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Soft Computing Tools for Multiobjective Optimization of Offshore Crude Oil and Gas Separation Plant for the Best Operational Condition

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***Abstract*— The selection of operating conditions in the oil and gas separation plants is obtained through data monitoring or through the experience of the operating personnel which can bring operational difficulties leading to inefficiencies and capital loss. The modern techniques of soft computing including artificial intelligence and genetic algorithm-based optimization can add value to this operation. In this work, five key controllable design variables of an oil and gas separation plant are optimized considering two performance indicators (oil flow productivity and gas compression power). The physical model of the plant is simulated using ASPEN HYSYS, and a digital twin model is generated using an artificial neural network. It is followed by a multiobjective optimization using non-dominating sorting genetic algorithm II to obtain the Pareto front. The results have indicated that operational optimization can enhance oil production by up to ~6.2% and decrease the compression work by ~3.2%. It is concluded that the proposed operation of the plant is energy-efficient and can increase productivity.**

Keywords*— *simulation, oil and gas separation, optimization, data science, soft computing, artificial neural network.

I. Introduction

Due to the decay of the pressure of the wells in the offshore oil facilities [1] of Mexico, the oil company has made important modifications to the offshore platforms by modifying its infrastructure for the maintenance of pressure of the wells through the injection of gas or water. It has created a need to establish modified operating conditions for separation and compression units. Thus, it is significant to evaluate and determine the optimal operating conditions of the existing separation systems with the new mixing conditions to maximize oil recovery [2] and minimize compression energy consumption.

In this context, different studies have been carried out. Anders [3] performed an optimization study applying rigorous simulation on a crude oil and gas separation plant. The authors determined that high pressure is required in the first stage of separation, and there are no single optimal pressure values for downstream separators. Rojas et al. [4] used a commercial simulator and analyzed two cases of a conceptual level design of the production and gas facilities. The first case optimized the separation pressures with respect to the maximum oil production and the second case optimized the energy of compression with respect to the compression pressures.

Pan-Echeverría et al. [5] simulated a gas separation and stabilization process. The authors carried out a sensitivity analysis by changing pressure, well composition, and temperature to determine the optimal operational region using a method of successive quadratic programming. The authors concluded that it is possible to determine new operating conditions, and this increased the profitability of the process.

Literature on crude oil stabilization has indicated that the most sensible variable in oil production is intermediate separation pressures. Bahadori et al. [6] published a method to calculate these intermediate pressures in a multistage separation. For the analyzed case study, there was an increase of 6 m^3/day to 5 m^3/day during summer and winter, respectively, in the recovered oil.

The selection of operating pressures in surface separators can have a remarkable impact on the quantity and quality of the oil produced at the stock tank. In the case of a three-stage separation process, where the operating pressures of the first and third stage (stock tank) are usually set by process considerations, the middle-stage separator pressure becomes the natural variable that lends itself to optimization [7].

Literature has shown that the search-based optimization of such plants is carried out extensively. However, such an optimization can be computationally expensive and can lead to local optima. It is desired to conduct a metaheuristic-based optimization to yield the global optima. The objective of this work is to optimize the operational characteristics of an offshore oil and gas separation plant considering five influential temperature and pressure variables. The simulation

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of a physical model of the system is translated into a digital twin with the usage of artificial intelligence. The problem is optimized using a metaheuristic technique called a non-dominating sorting genetic algorithm (NSGA-II) by using the digital twin model. At the end, a comparative assessment is carried out to compare the optimized performance with the base-case performance.

II. System Description

The crude extracted in the oil facilities is stabilized in the offshore production platforms. The gas associated with the crude is compressed in the compression platforms which is considered as one of the most significant operating variables (see Fig. 1).

