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Fuzzy Logic Model Development for Troubleshooting at Degumming and Bleaching Process

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In palm oil industries, troubleshooting to overcome plant or equipment failure is always performed by engineers or plant worker. Failures at the plant affect the sustainable development for industry. Failures can increase the operating cost, product waste and emotional stress of the plant workers. A more systematic troubleshooting method has been introduced to support troubleshooting work to reduce mistakes and increase efficiency. In this paper, a fuzzy logic model for troubleshooting cases that represent failures to obtain product quality at degumming and bleaching processes in a palm oil refinery is presented. Fuzzy logic model has been widely used in complex chemical processes due to its ability to capture human knowledge and combine it with numerical information. Fuzzy logic consists of three major elements which are fuzzification, fuzzy inference system (FIS) and defuzzification. In fuzzification step, crisp value data which is obtained from Distributed Control System (DCS) and technical documentation are converted into fuzzy value by mapping it to the membership function that represent linguistic labels such as "low", "normal" and "high". Fuzzy if-then rules are used to map the fuzzy input to fuzzy output using Mamdani approach in fuzzy inference system. The fuzzy if-then rules are developed based on expert knowledge and experience in palm oil industry. Lastly, the fuzzy value is defuzzified to obtain crisp value by using Centre of Gravity method. The model is developed using fuzzy logic toolbox in MATLAB software. The fuzzy logic model was tested with cases of bleaching temperature failures at degumming and bleaching processes. Based on the cases presented in this paper, the results show that the model is capable to diagnose failures and suggest action.

1. Introduction

Troubleshooting process is getting difficult due to the complexity of the plant process. Poor decision making does not only consume more time on the process and bring downturn to the company, but it also affects the sustainability of the process. Failures may occur due to human factors, where they tried to diagnose and solve the problem based on their experience in plant and judgement. This will not only affect the process, but to the product and profit as well. There is a need to have a computerised and systematic troubleshooting system.

Degumming and bleaching are two initial processes at a palm oil refinery before deodorisation process. One of the main concerns at these two processes is the quality of the bleached oil (Gee, 2007) which is maintained by the operating condition and dosage of acid and clay to its optimum level. Studies showed that acid activated clay is more efficient in removing the unwanted compound in palm oil during degumming and bleaching process (Wei et al., 2004). Morad et al. (2010) has identified the optimum dosage for phosphoric acid and bleaching earth to degumming and bleaching process by using artificial neural network. Based on the model, the optimum dosage of phosphoric acid is 0.4 wt% CPO and 1.0 % of bleaching earth. The deviation of the operating condition can cause poor quality of the bleached oil and the oil need to be recycled in order to achieve the required specification. Due to the difficulty to express the relationship between the bleached oil quality and the operating condition using mathematical model, a fuzzy logic model is proposed to describe the relationship.

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The application of fuzzy logic expert system has been widely used in many industries such as in transportation, automation, desalination and milling process. Falamarzi et al. (2016) has applied fuzzy expert system to improve the traffic system by employing knowledge from the domain experts. Nekooei et al. (2015) has employed fuzzy logic to optimise the fuel consumption and the level of emission produced by the car engine. Fuzzy logic has been used in decision making due to its similarity with human reasoning and its simplicity (Hong and Lee, 1996). Zahedi et al. (2011) has applied fuzzy expert system to assist operators and provide fast and accurate troubleshooting in crude oil desalination process. They performed off-line testing in order to check the performance of the fuzzy expert system.. Abdul-Wahab et al. (2007) in their study represented fuzzy logic expert system to troubleshoot brine heater of the multi stage flash plant. They developed the model by integrating the knowledge and experienced of plant workers in the plant. The success performance of the model to perform troubleshooting task has been testing using off-line data. Morgan et al. (2007) developed an expert system to troubleshoot sources of milling problems by utilising fuzzy logic model. It has been developed based on the operators' opinion and from Fourier spectrum data from the milling process.

In this study, fuzzy expert model is developed in the area of degumming and bleaching process to describe the possible failure to achieve good quality of the bleached oil. This model provides action to be taken in order to achieve good quality of bleached oil based on the operating condition at the process. The model integrates qualitative and quantitative data obtained from operators' and experts' opinion in plant with data from technical document, standard operating procedure (SOP) and Distributed Control System (DCS). The fuzzy expert model applied Mamdani for the inference system due to its simplicity and easy to understand.

