Optimization of Palm Oil Mill Effluent (POME) Solubilization Using Linguistic Fuzzy Logic and Machine Learning Techniques

Zuzana Jankova, Petr Dostal, Dipak Kumar Jana, Samyabrata Bhattacharjee, Barnali Bej, Priyanka Dey, and Sudipta Roy

Abstract The continuous hike in the price of the edible vegetable oil has directly impacted upon the price growth of the palm oil. In this palm oil production, Indonesia and Malaysia are in top leading position at present. It is found that an increase in palm oil mill setup is radically increasing the produce of effluent discharge which is a severe threat to our environment. Hence to maintain the balance of our already affected ecosystem, the proper treatment of this residual product is becoming the dire need of the hour. The conventional method used for solubilization of palm oil mill effluent (POME) is thermal alkaline pre-treatment. In this paper, the linguistic fuzzy logic (LFL) and machine learning (ML) techniques have been used to analyze the data, and type-2 fuzzy logic controller (T2FLC) has been used to optimize the solubilization of POME. The effect of reaction time, NaOH concentration, and temperature on the solubilization has been evaluated. From the investigation of the surface plot, which developed in T2FLC environment, it has been observed that NaOH concentration has a significant effect on the solubilization of POME. The prediction efficiency of T2FLC then has been compared with T1FLC and RSM. By evaluating some statistical analyses, the sensitivity and validity of the proposed model have finally been measured.

Keywords Palm oil mill effluent · Type-2 fuzzy logic · Solubilization · Thermo-alkaline pre-treatment · Statistical analysis

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1 Introduction

Palm oil is the main outcome from the agricultural zone, mainly obtained in the tropical regions. Indonesia and Malaysia are the leading hub in producing palm oil. Palm oil is obtained from the fruit of oil palm tree scientifically known as Elaeis guineensis. Palm oil is extensively used as raw material in the various food and non-food industries like cosmetics and pharmaceutical industry. An increase in population continuously increases the demand for food production from the agricultural sector which will make it the most water-polluting sector [1]. The gradual increase in the temperature range and frequent rainfall has increased the requirement of the water by the agriculture zones to meet the demand of the growing population [2]. The obstruction that is faced by palm oil production firm is the palm oil mill effluent, which is the waste product. According to some statistics, each tonne of palm oil production generates nearly 2.5–3.0 cubic meter of POME [3]. POME is the thick brownish color colloidal suspension whose characteristics are given in Table 1. The characteristics of the effluent vary which depend on the operational process used in mill for palm oil production. It has high value of COD and BOD which are present nearly 50,000 ppm and 25,000 ppm, respectively [4, 5]. The use of POME as a feedstock has picked up the enthusiasm of scientists to control squander creation in agriculture division obtained from the palm oil mill industry. Complex techniques have been widely evolved to treat and to use the waste product which can be categorized into four primary sections: biological, thermochemical, physiochemical, and the mix of the techniques thereof. Some of the techniques are dealt only to solve the waste-related problems, while part of them means to recoup vitality from the treatment. Each techniques has a few favorable circumstances and burdens, which is important before implementing it. Because of the degradable organic constituent, wastewaters have the potential to be utilised, where a net positive vitality addition could be accomplished with legitimate methodology [6].

For palm oil mill effluent, anaerobic digestion (AD) is commonly used by industries since it is a most cost-effective and ecofriendly process [16]. It is simply defined as the series of process in which the organic component breaks down into bio-energy in the absence of oxygen. The process of generation of bio-energy from anaerobic digestion can be divided into four sections: hydrolysis, acidogenesis, acetogenesis, and methanogenesis [17]. These techniques have several advantages as follows [18]:

- Anaerobic digestion differs from aerobic digestion in terms of availability of oxygen. Thus, the anaerobic digestion reduces the energy cost for the extensive supply of oxygen.
- Volatile solids content reduces through this operation. As per some literature, the addition of nitrite enhances the reduction of volatile suspended solid and increases the sludge treatment efficiency [19].
- By this operation, energy is recovered by the production of methane.
- It kills large percentage of pathogens present in sludge.