The crude oil mixture coming from the collection head of the wells is sent by means of a head to the first stage three-phase separator (V-100) where there is a separation of phases: gas, oil, and water. The gas comes out through the upper part of the separator and is sent to a first-stage rectifier (R-101) that removes the condensate. The gas at the output of the rectifier enters the compression platform and is regulated at a pressure of 4.5-8 kg/cm^2 in the suction of modules. The first compression stage (K-100) raises the gas pressure by up to 28 kg/cm^2 and a discharge temperature of approximately 144 ºC. Thus, the stream is cooled through a single air heat exchanger (E-101) to a temperature of approximately 45 ºC. The stream gas is sent to an interstage separator R-102 to remove the liquids that were formed by the temperature drop. Later, it enters the second compression stage (K-101) where the pressure rises to 70 kg/cm^2 with a discharge temperature of 144 ºC. Here, the gas is cooled using a single air heat exchanger (E-102) and passes through an interstage separator (R-103) for the removal of condensates. Subsequently, the shipment is transported to land facilities. The condensates from the suction and interstage separators are recovered and sent to the second separation stage (V-104).

The oil that comes out of the first stage separator is sent to the second stage of the separation system (V-104) that operates at a pressure range of 0.5 to 1.5 kg/cm^2. The container allows the separation of the liquid from the gas, the low-pressure gas comes out through the upper part of the container and is recovered through a K-102 compression system that raises the pressure to 4.5-8 kg/cm^2.

III. Methodology

A stepwise procedure is applied here to obtain the optimization results. First, the simulation of the physical model of the system is conducted using ASPEN HYSYS. A set of numerical experiments are generated from the simulator software. A digital twin model using an artificial neural network is developed using the generated numerical experiments. At the end, multiobjective optimization is carried out considering the objective functions, restrictions, and search space. Stepwise details are presented herewith.

A. Modeling and simulation

The system data was obtained using the ASPEN HYSYS V11 process simulator. The conditions of the inlet flow of the mixture were set to be 60 ºC and 12 kg/cm^2. The composition of the mixture is shown in Table I. Peng-Robinson thermodynamic model [8] was selected for the calculations of fluid properties and flash separation. The constant parameters for the simulation of processes are summarized in Table II. Finally, five sensible design variables are considered variables which are as follows:

- First stage separation pressure, $P_{S,I}$
- Second stage separation pressure, $P_{S,II}$
- Modules suction pressure, P_{MS}
- Compression discharge temperature 1, $T_{CD,I}$
- Compression discharge temperature 2, $T_{CD,II}$

B. Numerical experiments

A data set was created with the five aforementioned design variables selected for the study of the oil and gas separation offshore platform. These variables can be manipulated through the set points of the Digital Monitoring and Control System of the oil installations.

Fig. 2 shows the relationship between the 5 variables and the 2 performance indicators. The separation pressure of the first stage and the compression suction pressure has little influence on the oil flow obtained and the power of compression. As the second stage separation pressure increases, the oil flow increases, and the compression power decreases. Low temperatures in the discharge of the compressors increase the oil flow quantity.

