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Learning from a carbon dioxide capture system dataset: Application of the piecewise neural network algorithm

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ABSTRACT

This paper presents the application of a neural network rule extraction algorithm, called the piecewise linear artificial neural network or PWL-ANN algorithm, on a carbon capture process system dataset. The objective of the application is to enhance understanding of the intricate relationships among the key process parameters. The algorithm extracts rules in the form of multiple linear regression equations by approximating the sigmoid activation functions of the hidden neurons in an artificial neural network (ANN). The PWL-ANN algorithm overcomes the weaknesses of the statistical regression approach, in which accuracies of the generated predictive models are often not satisfactory, and the opaqueness of the ANN models. The results show that the generated PWL-ANN models have accuracies that are as high as the originally trained ANN models of the four datasets of the carbon capture process system. An analysis of the extracted rules and the magnitude of the coefficients in the equations revealed that the three most significant parameters of the CO_2 production rate are the steam flow rate through reboiler, reboiler pressure, and the CO_2 concentration in the flue gas.

1. Introduction

As a major component of the greenhouse gas, the CO_2 emitted from combustion of fossil fuels in various industrial processes has caused escalating public concern due to its contributions towards environmental pollution and global climate change. In the last two decades, the post-combustion CO_2 capture technology has emerged as an essential technology for mitigating CO_2 emissions from power plants and chemical process industries [1,2]. In fact, a good understanding of the key process parameters and their intricate relationships is critical for improving effectiveness and efficiency of the CO_2 capture process. A better understanding would enable the operator to better analyze the current conditions of the process and predict the underlying trends or events; it can also assist the operator in taking prompt and effective control actions targeted at particular process parameters for improving efficiency of plant operations.

Zhou *et al.* [3] compared three different data modeling techniques in an attempt to enhance understanding of the relationships between the predictor and predicted parameters of the CO_2 capture process system. The three data modeling techniques that were applied include statistical analysis [4], artificial neural network (ANN) modeling combined with sensitivity analysis (SA), and adaptive neuro-fuzzy inference system (ANFIS) modeling [5,6]. Each of the three techniques provided some insight to the problem; however, they also have their weaknesses. The statistical regression approach supports the development of mathematical models among the predictor or input and predicted or output variables, however, it does not uncover irregular nonlinear relationships, which likely exist among the key parameters of the CO_2 capture process system. The ANN approach supports a more comprehensive exploration and modeling of the problem domain; however, these models are opaque and cannot explicate the nature of the relationships among the parameters. Zhou et al. [3] suggested that the ANFIS approach was found to be the best methodology because it can accurately model the irregular nonlinear relationships among the parameters, and it can generate fuzzy inference systems, which emulate the relationship among the input and output

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variables. However, the ANFIS approach has its drawbacks as well. Firstly, the ANFIS algorithm can only generate fuzzy rules which require the parameters to be subdivided into categories such as high, medium and low. This subdivision of parameters requires expert knowledge on the problem domains, which can introduce subjective bias that directly affects the generated fuzzy inference system. Secondly, the number of rules generated is equal to the number of the input subspaces, and potentially, a large rule set can be generated. For example, in the heat duty fuzzy inference systems in Zhou et al.'s study [3], the input space is partitioned into $3^6 = 729$ subspaces, i.e. 729 rules are generated in the fuzzy inference systems. While the generated rules can provide some insight to the problem domain, the size of the rule set makes it almost impossible for humans to comprehend or validate it.

To overcome the weaknesses of the statistical regression, ANN and ANFIS approaches, we propose an algorithm, called the piecewise linear neural network or PWL-ANN algorithm, that extracts multiple linear equations from a trained ANN model. The algorithm approximates the activation functions of a given ANN model with piecewise linear (PWL) equations and generates explicit information in the form of numerical formulae. The advantages of this algorithm include: (i) it supports the development of a mathematical model like the statistical regression; (ii) it is applicable for nonlinear problem domains like the ANN approach; and (iii) it provides explicit knowledge in the form of rules. Unlike the ANFIS approach, which generates an implicit knowledge base in the inference system, the PWL-ANN algorithm provides an explicit set of linear equations. Rapidminer (trademark of Rapidminer) has been used to train the neural network, and the rule extraction algorithm is written in R.

