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Radial basis network estimator of oxygen content in the flue gas of debutanizer reboiler

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ABSTRACT

The energy efficiency in the debutanizer reboiler combustion can be monitored from the oxygen content of the flue gas of the reboiler. The measurement of the oxygen content can be conducted in situ using an oxygen sensor. However, soot that may appear around the sensor due to the combustion process in the debutanizer reboiler can obstruct the sensor's function. In-situ redundancy sensors' unavailability is a significant problem when the sensor is damaged, so measures must be made directly by workers using portable devices. On the other hand, worker safety is a primary concern when working in high-risk work areas. In this paper, we propose a software-based measurement or soft sensor to overcome the problems. The radial basis function network model makes soft sensors adapt to data updates because of their advantage as a universal approximator. The estimation of oxygen content with a soft sensor has been successfully carried out. The soft sensor generates an estimated mean square error of 0.216% with a standard deviation of 0.0242%. Stochastics gradient descent algorithm with momentum acceleration and dimension reduction using principal component analysis successfully improves the soft sensors' performance.

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1. INTRODUCTION

Climate change is one of the essential things that humankind needs to pay attention to live comfortably and peacefully both now and in the future. Experts have researched and discussed how a damaged environment can be repaired, and a good environment can be maintained in ideal and comfortable conditions for humans. One thing to pay attention to is the efficient use of energy and reducing exhaust gas levels from an industry that can damage the environment [1], [2].

One of the industries that need to be considered to save energy and be environmentally friendly is the oil refinery industry. In this industry, the debutanizer reboiler is one of the devices that need to be considered to achieve energy efficiency and environmental friendliness. A debutanizer reboiler with gas fuel has a percentage of oxygen content in the flue gas mixture of 2 to 3%, while with oil fuel, it reaches 3 to 5% [3]. The high oxygen content can cause a massive heat loss and achieve low combustion efficiency. On the other hand, low oxygen content can damage the wall structure damage in the combustion chamber, increase fuel demand, and emit harmful flue gases [4]. A debutanizer reboiler with higher combustion efficiency can decrease the fuel need and reduce the number of carbon dioxide and NOx, which are harmful to the environment [5]. The combustion efficiency can usually be estimated by measuring the flue gas content of the debutanizer reboiler [6], [7].

A reliable in-situ redundancy device's unavailability may become a significant problem when the oxygen analyzer device fails or breaks, so the measurement must be carried out manually with portable devices by workers. Meanwhile, worker safety needs to be carefully considered because the field has a high-level hazard risk. Implementing similar redundancy tools can be done, but it is costly to procure, construct the facilities, and maintain them. In this paper, we propose an intelligent system known as a soft sensor to overcome the problem. This soft sensor technology is a computational technique to estimate oxygen content by utilizing other variable measurements [8]–[10].

In an industrial process such as the debutanizer reboiler operation, sometimes there is a change in the set point of process variables. A monitoring system that is reliable and fast enough to respond is needed to monitor this dynamic system. In specific scenarios, a monitoring system is required to react quickly to the system's dynamics. To meet these demands, we propose using machine learning as the core component of the soft sensor.

Machine learning has been utilized to recognize patterns [11]–[13], estimate and control the output of a process [14]–[16] and predict industrial process variables [17]–[20]. One type of machine learning method is the radial basis function network (RBFN) [21]. Learning in the RBFN model can be conducted adaptively without having to change the structure of the model. Researches related to applying the RBFN model to soft sensors have been carried out [22]. RBFN model was used to estimate the membrane separation process's performance in the hydrogen recovery unit [23], to assess and monitor the NOx emission content in a water tube boiler with a production capacity of 160 MW [24] and to estimate the quality of light naphtha, heavy naphtha, and jet fuel products in the hydrocracking fractionator processing unit [25].

2. RESEARCH METHOD

2.1. Debutanizer reboiler

A debutanizer reboiler (H1), as shown in Figure 1, is a piece of process equipment used to heat the bottom product from the debutanizer column (V1) [26]. After heating, the product is recirculated to the debutanizer column for the distillation process [27]–[29]. The debutanizer column is a type of fractional distillation column used to separate butane from natural gas during the refining process into light components (i.e., top products such as C3 and C4) and heavy components (i.e., bottom products such as C5 and heavier ones) [30]–[32].