Among different pre-treatment methodology, the most well-known and broadly executing process is thermo-alkaline pre-treatment technique. In this paper, this

Table 1 Literature comparison of anaerobic digestion of different waste product

Waste	Pretreatment method	Experimental result	Reference
Microbial biomass	pH=8.5, Temperature $= 35°C$	Solubilization is 50.6%	[7]
Waste-activated sludge	7g/l NaOH concentration	Solubilization is 43.5%	[8]
Maize cob	microwave irradiation	Biogas yield increased by 46%	[9]
Wheat straw	Hydrogen peroxide	Methane yield increase by 50%	[10]
Waste-activated sludge	pH = 12 at ambient temperature	Solubilization is 30.7%	[11]
Brewery wastewater	Mesophilic at temperature 35°C	Methane yield efficiency is 0.52 to 0.53	[12]
POME	Ozonation method pH = 7.2	Methane yield is 64.1410 LCH_4/kg COD	[13]
POME	Ultrasonic method pH = 7.2 Temperature=32 °C to 37°C	Methane yield is 44 LCH_4/kg COD	[14]
POME	Temperature = 32.5 °C C time = 41.23 hr 8.83g/l of NaOH concentration	Solubilization	[15]
POME	Temperature = 35 °C Incubation time = 48 hr 8 g/l of NaOH concentration	Solubilization is 82.7%	This study

pre-treatment methodology is selected for solubilization and hydrolysis of macromolecule into simple monomers. The surface area and the rate of hydrolysis process increase due to the reduction of particle size which reduce the reaction time of the hydrolysis operation [20]. As per some previous study, sodium hydroxide (NaOH), calcium hydroxide (Ca(OH)2), and potassium hydroxide (KOH) are widely used as alkali in this pre-treatment process [21]. As per some study, the efficiency of sludge solution varies with the selection of alkali in a order of NaOH > KOH > $Mg(OH)_2$ and $Ca(OH)_2$ [8].

To increase the COD solubilization % of the effluent by thermo-alkaline pre-treatment methodology is optimized with respect to incubation time, NaOH concentration, and temperature by various soft computing techniques. It is frequently called as computational insight, covering a scope of strategies in the field of computer science, machine learning and AI. It is the collection of techniques that are dealt with the uncertain problem and provide low-cost optimum solution [22]. Soft computing techniques comprise artificial neural networks (ANN), fuzzy logic (FL) [23], adaptive neuro-fuzzy inference systems (ANFIS) [24], genetic algorithms (GAs) , data mining (DM), etc. The soft computing techniques used for the optimization the solubilization % of effluent obtain from palm oil mill by techniques like response surface methodology (RSM) [15] and fuzzy logic (FL) which is developed in this paper.

The type-1 fuzzy logic (T1FLC) is first proposed by Zadeh [25]. The most famous sort 1 fuzzy inference (T1FI) models are proposed by Mamdani and Assilian ([26]) and Sugeno (Takagi and Sugeno [27]). A sort 2 fuzzy set (T2FS) has grades of enrollment that are type-1 fuzzy [25, 28–34], so it very well may be known as a $fuzzyfuzzyset$, and in this way, IT2-FLS has the additional kind decrease measure. Therefore, the type-2 fuzzy logic controller (T2FLC) is widely used to handle uncertain and nonlinear environment more efficiently by making use of fuzzy sets [35–40]. Brief mathematical detailing is provided in Sect. 3

We have developed the following in this optimizing work:

- Optimization of COD solubilization % by T2FLC model is done.
- Influence of the independent parameter, time, temperature, and NaOH concentration is investigated.
- Legitimacy of the proposed model is finished by statistical analysis.
- The prediction efficiency of the proposed model, T2FLC, is compared with other soft computing techniques such as RSM and T1FLC.

The graphical abstract of the the proposed model is depicted in Fig. 1.