This paper is organized as follows: Section 2 provides a background literature review on the key parameters in the CO_2 capture process system, artificial neural network modeling, and ANN rule extraction algorithms. Section 3 describes the proposed methodology. Section 4 presents the analysis of the models and rules generated by the proposed algorithm to a CO_2 capture process system dataset. Section 5 discusses the application of the extracted rules for problem solving and presents some directions for future work. Section 6 presents the conclusion.

2. Background literature review

2.1. Key parameters in CO_2 capture process system

Some research that focuses on studying the key parameters in the CO_2 capture process related to plant performance and efficiency, are discussed as follows. Based on the experts' quantitative assessments, Rao et al. [7] focused on the important process parameters that significantly influence the performance and cost effectiveness of the system. The study also investigated the potential for performance improvements and cost reduction. Rao et al. [8] conducted technical, economic and environmental evaluation of the amine-based CO_2 capture technology by focusing on the key parameters that affect the performance, costs and environmental acceptability of different technology options. Idem et al. [9] suggested that to evaluate efficiency and plant performance of the CO_2 capture process, the parameters of reboiler heat duty, absorption efficiency and CO_2 production rate are most significant. Yokoyama [10] presented a broad overview of the key issues related to CO_2 capture technologies applied to large-scale power plants in Japan. He proposed that the key parameters affecting the process performance include reboiler heat duty, circulation rate of the solvent and the size of the CO_2 capture system. Sakwattanapong et al. [11] proposed that the level of heat duty is directly related to the quantity of CO_2 stripped from the regeneration column and the quality of lean solvent fed back to the absorber column. Since the quantity of CO_2 stripped from the regenerator column is directly related to CO_2 lean loading, this study found that there is an important relationship between the heat duty and CO_2 lean loading. Aroonwilas and Veawab [12] argue that the absorption performance of the plant could be enhanced by decreasing CO_2 loading of the solvent or increasing the solvent circulation rate. Aroonwilas and Veawab [13] concluded that the lower steam pressure supplied to the CO_2 capture plant for solvent regeneration results in lower heat duty and reduces the energy penalty.

2.2. ANN approach

An artificial neural network model is a group of interconnected neurons. It usually consists of an input layer of neurons, one or more layers of hidden neurons, followed by an output layer, as shown in Fig. 1. Each of these neurons has two functions: first, it sums up the product of each input and its weight and the bias. The bias is a constant value that allows the shifting of the activation function in order to give better fit to the data. The neuron then passes the summed value through a transfer function (or activation function) and transforms the sum to some finite value, usually in the range of [0, 1] or [-1, 1], depending on the chosen function. The transfer function introduces a nonlinearity into the network and output of the jth neuron is, O_j:

$$O_j = f_j\left(\sum_{i=1} w_{ij}x_i + \theta_j\right)$$

where x_i is the ith input, w_{ij} is the weight associated with the ith input to the jth neuron and θ is the bias.

The kth output of the neural network will be given by:

$$y_k = f_k\left(\sum_{j=1} w_{jk}O_j + \theta_k\right)$$

where w_{jk} is the weight associated with the output of the jth neuron, O_j, and θ is the bias.

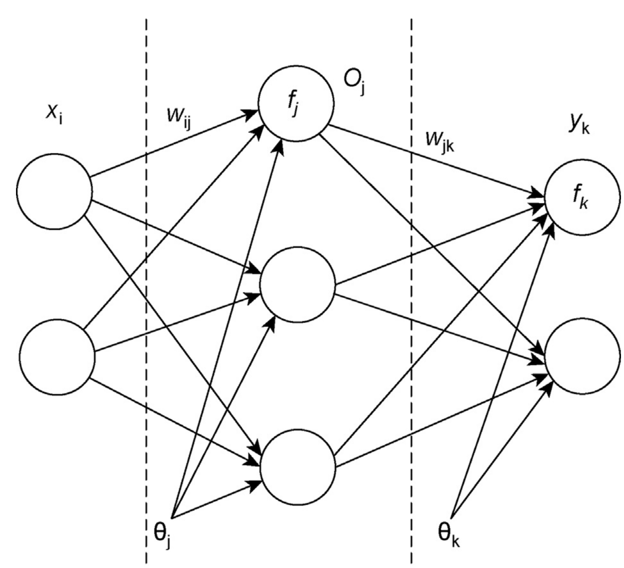

Fig. 1. An artificial neural network.