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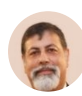

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A Computational Intelligence Based Approach for the Analysis and Optimization of a Crude Oil Desalting and Dehydration Process

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Water and salt associated with oil production can cause considerable operational problems. Therefore, desalting/dehydration plants are often installed in crude oil production units to remove water-soluble salts from an oil stream. The performance of the desalting/dehydration process depends on various process parameters interacting with each other. These parameters include concentration of demulsifying agents, heating, wash water, salt concentration, and rate of mixing with wash water. In this study, the performance of the desalting/dehydration process was evaluated by calculating the salinity and water cut efficiencies that are expected to depend on the values of these five process parameters. The work concentrated on modeling and optimizing the performance of the desalting/dehydration process system. It was an attempt to develop and apply an artificial neural network (ANN) as a modeling technique for simulating and optimizing the desalting/dehydration process system. ANNs were selected due to their potential for modeling highly nonlinear relationships of the parameters involved in the desalting/dehydration process system. The neural network model predictions were compared with the actual observations, and the results were shown to be consistent. The prepared neural network model was then used to optimize the performance of the process. A composite objective function for measuring the performance of the desalting process was used in conjunction with the prepared ANN within an optimization model. The outcome of this research will help in improving oil production operations and therefore in lowering the cost per barrel produced.

1. Introduction

Most of the oil fields around the globe are producing oil that is often accompanied by significant amounts of water.[1] Consequently, the need to provide desalting/dehydration (DDP) systems to separate the oil and water before the oil can be sold has been a necessity rather than just an upgrade for the product. Oil desalting/dehydration system is the process of removing water-soluble salts from an oil stream. One main reason of installing desalting plants is to decrease the flow of salt content to refinery distillation feedstocks and to minimize the energy required for pumping and transportation. Among the important reasons for treating water-in-oil emulsions are scale accumulations, corrosion, and lowering of activity of catalyst. A typical desalting/dehydration plant operation usually comprises the following six major steps: separation by gravity settling, chemical injection, heating, addition of fresh (less salty) water, mixing, and electrical coalescing. The treatment involves allowing time for water drops to settle out and be drained off. Settling time and draining are accomplished in wash tanks, separators, and desalting vessels. Settling and draining can be speeded up using one or more of the following actions: injecting chemicals (demulsifier), applying heat, adding diluents (freshwater), and applying electricity.[2] Therefore, it is expected that the most important parameters affecting performance of the desalting/dehydration are settling time, mixing time, chemical dosage, crude temperature, and wash water flow rate ratio.

Nowadays modeling and optimizing the desalting/dehydration process is an important issue in the production and refinery processing industries to improve the performance of the desalting/dehydration process in terms of various process parameters. Al-Otaibi[1] pointed out that the effects of multivariate factors influencing the performance of the desalting/dehydration process can only be described by highly nonlinear relations. One of the most powerful tools available for this problem is the artificial neural network (ANN) approach. The

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neural networks can be thought of as black box devices that accept inputs and produce outputs.[3] Artificial neural networks can handle multivariable problems and have a unique ability in providing solutions for nonlinear problems. Their results have the potential to describe nonlinear relationships and interactions of the various parameters involved in the desalting/dehydration process system. Therefore, ANNs can be used to explore the possible relationships between the various parameters in the desalting/dehydration process. They can be used to offer insight into the actual dependence of performance of desalting/dehydration process on other process parameters.

The ANN approach has been used in the oil and chemical industry quite recently. It is regarded as a very powerful tool for a wide range of applications in these industries. This has been demonstrated by several recent publications.[4−7] In practical cases, process control optimizations have been by far the most popular area of neural network applications in chemical engineering.[8]

The present work focuses on modeling and optimizing the performance of the desalting/dehydration process system. The experimental work was conducted to study the effect of a number of process parameters on the performance of the desalting/dehydration process. The considered parameters in this study included chemical dosage (ppm), crude temperature (°C), wash water flow rate ratio (%), mixing time (min), and settling time (min). The performance of the desalting/dehydration process was evaluated by calculating the salinity and water cut efficiencies (η_1 and η_2, respectively). The specific objective of the study was to model and optimize the desalting/dehydration process. The general main objectives of the investigation were to:

(1) Study the effect of variations of a number of process parameters on the desalting/dehydration process. All parameters were applied to a sample of actual Kuwaiti crude oil.

(2) Model the desalting/dehydration process via ANN to predict the performance of a desalting system as a function of the above five parameters.

(3) Use the prepared neural network model to optimize the desalting/dehydration process to obtain the best desalting efficiency.

2. Desalting/Dehydration Plant Operation

The main objective of an oil desalting and dehydration plant is to remove water-soluble salts and entrained water. Principally, water normally contains chlorides of sodium, calcium, and magnesium. When designing a desalter, its type and size are all dependent on a number of operational factors such as required pressure, temperature, viscosity, and flow rate, as well as user specification relating to maximum salt amount allowed in the product oil stream. A typical desalting/dehydration plant operation comprises six major steps: separation by gravity settling, chemical injection, heating, addition of fresh (less salty) water, mixing, and electrical coalescing.

Figure 1 is a process flow diagram of a typical desalting/dehydration plant that shows the above six major steps and the main equipment.[9,10] At point no. 1, an emulsion comprising water and oil flows to a wet tank. Such a common emulsion may contain up to 25% water cut. As per design, a typical desalting/dehydration plant would meet acceptable crude oil specifications; that is, water and salt of the crude must be reduced to 0.10% vol and 5.0 pounds per thousand barrels (PTB), respectively.[10] To remove such large quantities of water from the oil stream, a two-stage desalting system is used. At point no. 2, the emulsion leaves the wet tank, where the primary water separation takes place. At this point, chemical/demulsifier is injected into the stream prior to feed pumps. After settling for a period of several hours, formation water, stream 13, flows to a wastewater treatment plant or is disposed of to a designated disposal pit.