2 Type-2 Fuzzy Sets

A type-2 fuzzy set (T2FS) communicates by the non-deterministic truth degree having imprecision and weakness for a part that has a spot with a set [41]. A type-2 fuzzy set (T2FS) denoted by $\tilde{\tilde{A}}$ [42] is portrayed by a type-2 membership function (T2MF) $\mu_{\tilde{A}}(s,t)$ where $s \in X, \forall t \in J_s^t \subseteq [0,1]$ and $0 \leq \mu_{\tilde{A}}(s,t) \leq 1$ are defined in equation (1)

$$\tilde{\tilde{A}} = \{(s, t, \mu_{\tilde{A}}(s,t)) | s \in X, \forall t \in J_s^t \subseteq [0,1]\} \tag{1}$$

If $\tilde{\tilde{A}}$ is fuzzy type-2 (FT2) continuous variable, it is denoted in Eq. (2)

$$\tilde{\tilde{A}} = \left\{ \int_{s \in X} \left[\int_{t \in J_s^t} f_s(t)/t \right] /s \right\} \tag{2}$$

where $\int \int$ denotes as the union of s and t. If A is FT2 discrete, then it is denoted by equation (3)

$$\tilde{\tilde{A}} = \left\{ \sum_{s \in X} \mu_{\tilde{\tilde{A}}}(s)/s \right\} = \left\{ \sum_{i=1}^{N} \left[\sum_{k=1}^{M_i} f_{s_i}(t_k)/t_{ik} \right] /s_i \right\} \tag{3}$$

