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PREDICTION OF FOULING BY CALCIUM PHOSPHATE IN A COOLING WATER SYSTEM USING MACHINE LEARNING

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1. ABSTRACT

Fouling in cooling water systems of power plants generates a progressive decay in overall condenser performance that leads to severe economic penalties. This work focuses on studying fouling by calcium phosphate using a new machine-learning (ML) framework. Specifically, we will discuss the most relevant variables impacting deposition and develop an ML-based model that accurately predicts phosphate deposition.

2. INTRODUCTION

Power stations in the UK often employ cooling water systems fed by rivers to condense the exhaust steam discharged from the turbines [1, 2]. This river-derived water is characterized by a high concentration of salts such as calcium carbonates and calcium phosphates. These salts are prone to precipitate and deposit on heat transfer surfaces in the form of scales. Such depositions lead to a loss of efficiency, ultimately affecting both economics and environmental impact of power generation [3]. Generally, the calcium carbonate scale is controlled by maintaining the concentration factors (CF) in the circulating water greater than 1.5. However, controlling calcium phosphate scaling is challenging. Thus, to quantify the parameters controlling calcium phosphate scaling in condensers, several empirical and semi-empirical models have been developed in the literature. For example, Hawthorn [1] collected experimental data for water fouling and used traditional regression methodologies to develop a correlation for calcium phosphate scaling as a function of the concentrations of phosphate and calcium in the circulating water, water pH, and temperature [1, 2]. However, despite these efforts, detailed phenomenological knowledge and affordable mitigation strategies are still lacking.

In this article, we explore the use of machine learning (ML) to predict the deposition of calcium phosphate in cooling water systems. To this aim, we consider the experiments performed by Hawthorn [1] that mimic the precipitation and deposition of calcium phosphate in the form of scale happening within an operating condenser of a power station situated along the Trent River.

3. METHODOLOGY

To develop an ML-based model to predict the deposition rate of calcium phosphate, we adopt the six-step framework proposed by Loyola-Fuentes *et al.* [4] and sketched in Figure 6 of their work. The raw data are first preprocessed, and the missing values for the magnesium concentrations are derived considering a surrogate model. The resulting dataset contains the following independent variables: outlet temperature (T_{out}), temperature difference (DT), steam temperature (T_{steam}), circulating water velocity (vel_{cw}), circulating water total alkalinity (Alk_{cw}), circulating water alkalinity in terms of $CaCO_3$ (pp_{cw}), inlet water flowrate (FR_{in}), inlet water alkalinity (Alk_{in}), number of times water flows through the system before purging (N_C),

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concentration factor (CF), half-life of water in the system (t_{half}), concentration of calcium, phosphate and magnesium in both inlet and circulating water, namely $[Ca]_{in}$, $[Ca]_{cw}$, $[PO_4]_{in}$, $[PO_4]_{cw}$, $[Mg]_{in}$, $[Mg]_{cw}$,concentration of phosphate that has precipitated, i.e., $[PO_4]_{PPT}$, and concentration of hydrogen ions $[H^+]_{cw}$. After pre-processing the data, a preliminary feature importance analysis is performed. The analysis, which is here based on a random forest recursive feature elimination approach with 10-fold cross-validation, ranks the *relevant* features based on their importance. It thus provides the first insights into the problem, and, most importantly, helps develop physically sound machine learning models. The dataset containing only the relevant features is, at this point, randomly split into a training (80%) and a test (20%) set. The training set is used to train an artificial neural network (ANN) with two hidden layers having 16 and 8 neurons, respectively, while the test set is used to evaluate the predictive performance of the trained model. Note that, before training, it is crucial to tune the model hyperparameters. In this work, hyperparameters tuning is done via a 5-fold cross-validation grid search approach exploring the following set of parameter values: 50, 100, 200, 400 and 600 epochs; 5, 10 and 20 batches; mean absolute error (MAE) and mean squared error (MSE) as loss functions; and Adam and SGD as optimization algorithms.

