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Analysis of Fouling Data Based on Prior Knowledge

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ANALYSIS OF FOULING DATA BASED ON PRIOR KNOWLEDGE

EXTENDED ABSTRACT

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INTRODUCTION

Conventional regression methods are generally unable to analyse extremely complicated processes involving a considerable number of independent variables with poorly understood interaction. These methods use a defined equation for which the parameters of this equation have to be determined. It is however questionable whether any arbitrarily chosen equation is the best. This study aims to implement the powerful neural network architecture for a comprehensive data bank. The HTRI data bank contains a large and unique set of experimental data for cooling water fouling. Only a selection of the data bank is being used at the present time, due to the large number of independent variables investigated in this experimental study.

Malayeri and Müller-Steinhagen (2001) presented the use of Neural Network Analysis for the prediction of fouling behaviour under subcooled flow boiling. They reported the advantages and disadvantages of the neural network architecture when the technique is applied to fouling data. It has been shown that the predictability of the network is promising when dominant variables are known and also adequate data are presented to the network.

NEURAL NETWORK APPLICATION

Neural networks have recently become the focus of much attention, largely because of their capability to handle complicated and non-linear systems. Neural networks are basically unsupervised methods because they can synthesise without detailed knowledge of the underlying process. This is certainly a benefit for modelling phenomena such as fouling in which the behaviour of the dominant variables is not firmly established. The method can also be used for processing very substantial data-sets, which is difficult to handle in conventional approaches. No fundamental study has been found in the open literature which attempts to analyse and correlate fouling data with a Neural Network. In this study, the well-established radial basis function neural network architecture is investigated. More backgrounds about this network have been reported elsewhere (Malayeri *et al*, 2003).

The first step in the analysis is to recognise the variables involved in the process. This assessment is then used as "*prior knowledge*" in training the neural network. Attempts were subsequently made to utilise the artificial neural network for generating improved fouling models for heat exchanger design. The ultimate goal is to present the inputs to the network in terms of non-dimensional groups as it is highly recommended by HTRI (1987) for characterising fouling and removal mechanisms in cooling water service. Furthermore, the neural network for a specific data set can be used to interpolate within the range of data or permit careful extrapolations. The established network algorithm can be easily used by design engineers, once satisfactory convergence and results have been achieved. This capability will have to be assessed by a parametric study.

RESULTS AND DISCUSSION

Fig. 1 shows the comparison of the experimental data and those predicted by HTRI model (1987) for estimation of the asymptotic cooling water fouling resistance. The comparison exhibits a mean average error of 38%. It should be pointed out that the comparison is based on early HTRI results (1987). However, latter efforts have improved the predictability of the model (HTRI report, F-8, 1999). Fig. 2 exhibits the relative error as a function of liquid velocity of the working fluid. It is evident that the error is lower above a velocity of 0.5 m/s. This is because the curve-fitting was mainly based on this region where most data are accumulated. Nevertheless the validity of the model deteriorates below 0.5 m/s due to the lack of sufficient experimental data. Therefore the selection of input and output variables and of the data set for training must be done carefully, to cover the whole range of variables.

In this study 87 HTRI fouling runs are used. They were obtained for hard water with 17 different water qualities and for forced convective heat transfer. The experimental data points are divided into two parts, the training and generalisation phases respectively. In the training phase, 51 experimental data points are presented to the network. The remaining 36 experimental data points are used for the generalisation phase. In order to correlate the above data, the radial basis function neural network architecture is investigated. Three dimensionless input groups (Re, $(-E/RT_s)$, (θ, dimensionless time), Ω (water quality)) are defined as inputs to the network and one output which is the fouling rate. All previous HTRI fouling models were based on these parameters. Fig. 3 shows the comparison between the experimental and predicted fouling resistances for the data used in the training phase. The resulting neural network predicts the fouling resistance with an overall average relative error of about 15%.

CONCLUSIONS

A data bank is used which includes 87 fouling runs divided into two phases, the training and generalisation phases respectively. Filtration of imprecise and noisy data was essential to prevent any impact on the training phase. Many fouling data exhibit such behaviour particularly in the induction period. The second phase is the generalisation where the network is subjected to those data that have not been used before. The resulting network predicts the fouling resistance with an error of 15% compared to 38% (conventional HTRI model). The work will continue to discern the feasibility of more accurate relationships in form of non-dimensional groups.

