Metamodeling of the deposition process in oil pre-processing to optimise the cleaning of the heat exchanger network: A systematic review

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ABSTRACT

Identifying and analysing possible metamodelling techniques to optimise the performance of heat exchangers in oil pre-processing from the point of view of the deposition process is of great importance for evaluating the performance of heat exchangers in different operating and maintenance configurations in order to increase their energy efficiency, since during the operation of heat exchanger networks, deposition on the heat exchange surfaces is common, reducing their effectiveness. In this article, a systematic review was carried out to study the metamodelling techniques and optimisation tools used. The results of the study showed that there are some techniques used such as: Recurrent Neural Networks (RNN); Multi-Layer Perceptron (MPL); Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Recurrent Convolutional Neural Network (RCNN), and tools that will be covered in this study.

Keywords: Metamodelling, Artificial intelligence, Heat exchangers, Deposition process.

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INTRODUCTION

Oil pre-processing is an essential stage in the production of oil and gas. However, during this process, the deposition of solids in heat exchangers (fig. 1) can occur, and the obstruction of pipes and equipment (fig. 3,4,5), in addition to reducing the efficiency of the process, represents a significant problem to be managed. The study of the prediction and minimisation of deposition is therefore of great importance to guarantee the safety and efficiency of production (Lira et al, 2022). Metamodelling is a technique widely used in process engineering, allowing for more efficient analysis and process optimisation. In this work, we propose a systematic review of the application of metamodelling to the deposition process in oil pre-processing (fig. 2). It is hoped that this work can contribute to a path towards metamodelling in the optimisation of heat exchanger networks since the use of recurrent neural networks (RNNs), such as MPL (Multi-Layer Perceptron) or LSTM (Long Short-Term Memory), can be a promising approach to metamodelling in the deposition process in oil pre-processing. RNNs are machine learning models capable of processing sequential data, which is particularly useful in the case of deposition processes that evolve over time. With regard to recurrent neural network (RNN) design, there are a number of options that can be explored and some suggestions are: Multi-layer Perceptron (MLP); Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Recurrent Convolutional Neural Network (RCNN). Each of these has its advantages and disadvantages, and the most suitable model may vary according to the case in question. It is important to evaluate the performance of different models in relation to the available data before choosing the final model for metamodelling. It is also important to bear in mind that choosing the neural network design is only one part of the metamodelling process. It is also necessary to define the architecture of the network (i.e. the number of layers, the number of neurons in each layer, etc.), the activation function to be used in each layer, the method for training and optimising the parameters, among other aspects. Once the neural network has been defined and optimised, it can be used to make predictions about the deposition process. The neural network can be trained with historical or simulated data from the deposition process and the parameters of the heat exchange system, and can be used to make predictions about the system's performance under different operating conditions. Several algorithms are available for training the neural network, the most common of which are: Backpropagation; Gradient descent; Levenberg-Marquardt and Adam(Zabihi, et al, 2019). As for defining the architecture of the neural network, some popular algorithms are: Convolutional neural networks (CNN); Recurrent neural networks (RNN) and Autoencoders(Zabihi et al, 2019).

Figure 1: Figure 2:

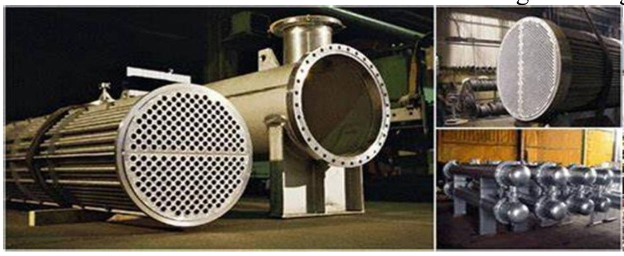

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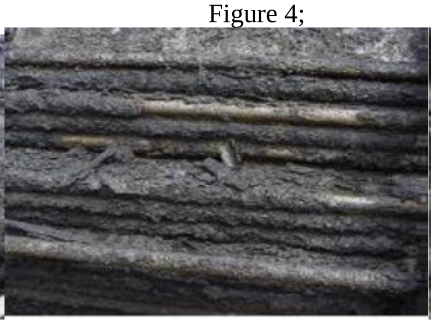
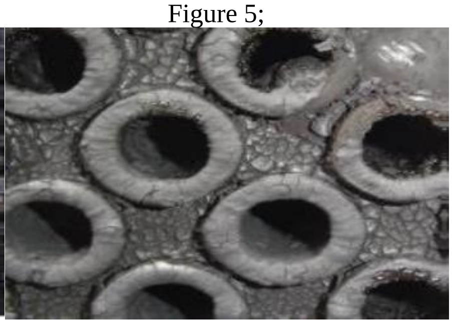
Figure 3; Figure 4; Figure 5;