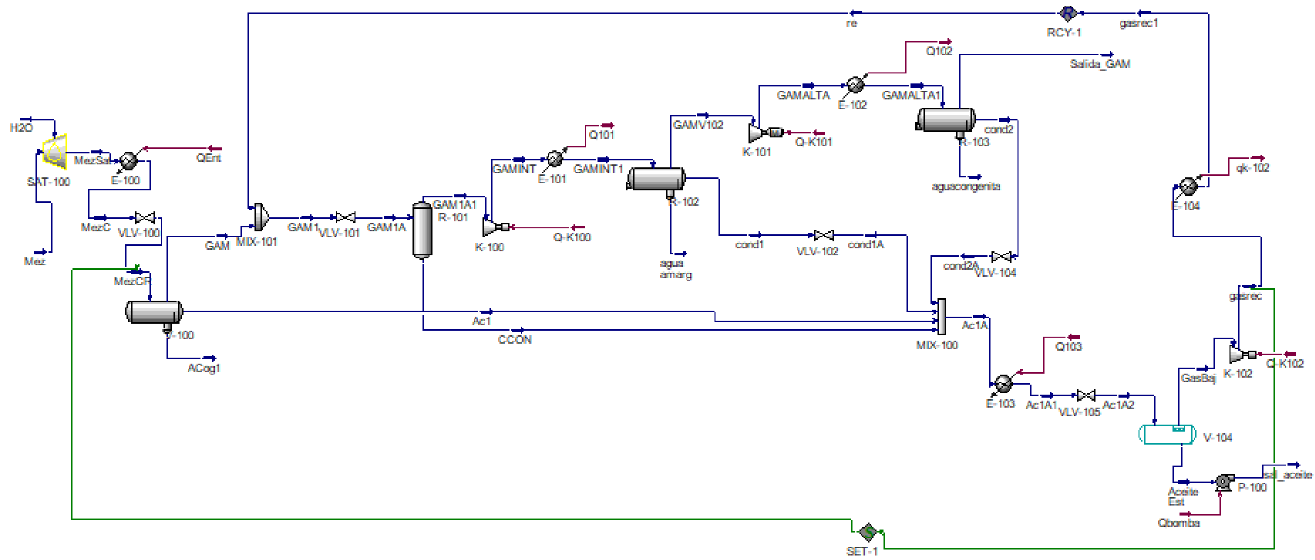

Fig. 1. System flow diagram simulated using ASPEN HYSYS.

TABLE I. WELL FLUID COMPOSITION.

Component	Mole fraction
H_2S	0.0232
Propane	0.0498
i-Butane	0.0593
n-Butane	0.0498
i-Pentane	0.0493
n-Pentane	0.0629
CO_2	0.0095
Ethane	0.1132
Oxygen	0.0052
Nitrogen	0.0205
Methane	0.2788
n-Hexane	0.0598
Benzene	0.0015
Cyclohexane	0.0503
Toluene	0.0199
n-Heptane	0.0498
n-Octane	0.0398
n-Nonane	0.0498
H_2O	0.0075

TABLE II. PROCESS ASSUMPTIONS.

Specification	Value
Well feed flow rate	501,300 kg/h
Pressure of gas product	70 kg/cm^2
Interstage gas discharge pressure	28 kg/cm^2
Isentropic efficiency of centrifugal compressor	75 %

TABLE III. PARAMETERS USED FOR THE OPTIMIZATION OF GENETIC ALGORITHMS.

Population	50
Selection Function/size	Tournament/2
Reproduction/ Crossover fraction	0.8
Mutation function	Constrain dependent
Crosover function/ratio	Intermediate/1.0
Migration/Fraction/interval	Forward/0.2/20
Pareto front population fraction	0.35
Max. No. of generations	100

C. *Digital twin model using artificial neural network*

Artificial neural network (ANN) models can be used as an alternative method in engineering analyses and predictions. ANNs mimic somewhat the learning process of the human brain. They operate like a "black box" model and require no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by recording previous data. In this way, it can be like how a non-linear regression might be performed. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance and concentrate on the important inputs. The network usually consists of an input layer, some hidden layers, and an output layer. In its simple form, every single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights (presumably corresponding to synapse-efficacy in biological neural systems) [9].

In this work, the Artificial Neural Networks algorithm is used to obtain a digital twin model. The purpose of the digital twin is to obtain the relationship between the five design variables and the two performance indicators. This implementation is conducted on MATLAB 2019 [10] software. The database is divided into three sets: training (70%), validation (15%), and testing (15%). The training data is used to train the algorithm; the validation base ensures that the algorithm is not overfitted in the training process and the test database is used to test the resulting model. For the training phase, the Levenberg-Marquardt algorithm is chosen [11]. The Levenberg-Marquardt algorithm was originally developed for the solution of non-linear least-square problems. It uses the characteristics of the Gauss-Newton algorithm and method of gradient descent with an objective to find the optimized values of the bias in the ANN architecture. Normally this algorithm requires a greater allocation of computational memory; however, their training time is considerably less as compared to other options like Bayesian regularization and Scaled conjugate gradient algorithm [12].