Point no. 3 shows emulsion flow from the wet tank to a heat exchanger, where heat is recovered from the treated crude product stream (stream no. 10). The emulsion then flows to a water bath indirect heater, raising its temperature (point no. 4). Water recycled from second stage vessel (stream no. 5) is injected into the emulsion flow coming out of the heater. This system, recycling water from second stage back to first stage, aims at minimizing freshwater consumption where a counter current flow is employed in which the dispersed brine in the crude is contacted with freshwater streams each time. At the mixing valve (no. 6), recycled water and emulsion are agitated by an induced shearing force. The operation of a mixing valve is carried out by a simple globe valve where an operator would set the differential pressure across the valve to be as high as possible, ensuring better mixing of the two fluids. Stream no. 7 leaves the mixing valve to enter the first stage desalter vessel. Inside the first stage vessel, an emulsion is exposed to a high voltage electrostatic field. The action of the electrostatic field coalesces the dispersed water phase, and gravity causes the enlarged water droplets to fall and collect in the bottom of the vessel. Effluent water from the first stage, stream no. 11, leaves the system to a wastewater treatment plant or the disposal pit. This effluent water contains various impurities and salts removed from the water-in-oil emulsion.

Treatment of an emulsion is further enhanced in the second stage desalting vessel. Stream no. 8 flows to a mixing valve on the entrance of the second stage vessel. Still containing saltwater, the emulsion is mixed with freshwater (stream no. 9). The differential pressure across the mixing valve is normally around 15 psi. Then partially treated emulsion is introduced near the bottom of the second stage and, once more, travels upward through the electrical voltage grids. Also in this stage, water droplets are enlarged by means of high voltage electrostatic field and separated by gravity. The sepa-

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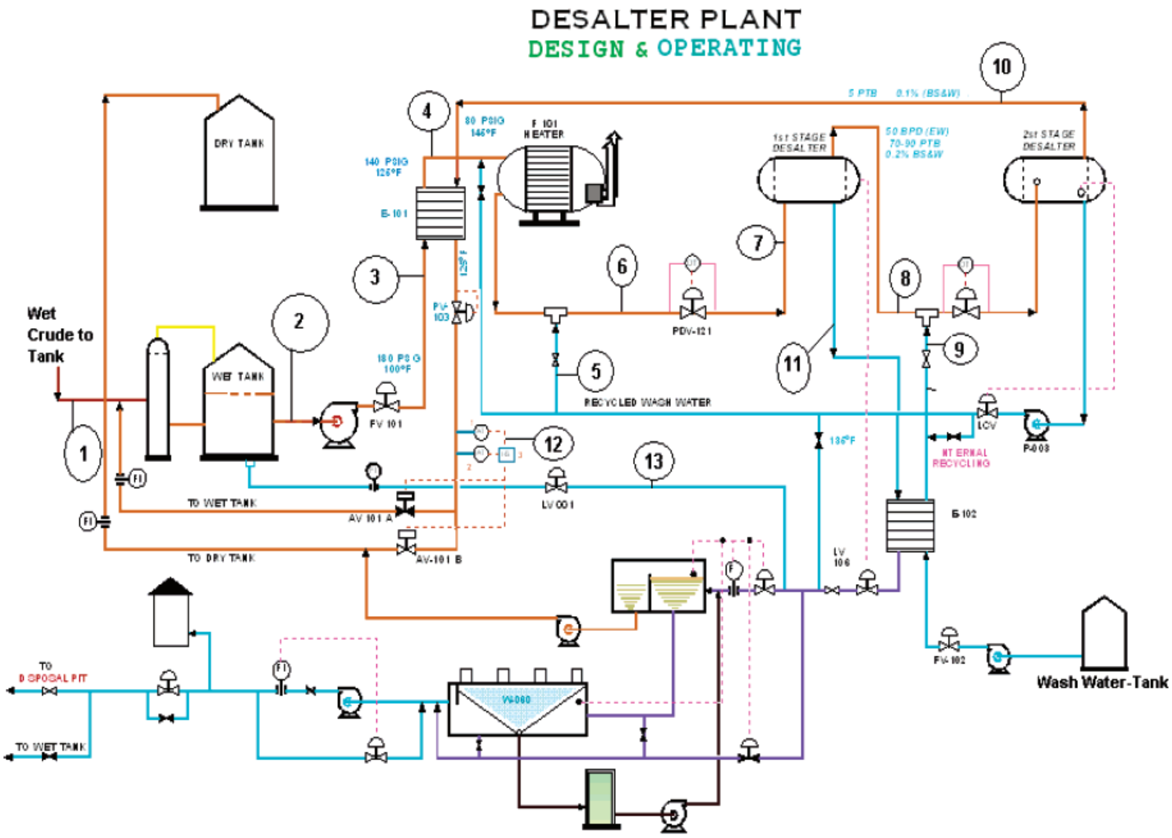

Figure 1. A typical desalting/dehydration plant.[9] (1) Wet crude flow to wet tank. (2) Demulsifier/chemical injection. (3) Crude flow to heat exchanger. (4) Flow to heater. (5) Wash water recycled from second stage vessel. (6) Flow to first stage desalting mixing valve. (7) Mixed fluid to first stage vessel. (8) Flow to second stage desalting mixing valve. (9) Freshwater from water−water heat exchanger originated from wash water tank. (10) Treated crude flow. (11) Effluent water from first stage desalter vessel to water treatment plant and/or disposal pit. (12) BS&W Analyzer. A signal to diverting valve. (13) Formation water settled at the bottom of wet tank, to water treatment plant, and/or disposal pit.

rated water is collected at the bottom of the vessel and recycled to the first stage desalter (stream 5), while the treated crude flows from the top of the vessel (stream no. 10). The latter stream (treated) continues to pass through a BS&W analyzer (stream no.12). If the treated crude is within the specification, a signal is sent to the diverting valve to open the dry tank, otherwise the flow is directed back to the wet tank.

