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PREDICTION AND OPTIMIZATION OF ETHANOL CONCENTRATION IN BIOFUEL PRODUCTION USING FUZZY NEURAL NETWORK

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Abstract

In recent years, producing economical biofuels especially bio-ethanol from lignocellulosic materials has been widely considered. Fermentation is an important step in ethanol production process. Fermentation process is completely nonlinear and depends on some parameters such as temperature, sugar content, and PH. One of the difficulties in producing biomass is finding the optimum point of the interrelated parameters in the fermentation step. In this study, an elaborate prediction Neuro-Fuzzy model was built to predict the bio-ethanol production from corn stover. Also, particle swarm optimization (PSO) method was used to optimize the three studied parameters: temperature, glucose content, and fermentation time. The attained correlation coefficient (0.99), and root mean square error (0.637) for model validation show the reliability of the model. Optimization of the model shows the optimum fermentation time and required temperature quantities, 69.39hours and 34.50°C, respectively. The good result for ANFIS modeling on fermentation process in bio-ethanol production from corn stover shows that this method can be used to investigate more about other biomass lignocellulos sources.

Keywords: Lignocellulose, neuro-Fuzzy, corn stover

Abstrak

Dalam tahun-tahun kebelakangan ini, menghasilkan biofuel ekonomi terutamanya bio-ethanol daripada bahan lignoselulosa telah dianggap secara meluas. Penapaian adalah satu langkah yang penting dalam proses pengeluaran etanol. Proses penapaian adalah linear dan bergantung kepada beberapa parameter seperti suhu, kandungan gula, dan PH. Salah satu kesukaran dalam menghasilkan biomass adalah mencari titik optimum parameter yang saling berkaitan dalam langkah penapaian. Dalam kajian ini, model ramalan Neuro-Fuzzy rumit dibina untuk meramalkan pengeluaran bio-etanol dari Stover jagung. Selain itu, kaedah zarah swarm pengoptimuman (PSO) telah digunakan untuk mengoptimumkan tiga parameter yang dikaji: suhu, kandungan glukosa, dan masa penapaian. Pekali korelasi mencapai (0.99), dan punca min ralat persegi (0,637) untuk pengesahan model menunjukkan kebolehpercayaan model. Optimization model yang menunjukkan masa yang optimum penapaian dan memerlukan kuantiti suhu, 69.39hours dan 34.50 C, masing-masing. Hasil baik untuk model ANFIS pada proses penapaian dalam pengeluaran bio-etanol daripada jagung Stover menunjukkan bahawa kaedah ini boleh digunakan untuk menyiasat lebih lanjut mengenai lain-lain sumber lignocellulos biomass.

Kata kunci: Lignoselulosa, neuro-Fuzzy, stover Corn

1.0 INTRODUCTION

In recent years, there has been an explosive growth of interest in bio-ethanol production from lignocellulosic biomass. Bio-ethanol is an alternative source of energy to replace of fossil fuels. Burning of bio-ethanol does not increase combustion heat, rather, it helps to solve the problem of global warming. In addition, it has no conflict with food sources, and less air pollution [1].

Bio-ethanol production process includes four main steps namely; pretreatment, hydrolysis, fermentation and distillation. These four major operations have been previously studied by researchers to produce a successful and economically viable process plant [2-5]. Nonetheless, lignocellulosic bio-mass sources as a promising material for producing ethanol is not economical, and still relatively expensive [6].

Biochemical process which involves the growth of microorganisms to obtain profitable products is a short description of fermentation. To improve the production of bio-ethanol from lignocellulosic feedstock, many studies were focused on fermentation process as the heart of bio refining process [7]; to enable the production of bio-ethanol commercially and economically. In this way, the vast studies on microorganism have been done to find the advantages and disadvantages of potential organism in lignocellulosic-based fermentation process [8-9]. Different ethanol fermentation processes have been studied for developing, controlling, and optimizing the fermentation process [10-13]. Precise mathematical relationship between feeds (inputs) and products (outputs) is required to be able to model such processes. Using mathematical modeling in model development on poorly understood processes/systems is very difficult, and uncontrollable [14]. As a substitute for time varying, nonlinear, unclear process modeling, soft computing techniques have recently been used. Among them is the Neuro-fuzzy models; with advantages of both fuzzy logic and neural network models, capable of combining learning ability of neural network and the transparency of fuzzy systems [15].