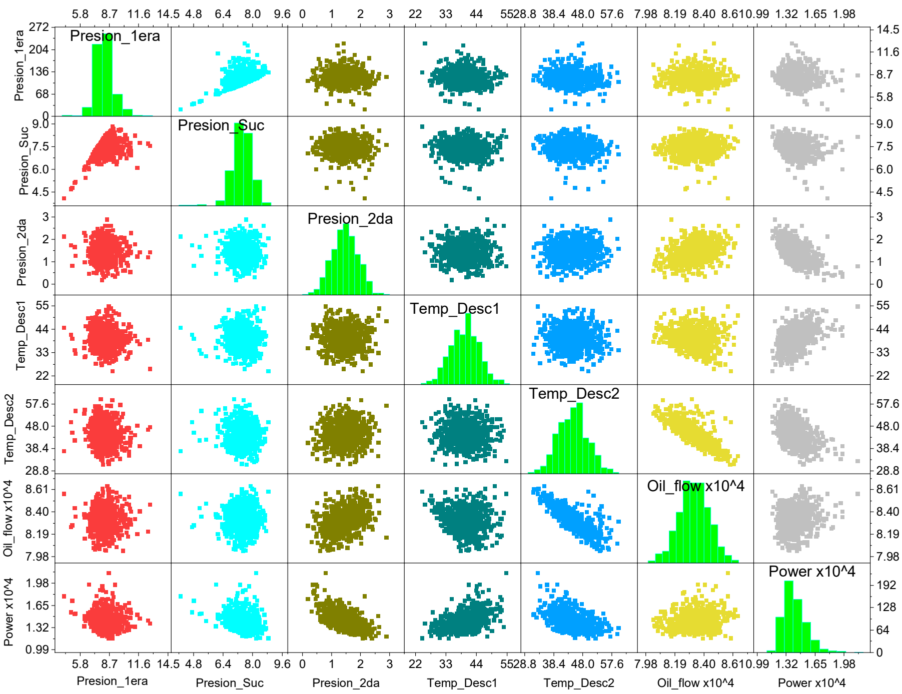

Fig. 2. Scatter matrix of the five design variables and two performance indicators (oil flow and compression power).

D. Formulation of the optimization problem

The motivation for this work is to optimize the set of operating parameters that provide maximum oil production and minimum compression power. The formulation of an optimization problem consists of the objective functions, design variables, search space, and restrictions.

1) Multi-objective optimization function

The objective function for the optimization of the separation battery can be formulated as follows:

$$Min(Obj) = \begin{cases} Obj_1 = -Separate\ oil\ flow \\ Obj_2 = Compression\ power \end{cases} \quad (1)$$

The equations of separate oil flow and compression power implemented in MATLAB for optimization purposes are not known directly because the physical process is simulated on ASPEN HYSYS. Thus, these equations are developed using the technique of artificial intelligence, i.e., the digital twin model. More details are displayed in the heading "Research Data".

2) Design variables

Since several variables affect the operation of a separation platform, it is decided to set the parameters that vary a little over time. For example, the composition of the mix, the pressure, and temperature of the inlet mix, the inlet flow, the compression pressures. The variables that can be manipulated and monitored are those that are chosen as design variables, which are the following:

a. First stage separation pressure $P_{S,I}$
b. Second stage separation pressure $P_{S,II}$
c. Modules suction pressure P_{MS}
d. Compression discharge temperature $T_{CD,I}$
e. Compression discharge temperature $T_{CD,II}$

3) Search space for the optimization problem

The optimization problem has a search space that consists of the minimum and maximum values of each of the design variables. This optimization space can be expressed as in the following equation:

$$\begin{aligned} &4.2\ kg/cm^2 \le First\ stage\ separation\ pressure \le 12.7\ kg/cm^2 \\ &0.19\ kg/cm^2 \le Second\ stage\ separation\ pressure \le 3.0\ kg/cm^2 \\ &4.1\ kg/cm^2 \le Modules\ suction\ pressure \le 9.0\ kg/cm^2 \\ &25^oC \le Compression\ discharge\ temperature\ 1 \le 60^oC \\ &25^oC \le Compression\ discharge\ temperature\ 2 \le 60^oC \end{aligned} \quad (4)$$

The minimum and maximum ranges for the pressures were determined according to the typical operating conditions of the wells and the maximum operating pressures of the vessels. The temperature range of the compressor discharge was selected according to the thermal capacity of the heat exchanger.

4) Constraints

The constraints of the optimization problem can be expressed as:

a. The operating pressures in the vessels must not exceed the maximum allowable pressure.

$$(P_{firts}, P_{Second}) < P_{allowable} \quad (2)$$

b. The pressure of a separator cannot exceed the pressure of the previous separator.

$$P_{i+1} < P_i \quad (3)$$

E. Theory and implementation of the optimization problem

Genetic algorithms (GAs) belong to the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by natural evolution, such as mutation, selection, and crossover. A GA starts with a set of randomly generated possible solutions, called a population. Each solution in the population is known as a chromosome or an individual. Each chromosome may be represented as a simple string or an array of genes, which contain a part of the solution. The values of genes are called alleles. A fitness function is provided to assign the fitness value for each individual. This function is based on how close an individual is to the optimal solution. Two randomly selected chromosomes, known as parents, can exchange genetic information in a process called recombination or crossover to produce two new chromosomes known as children or offspring. If both parents share a particular pattern in their chromosomes, then the same pattern will be carried over to the offspring. More details of this algorithm can be seen in the reference [13].