2. Process description

Crude palm oil (CPO) undergoes the refining process to produce the refined, bleached, and deodorised (RBD) palm oil. The purpose of refining is to obtain a light colour, a bland taste and a good oxidative and stability refined oil (Gibon et al., 2007). The refining process starts with degumming, where the degummed component is removed from the CPO by treating it with phosphoric or citric acid. The gummy component will be coagulated and adsorbed to the bleaching earth at the bleaching process. During the process, the colouring pigments, trace metal ions and oxidative products is removed to produce light colour bleached oil. Bleaching process is carried out under vacuum condition, temperature of 90 °C to 110 °C with a specific retention time of 20 to 30 min. At the final stage, the RBD palm oil will undergo the deodorisation process to remove the volatile component such as free fatty acid (FFA) and odoriferous pigments. Figure 1 illustrates the overall process of the palm oil refining process (Sulaiman and Mohd Yusof, 2015).

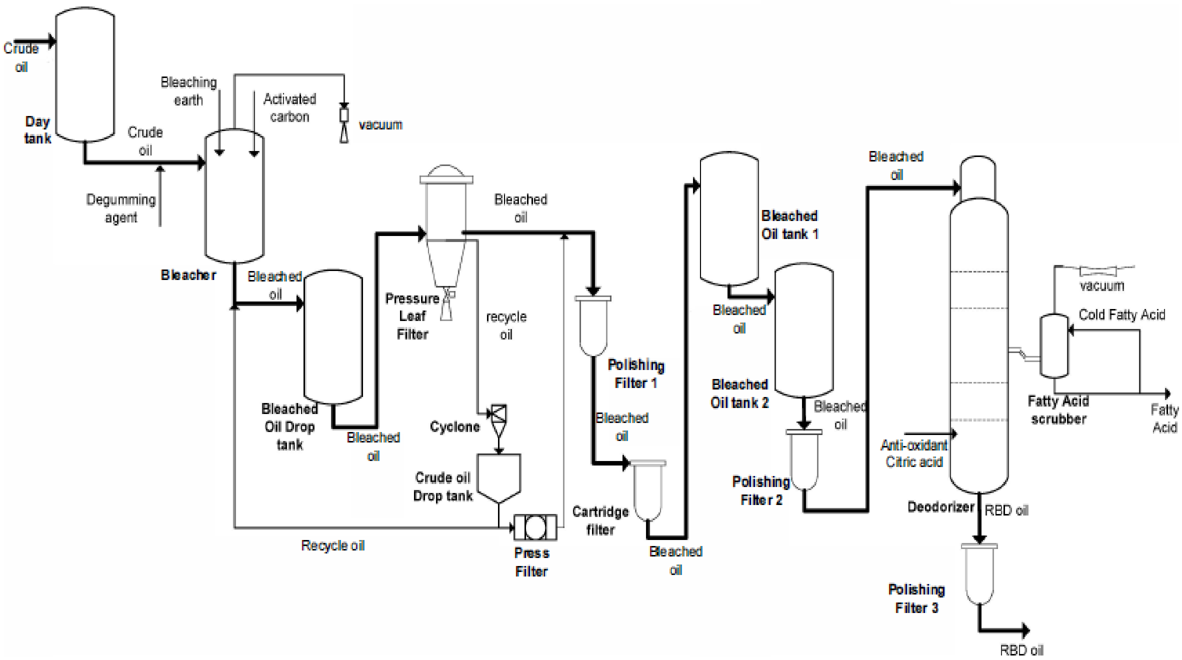

Figure 1: Overall palm oil refining process (Sulaiman and Mohd Yusof, 2015)

3. Development of fuzzy logic model

Fuzzy logic was chosen in this study because of its flexibility and tolerance with imprecise data. It has the ability to be built based on human knowledge and combined with natural language that is easily understood, and able to model the complex non-linear functions (Carrasco, 2004). The model is developed through three stages, fuzzification, inference engine and defuzzification and were explained in the later section.

3.1 Fuzzy membership function for input and output variables

The first step to troubleshoot fault at degumming and bleaching process is by identifying the possible variables that can cause failures to the system. The variables can be divided into qualitative and quantitative data. Qualitative data was obtained through interview sessions and discussion with plant workers and observation at palm oil plant located at Southern Johor, Malaysia. All of the data were analysed using thematic analysis. Data familiarisation, generating initial codes, searching for themes, reviewing and defining themes are the five steps in thematic analysis (Braun and Clarke 2006). These qualitative data were used as the linguistic variables for fuzzy input and output membership function.

Quantitative data was used as range for the input and output membership function in the fuzzy logic model. The quantitative data was obtained from standard operating procedure (SOP) and technical document. Based on the data collected, 9 variables were identified as failures to achieve good quality of bleached oil at the degumming and bleaching process. The variables are as listed in Table 1.

Table 1: Input variables to the fuzzy troubleshooting system

Variables	High Level	Low Level
Vacuum pressure (torr)	100	< 50
Bleaching temperature (°C)	110	< 95
Bleaching earth dosage (wt%)	2.5	< 0.5
Citric acid dosage (wt%)	0.04	< 0.03
Retention time (min)	30	< 15
Agitator (rpm)	100	< 50
Sparge steam pressure (bar)	4	< -1
Sparge steam quality (%)	97	< 96
Bleaching level (%)	70	< 10
Feed flow rate (Mt/hr)	12	< 9

As shown in Table 1, there is a condition of high and low level for each variable. These levels are used to develop the input membership function.