NOMENCLATURES

E	energy of deposition, J/gmol
F_v	velocity function, -
R	gas constant, J/gmol.K
Re	Reynolds number, -
T_s	temperature, K
θ	dimensionless time, -
Ω	water quality, -

References

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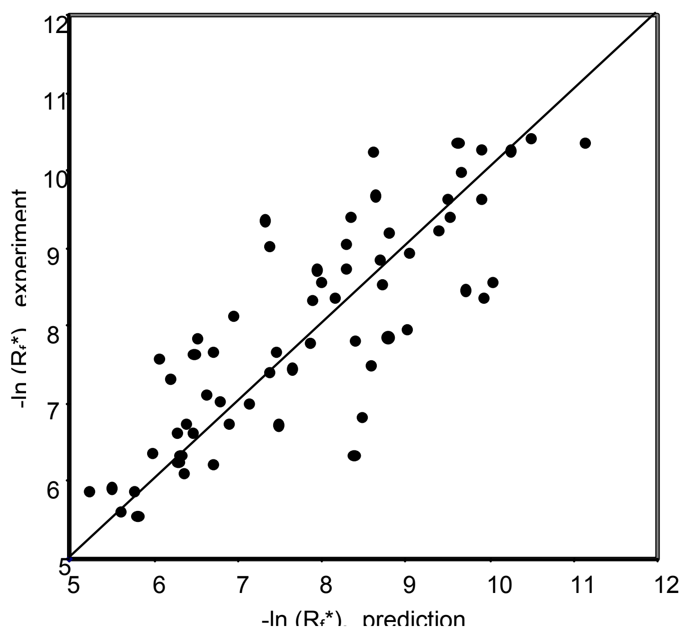

Fig. 1 Experimental vs HTRI model (1987) prediction of asymptotic cooling water fouling resistance (Mean average error of 38%).

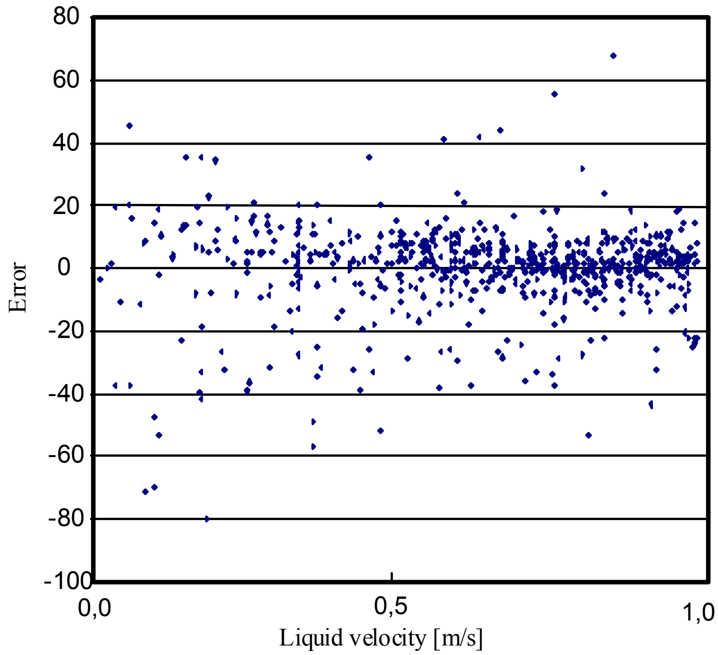

Fig. 2 Relative error of HTRI model vs velocity.

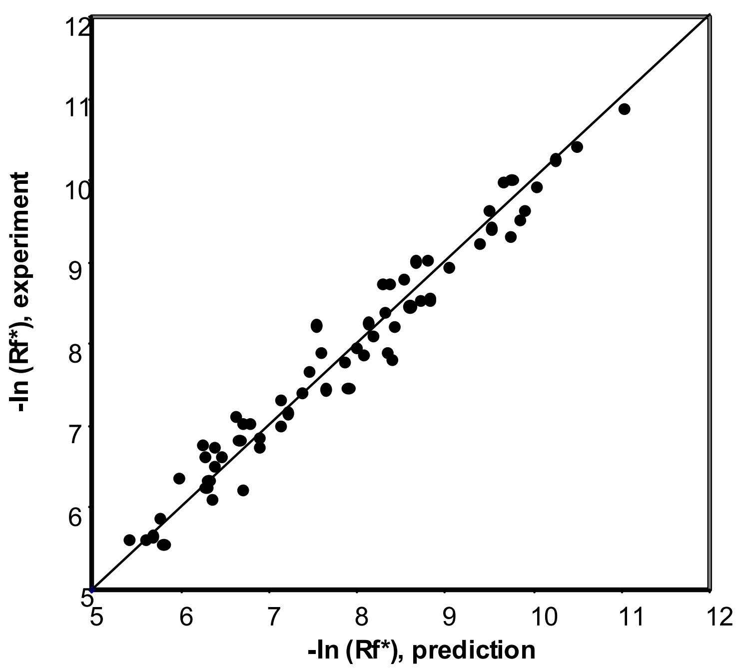

Fig. 3 Experimental vs neural network prediction of asymptotic cooling water fouling resistance (Mean average error of 15%).