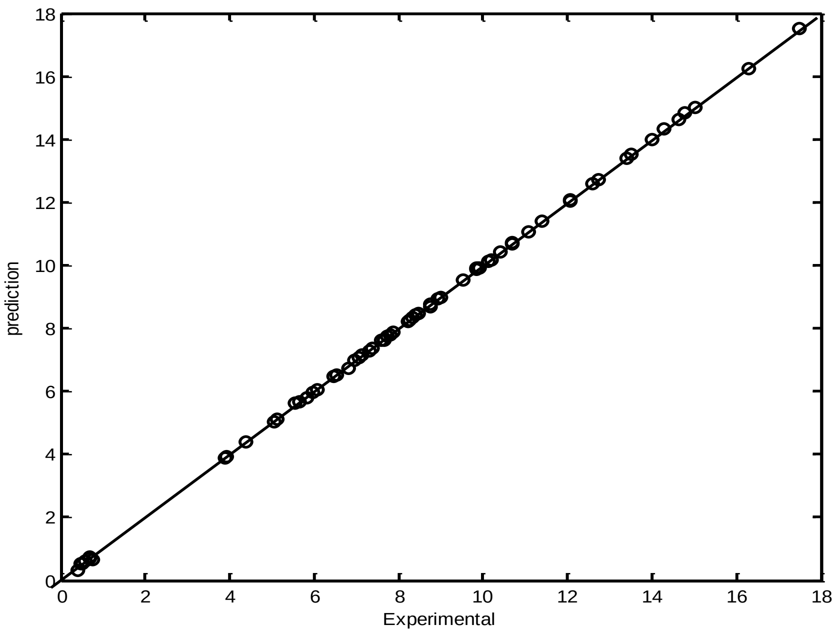

Figure (4): Comparison between experimental and prediction for scale removal weight training set.

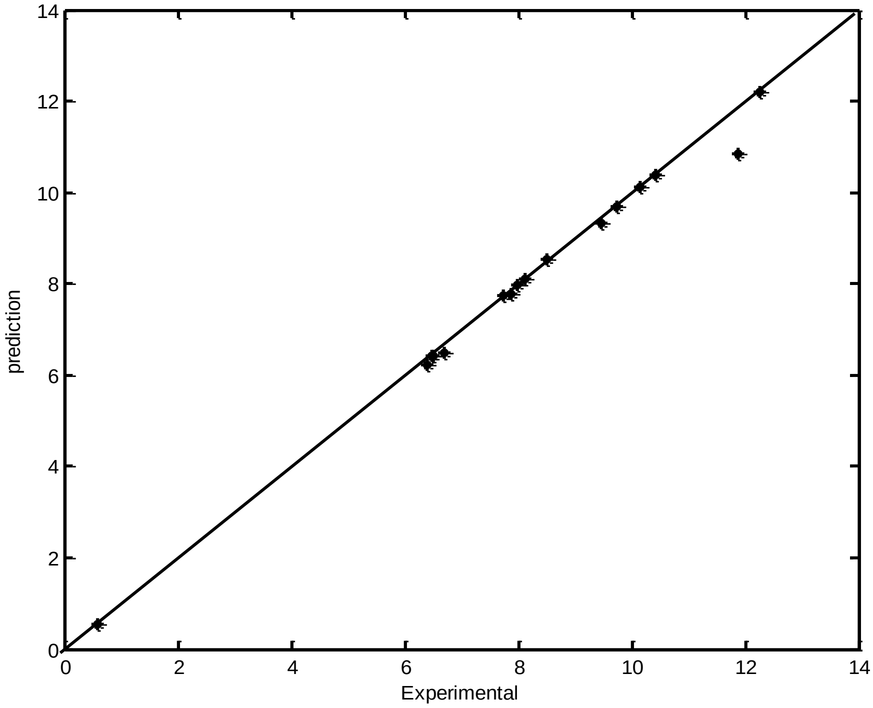

Figure (5): Comparison between experimental and prediction for scale removal weight in testing set.

التنبؤ بإزالة وزن القشرة المترسبة لأنابيب مبادل حراري باستخدام الشبكات العصبية الاصطناعية

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الخلاصة

إزالة الترسبات من السطوح الداخلية لأنابيب المبادلات الحرارية والمراجل والمبخرات وغيرها فقد حاز على اهتمام الكثيرين قي السنوات الأخيرة فكان لابد من التنبؤ في إزالة وزن القشرة المترسبة لأنابيب مبادل حراري ولوجود التعقيدات والمتغيرات في التصميم تم استخدام الشبكات العصبية الاصطناعية للتنبؤ بإزالة وزن القشرة المترسبة كدالة لعدد من الخواص اعتمدت على جمع نتائج لأنابيب مبادل حراري من مصفى الدورة وهي الزمن، التركيز أملاح الحوامض العضوية, درجة الحرارة, الكثافة واللزوجة.قد برهنت النتائج قوة الشبكة العصبية في إظهار النتائج بشكل مقارب للنتائج العملية.