Crude oil fouling in Shell and Tube PHTs;Tube-side; Shell side (F. Coletti et al, 2015)

METHODOLOGY

A systematic review is a type of scientific investigation. These reviews are considered retrospective observational studies or experimental studies that retrieve and critically analyse the literature. They test hypotheses and aim to survey, gather, critically evaluate and synthesise the results of several primary studies (Donato et al, 2019). The research was carried out in the period from 2017 to 2023 of national and international publications that study the metamodelling techniques used to optimise the performance of heat exchangers in oil pre-processing, from the point of view of the deposition process with a view to increasing energy efficiency. In order to meet this objective, it was necessary to use a research methodology to gain access to current studies. All the research was carried out on reference websites, with consolidated academic recognition and international and national journals and repositories, making it possible to the studies on Recurrent Neural Networks (RNN); Multi-Layer Perceptron (MPL); Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Recurrent Convolutional Neural Network (RCNN), and the tools that will be covered in this study. In this systematic review process, the Mendeley, Google Scholar and Dimensios databases were used to survey the articles to be studied, followed by selection based on the journal's impact factor, and they were organised into groups. After collecting the data and selecting the material, ninety-two articles were found, all of which were searched using the descriptors "metamodelling in the deposition process", "optimisation of heat exchangers", "metamodels and simulation in petrochemicals", "LSTM (long short-term memory) networks and oil" and "MPL (mult lear preceptor) and oil". After mining the database of articles to be used, this number was reduced to 61 articles. This research found important metamodelling techniques for optimising the performance of heat exchangers in oil pre-processing, from the point of view of the deposition process.

DISCUSSION

METAMODELLING IN OIL PRE-PROCESSING

A review of state-of-the-art metamodelling-based techniques in support of design optimisation, including model approximation, design space exploration, problem formulation and solving various types of optimisation problems to address the challenges and future development of metamodelling in support of engineering design, is needed to be analysed and discussed (Amaral et al, 2021). Different software platforms for process simulation, control and supervision are used to design and implement the complex processes of the petrochemical industry. A common mistake made in process calculations is to treat problems on a one-off basis rather than as a range, without considering the uncertainties associated with the measurement parameters (Kalid et al, 2012). It is necessary to know the importance of data reliability and to understand how small uncertainties in this information can significantly affect the technical and economic performance of an industrial plant (Santana et al, 2021). The literature surveyed shows a proposal for an MDE (Model- Driven Engineering) infrastructure for developing operation, control and simulation applications in the petrochemical industry, more specifically in the field of defining industrial plant equipment classes (fig. 2), where the infrastructure, called M4PIA (Model-Driven Engineering for Petrochemical Industry Automation), is made up of three metamodels at two levels of abstraction (independent and dependent on the target platform on which the application will be implemented) and the mappings needed to automatically transform the system modelled at the highest level of abstraction into a platform-specific model and then automatically generate the application source code to be used in the implementation on the defined platform. This analysis proposes two software platforms: MPA, for industrial processoperation, automation and control applications; and EMSO, for petrochemical process simulation. This application serves to illustrate the use of the proposed solutions, as well as to allow a systematic analysis of the proposal in terms of the desired characteristics for an MDE infrastructure (Damo et al, 2019). As mentioned, previous work has proposed the infrastructure called Model-Driven Engineering for Petrochemical Industry Automation (M4PIA), which makes it possible to represent industrial plants using differentiated, compatible and object-oriented models. Through model transformations, the infrastructure supports the automatic generation of code from a high-level abstraction model for specific software platforms. The literature researched proposes the use of model-based reverse engineering in the M4PIA infrastructure, so that from a model of legacy systems developed at the lowest level, it is possible, through Text- to-Model (T2M) and Model-to-Model (M2M) transformations, to obtain a model at a higher level of abstraction. The M4PIA infrastructure supports two domain platforms that are widely used in the petrochemical industry: the

Automated Procedures Module (MPA), for industrial process operation, automation and control applications; and the Environment for Modeling, Simulation and Optimisation (EMSO), for petrochemical process simulation. The solution proved to be suitable for reverse engineering, making it easier to re-engineer legacy systems in the petrochemical industry (Cruz et al, 2021).