3. Artificial Neural Networks

ANNs employ historical data to map out the relationships between a set of input variables and the output variable(s) modeled. Neuron or the processing element is the major building block for any ANN architecture.[11] These neurons are analogous to the neurons in the human brain that are responsible for information processing.[12] They are commonly interconnected in a variety of structures, the most common being a three-layer structure that is called a three-layer multilayer perceptron. The neurons will be located in one of three types of layers: the input layer, the hidden layer(s), and the output layer. These neurons are connected together by a line of communication called connection.[11] The input layer neurons are acting as distribution channels. They receive input data from the outside environment and pass it to the hidden layer for processing.[13] The neurons in the hidden layer process the data, and the neurons in the output layer report the results from the network to the external environment. At least one hidden layer must be employed in the ANN architecture.

The number of input and output neurons in a given ANN architecture is determined by the nature of the problem under study. The number of input neurons is the same as the number of input variables into the ANN; each neuron in the input layer is representing a single input parameter. Also, the number of output neurons is the same as the number of desired output variables. On the other hand, the number of neurons in the hidden layer is often determined by the required degree of accuracy and is therefore a parameter in formulating an ANN model.

One special form of ANN is a multilayered feed forward neural network, which represents a special form of connecting model parameters and performs a mapping from an input space to an output one.[2] Each neuron has a straightforward assignment. An input coming to a neuron is associated with a weight indicating its strength. In the neurons, the values of the input are multiplied by the corresponding weights and all products are added to obtain a net value. After summation, the net input of the neurons is combined with the previous state of the neurons to produce a new activa-

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Table 1. Characteristics of the Crude Oil Samples

property	value
specific gravity (60°/60°)	0.864
Reid vap. pressure (Psia)	10.5
pour point (°F)	less than −30.0
average API gravity at 60 °F	31.7
viscosity (Cs) @ 70 °F	17.4
100 °F	10.5
130 °F	6.79
160 °F	4.8
average sulfur content (% by wt)	2.7
asphaltenes (wt %)	2.23

tion value. The activation is then passed through an output or a transfer function that generates the actual neuron output. The transfer function modifies the value of the output signal.[11]

Historical data that are representative of the process are introduced to the ANN during training to allow the ANN to learn the relationships between the inputs and the output(s). ANN models come in a variety of topologies or paradigms.[14] One of the most commonly used rules for training multilayer perceptron networks is the back-propagation rule.[15] Simpson[16] provides a coherent description of 27 different popular ANN paradigms and presents comparative analyses, applications, and implementations of these paradigms. Of these, the most frequently used is the back-propagation paradigm. A back-propagation, by definition, refers to the manner in which a gradient descent algorithm forces the network weights along the negative gradient when computing nonlinear multilayered networks. The actual mechanism of ANN using back-propagation algorithm is to minimize an error function by adjusting the weights. It is used to determine the weights that lead to the least sum square error (SSE) between the actual outputs and the predicted outputs by the ANN. In this approach, connection weights are initially set at small, random values. The training data are fed to the network to generate an output. The network output is compared to the actual value of the output, and the connection weights are adjusted to improve the match of the two values. This process is repeated until a satisfactory level of accuracy is achieved.

In addition, the network must be tested on a continuous basis and must be monitored during training and testing operations. The testing operations are performed by passing a separate testing set to the trained ANN model. The results are then compared to actual results. The trained model is assumed to be successful if the model gives results for that test set.[11,14]

4. Materials and Methods

4.1. Materials and Instruments. Crude oil, collected from the Kuwaiti oil well, was supplied by Kuwait Oil Company (KOC). The characteristics of this crude oil are illustrated in Table 1. Dilution water used in the experiments was collected from field operation in KOC. Table 2 gives the characteristics of the used freshwater. The chemical used as a demulsifier in

Table 2. Chemical Analysis of the Used Brackish Water

property	value
specific gravity (60°/60°)	1.009
total dissolved solids, ppm	8900
oxygen content (max), ppm	8
electrical conductivity micromhos/CC	12714
calcium as Ca, ppm	801
magnesium as Mg, ppm	450
total iron as Fe, ppm	0.25
sodium as Na, ppm	1926
chloride as Cl, ppm	4045
sulfate as SO_4, ppm	1500
bicarbonate as HCO_3, ppm	285
fluoride as F, ppm	2.5
nitrate as NO_3, ppm	13.2
nitrate as NO_2, ppm	6
phosphate as SPO_4, ppm	10
hydrogen sulfide as H_2S, ppm	–
chloride as Cl_2, ppm	–
sodium chloride as NaCl, ppm	6665
silica as SiO_2, ppm	30
carbonate as CO_3, ppm	–
caustic alkalinity as NaOH, ppm	–
total alkalinity as $CaCO_3$, ppm	289

the experiment is under the trade name Servo CC 3408 supplied by Servo Delden BV (Netherlands). Details of the laboratory's instruments are given in Table 3. In addition, centrifuge tubes, stoppers, 100-mL graduated cylinders, micromilliliter syringe, stopwatch, and gloves and chemical safety gear were used.

