Modeling a FCC Riser with the RBF Neural Network

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Abstract. A radial basis function (RBF) neural network model has been proposed for predicting production yields and reducing simulation times of a modified special pseudo-components (SPCs) fluid catalytic cracking riser. Subsequently, a modified special pseudo-components riser, served as the source of reliable data for artificial neural network (ANN) model training and testing. The ANN model experimental results show a substantial reduction of computation time and good match compared to special pseudo-components fluid catalytic cracking riser mechanism model. Its potential use for modeling optimize and control of the riser is enormous.

1. Introduction

Fluid catalytic cracking unit (FCCU) is a core technology which used in modern refineries to modify heavy gas oil and residuum. FCCU is a process of transforming heavy hydrocarbon molecules into light hydrocarbons, any enhancement of this process leads to important economic reward [1-2].

Developing a high quality and robust physical model is very hard due to the complexity of FCC process [3-4]. Therefore, many scientists have proposed a statistical model [5-6]. Where, artificial neural networks could be a good alternative to the whole FCC process [7-8].

Ali, Rohani et al. [9] used artificial neural network in identification and control of a riser-type FCC unit, Malay et al. modified and integrated dynamic model by neural adaptive control, discussed the robust of feedforward neural network in steady state. While the accuracy of predicting oil production remains to be improved. Maria Mihe et al. based on the data of five-lumped catalytic cracking reaction models, established a feedforward neural network. Li Quan-shan et al. continue to train the catalytic cracking reaction model with an improved RBF neural networks. However, petroleum oils are complicated mixtures of numerous hydrocarbons and non-hydrocarbons, cracking reaction schemes using a few lumps suffer from the disadvantage that a change in product specifications or in the number of products requires reformulating the model and refitting the data.

According to Zhang [10] and Li [11] et al. proposed and improved a special pseudo-components model, assuming all pseudo components are composed of a group of characteristic factors ($K_{W,1}$, $K_{W,11}$), when the properties of crude oil changed, keep temperature constant, it can be seen that mixing ratio of light and heavy fraction ($K_{W,1}$, $K_{W,11}$) changes. As a mechanism model proposed by our group have same weakness with traditional mechanism model that more partial differential equations, algebraic equations need to be solved and long simulation time caused by over parameters. There are 9 tune parameters which took several months for parameter identification. In this paper, a modified special pseudo-component riser was used as the first principle model. Which served as reliable data for...
artificial neural network (ANN) model. Based on it, a RBF neural network model was built and compared the fitting degree of BP (Back-Propagation) neural network model.

2. The physical model of riser
Cracking reactions take place in riser as shown in figure 1. The length of a riser is generally 25-40 meters, fresh raw oil enters from the bottom of it. After steam atomization at the bottom entrance, catalyst vaporized and then moves upward along the riser with catalytic cracking reaction. This process generally lasts for 3-5s.

![Figure 1. FCCU system structure](image)

Gupta [12] proposed a pseudo component model of FCC riser, used to divide crude oil. While, in industrial practice, when the property of crude oil changed and pseudo component model also needs to be rebuilt. Special pseudo components (SPCs) are used to express the feedstock and product oils, as suggested by Zhang [10] et al. Competition among reactant PCs is estimated from the transition state theory, as suggested by Li et al. [11].

This paper modified the formula of catalyst concentration $C_{\text{CAT}}$, component concentration $C_i$, the calculation formula of entropy correction reaction based on a steady state model of riser proposed Li et al. [11]:

$$
c_i = \frac{F_i}{(v_g \delta_g + v_c \delta_c)\Omega_{RS}} \quad (1)
$$

$$
c_{\text{CAT}} = \frac{F_{\text{CAT}}}{(v_g \delta_g + v_c \delta_c)\Omega_{RS}} \quad (2)
$$

The formula for calculating the concentration in Li et al. as follows:

$$
c_i = \frac{F_i}{v_c \delta_c \Omega_{RS}} \quad (3)
$$

$$
c_{\text{CAT}} = \frac{F_{\text{CAT}}}{v_c \Omega_{RS}} \quad (4)
$$

Where $v_g$ and $v_c$ are respectively gas and cluster phase velocities in m/s, $\delta_g$ is volume fraction of the gas phase, $\Omega_{RS}$ is cross section area of the riser in m$^2$, and $F_C = F_{\text{CK}} + F_{\text{CAT}}$ the cluster phase flowrate in kg/s. In comparison with (1-2) and (3-4), cracking reaction take place in the whole riser. To get a better fitting, solid phase and gas phase mixed with each other as shown in (1-2).
According to transition state theory [13-14], If feedstock and product oils are mixture of pseudo components, \( \text{PC}_i \), \( i = 1, 2, \ldots, c \), cracking of \( \text{PC}_i \) can be generally expressed as:

\[
\text{PC}_i \rightleftharpoons [\text{PC}_i]^* \rightarrow \text{PC}_m + \text{surplusage} + \lambda_{i,m} \text{CK}
\]  

(5)

\( \text{PC}_m \) is produced from cracking \( \text{PC}_i \), surplusage in the above reaction is not given a name, CK the coke, \( \lambda_{i,m} \) the amount of the coke in kg/kmol-\( \text{PC}_i \), and \( \Delta H_{i,m} \) the heat consumed in kJ/kmol-\( \text{PC}_i \). Detailed equation of modeling a riser is referred to Li et al. [11].