To study the fermentation process without any laboratory limitation, Neuro-Fuzzy model has been used for the first time to model the fermentation process in producing bio-ethanol from corn stover in this research. Finally, particle swarm optimization method has been used to optimize different variables in achieving the maximum amount of ethanol produced.

2.0 METHODOLOGY

The valuable information on fermentation process with 96 hours' process time and different examined temperatures have been extracted from a published paper by Jia-Qing Zhu [16]. The extracted data was saved in excel file for further study on predicting bio-ethanol production using Neuro-Fuzzy method.

2.1 Neuro-Fuzzy Technique

Neuro-Fuzzy technique, a hybrid intelligent system was built on the combination of neural network and fuzzy logic. Learning abilities of neural network and explanation capabilities based on expert knowledge of fuzzy system make a system with the advantages of both. Consequently, fuzzy system has become capable of learning and neural network become explicit.

In addition, when a representative set of instances is examined, a Neuro-Fuzzy system is capable of spontaneously alter it into a strong set of fuzzy IFTHEN rules. Moreover, built Neuro-Fuzzy intelligent systems has less dependency on expert knowledge [17].

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS with specific Neuro-Fuzzy construction has been implemented in engineering firms for many application. ANFIS as a hybrid neuro fuzzy inference expert systems, has shown significant results for nonlinear functions modeling. In 1993 Takagi-Sugeno-type fuzzy (TSK) inference system was developed by Jang. ANFIS works in TSK system [18].

In the rule base of ANFIS, fuzzy IF-THEN Sugeno type rules have been applied. For a first order two rules Sugeno fuzzy inference system [19], the two rules may be shown by:

Rule 1: If x is A_1 and y is B_1, then $f_1 = a_1x+b_1y+c_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = a_2x+b_2y+c_2$

A zero order TSK fuzzy model will be generated if f_1 and f_2 are constants rather than linear equations. The most accepted inference system implemented in ANFIS is the first order Sugeno-type FIS. To achieve more acceptable and correct output with lowermost error, antecedent and consequent parameters as rule parameters will be adjusted during the training process. In fuzzy system, previous knowledge of rule consequent is needed, but ANFIS method has the ability to learn these parameters and adjust the membership function [20]. Construction in ANFIS and multilayer feed forward neural network is similar, but the connections in the ANFIS only consider the current direction of signals between nodes and no weights are linked with the connections [21]. Figure 1 shows the ANFIS construction, after that there is a brief description for the neuron function that has been used by each layer.

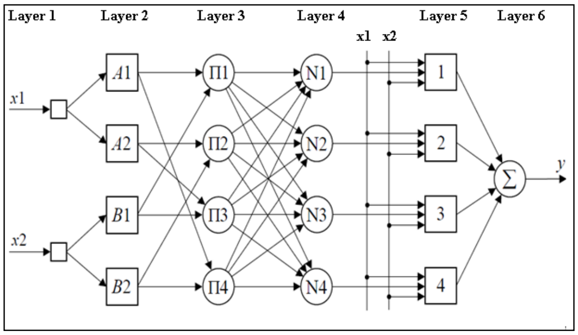

Figure 1 Structure of ANFIS

Layer 1: This layer is the input layer and external crisp is simply passed to the second layer by neurons.
Layer *2:* Fuzzification is implemented by neurons in this layer. Most common membership functions use in fuzzification neurons are bell and gaussian membership function.
Layer 3: Each neuron in this layer links to a single Sugeno type fuzzy rule known as rule layer. A rule neuron gains inputs from the relevant fuzzification neurons and analyzes the firing strength of the rule it represents. The product operator is implemented in ANFIS to calculate the conjunction of the rule antecedents. Accordingly, the output of neuron *i* in Layer 3 is calculated as:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \qquad y_{\prod 1}^{(3)} = \xi_{A1} \times \xi_{B1} = \xi_1 \qquad (1)$$

where the value of ξ_1 shows the firing strength, or the truth value, of Rule1.
Layer *4*: Neurons in the fourth layer are known as normalization layer. After receiving inputs from neurons in the third layer, they computes and normalized firing strength of a given rule. The attained firing strength is equivalent to the ratio of the firing strength of a given rule to the sum of firing strengths of all rules. In other words, contribution of a given rule to the final result is represented by normalized firing strength. Therefore, the output of neuron *i* in this layer is determined as:

$$y_i^{(4)} = \frac{x_{ii}^{(4)}}{\sum_{j=1}^{n} x_{ji}^{(4)}} = \frac{\xi_i}{\sum_{j=1}^{n} \xi_j} = \bar{\xi}_i \qquad (2)$$

$$y_{N1}^{(4)} = \frac{\xi_1}{\xi_1 + \xi_2 + \xi_3 + \xi_4} = \bar{\xi}_1 \qquad (3)$$