4.2. Experimental Setup and Procedures. In carrying out the experiments, crude oil samples were first analyzed for salt result (S/R) in PTB and water cut (W/C) in volume percent. The details of these tests, which were conducted as per KOC standards, were presented elsewhere.[1,17] Figure 2 explains the steps followed in carrying out one cycle of the experiment. First, freshwater was added, followed by the addition of chemical/demulsifier. The mixture was then heated in a water bath heater. The heated mixture was then mixed and poured into a 100-mL centrifuge tube and rotated at 1000 rpm. The final step in completing one cycle was to suck out the top crude volume in the centrifuge tube and to test it for S/R and W/C. The top volume was taken because of what happened in real operation processes: the treated crude after mixing and heating gets out from the top of the desalting vessel. The order shown in Figure 2 was followed to mimic the real process. In a real process, an emulsion that was introduced into the system was subjected to freshwater injection and then chemical dosage followed. The mixture, emulsion, freshwater, and chemical were then heated to a certain temperature and then mixed together. The blend then entered a vessel where settling took place, allowing water and salt to be drained off. At the final stage, the process produced dry or treated crude oil samples that were tested and analyzed for S/R and W/C.

In each cycle of the experiment, a sample of crude oil to be tested was taken in a sample tube or graduated cylinder of about 100 mL. Then both freshwater and chemical demulsifier were added according to previously set ranges. Crude oil, freshwater, and chemical were next heated and then mixed for a certain time (min). Then, the mixture was taken to a centrifuge where it was rotated for settling purposes. From the top of the centrifuge tube, a certain volume of dry crude was withdrawn by a micromilliliter syringe and then transferred to a test beaker. The S/R test was conducted on a partial volume of that dry crude (about 10 mL), and then 50 mL was transferred to a centrifuge for W/C test.

4.3. Methodology and Data Collection. In a desalting/dehydration process, there are several parameters that can be altered to reach an optimum combination of operating

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Table 3. Details of the Instruments

instrument	instrument make and model	purpose of the instrument
salt-in-crude analyzer	Precision Scientific Petroleum Instruments Co. catalog 74700: TS-74700 AN 10	measure the amount of salt in crude oil in correlation with ASTM procedure D3230
centrifuge	model Z 510, Manufacturer Berthold Hermle AG, type Z 510	read basic sediment and water (BS&W) or water cut by weight percentage through small graduated tubes
fixed-speed mixer	a multi-mixer	hold and mix five samples at a time
simple water bath heaters[a]	model K6 LAUDA	control the temperature via an automatic knob

[a] Tap water was used to fill the water bath heaters.

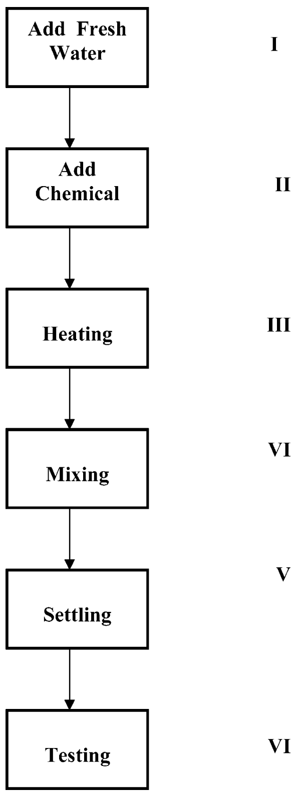

Figure 2. Steps followed in carrying out a single experiment.

conditions. In this study, five parameters that were expected to affect the desalting/dehydration process were investigated. To predict the interactions and the optimum combination of these parameters, different variables were allowed to vary according to a predesigned experiment. The variables that were considered in this work included crude temperature (°C), mixing time (min), settling time (min), chemical/demulsifier dosage (ppm), and the amount of freshwater added in ratio to that of the wet crude's quantity (%). The desalting/dehydration process was evaluated by conducting a series of runs. The experimental design was constructed to include all possible combinations of different values of these parameters. Table 4 shows the values covered for each parameter. It can be seen that there were 980 combinations or runs ($2 \times 2 \times 5 \times 7 \times 7$ runs) that were carried out to determine the interactions of all of these parameters.

Temperature and settling time were the factors that were found to be the least varied in real processes. Further, it is widely known how temperature and settling time affect oil viscosity and the rate of downward settling.[1] Accordingly, this work focused on chemical dosage, freshwater addition, and the mixing time variables that were tested in various varied values, whereas temperature and settling time were investigated only at high and low values. Hence, the five parameters were classified into two groups: two-point and multipoint variations groups. The two-point group consisted mainly of temperature and settling time. The multipoint group, on the other hand, consisted of chemical dosage, freshwater addition, and the mixing time. It is worth noting here that the values of settling time and temperature used in this study were selected from real field experience.[9,10] The parameters of the multipoint variations group were carefully selected to have values that were practically encountered in a real desalting/dehydration process system.