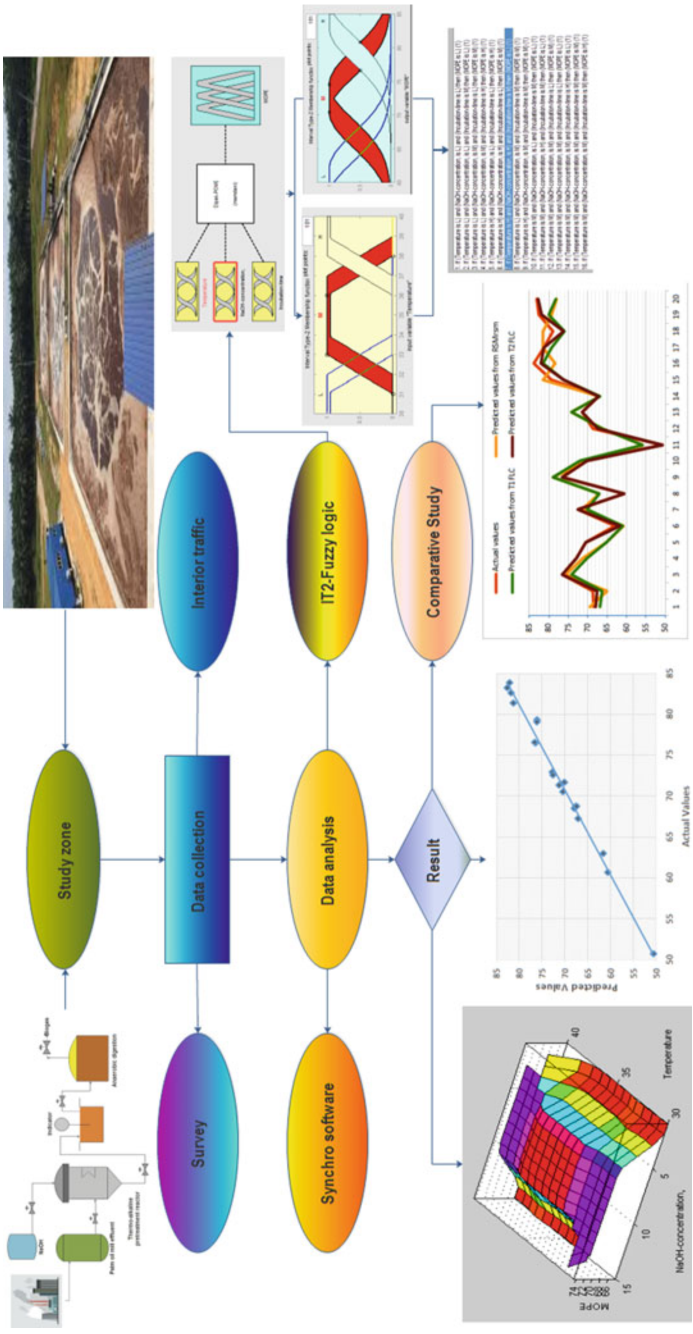

Fig. 1 Graphical abstract of the proposed model

where $\sum\sum$ denotes the union of s and t. If $f_s(t) = 1, \forall t \in [\underline{J}_s^t, \overline{J}_s^t] \subseteq [0, 1]$, the T2MF $\mu_{\tilde{\tilde{A}}}(s, t)$ is expressed by one type-1 inferior membership function, $\underline{J}_s^t = \mu_A(s)$ and one type-1 superior, $\overline{J}_s^t = \mu_A(s)$, then it is called an interval type-2 fuzzy set (IT2FS) defined by equations (4) and (5).

$$\tilde{\tilde{A}} = \left\{(s, t, 1) | \forall s \in X, \forall t \in [\underline{\mu}_A(s), \overline{\mu}_A(s)] \subseteq [0, 1]\right\} \tag{4}$$

The union of all the primary memberships is called the footprint of uncertainty (FOU) of $\tilde{A}$. The FOU$\tilde{A}$ can be characterized as

$$\text{FOU}(\tilde{A}) = \cup_{\forall s \in X} J_s = (s, t) : t \in J_s \subseteq [0, 1] \tag{5}$$

The FOU of type-2 fuzzy set $(\tilde{A})$ has been limited by two type-1 MFs called as lower membership function (LMF) and the upper membership function (UMF). The UMF and LMF are signified as $\overline{\mu}_{\tilde{A}}$ (s) and $\underline{\mu}_{\tilde{A}}$ (s) , individually, and are characterized as follows:

$$\overline{\mu}_{\tilde{A}}(s) = \overline{\text{FOU}(\tilde{A})} \tag{6}$$

and,

$$\underline{\mu}_{\tilde{A}}(s) = \underline{\text{FOU}(\tilde{A})} \tag{7}$$

where $\forall_s \in X$. Note that J_s is an interval set, i.e.,

$$J_s = (s, t) : t \in [\underline{\mu_{\tilde{A}}(s)}], [\overline{\mu}_{\tilde{A}}(s)] \tag{8}$$

3 Raw Material

Palm oil factory gushing (POME) was stored up from neighborhood palm oil factory. The collected effluent was stored in very low temperature, at the range of 4–6$^\circ C$. The reason for keeping it at a low temperature is to prevent microorganism deterioration. At the beginning of experiment, collected sample of POME was brought to room temperature. NaOH used for the experiment is of analytical grade, brought from MERCK.

3.1 Physicochemical Analyses and Experimental Method

Collected samples of POME are analyzed before anaerobic digestion, the total solid (TS), total suspended solid (TSS), volatile solids (VS), and volatile suspended solids (VSS) measured in accordance with standard methods used for the examination of water [43].

The pH of the sample POME is marked with a pH meter. The total chemical oxygen demand (TCOD) and soluble chemical oxygen demand (SCOD) were analyzed using the closed reflux colorimetric method. Characterization of the samples collected from mill is given in Table 1. The ratio of SCOD and TCOD is always used for evolution in the extent of hydrolysis reaction [44]. The COD solubilization % is calculated by Eq. (9) [8].

A series of tests is performed in this batch experiment under different criteria of the independent parameter, time, temperature, and NaOH concentration. In the experimental process, every flask contains 100 ml of the collected sample of POME, and a different quantity of NaOH added. The concentration range of NaOH used is given in Table 4. For achieving the anaerobic condition, every flask was purged with nitrogen gas and sealed with parafilm to make the system gastight. Finally, the series of samples is incubated for different time and temperature. The time and temperature range in operation is given in Table 4.

$$\text{COD Solubilization\%} = \frac{\text{Soluble Chemical oxygen demand after treatment}}{\text{Total Chemical Oxygen Demand after treatment}} \times 100 \qquad (9)$$

3.2 Experimental Design

Here, we have developed a triple-input and single-output type-2 fuzzy logic system for optimizing the solubilization of POME. The input parameters temperature, reaction time, and NaOH concentration are considered. The optimality of output from the pre-treatment of POME by the thermo-alkaline method depends on the extent of COD solubilization. Therefore, we consider this as an output parameter of the developed model. Range of all the independent parameter is considered for experimentation as well for optimization given in Table 2.