Layer *5*: Neurons in the fifth Layer, defuzzification layer are linked to the respective neuron in normalization layer. They also receives x_1 and x_2 as initial inputs. A defuzzification neuron calculates the weighted consequent value of a given rule as:

$$y_i^{(5)} = x_i^{(5)}[c_{i0} + a_{i1} x_1 + b_{i2} x_2] = \bar{\xi}_i [c_{i0} + a_{i1} x_1 + b_{i2} x_2] \qquad (4)$$

where $x_i^{(5)}$ and $y_i^{(5)}$ are the input and the output of defuzzification neuron *i* in the defuzzification layer, respectively. Also, c_{i0}, a_{i1} and b_{i2} are a set of consequent parameters of rule i.
Layer *6:* A single summation neuron is implemented in this layer to generate the overall ANFIS output, y, after computing the sum of outputs of all defuzzification neurons.

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} \bar{\xi}_i [c_{i0} + a_{i1} x_1 + b_{i2} x_2] \qquad (5)$$

3.0 RESULTS AND DISCUSSION

3.1 Collection of Main Parameter

Fermentation process is highly dependent on environmental factors to be count as successful. The fermenter require to be able to control such factors as temperature, pH, and dissolved oxygen levels [22]. Therefore, temperature, time, and glucose have been chosen as the inputs of ANFIS modeling to predict the bio-ethanol production. Inputs and outputs of Fuzzy neural network are shown in Figure 2. Almost 42 g/l were converted to ethanol and the results observed for 30°C, 35°C, 38°C, 42°C, 45°C and in 0, 6, 12, 24, 48, 72, 96 hours fermentation time.

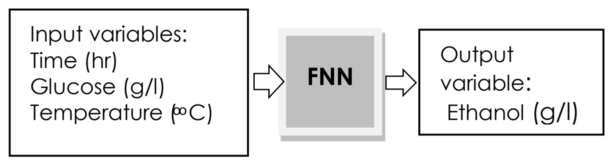

Figure 2 Structure of FNN method, inputs and output

3.2 Dynamic Model

The membership functions of the input variables were initialized by the ANFIS before the training process started. The training process changed the parameters of the initial membership functions to optimize their representation of the input and output mappings, thereby changing the shapes of the membership functions. Therefore, as shown in Figure 3 the final membership functions would display different forms from the initial ones.

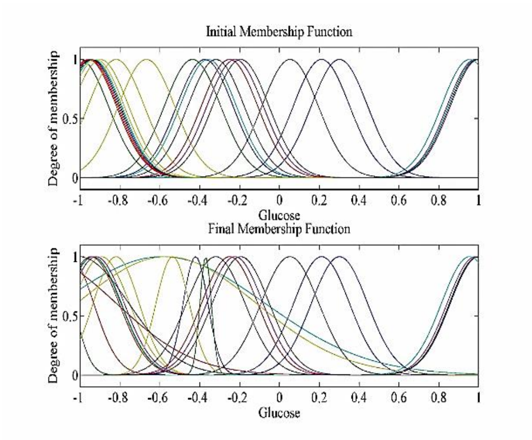

Figure 3 Initial and final membership function for glucose

The performance of the model during training and testing was verified through two statistical indices, Correlation Coefficient (Regression), and Root Mean Square Error (RMSE):

$$R = \frac{\sum_{x=i}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{x=i}^{n}(x_i-\overline{x})^2(y_i-\overline{y})^2}} \tag{6}$$

R is correlation coefficient, x_i is the target of ith observation, $\overline{x}$ and $\overline{y}$ denote the average value of targets and predicted values, respectively, and n is the total number of observations.

$$RMSE = \sqrt{\frac{1}{n}\sum(x^{exp} - x^{sim})^2} \tag{7}$$

Where x^{exp} is the target value, x^{sim} is the output value and n is the number of the experimental data.

Figures 4 and 5 show the regression for the train and test data respectively.