The performance of the desalting/dehydration process was evaluated by calculating the salinity and water cut efficiencies (η_1, η_2). These efficiencies were obtained from correlations using the collected experimental data.[2] These efficiencies are therefore expected to depend on the mixing rate, the wash water rate, the demulsifying chemical dosage, and the rate of heating. The salinity efficiency (η_1) was calculated from eq 1, whereas water cut efficiency (η_2) was calculated from eq 2.

$$\eta_1 = 1 - Z_{out}/Z_{in} \quad (1)$$

$$\eta_2 = 1 - X_{out}/X_{in} \quad (2)$$

where Z_{out} is the outlet salt result (PTB); Z_{in} is the inlet salt result (PTB); X_{out} is the outlet water cut (%); and X_{in} is the inlet water cut (%).

The calculations of the salinity and water cut efficiencies at different experimental conditions were evaluated to determine the effect of the various parameters on the performance of the desalting/dehydration process. More detailed information about the calculation of these efficiencies can be found elsewhere.[2,17]

5. Modeling the Desalting/Dehydration Process with ANN

5.1. ANN Development. The data collected for the variation in salinity and water cut efficiencies as a function of temperatures (X_1), settling times (X_2), mixing times (X_3), chemical concentration (X_4), and the dilution wash water (X_5) were used to train an ANN. This means that the salinity and water cut efficiencies were what the network was trained to output.

Before training, all the input and output parameters were normalized (i.e., they ranged from 0 to 1) using their minimum and maximum values (Table 5). Normalization is important so that the inputs and outputs have the same order of magnitude and the same significance.[3] The normalization of inputs also avoids overflows due to very large or very small weights. Furthermore, the used transfer function of the S-shaped logistic sigmoid transfer function necessitates the normalization of input−output data so that they are in the same range of the transfer function used.

The data were then randomly divided into two distinct sets: a training set and a testing set. The training set consisted of 90% of the data sets collected, or 882 patterns, that were then used for training the model. The remaining 10%, or 98 patterns, were excluded from

Table 4. Description, Nomenclature, and the Values of the Investigated Process Parameters

parameter	description	nomenclature	values	number of runs
		Two-Point Variations Group		
temperature, °C	temperature of the outlet crude	X_1	55 °C (low), 70 °C (high)	2
settling time, min	settling time	X_2	1 min (low), 3 min (high)	2
		Multipoint Variations Group		
mixing time, min	mixing time	X_3	1, 3, 5, 7, and 9	5
chemical dosage, ppm	chemical addition	X_4	1, 2, 5, 8, 10, 12, and 15	7
dilution water (%)	freshwater addition	X_5	1, 2, 3, 4, 6, 8, and 10	7
total number of runs				980

Table 5. Normalizing the Input and Output Variables

variable	scaled value (variable − low)/(high − low)
temperature (X_1)	$(X_1 - 55)/(70 - 55)$
settling time (X_2)	$(X_2 - 1)/(3 - 1)$
mixing time (X_3)	$(X_3 - 1)/(9 - 1)$
chemical dosage (X_4)	$(X_4 - 1)/(15 - 1)$
dilution water (X_5)	$(X_5 - 1)/(10 - 1)$
salt removal efficiency ($\eta 1$) = Y_1	$(\eta_1 - 38)/(93.4 - 38)$
water cut removal efficiency ($\eta 2$) = Y_2	$(\eta_2 - 7.14)/(94.38 - 7.14)$

the training set and used later, once the model was developed, to test the performance of the model.

Since there were five input independent parameters into the ANN (X_1; X_2; X_3; X_4; X_5), the architecture of the ANN consisted of an input layer of five neurons. Also, since there was one output parameter (salinity efficiency or water cut efficiency), the architecture of the ANN consisted of an output layer of one neuron. For the hidden layers, only one hidden layer was initially used. Several network factors such as momentum, learning rate, and number of hidden nodes were tried during the training process to improve network prediction accuracy. It was found that one hidden layer network of 10 neurons was able to give sufficiently accurate predictions (i.e., achieve the required error target). The use of more neurons or more hidden layers did not result in improved accuracy. Simpson[16] describes the system of equations that provides a generalized description of how the learning process is performed by the back-propagation algorithm.

Figure 3 depicts the architecture of the subject network. An input vector was introduced to the network as $p = [X_1; X_2; X_3; X_4; X_5]$ and a target output as T; containing once η_1 and in another network η_2. It can be seen that there are 10 neurons in the hidden layer and one neuron on the output layer (either η_1 or η_2). The hidden layer contains neurons of the log sig functions, and the output layer has a linear function; its synopsis in ANN (MATLAB) as *purelin*.

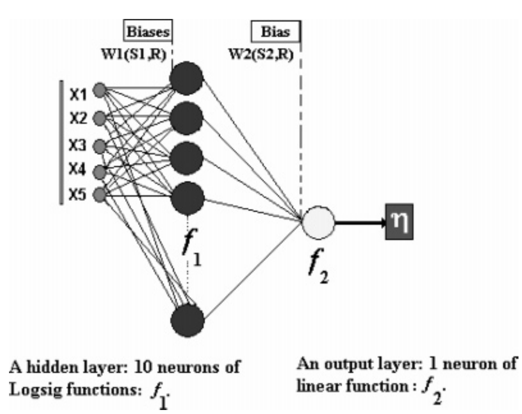

Figure 3. Architecture of neural network designed for the problem under study.

In training the data, the Levenberg−Marquardt (LM) algorithm was used. This algorithm proved to be the fastest method for training moderate-sized feed forward neural networks (less than several hundred weights). It also had a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function. The typical performance function that was used for training feed forward neural networks was the mean sum of squares of the network errors.[2] As each input was applied to the network, the network output was compared to the target. The error was calculated as the difference between the target output and the network output. This function is illustrated as follows:

$$F = \text{mse} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad (3)$$

where e_i is the error calculated in each run and t_i and a_i are the target and network output values, respectively. The weights were adjusted until the error between the output data and the actual data was minimized. The goal of training the ANN was to get the best connection weights on a given network architecture.