2.2. Data collection

The data used in this paper are historical data on the measurement of process variables on the debutanizer reboiler on an oil refinery unit in Indonesia, as shown in Table 1. The information is collected from the distributed control system database in the continuous catalyst regeneration platforming-II unit via the client system [33]. The data collection was carried out during the period between 1 January and 20 July.

Table 1. Process variable in a debutanizer reboiler

No.	Process Variable	Unit
1.	Fuel Gas Flow	m^3/hour
2.	Fuel Gas Pressure	bar
3.	Coil Inlet Temperature	°C
4.	Coil Outlet Temperature	°C
5.	Tube Skin Temperature	°C
6.	Bridge Wall Temperature	°C
7.	Stack Temperature	°C
8.	O2 Content	%
9.	Feed Flow	m^3/hour

2.3. RBFN-based soft sensor design

The soft sensor in this study is designed to estimate the oxygen content of the flue gas of a debutanizer reboiler. The input of the soft sensor is in the form of the measurement data of the process variables in the debutanizer reboiler, such as feed flow rate, feed inlet temperature, feed outlet temperature, fuel pressure, fuel temperature, and other available process variables as shown in Table 1. The output of the soft sensor is the estimation of oxygen content as shown in Figure 2. In this paper, the data preprocessing and RBFN have been designed using python with libraries of pandas, NumPy, Matplotlib, and Keras API [33], [34].

