Optimization in heat exchangers using artificial intelligence: A hybrid neural network approach for predicting deposit accumulation and equipment efficiency

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ABSTRACT
This article presents an approach based on artificial intelligence techniques to predict critical deposition in heat exchangers used in petroleum preprocessing. Deposition on the heat exchange surface during operation can reduce equipment efficiency and cause maintenance problems. The proposed method uses a recurrent neural network in a Multi Layer Perceptron (MLP) model. Data was collected from exchangers of a petroleum preheating battery with data from 2014 to 2021. The neural network was trained with the data to predict the occurrence of deposition. The results showed that the neural network is capable of accurately predicting the occurrence of deposition in heat exchangers. Predicting deposition in advance can help minimize maintenance costs and increase energy efficiency, making operations safer and more efficient. Thus, the proposed approach can bring significant benefits to the petroleum industry by allowing early prediction of critical deposition in heat exchangers.

Keywords: Artificial intelligence, Heat exchanger, Deposition process, Petroleum.

1 INTRODUCTION

Fouling is a common phenomenon during the operation of heat exchangers, consisting of the formation of deposits on the surface of this equipment. Currently, in the literature, it is conceptualized that fouling can occur basically from three causes, as a result of the phase change that arises from the temperature differences between the surface and the fluid (deposition by crystallization), by chemical reactions in the surface and by the fluid (deposition by crystallization) and by growth of organisms on the surface (biodeposition) (BOTT, 1995).

This phenomenon is important to study because, over time, fouling reduces the cross-sectional area of the fluid flow, which results in the need for additional fuel to compensate for the reduction in the heat exchange area and greater pumping power due to the increase in load losses in the equipment, leading to a considerable increase in energy costs.

Knowledge of the phenomenon of deposition and its prediction can bring significant savings in the processing of oils and their mixtures, as it will make it possible to predict its occurrence and consequences, as well as avoiding, as far as possible, the appearance of deposition throughout the operation (SMITH, 2015). Currently, the most common models for predicting deposition are semi-empirical or threshold models, which basically use experimental data to predict the phenomenon; however, although these predict fouling rates satisfactorily, there are still gaps in terms of prediction efficiency (DESHANNAVAR, 2020).

The development of artificial intelligence technologies has made it possible to use machine learning tools to predict complex phenomena such as deposition. Machine learning algorithms such as recurrent neural networks (RNN), long short-term memory (LSTM) and multilayer perceptron (MLP) networks can easily correlate operating conditions and detect changing conditions by analyzing data acquired during equipment operation (DOBBLELARE, 2021). Oil pre-processing is a crucial stage in oil and gas production, which involves separating impurities and reducing the oil's viscosity to facilitate flow. The efficiency and effectiveness of heat exchangers are of great importance to various industrial sectors, since this equipment plays a crucial role in the transfer of thermal energy between fluids (BOTT, 1995).

Heat exchange between fluids of different temperatures is extremely important for industrial processes and has many applications in engineering. Predictive maintenance uses various methods to monitor the condition of the equipment used in industrial plants (Araújo et al, 2021). The problem of fouling in heat exchangers and loss of efficiency in the process has been the subject of several studies and could not be different in oil refining, especially in oil preheating (Júnior et al, 2020). In this sense, taking into account the uncertainties and thinking about deposition (Santana et al, 2021), the use of laboratory experimental apparatus has been quite common for the development of models, however the application of these models in the evaluation and prediction of the phenomenon in industrial plants encounters obstacles (Santamaria et al 2018), since the models available in the literature do not come close to predicting satisfactorily the behavior of deposition in industrial exchangers.