The structure of the Mamdani fuzzy inference system is depicted in Fig. 2. The input parameters, temperature, reaction time, NaOH concentration, and outer parameter used for the development of the model are divided into three linguistic terms, low (L), middle (M), and high (H), which is quickly processed by the type-2 fuzzy set theory lucidly. Interval type-2 fuzzy (IT2F) semantic factors are delays of mathematical factors as in they can address the state of a trait at a given interval by taking IT2F sets as their qualities. Membership function of input and output parameters is depicted in Figs. 3 and 4.

Table 2 Parametric analysis of raw POME sample

Parameter use for analyzing raw POME	Units	Ranges
Ph	–	4.1–5.0
Total solids-	mg/lit	34,110–60,800
Volatile solids	mg/lit	28,000–54,000
Total suspended solids	mg/lit	16,000–32,550
Volatile suspended solid	mg/lit	15,180–30,700
Total chemical oxygen demand	mg/lit	54,100–95,500
Soluble chemical oxygen demand	mg/lit	22,000–32,500

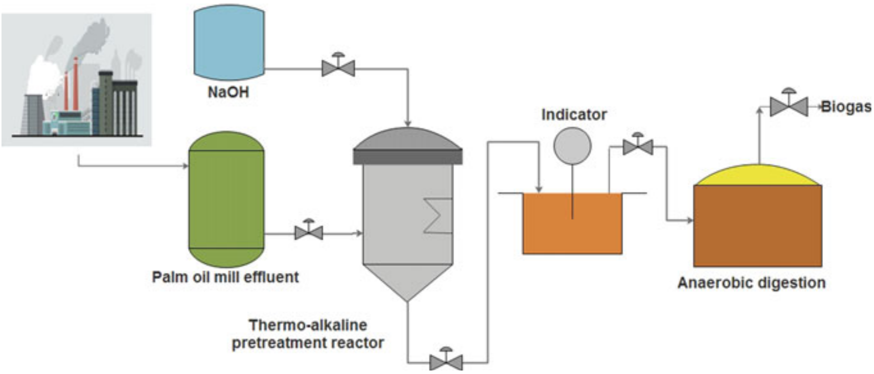

Fig. 2 Pre-treatment process diagram of the POME

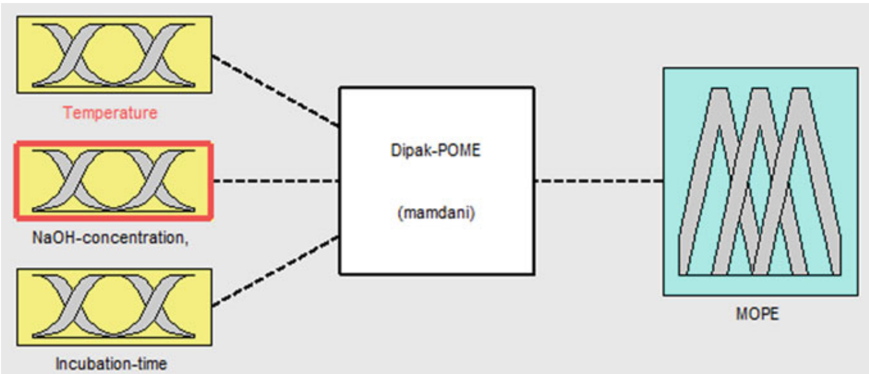

Fig. 3 Block diagram of the proposed model

Table 3 Ranges of parameter

Input parameter	Units	Labels				
		−1.682	−1	0	1	1.682
Temperature	C	26.6	30	35	40	43.4
NaOH concentration	g/L	1.27	4	8	12	14.73
Incubation time	h	7.64	24	48	72	88.36