To determine the best-operating conditions of the separation platform, the non-dominating sorting genetic algorithm II optimization method was implemented on MATLAB 2019 [10] using some default parameters as indicated in Table III. The default parameters of MATLAB are robust enough to provide satisfactory results for an applied application of the current problem.

IV. Results and Discussion

The developed neural network consists of 8 hidden layers, 5 input neurons, and 1 output neuron for each of the two performance indicators. The results of the training and testing of the ANN proposed were satisfactory considering their coefficient of determination (R^2). Therefore, the neural network accurately predicts the system.

For the prediction network of oil production, Fig. 3(a) shows the graph of real data against the ANN predictions. The degree of dispersion around the unit slope line is minimal and it covers the variability of the output parameter for each of the training, testing, and validation phase. In Fig. 3(b) the error histogram for the training, validation, and test data is shown. They have a normal distribution and fall between the range: -57 to 55, thus, this regression follows the normality assumption. Fig. 3(c) exhibits the values of the mean square of error. The best validation performance is 1866 on iteration 53 for a total number of iterations of 59. With this, it is demonstrated that the ANN is capable of successfully predicting the oil flow based on the 5 design variables of this analyzed system.

The regression fit for the prediction of the compression power is displayed in Fig. 4(a) where the actual data is plotted against the predicted data. The degree of dispersion around the unit slope line is minimal and is covered the range of variability of the output parameter. In Fig. 4(b), the error histogram is shown for the training, validation, and test data, they have a normal distribution and fall between the range: -30 to 28. In Fig. 4(c), the mean square values are error. The best validation performance is 1380 on iteration 34 for a total iteration of 40. This has demonstrated that the digital twin model generated with the implementation of ANN is capable to successfully replicate the real value of this design variable.