PERFORMANCE EVALUATION, DEPOSITION PROCESS AND OPTIMISATION OF HEAT EXCHANGERS

Heat exchangers are pieces of equipment used in industry to exchange heat between fluids at different temperatures that are not in direct contact. In the refining industry, they are used for cooling gases, condensation, heating or in treatment processes such as breaking emulsions (Abbasi et al, 2020). Heat exchange between fluids of different temperatures is of paramount importance for industrial processes and has many applications in engineering. Predictive maintenance uses various methods to monitor the condition of equipment used in industrial plants (Araújo et al, 2021). The efficient use of energy is a critical factor for industries and can be an economically attractive and competitive process. One of the main factors that cause exchangers to reduce their energy efficiency and, consequently, the overall heat transfer coefficient is fouling (fig.3,4,5), defined as the formation of undesirable deposits on the surface of process equipment (Valle, 2012). Another point to take into account is the environmental issue, since the search for the global optimum and for more robust and efficient techniques has somewhat slowed down the development of applications for practical use in industry (Calixto 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 satisfactorily predicting deposition behaviour in industrial exchangers. The information needed to apply the models to operational data is necessary to generate accurate and fast models to optimise the design (Krzywanski et al 2019), control and operation of shell and tube heat exchangers (STHE) subject to fouling. To date, research efforts have focused mainly on lateral tube fouling. The techniques proposed for shell side fouling are limited to: Thermo-hydraulic mechanistic models with simple flow analysis (FSA); Computational fluid dynamics (CFD) models. The former ignores the flow dynamics on the hull side and the latter cannot quantitatively predict fouling, as well as being computationally very heavy and cannot be used for optimisation and control. It is important to combine the benefits of FSA and CFD methods by creating a hybrid Compartmental Model (CM) (Godke et al, 2018). The dynamic characteristics of fouling can be included in the design and retrofit procedure, so that fouling can be mitigated simultaneously through operating cycles by systematically manipulating operating conditions and optimising cleaning schedules.

THE USE OF RECURRENT NEURAL NETWORKS (RNN), MPL (MULTI LEARNER PRECEPTOR) AND LSTM (LONG SHORT TERM MEMORY) FOR AN OPTIMAL CLEANING CAMPAIGN OF THE HEAT EXCHANGER NETWORK

An efficient way of determining when cleaning stops need to be made is through the use of Artificial Neural Networks (ANNs), which are mathematical modelling techniques based on the human brain for solving the simplest to the most complex problems. To do this, it is necessary to control the evolution of fouling in a heat exchanger by training Artificial Neural Networks and testing the types of strategies and structures that best perform the simulation for this system (Júnior et al, 2019). Here is an example of research where, with the data obtained from a shell-and-tube exchanger, which serves to cool propane by means of cooling water, located in a Petrochemical Industry in São Paulo, where the input variables of the ANN were the inlet temperatures of the hot and cold fluid and the outlet flow rate of the cold fluid, and, the output variable generated by the network was the cold fluid output flow rate and the ANN structure and optimisation method used were, respectively, MLPs (Multilayer Perceptron) or multilayer perceptron with one or two hidden layers and the back-propagation algorithms with Marquardt Levenberg and Marquardt Levenberg with Bayesian regularisation(F. Coletti et al, 2015). Two strategies were used for the simulation. In the first, the previous inlet temperature of the cold and hot fluids and the previous and current outflow of the cold fluid were fed into the network, while the output was the subsequent outflow of the cold fluid. This strategy was unsuccessful as the best correlation coefficient (R2) value for the simulation was 0.3362. The second strategy used the current temperatures and flow rates as the network input and the subsequent flow rate as the output. Three models were tested and the one that best represented the industrial system studied was the '3-30-30-1' structure with a Levenberg Marquardt training function and a tangent sigmoidal transfer function in the intermediate layers and linear in the output layer. The R2 for this model was 0.9435, the average error was 155.10% and the median was 13.31%. The objective of the study was achieved as the network simulations represented the behaviour of the experimental data well, i.e. it was proven that ANN can be used to predict fouling in industrial heat exchangers (Godke et al, 2018)]. This systematic review also points out that the use of Recurrent Neural Networks (RNN), MPL (multilearning preceptor) and LSTM (long short term memory) has a wide application in petrochemicals, as mentioned above and as can also be seen with the following two studies, where the first deals with an alternative way of predicting the distribution of water saturation in reservoirs with a machine learning method (Sheikhoushaghi, et al, 2022). Long Short-