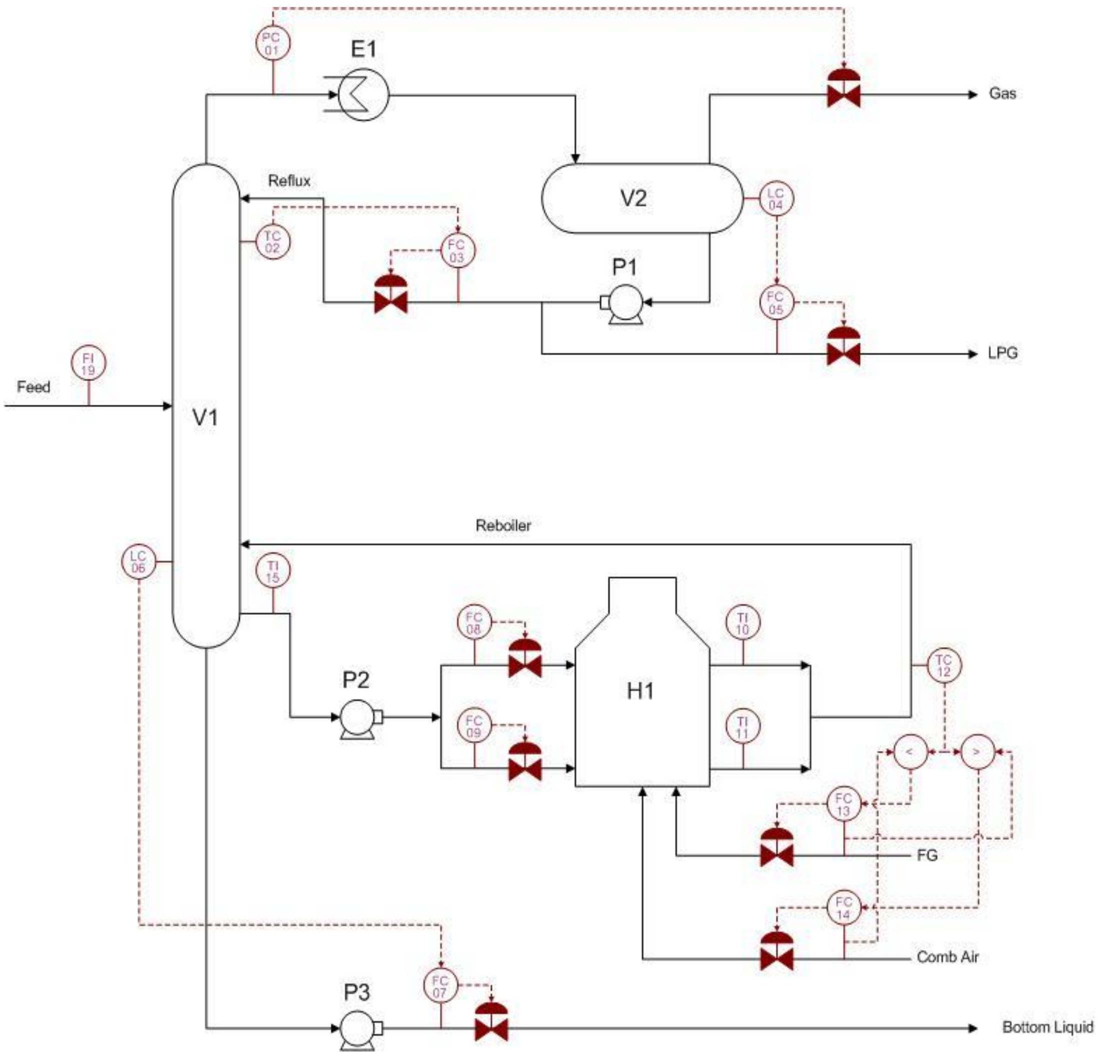

Figure 1. Refinery fluid catalytic cracking (FCC) debutanizer configuration [26]

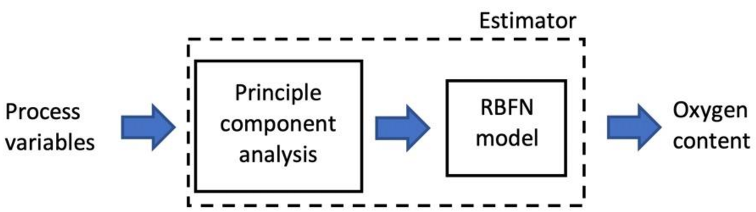

Figure 2. Block diagram of the preprocessing (PCA) and RBFN as a soft sensor to estimate oxygen content of the flue gas of a debutanizer reboiler

2.4. Data preprocessing

The data preprocessing stage was carried out using principal component analysis (PCA). PCA has been used for the early detection of faults or anomalies in the process industry [35]. The data preprocessing consists of a data scaling process, selecting features using the PCA method, and data division for training and testing the system. Initially, the data were scaled to eliminate the domination of some process variables over other variables. The data scaling stage was carried out using a scaling factor, namely, the interquartile range (Q1 to Q3).

The data resulted from the scaling is transformed into new independent variables based on the variance or known as the principal component. The variable transformation aims to eliminate redundancy and noise and can be used to reduce the dimensions of the model input [36]. The selection of the number of principal components depends on the cut-off limit of the cumulative variance percentage, i.e., 90%. The selected principal component data is then divided by the ratio of 80% as training data and 20% as test data.

2.5. Radial basis function network

The modeling and test stages were carried out using RBFN [17], [37], [38]. RBFN is a type of feed-forward machine learning that can be a universal approximator, simple architectural design, and fast learning process [39]–[41]. One typical RBFN architecture, as shown in Figure 3, consists of one input layer, one hidden layer with Gaussian activation functions, and one output layer. Bias neurons are optional to add and serve as a corrector of the estimated value.

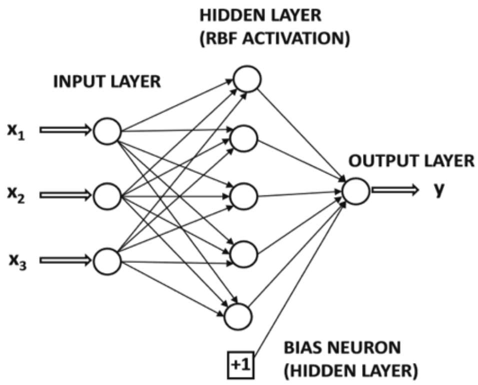

Figure 3. A typical RBFN architecture [42]

There are two parameters of the Gaussian function in each hidden layer node, namely the prototype vector of the i^{th} hidden unit ($\bar{\mu}_i$) and the bandwidth (σ_i). Both have a role in producing a symmetrical response from each input data. For any specific training point ($\bar{X}$), the response results from each node are scaled with the output weights (w_i), accumulated, and processed in an activation function (ϕ_i), so that the estimated value ($\hat{y}$) is obtained, which can be mathematically denoted by (1) [42].