In this study, trapezoidal membership function was used for the input and output membership function due to its simplicity, easy to calculate and appropriate in describing the input and output variables. The trapezoidal membership functions were employed to express the failure and suggested actions in terms of graphical representation. The trapezoidal membership function's is defined as Eq(1):

$$\mathrm{trapezoid}(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases} \tag{1}$$

where a, b, c, and d are the four values for trapezoidal membership function and *x* is the conditional data. Figure 2 and Figure 3 illustrate the input and output fuzzy membership functions for bleaching temperature variable.

3.2 Fuzzy inference engine

The next step in fuzzy troubleshooting is to create the fuzzy if-then rules. The if-then rules were used to explain the relationship between the faults and actions to be taken in different cases. The “if” parts represent the normal and abnormal conditions for the antecedent, while actions to be taken are represented as the consequence part. Due to the complexity of the process, “AND” and “OR” operator was used to describe the normal and abnormal condition for each case.

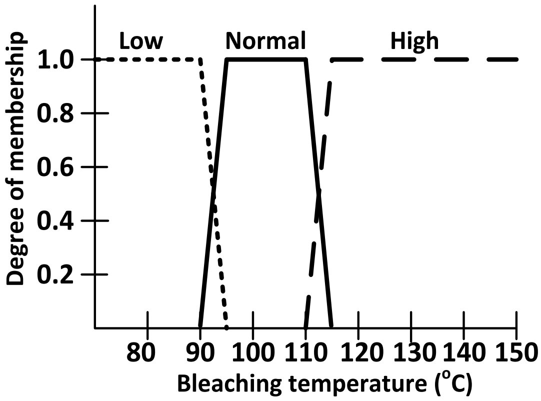

Figure 2: Input fuzzy membership function for bleaching temperature

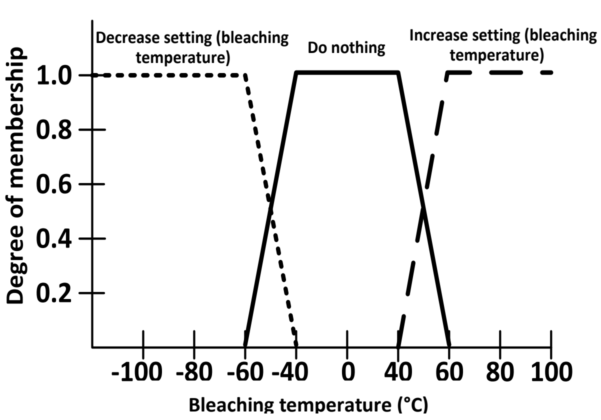

Figure 3: Output fuzzy membership function for bleaching temperature at three different actions

The rules were developed based on interview with experienced workers in palm oil refining. Seven rules were formulated in describing possible faults and action suggested to obtain good quality of bleached oil in degumming and bleaching process. These rules were formulated based on the experience and knowledge of the plant workers. For example, rule 1 is describing normal condition at degumming and bleaching process.

Rule 1: If (vacuum pressure is normal) AND (bleaching temperature is normal) AND (bleaching earth dosage is normal) AND (citric acid dosage is normal) AND (retention time is normal) AND (agitator speed is normal) AND (sparging steam pressure is normal) AND (sparging steam quality is dry) AND (bleaching level is normal) AND (feed flow rate is normal) then (vacuum pressure is do nothing) AND (bleaching temperature is do nothing) AND (bleaching earth dosage is do nothing) AND (citric acid dosage is do nothing) AND (retention time is do nothing) AND (agitator speed is do nothing) AND (sparging steam pressure is do nothing) AND (sparging steam quality is do nothing) AND (bleaching level is do nothing) AND (feed flow rate is do nothing).

Rule 2 to rule 7 describe the failure conditions that may occur at the process such as high moisture content and high bleached colour, high retention time, high bleaching temperature, high agitator speed, high bleaching earth dosage and high citric acid dosage. Table 2 shows the summary of fuzzy if then rules for cases in degumming and bleaching process.