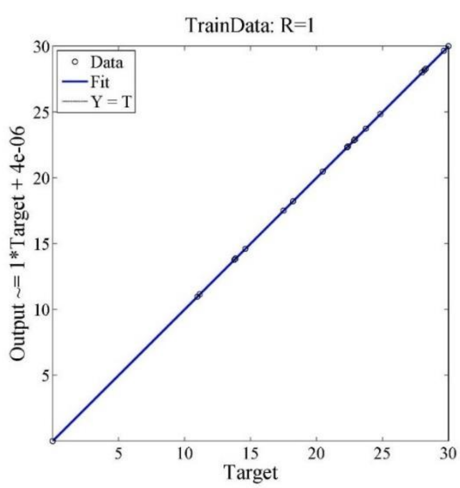

Figure 4 Regression for the train data set

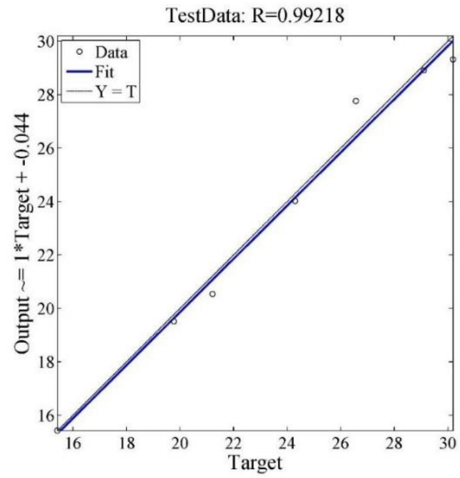

Figure 5 Regression for the test data set

Table 1 shows the statistics of predictive model for train data and test data. Here, M_T stands for membership function type. trnRMSE represents RMSE for train data, and testRMSE stands for RMSE for test data.

Table 1 Statistics of predictive model

Parameter	Value
M_T	gaussmf
Norm_F	mapminmax(-1,1)
radii	0.2
Epoch	57
trnRMSE	3.5464e-6
testRMSE	0.637095

This research is targeted at predicting nonlinear process of bio-ethanol production using ANFIS based system. The obtained results show that ANFIS can successfully predict ethanol concentration through investigation of relation between time, temperature, and glucose. The low amount of RMSE and less than 6% relative error (Figure 6) for train and test data show the success of this method in estimating the bio-ethanol concentration.

PSO optimization method has been used to optimize different variables and see the points that has never been noticed in the laboratory to achieve maximum product. The results are shown in Table 2.

Table 2 PSO results to optimize the parameter

Time (hr)	Glucose (g/l)	Temperature (°C)	Ethanol (g/l)
69.39	0.23	34.50	30.01

The results of PSO optimization method show that the optimum fermentation time is 69.39 hours and the required temperature for converting almost all glucose to ethanol is 33.51. 72 hours and 38°C were achieved as the optimum condition in the laboratory to obtain maximum ethanol. By comparing the experimental result and simulated result, the optimum point can be in the condition that has never been examined in the laboratory, with more glucose consumption, less temperature and less fermentation time.

The result of this study show that the fermentation process has been simulated successfully based on the measured reliant parameters by Neuro-Fuzzy technique. After that, the built model has been used to further study the experimental research by testing many other states that were not considered in laboratory. Following the same technique in large scale production process will be very valuable to finding the optimum point and reducing the cost of bio-ethanol production.

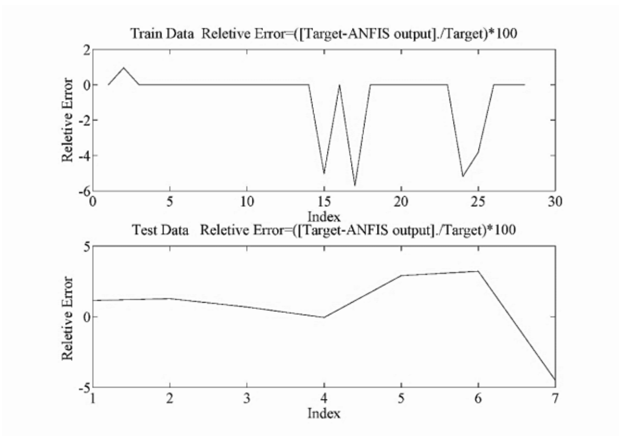

Figure 6 Error relative for test and train data set

4.0 CONCLUSION

Since fermentation is a highly nonlinear process, the prediction of bio-ethanol concentration is complicated and difficult, and it is commonly obtained through many experimental measurements. Through this study, a computer-based ANFIS model has been used to estimate the bio-ethanol concentration based on quantitative relationship between three parameters: time, temperature, and glucose of the nonlinear fermentation process. In future, the proposed computer-based ANFIS method can be used in large scale bio-ethanol production process to predict and optimize final ethanol concentration.

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