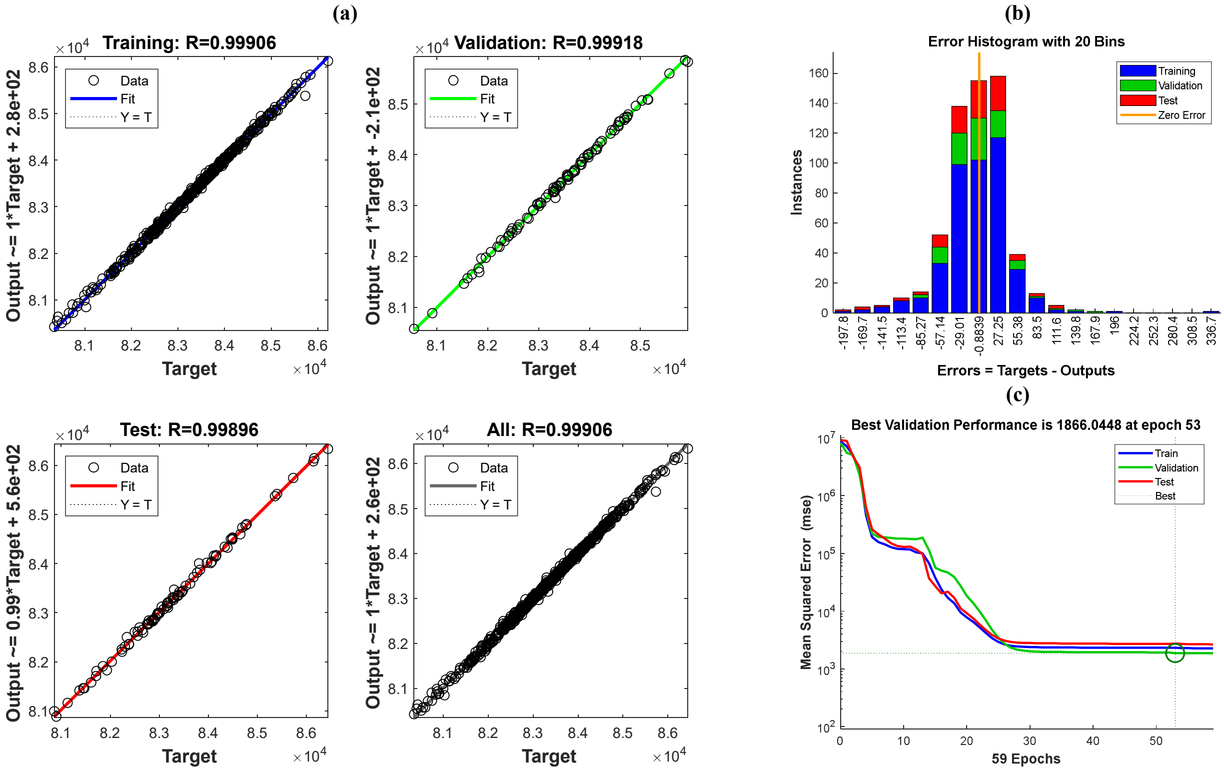

Fig. 3. (a) Linear regression fit between the numerical experiment and output data of the first performance indicator for training, validation, test, and total data. (b) Histogram of errors, (c) mean square of error of the first performance indicator.

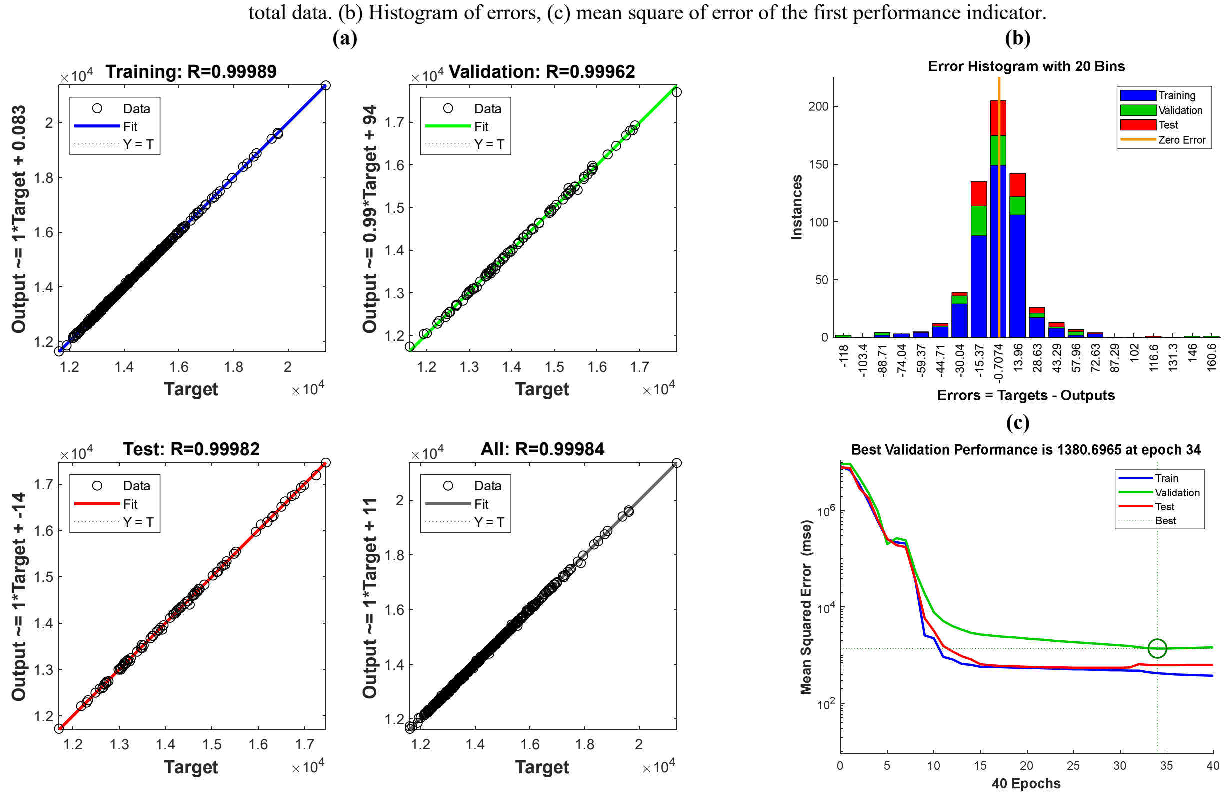

Fig. 4. (a) Linear regression fit between the numerical experiment and output data of the second performance indicator for training, validation, test, and total data. (b) Histogram of errors, (c) mean square of error of the second performance indicator.