$$\hat{y} = \sum_{i=1}^{m} w_i \phi_i(\bar{X}) = \sum_{i=1}^{m} w_i \exp\left(-\frac{\|\bar{X}-\bar{\mu}_i\|^2}{2\sigma_i{}^2}\right) \tag{1}$$

The central location's determination can be done with three strategies: random selection, selection based on input data classification, and supervised selection, such as an evolutionary algorithm [41]. The classification strategy, especially the k-means clustering technique, is more likely to be used because it is efficient for large amounts of data [43]. The classification strategy is combined with the stochastic gradient descent (SGD) algorithm and momentum acceleration to optimize the model performance. We used the center location, width, and output weight parameters as the optimization target with a learning rate of 1.0×10^{-5} for 3500 epochs. The model performance evaluation is represented as the mean squared error (MSE) and validated by the 10-fold cross-validation technique.

3. RESULTS AND DISCUSSION

3.1. Feature selection

The process of Eigen decomposition from the process variable covariance matrix produces eigenvalues, as shown in Table 2. Simultaneously, the cumulative variance percentage data is included in determining the number of principal components [17]. The first principal component always has the highest eigenvalue, and the last principal component has the lowest eigenvalue. The eigenvalues represent the variance of the process variable data, which the associated principal component can explain.

In this case, the eigenvalues are always positive because the data's variance may not be negative. The larger the principal component index, the closer to zero the eigenvalue. It suggests that the process variables are multi-linearly correlated. The first few principal components can represent the original data's variance, and between the principal components will be mutually independent. Based on the empirical criteria, four principal components are selected as model inputs, while the rest are ignored.

Table 2. The eigenvalue of the principal component

Principal Component	Eigenvalue	Cumulative variance
1	2.409	0.4322
2	1.614	0.7218
3	0.618	0.8326
4	0.522	0.9251
5	0.219	0.9644
6	0.081	0.9787
7	0.056	0.9881
8	0.022	0.9920
9	0.020	0.9955
10	0.013	0.9978
11	0.008	0.9992
12	0.005	1.0000

3.2. RBFN-based soft sensor performance

The test and validation of the system are carried out by varying the number of hidden nodes. The experimental results are shown in Table 3. The best model performance is obtained when the system uses twenty-five hidden nodes and achieved an MSE of 2.16×10^{-3} and a standard deviation of 2.42×10^{-4}. The increase of hidden nodes from five to twenty-five successfully decreases the MSE. However, further addition of the nodes causes the growth of the MSE. In RBFN, with the number of hidden nodes in the range between five to 25, the higher number of nodes in the hidden layer tends to make RBFN more tolerant to different test data and noise [44]. However, RBFN with more than twenty-five hidden nodes, the higher number of nodes makes RBFN less general. MSE is the mean of the squared error between the estimated and the actual output. The MSE of this experiment was relatively small in the order of 10^{-3} with a standard deviation in the order of 10^{-4}. The small MSE means that the predicted value of oxygen content is similar to the actual value.

Table 3. MSE of the test and validation of the estimation system of oxygen content in the flue gas of a debutanizer reboiler

#Hidden Nodes	MSE	Standard Deviation
5	2.69×10^{-3}	3.15×10^{-4}
10	2.35×10^{-3}	2.88×10^{-4}
15	2.25×10^{-3}	2.61×10^{-4}
20	2.21×10^{-3}	2.56×10^{-4}
25	$\mathbf{2.16 \times 10^{-3}}$	$\mathbf{2.42 \times 10^{-4}}$
30	2.27×10^{-3}	2.34×10^{-4}
35	2.36×10^{-3}	2.17×10^{-4}
40	2.41×10^{-3}	2.21×10^{-4}

4. CONCLUSION

This paper presents the design of an RBFN-based soft sensor for the estimation of the oxygen content of the flue gas of a debutanizer reboiler. The soft sensor has been successfully carried out. The system achieves a validated MSE mean of 0.216% with a standard deviation of 0.0242% in the debutanizer reboiler test. The proposed RBFN model can adapt and learn quickly to data variation.

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