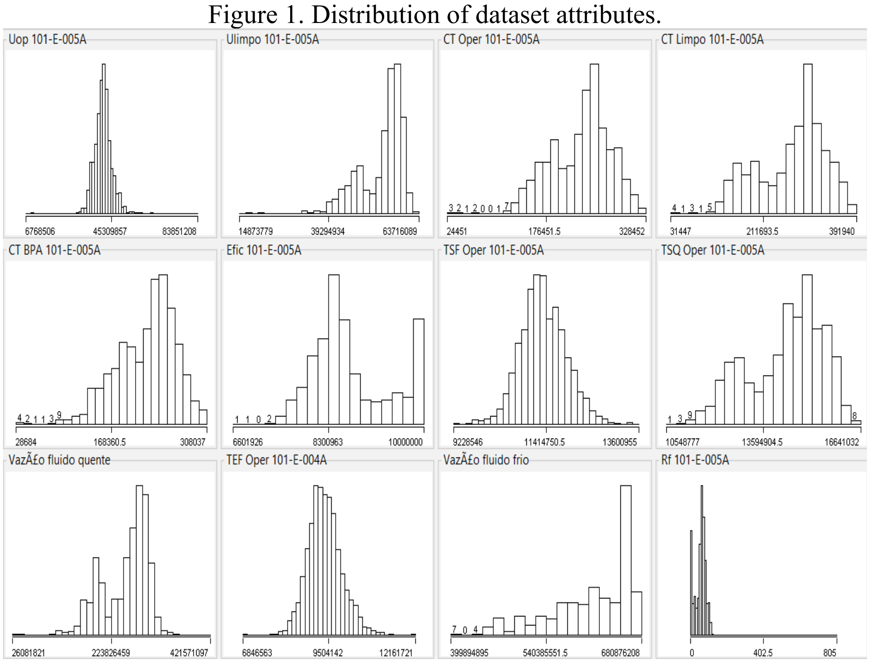
2 MATERIAL AND METHODS

2.1 DATA PREPARATION

The data used to build the prediction model was obtained from REGAP U-101's BPA measurement history from 01/09/2014 to 25/07/2021, totaling 2289 records stored in a CSV (Comma- separated values) file. For the prediction, the independent variables were the exchanger's operating parameters, such as operating temperature and flow rates, and the dependent variable was the deposition coefficient, which is measured using the Rf calculation, which quantifies the resistance to deposition.

Figure 1 shows the distribution of the data contained in the dataset used to train and validate the model after applying the filters.

Figure 1. Distribution of dataset attributes.



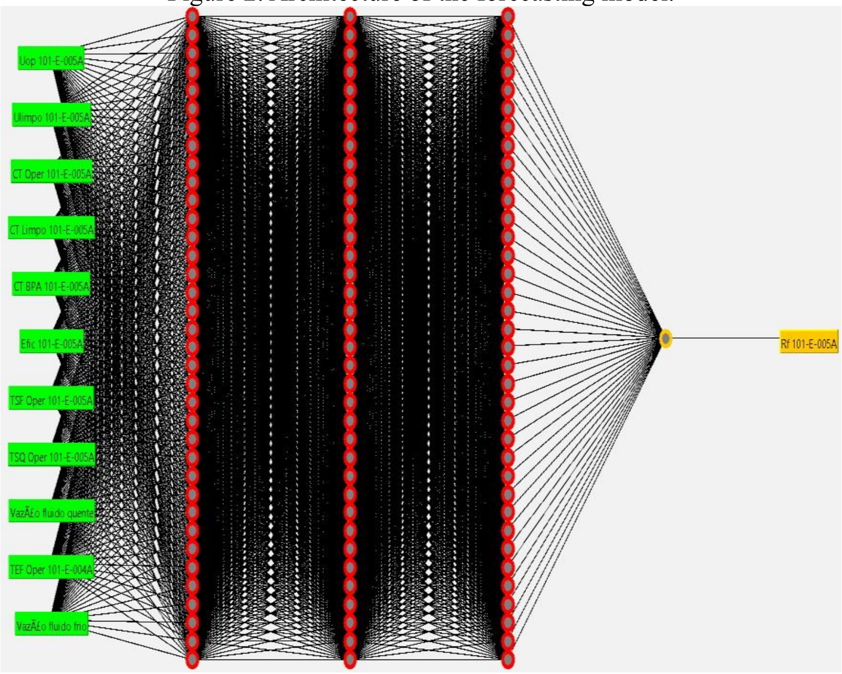
Source: Author.

For the quality of the forecasting model's performance, the data must be free of errors and disturbances caused by faulty measuring equipment and sensors. Errors and disturbances lead to outliers, discontinuities and data gaps, compromising the fit of the model and the quality of its forecasts. To this end, filters were applied to pre-process the data: (i) treatment of null values and (ii) filtering out overestimated records.

2.2 FORECASTING MODEL

The artificial neural network (ANN) model used in this work was based on the Multi Layer Perceptron (MLP) architecture with the Backpropagation algorithm. The main feature that makes the MLP interesting for solving problems is its ability to learn from examples and to generalize this learning so that it can reproduce a result for a different input. Figure 2 shows the architecture of the forecasting model built in this work.

Figure 2. Architecture of the forecasting model.



Source: Author.

The model based on an ANN is made up of 5 layers, with the input layer consisting of 11 neurons representing the attributes of the dataset used to build the model, 3 hidden layers made up of 36 neurons and an output layer representing the attribute (deposition coefficient) that the model should predict. The 10-fold cross-validation technique was used to train and build the model. In 10-fold cross-validation, the data set is randomly divided into 10 parts in which each class is represented in approximately the same proportion as the whole set. Of these 10 parts, 9 parts are used for training and one serves as a test base. The process is repeated 10 times, so that each part is used once as a test set. At the end, the total correction is calculated by averaging the results obtained at each stage, thus obtaining an estimate of the model's quality.

As a result, the algorithm predicts how similar recently received observations are to the training observation. During the learning phase, this algorithm maintains the complete training set. Unknown samples (i.e. new input data) have their labels (classes) compared to each instance of the training set and, by finding the average of the response variables, we can predict them.

3 RESULTS AND DISCUSSION

Once the model was built, its accuracy and generalization capacity were tested using the data that made up the sample set for training and testing, totaling 2286 instances. The model was trained for up to 1000 epochs, using a learning rate of 0.01 and a momentum constant of 0.9. Table 1 shows the mean absolute error, the relative absolute error and the root mean square error of the model. The correlation coefficient obtained was 0.98.