TABLE IV. COMPARISON OF OPTIMIZATION RESULTS WITH BASE CASE CONDITIONS.

Characteristic	Separation Battery Conditions	Base case	Optimized case	Performance enhancement
Design variable 1	First stage separation pressure	7.5 kg/cm^2	6.4 kg/cm^2	14.6%↓
Design variable 2	Second stage separation pressure	1.0 kg/cm^2	1.5 kg/cm^2	50%↑
Design variable 3	Compression modulus suction pressure	6.5 kg/cm^2	6.2 kg/cm^2	4.6%↓
Design variable 4	Compression discharge temperature 1	45 ºC	31.5 ºC	30.0%↓
Design variable 5	Compression discharge temperature 2	45 ºC	30 ºC	33.3%↓
Performance indicator 1	Oil flow production rate	81600 bbl	86660 bbl	6.2%↑
Performance indicator 2	Compression power	16170 kW	15651 kW	3.2%↓

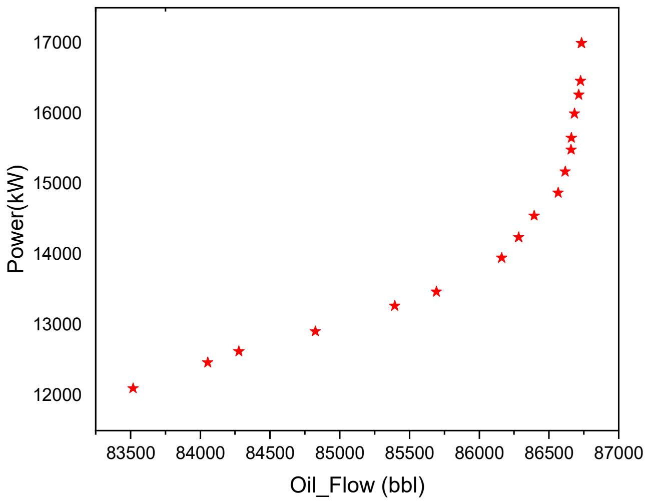

Fig. 5. Pareto front indicating the optimal performance points of the subject system.

The results obtained from the multiobjective optimization are displayed in Fig. 5. The values obtained in the Pareto Front fall within the lower and upper limits of our performance indicators according to the database used (oil flow and compression power). All the points in the Pareto front are non-dominating i.e., all the points on this Pareto front correspond to the optimality of the solution.

The obtained results in the optimization of the operating conditions for a separation battery with two stages of separation and compression have indicated that for the optimized case, a 6.2% increase in oil flow was obtained and a decrease in compression power of 3.2% in relation to the base case (see Table IV). The increased oil flow is strongly related to the compression discharge temperatures and the second stage separation pressure. The design variables of the optimized case that decreased their value were: first stage separation pressure, module suction pressure, compressor 1 discharge temperature, and compressor 2 discharge temperature by 14.6%, 4.6%, 30%, and 33.3% respectively. The second stage pressure had an increase of 50% with respect to the value of the base case.

Conclusion

In this work, a reliable prediction model of the oil and gas separation battery system was successfully obtained using artificial neural networks. For this model, the Pareto front set was obtained that optimizes the said system. The proposed operation can be used for the selection of the set-points of the variables for the optimal operation of the oil installations. This study can be used to establish the operating conditions for the designs of oil and gas separation batteries normally described in the customer's user bases. It has vital importance since these conditions are the starting point to develop basic engineering. It also ensures that all designed environmental equipment operates in optimal conditions, which results in the best use of non-renewable resources with the least environmental impact.

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Research Data

The function files of the "digital twin" model generated using an artificial neural network is available as research data on the following website: https://sites.google.com/view/rasikhtariq/metadata-for-research-articles/soft-computing-tools-for-multiobjective-optimization-of-offshore-crude-oil.

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