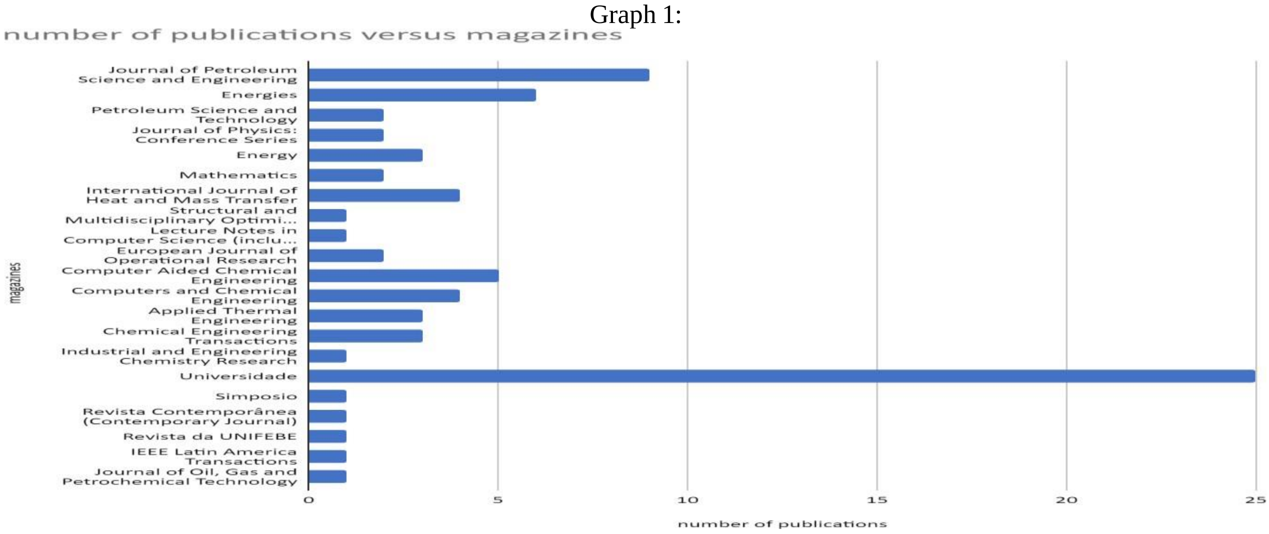
Term Memory (LSTM) was used to build a predictive model for forecasting water saturation distribution. The data set resulting from the monitoring and simulation of a real reservoir was used to train and test the model. The data model after training was validated and used to predict water saturation distribution, pressure distribution and oil production. The standard Recurrent Neural Network (RNN) and Closed Recurrent Unit (GRU), which are popular machine learning methods, were also compared with the LSTM for better water saturation prediction. The results show that the LSTM method performs well in predicting water saturation with an overall average absolute relative deviation (AARD) below 14.82 per cent. Compared with other machine learning methods, such as GRU and standard RNN, LSTM performs better in calculation accuracy, so the study presented an alternative way for fast and robust prediction of water saturation distribution in the reservoir(Zhang et al, 2019).The second research takes a comparative approach to finding an appropriate network for predicting the oil production rate of an Iranian oil field. The performance of various networks such as Rough Neural Network (Rough NN), Long-Short- Term Memory (LSTM), Artificial Neural Network (ANN) with only dense layer and 1D Convolutional Neural Network (CONV-1D) was monitored by investigating various statistical parameters such as error value, cross plot of actual data and predicted data and error distribution. A combination of five static and dynamic input parameters was taken as input to the model. All networks were trained on 80 per cent of all data (10,025 points) and the remainder was divided equally for testing and validation. The highest performance was seen in the Rough-NN results with a coefficient of determination of 0.82 for predicting the test data. The results showed slightly lower accuracy than Rough-NN for the CONV-1D case (R2 = 0.79). However, the worst performance concerned ANN and LSTM where its R-squared was around 0.54 (Sheikhoushaghi et al, 2022).