4. RESULTS

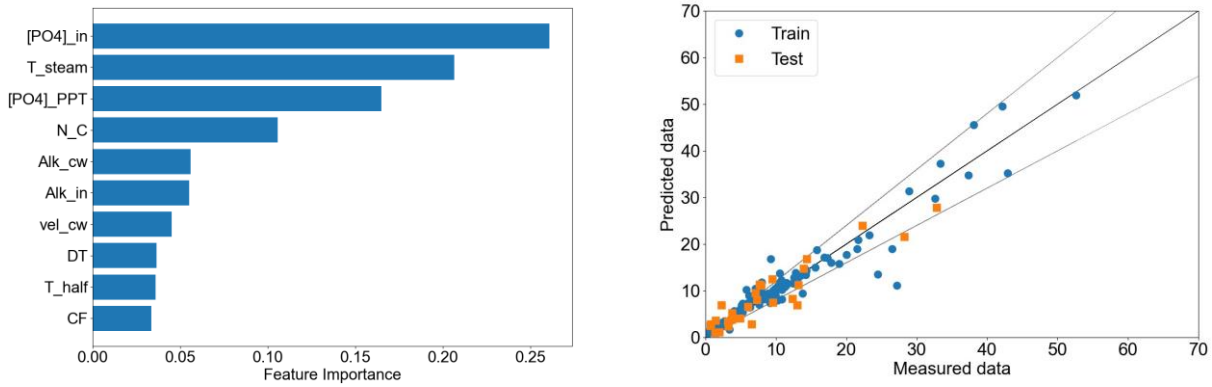
Figure 1.a shows the subset of relevant features obtained via the random forest algorithm. The deposition rate of calcium phosphate on the heated surface (tube side) is dominated by the concentration of phosphate in the inlet water, steam temperature, and concentration of calcium phosphate that has precipitated (*i.e.*, that is lost from the solution). The deposition rate is then observed to decrease with the number of times water flows through the system before purging. Water alkalinity is another important feature impacting scaling since it enhances the calcium phosphate precipitation process and, in turn, its deposition rate. Other relevant variables are the circulating water velocity, the difference between the outlet and the inlet water temperature to the heated tube, the size of the pond, which is used to determine the half-life of water (and scalants) in the system, and the concentration factor. Since the variability in pH is low (8.46±0.18) we cannot draw any conclusions about the impact of pH on the deposition rate. However, it has been observed experimentally that small variations in pH significantly affect deposition, with no scaling occurring at pH lower than 8 [1].

Based on these insights into the deposition process of calcium phosphate, which are consistent with previous findings by Hawthorn [1], we have trained an ANN for the deposition rate having the optimal hyperparameters selected by the grid search approach, namely 200 epochs, 5 batches, MAE loss function and SGD optimiser, and 10 neurons in the input layer, corresponding to the 10 relevant features. This approach results in 1) fewer parameters to train and 2) a more interpretable model. Figure 1.b shows the resulting parity plot. The regression performance of the ANN remains consistent across both training and test sets, with MAE equal to 1.73 and 2.35, respectively. This outperforms the predictive performance of the multiple linear regression model published in [2], for which we estimated a MAE of 4.72.

5. CONCLUSIONS

This work implements a new machine learning framework [4] to get insights into the deposition process of calcium phosphate in a cooling water condenser. The most relevant features, as provided by the preliminary feature importance analysis, are consistent with previous findings in empirical research [1, 2] and suggest that phosphate scaling could be reduced by ridding the river of phosphates from sewage, by reducing the runoff of agricultural fertilisers, or by controlling water alkalinity. The relevant features are then used as input variables in an ANN. The ANN, developed considering rig test data, is shown to predict the deposition rate of calcium phosphate properly and to outperform traditional multivariate regression models. In the future,

the predictive performance of this ANN will be tested by considering data from a condenser operating in a power station situated along the Trent River.



(a) (b)

Fig. 1. Feature importance analysis (a) and parity plot for the deposition rate of phosphate in mg/hr (b) when training an ANN with relevant features as input variables. The plot includes the error lines for 0% (black) and 20% (grey).

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