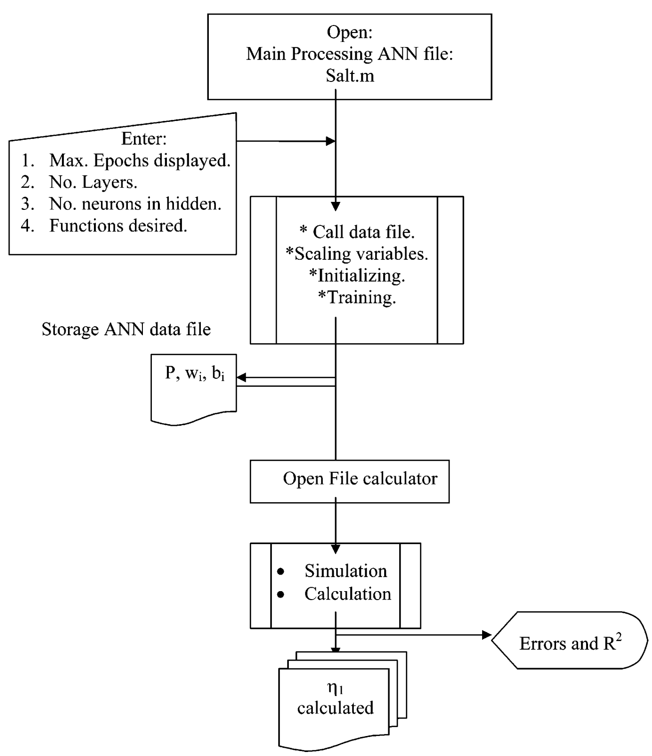

Figure 4. Flowchart of the MATLAB program (salinity efficiency).

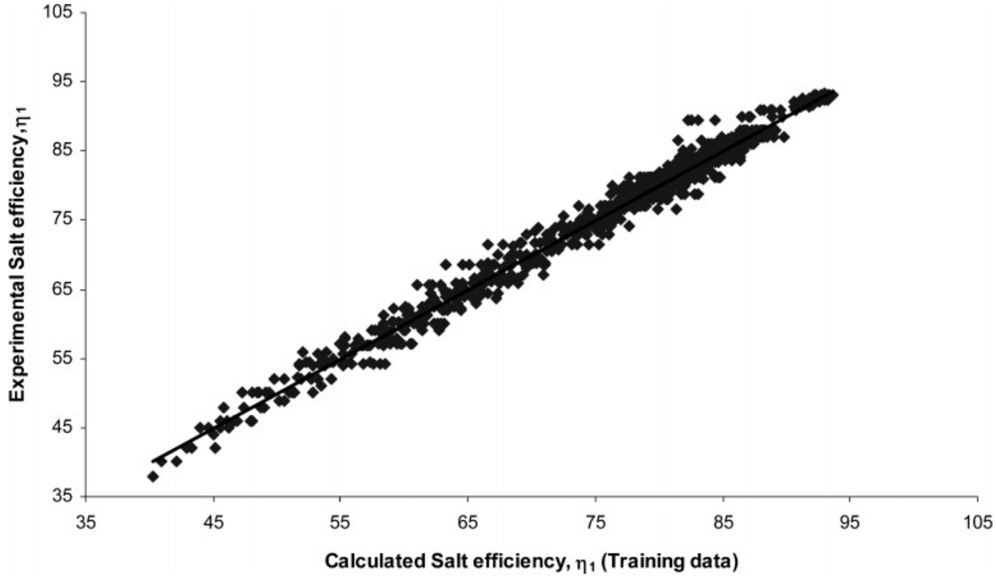

Figure 5. Experimental salt efficiency vs calculated salt efficiency for the training data set.

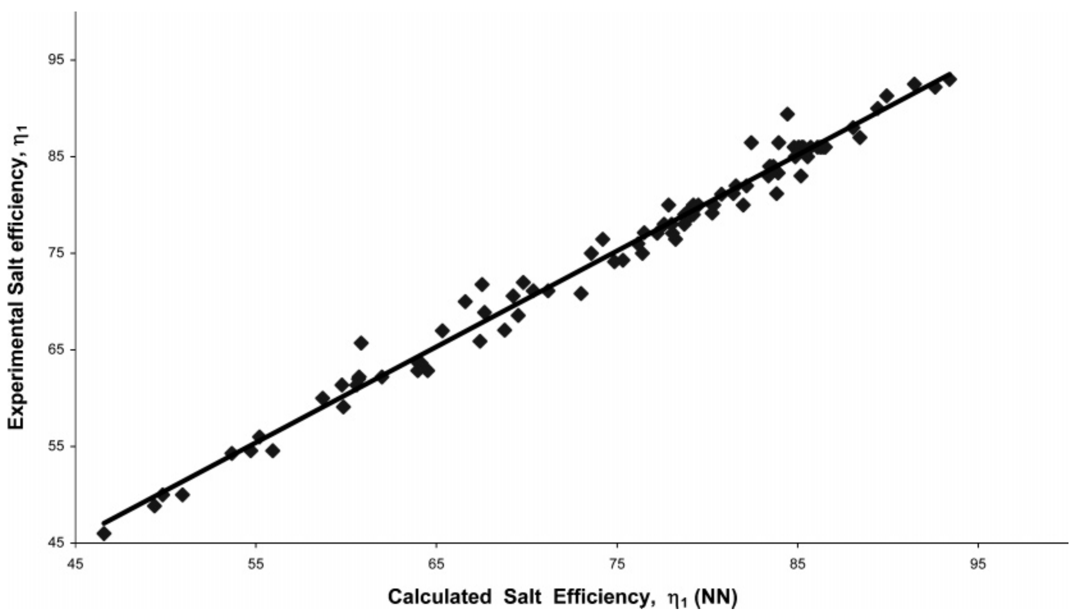

Figure 6. Experimental salt efficiency vs calculated salt efficiency for the testing data set.