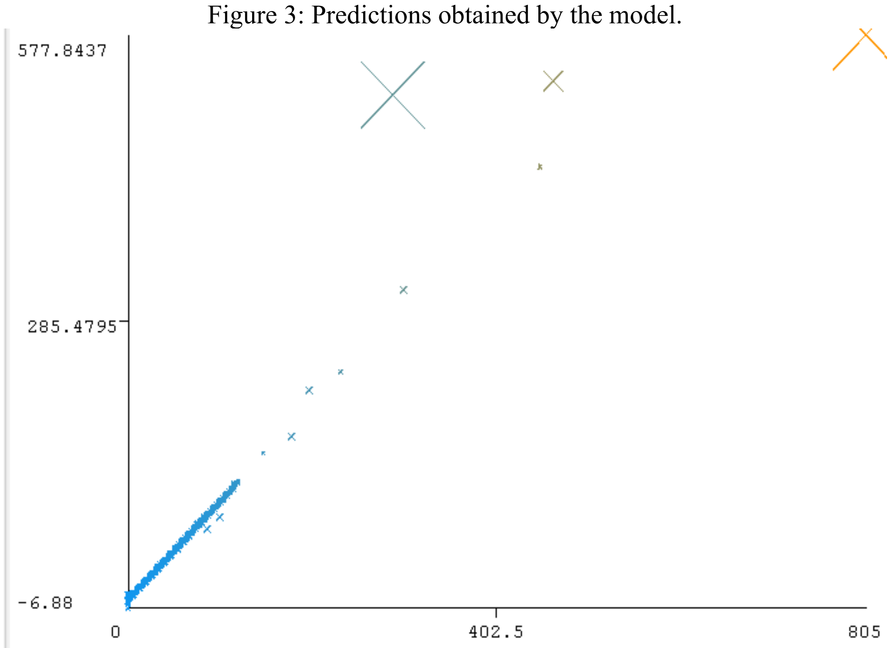
Table 1. Forecast error.

Average error absolute	Relative error absolute	Root of mean error quadratic
1,0	4,0 %	6,9 %

Source: Author.

The error values are used to measure how close the predictions are to the results. Figure 3 shows the model's predicted and actual values. The y-axis projects values for each prediction, while the x-axis shows the actual values. The model closely follows the prediction of the deposition coefficient, although it shows slight variations.

Figure 3: Predictions obtained by the model.



Source: Author.

In this context, the model was evaluated to determine its accuracy and generalization capacity. The model showed good fit statistics, with a relative absolute error of 4% and a root mean square error of 6.9%.

4 CONCLUSION

Accurate prediction of the deposition coefficient is critical for operational planning of the heat exchanger network in oil pre-processing. The results show reasonable agreement between the actual and predicted values. This study implies that machine learning techniques, particularly ANN/MLP, can be used to reduce the costs and risks associated with fouling in the oil pre-processing heat exchanger network, providing an efficient approach to process optimization. Future research will analyze other databases to find appropriate indicators of merit.

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REFERENCES

Araújo, Álvaro Souza de; Rocha, Oberdan Pinheiro; Santos, Alex Álisson Bandeira; Modelo computacional para análise de condições e monitoramento de motores elétricos, p. 303-310 .In: VII International Symposium on Innovation and Technology. São Paulo: Blucher, 2021.

Bott, T. R Fouling of Heat Exchangers. In Chemical Engineering monographs. Elsevier. 1995.

Deshannavar, U. B., & Marappagounder, R. Revisiting Threshold Fouling Models for Crude Oil Fouling. Heat Transfer Engineering, 0(0), 1–17. (2020).

Dobbelaere, M. R. et al. Machine Learning in Chemical Engineering: Strengths, Weaknesses, Opportunities, and Threats. Engineering, [s. l.], v. 7, n. 9, p. 1201–1211,2021.

Júnior, A. R. M.; Análise comparativa de desempenho de modelos semi-empíricos napredição de deposição em baterias de trocadores de calor de refinarias de petróleo; Programa de Pós Graduação, Centro Universitário SENAI CIMATEC , Salvador, 2020.

Santamaria, F. L.; Macchietto, S.; Integration of Optimal Cleaning Scheduling and Flow Split Control for Crude Oil Fouling Mitigation in the Operation of Refinery Heat Exchanger Networks; Computer Aided Chemical Engineering, 2018.

Santana, L. O. S. de; Calixto, Ewerton E. da S.; Pessoa, F. L. P.; Análise de incertezas aplicada ao cálculo da temperatura de bolha de misturas, p. 113-120 . In: VII International Symposium on Innovation and Technology. São Paulo: Blucher, 2021.

Smith, A. D., & Joshi, H. M. (2015). A Critical Look at the Use of Activation Energyin Crude Oil Fouling Models. International Conference on Heat Exchanger Fouling andCleaning, 2015, 13–21.