Predictive production as follows:

**Table 1. Fitting error of the riser model**

| Prod.     | case1 | case2 |
|-----------|-------|-------|
| RO, wt%   | 10.13 | -0.86 | 0.18 |
| LCO, wt%  | 22.15 | 2.79  | 3.65 |
| GSL, wt%  | 40.85 | 0.65  | -0.32|
| LPG, wt%  | 11.96 | -0.38 | -0.46|
| GS, wt%   | 4.37  | -0.36 | -0.78|
| CK, wt%   | 7.63  | -0.14 | -0.5 |
| ROT, °C   | 515.00| 1.4   | 2.4  |

Case 1 respectively the correct first principle model in this paper, case 2 respectively listed in Li. et al. The first principle model simulation results show that oil production and temperature are closer to industrial value than case 2, which provides a more stable and accurate data for RBF simplified model training.

Fluid catalytic cracking riser is a complex unit due to its multivariable nature, with nonlinear, large delay, strong coupling [15]. Li et al. makes parameter identification extremely tedious. There are 9 tune parameters which took several months for parameter identification. The operating conditions of fluid catalytic cracking riser are as shown in Table 2.

**Table 2. Range of operating variables**

| Process variable          | Range         |
|---------------------------|---------------|
| Crude oil flow, kg/s      | 3.9667-4.2667 |
| Recycle oil flow, kg/s    | 33.8260-36.8260|
| Temperature of crude oil, K| 473.15-503.15 |
| Temperature of recycle oil, K| 553.15-583.15 |
| Flow rate of raw catalyst, kg/s | 296-300 |
| Temperature of spent catalyst, K| 776-782 |
| Catalyst to oil ratio     | 7.79-8.09     |

3. Artificial neural network model

Feedforward neural network has simple structure and easy to achieve, researchers have proved that 3-layer feedforward neural network model has ability to approximate any nonlinear function [16]. To solve the challenge of long computational time and complex modeling mechanism of the first principle model by Li et al. Back Propagation(BP) algorithm and Radial Basis Function(RBF) algorithm as classical feedforward neural networks are simulated in simplified riser modeling.
Radial Basis Function (RBF) network is a feedforward neural network, which is used to establish the nonlinear mapping relationship between process parameters [17]. Mapping from input layer to hidden layer is nonlinear, while mapping from hidden layer to output layer is linear [18]. Radial basis function which from hidden layer adopts the Gauss function, can be applied to multi output nonlinear system [19].

\[ X = (x_1, x_2, \ldots, x_d)^T \] and \[ \hat{y} = (\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_p)^T \] represent inputs and outputs. \( \Phi = (\varphi_1, \varphi_2, \ldots, \varphi_m)^T \) as hidden layer neurons, \( m \) represents the number of hidden layer neural, \( w_{jk} \) represents the weight of the hidden and output layers.

Radial basis Gauss function of hidden layer can be applied to multi output nonlinear system, which is defined as follows:

\[ \hat{y}_k = w_0 + \sum_{j=1}^{m} w_{jk} \varphi(x, c_j, \delta_j) \]  
\[ \varphi = \exp\left( \frac{||x - c_j||^2}{\delta_j^2} \right) \]

\( C_j \) and \( \delta_j \) RBF as center and width, \( ||\cdot|| \) the euclidean distance of \( x \) and \( C_j \), \( w_0 \) Output bias. Some result represents that center and width of RBF affect the performance of the neural network.

The regression and prediction capabilities of RBF model are characterized by the following:

\[ \text{RMSE} = \sqrt{\frac{1}{N_p} \sum_{p} (Y_p / Y_p^{*} - 1)^2 + (t_{RO} / t_{RO}^{*} - 1)^2} \]
\[ E_{\text{max}} = \max \{|Y_p / Y_p^{*} - 1|_{\text{LO,RO,CK}}|t_{RO} / t_{RO}^{*} - 1|\} \]

Table 3. Prediction results

|                      | RBF Testing error | BP Testing error |
|----------------------|-------------------|------------------|
| MSE(max), %          | 1.18e^{-5}        | 7.68e^{-4}       |
| RMSE(average), %     | 3.95e^{-4}        | 8.71e^{-3}       |
| Time, s              | 31.59             | 44.23            |
Figure 2. The prediction output error of RO with RBF&BP caption

Figure 3. The prediction output error of LCO with RBF&BP caption

Figure 4. The prediction output error of GSL with RBF&BP caption

Figure 5. The prediction output error of LPG with RBF&BP caption

Figure 6. The prediction output error of GAS with RBF&BP caption

Figure 7. The prediction output error of COKE with RBF&BP caption

Figure 8. The prediction output error of temperature with RBF&BP caption

Figure 9. Temperature with predictive and expected output in RBF.
4. Conclusion
When modified the concentration of components($C_i$) and catalyst($C_{CAT}$), results as shown in table 1 that oil production and temperature are closer to industrial value than Li.

A modified special pseudo-components fluid catalytic cracking riser was used to provide a random varying inputs and outputs data for the ANN model. Results as shown in table 3 and Fig2-8, RBF neural network model shown a very good regression and generalization performance with first principle model than BP neural network model.

Set up a RBF neural network model needs only 31.59 seconds, while the optimization process of first principle model takes several months. Compared with complex mechanism modeling, RBF neural network model can better excavate latent knowledge behind process data.

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