The network used for the problem under study was a 5−10−1 with five neurons in the input layer, 10 log sig neurons in the hidden layer, and a linear neuron in the output layer (either η_1 or η_2). The network was trained until the squared error was less than 0.001. A MATLAB program was written to solve the problem. Figure 4 displays the flowchart of the written MATLAB program for predicting the salt removal efficiency (η_1). In Figure 4, an epoch is an entire pass through all the input training vectors. The water cut efficiency (η_2) was simulated, trained, and then calculated using a flowchart similar to the one shown in Figure 4 for salt removal efficiency.

The cross plots of predicted and measured salinity and water cut efficiencies for the training sets are shown in Figures 5 and 6, respectively. The figures showed good accuracy in predictions by the ANN model. Looking at these two figures, it can be seen that the calculated and measured values were clustered around the diagonal that entails the validity of the neural network model. Thus, there was a strong correlation between the measured and the calculated values.

5.2. Neural Network Model Testing and Validation. The system was then calibrated by testing the network on data it had never seen in training the network. This validation step was important to check the generalization characteristics of the neural network prepared. Figures 7 and 8 show a cross plot of the predicted and measured salinity and water cut efficiencies data. The data indicated that the predictions were also good for the testing data set.

6. Optimization

In this section, the developed ANN was used to optimize the operation of the DDP plant. An objective function that consists of the variables of DDP was used

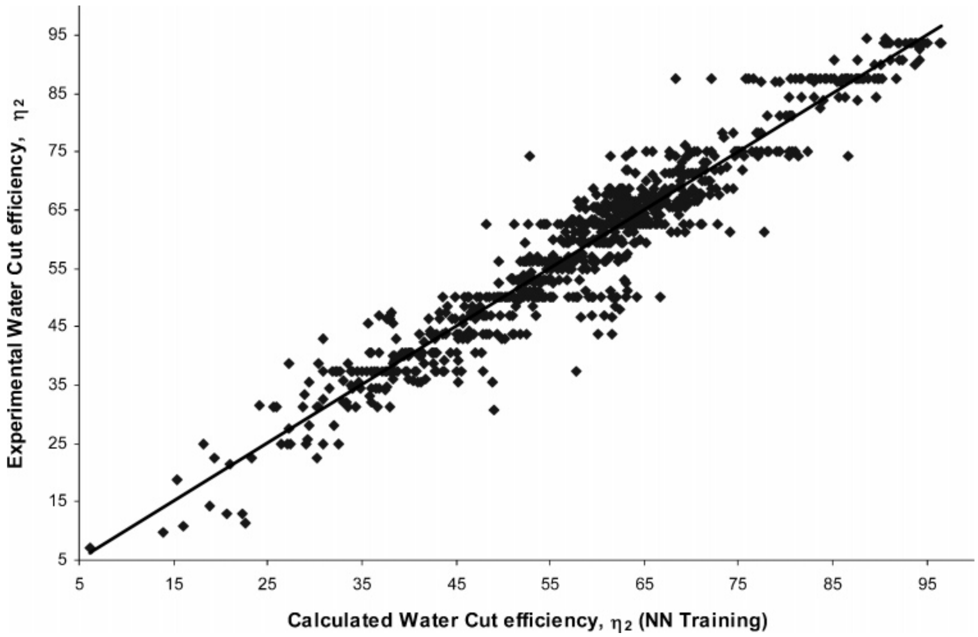

Figure 7. Experimental water cut efficiency vs calculated water cut efficiency for the training data set.

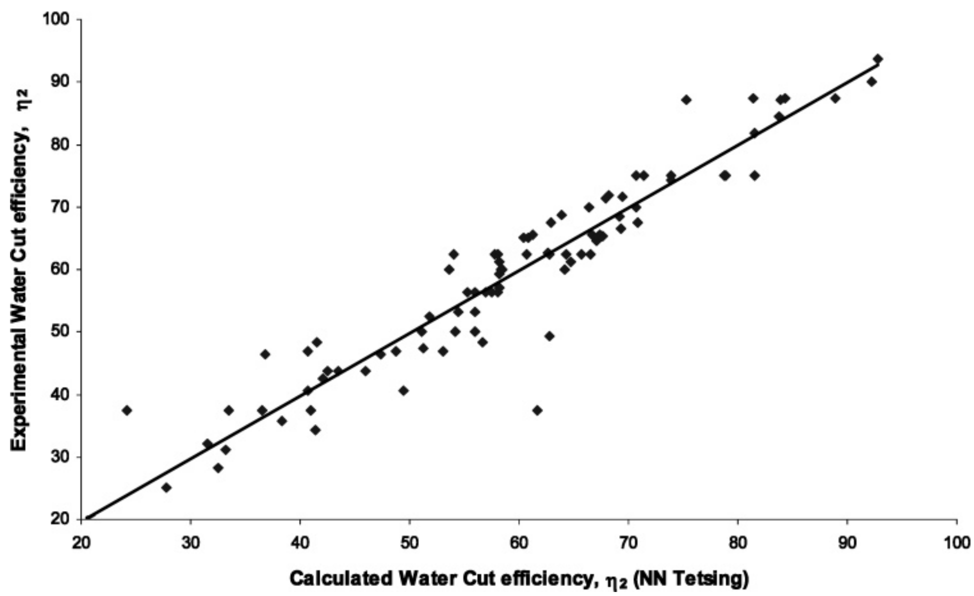

Figure 8. Experimental water cut efficiency vs calculated water cut efficiency for the testing data set.