Table 2: Fuzzy if-then rules for degumming and bleaching process

	If (antecedent)							Then (consequence)						
Variables \ Rule	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Vacuum pressure	N	H	N	N	N	N	N	DN	DS	DN	DN	DN	DN	DN
Bleaching temperature	N	L	N	H	N	N	N	DN	IS	DN	DS	DN	DN	DN
Bleaching earth dosage	N	L	N	N	N	H	N	DN	IS	DN	DN	DN	DS	DN
Citric acid dosage	N	L	N	N	N	N	H	DN	IS	DN	DN	DN	DN	DS
Retention time	N	L	H	N	N	N	N	DN	IS	DS	DN	DN	DN	DN
Agitator speed	N	L	N	N	H	N	N	DN	IS	DN	DN	DS	DN	DN
Sparging steam pressure	N	H	N	N	N	N	N	DN	DS	DN	DN	DN	DN	DN
Sparging steam quality	D	W	D	D	D	D	D	DN	DS	DN	DN	DN	DN	DN
Bleaching level	N	L	N	N	N	N	N	DN	IS	DN	DN	DN	DN	DN
Feed flow rate	N	L	N	N	N	N	N	DN	IS	DN	DN	DN	DN	DN

In Table 2, there are two parts which are antecedent and consequence. In antecedent part, “N” is denoted as “normal”, “H” as “high”, “L” as “low”, “D” as “dry” and “W” as wet”. For consequence part, “DN” is denoted as “do nothing”, “DS” as “decrease setting” and “IS” as “increase setting”.

Taking bleaching temperature as an example, it can be seen that bleaching temperature has three fuzzy membership function, which are “low”, “normal” and “high” and these membership function have three output such as “increase setting (bleaching temperature)”, “do nothing (bleaching temperature)” and “decrease setting (bleaching temperature)”. The weight value for each fuzzy rule was set as 1 because all rules have the same urgency factor. In this study, Mamdani fuzzy inference was selected as the inference engine due to its intuitive, widespread acceptance (Sivanandam et al., 2007) and better for discovery of human understandable knowledge from real world problem (Liao, 2003).

The final step in the development of the fuzzy troubleshooting model is evaluating its troubleshooting performance. The performance was evaluated by feeding the input data to the troubleshooting model. The inputs of this model are the vacuum pressure, bleaching temperature, bleaching earth dosage, citric acid dosage, retention time, agitator speed, sparging steam pressure, sparging steam quality, bleaching level and feed flow rate. The defuzzified output from the FIS was calculated using Centre of Gravity (COG) as shown in Eq(2):

$$Z_{COG} = \frac{\int_a^b \mu_A(x)x\,dx}{\int_a^b \mu_A x\,dx} \tag{2}$$

where $\mu_A(x)$ is the aggregated membership function and Z_{COG} is the output variables. The defuzzified will be varied between -100 to 100. The model was evaluated by comparing the conclusion given by the model with the human judgment. Fuzzy if-then rules in the inference system were updated in order to ensure the results from the model are acceptable.

3.3 Testing of fuzzy expert system

The fuzzy troubleshooting model was tested with several off-line test. Real plant data for each variable were fed as input data to FIS. The model will verify the data and returned with conclusion for each fault as normal or abnormal condition. If the variable is in normal state, the model will return to a conclusion as “do nothing”, while if the variable is in abnormal state, the model will give suggestions to overcome the failure. The input data fed to the system are 208.5, 87, 2, 0.04, 30, 120, 1, 99, 70 and 10. The input data were fuzzified to a fuzzy value for rule evaluation process. All the input values were in normal condition except for vacuum pressure and bleaching temperature. The system diagnosed vacuum pressure is at high condition, whilst bleaching temperature is at low condition. Rule 2 were being fired by the system due to fault of vacuum pressure and high bleaching temperature.

Based on the evaluation using COG method, the output given by the fuzzy inference engine are -75 and 75 for vacuum pressure and bleaching temperature fault. Bleaching process efficiency is largely dependent on vacuum pressure, moisture and temperature. In this case, high vacuum pressure can decrease the process of removing phospholipids and pigments from the oil. While low bleaching temperature affect the oil viscosity and adsorption process between the bleaching earth particles and oils.

It is shown that, the output for vacuum pressure value is located in the range of -100 to -40. When the output is in the range of -100 to -40, it means that the input was in abnormal condition and the troubleshooting model will suggest the necessary actions to be taken for the fault. The system suggests to decrease the setting for vacuum pressure, which includes the need to check the overall performance of vacuum system such as ejector, condenser and cooling tower system. Poor motive steam quality supply to the system, high cooling water temperature, or low cooling water pressure to the process can reduce the performance of the bleaching process. The output for bleaching temperature value is located in the range of 40 to 100 which indicates increase setting for bleaching temperature. Lower temperature for bleaching process can be due to lower heating steam supply to the system. This fault may be occurring due to coil leaking at the bleaching vessel.

4. Conclusions

A fuzzy logic expert system was developed for troubleshooting failure that caused off-specification product due to deviation of operating condition at degumming and bleaching process of palm oil refining. The model was developed by acquiring human knowledge in refining process. Mamdani inference was used as inference system in this study. The system was tested with real plant data to evaluate the performance of the model. The results show the model successfulness to perform the troubleshooting task.

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