RESULTS

Analysing Graph 1, which shows the relationship between the number of **publications and the journals**, it can be seen that, in general, universities have published a greater number of articles(25) on the themes proposed in the descriptors. The Journal of Petroleum Science and Engineering(9) also published a good number of articles.

MAGAZINES X NUMBER OF PUBLICATIONS

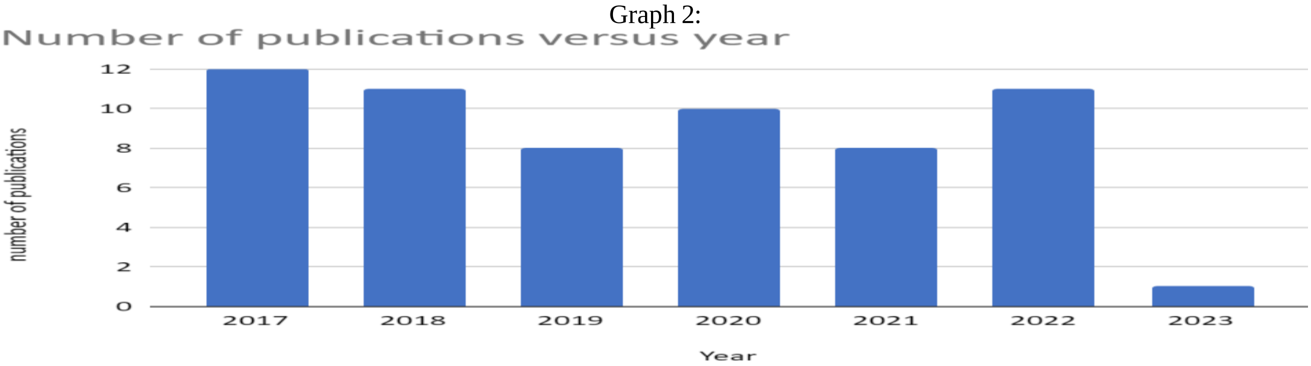
Graph 1:



Analysing Graph 2, which shows the relationship between the number of publications and the **year** of publication, it can be seen that 2017 had a significant number of publications, while 2019 and 2021 had fewer publications. It should also be noted that in 2023, there was only one publication on the subject.

NUMBER OF PUBLICATIONS X YEAR

Graph 2:



CONCLUSION

This review was a process of searching, analysing and describing a body of knowledge and shows optimisation techniques in the heat exchanger network deposition process using artificial intelligence. We found robust evidence that the current literature in the period described from 2017 to 2023 has an expressive quality of research using recurrent neural networks, especially MLP and LSTM, and the use of these techniques requires extensive testing with different configurations to experimentally obtain the model that best adapts to the problem[5]. Therefore, the objective of surveying, gathering and critically evaluating, synthesising the results of various primary studies on the proposed theme was achieved. Research into the use of artificial intelligence in the optimisation of the deposition process in a heat exchanger network, especially with regard to the economic benefits that come from the links between the areas of design and optimisation of operation, requires further work to be carried out that provides simulation and optimisation with a greater number of branches, and that allows the optimisation of the complete network, using artificial intelligence to bring greater benefits to various petrochemical plants.

A gap has emerged after this study, and an unprecedented proposal will be developed with a greater number of branches of the heat exchanger network, using metamodelling and aiming to predict deposition, with the use of artificial intelligence, in a hybrid MLP+LSTM+Transformer model, because among what has been seen in the research literature, there is no metamodel for accurately predicting deposition that works with a large amount of real data and a long data set that signals characteristics of the decrease in flow and reduction in heat exchange at rates below those specified in the operating plant, in order to train the network in good operating conditions and in critical operation. This way we'll have good predictability and advance notice for operation and maintenance actions. This data set will be obtained from BPA's battery of heat exchangers with 7 branches (A,B,C,D,E,F,G) in a refinery in the south-east of Brazil, totalling 25 shell and tube heat exchangers.

Therefore, the innovation of this study is based on the challenges associated with the technical characteristics and specificities for optimising the performance of heat exchangers in oil pre-processing. Based on the review carried out, the proposed work will provide a step forward in relation to the state of the art. The intelligent maintenance of heat exchangers, based on deep machine learning, should fill an academic gap in this thematic line, indicating the most effective way of carrying out a given activity and helping with decision-making.

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