in conjunction with the prepared neural network within an optimization model. The variables in the optimization model were subjected to constraints to ensure that maximum and minimum bounds were adhered to. The optimization technique of the physical process based on an ANN model was basically to replace the desalting process by an equivalent ANN and use this ANN to carry out the required optimization. This was considered an advantage because of the high speed processing, since simulating with a neural network involves only a few algebraic calculations.

To determine the optimal operating policy, the neural network models can be integrated within an optimization strategy. The objective of the optimization is to minimize the final water and salt content in the produced oil. The functions to be minimized are obtained from the prepared neural network models. The model can be stated as:

$$\text{Maximize} \sum_i w_i \eta_i(x_j) \tag{4}$$

Subject to:

$$L_j \leq x_j \leq U_j \tag{5}$$

Equation 4 in the above model represents the objective function, which is the functional relationship of the efficiencies obtained previously. The x's are the five variables in the desalting process, and eq 5 gives lower and upper bounds on them. These bounds can be imposed according to the range of the training data for the NN models and can also represent reasonable practical operating points. For instance, the upper limit on temperature corresponds to the requirement of

Table 6. Upper and Lower Bounds of Variables

variables/modes	summer		winter	
	lower	upper	lower	upper
X_1, °C	50	65	55	70
X_2, min	1	2	1	3
X_3, min	3	7	5	10
X_4, ppm	2	5	5	10
X_5, %	3	6	4	8

specific rate of crude boiling and evaporation of the volatile elements. The lower limit temperature, however, is restricted by the requirement of electrical transformers startup (i.e., a minimum temperature that was specified by design). For the settling time, a lower limit must be fixed to avoid crude being carried out with the disposal water stream. Further, if the feed to DDP flow rate is low, then a high water interface between stages may be inevitable. As a result, the process will be unstable leading to an inefficient operation. An upper limit was, therefore, imposed to avoid carryover of brine with the treated crude. Similarly, limits must be imposed on chemical dosage. A de-emulsifier injection cannot be raised above a certain value due to reverse emulsion problems. The upper value depends on the characteristics of crude processed for feed treatment and on the feedwater concentration. On the other hand, a lower bound should also be imposed on chemical dosage because too much reduction can cause an emulsion dispersion band to increase the water–crude contact region where the water droplets experience the coalescing and falling in both the wet tank and desalter vessels. Equality constraints can also be imposed to indicate that some of the variables are fixed. For instance, the mixing (Mix) is usually a known factor fixed per design specifications.

The model considered is a nonlinear-constrained optimization problem and was solved using the MATLAB optimization toolbox. The operation of the desalting process is often carried out according to two modes: summer at which the ambient temperature reaches more than 55 °C and winter where the ambient temperature drops just below 0 °C. Also, upper and lower bounds were imposed on the variables according to the minimum and maximum values given in Table 6.

The optimization study showed a comparison of the ANN recommended optimum set of variables obtained from the simulated network and those values that were entered manually considering both summer and winter modes. The results of the optimization are shown in Table 7. The optimization program was run several times with different starting guesses of the decision (input) variables. The reported values given in Table 7 represent the optimum set at which a DDP should operate to maximize the system efficiency. There is no guarantee, however, that these optimum solutions are applicable to all kinds of emulsion treatment systems. Further advanced research studies on emulsion characteristics can be used for future studies to find a solution covering most types of emulsions.

Table 7. Optimum Set of Variables

variables/methods	ANN optimization	summer	winter
X_1	69.99	61.00	69.99
X_2	2.87	2.99	2.86
X_3	5.17	5.59	5.10
X_4	8.07	8.00	7.99
X_5	5.56	5.49	5.50

7. Conclusions

A simplified model of a crude oil desalting system was presented. The model was based on the application of material balances and the definition of efficiencies of the process. The neural network correlations for these efficiencies were prepared from experimental data. The present model covered a large operating range and presented a first effort at simplifying the modeling of the desalting system.

The performance of the desalting/dehydration process was calculated by determining the salinity and water cut efficiencies in terms of five process parameters: concentration of demulsifying agents, heating, wash water, salt concentration, and rate of mixing with wash water. The neural network model predictions for the salinity and water cut efficiencies were then compared with the real experimental observations, and the results were shown to be consistent. Furthermore, a composite objective function for measuring the salinity and water cut efficiencies was used in conjunction with the prepared neural network.

The outcome of this research will help in lowering the cost per crude oil barrel produced. One aspect of cost is fuel consumption (i.e., when heating crude oil). Another cost is freshwater consumption, especially at dry places where water is scarce. Chemical treatment also adds to the overall cost of oil production per barrel. At KOC, for instance, the consumption of chemicals in the desalting/dehydration systems costs the company roughly around \$200 000/month. Therefore, if chemical consumption during the desalting process is minimized while maintaining the same performance by selecting the appropriate combinations of the other four factors, major savings can be achieved.

Future work is needed on the development of extended correlations for the efficiencies that will take into account all factors affecting the system, including the applied voltage.

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