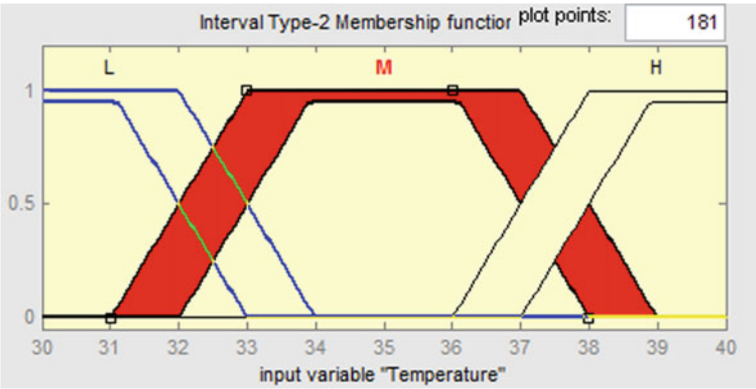

Fig. 4 Membership function of the input variable temperature

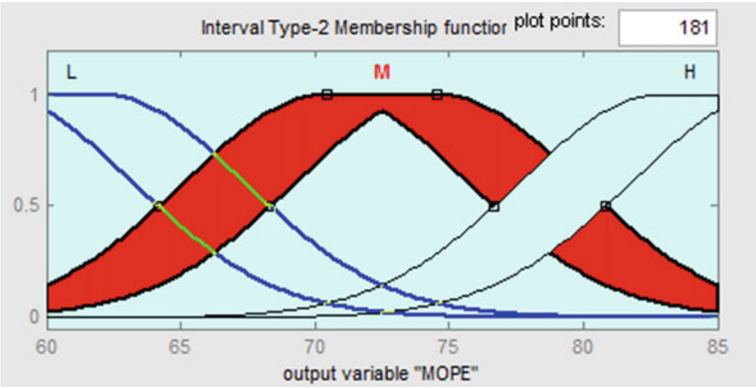

Fig. 5 Membership function of the input variable and COD solubilization%

1. If (Temperature is L) and (NaOH-concentration, is L) and (Incubation-time is L) then (MOPE is L) (1)
2. If (Temperature is L) and (NaOH-concentration, is L) and (Incubation-time is M) then (MOPE is L) (1)
3. If (Temperature is L) and (NaOH-concentration, is M) and (Incubation-time is L) then (MOPE is M) (1)
4. If (Temperature is L) and (NaOH-concentration, is M) and (Incubation-time is H) then (MOPE is H) (1)
5. If (Temperature is H) and (NaOH-concentration, is L) and (Incubation-time is L) then (MOPE is H) (1)
6. If (Temperature is H) and (NaOH-concentration, is H) and (Incubation-time is L) then (MOPE is M) (1)
7. If (Temperature is H) and (NaOH-concentration, is H) and (Incubation-time is M) then (MOPE is L) (1)
8. If (Temperature is L) and (NaOH-concentration, is M) and (Incubation-time is M) then (MOPE is M) (1)
9. If (Temperature is H) and (NaOH-concentration, is M) and (Incubation-time is M) then (MOPE is M) (1)
10. If (Temperature is M) and (NaOH-concentration, is L) and (Incubation-time is M) then (MOPE is L) (1)
11. If (Temperature is M) and (NaOH-concentration, is H) and (Incubation-time is M) then (MOPE is L) (1)
12. If (Temperature is M) and (NaOH-concentration, is M) and (Incubation-time is L) then (MOPE is M) (1)
13. If (Temperature is M) and (NaOH-concentration, is M) and (Incubation-time is L) then (MOPE is L) (1)
14. If (Temperature is M) and (NaOH-concentration, is M) and (Incubation-time is H) then (MOPE is L) (1)
15. If (Temperature is M) and (NaOH-concentration, is M) and (Incubation-time is M) then (MOPE is M) (1)
16. If (Temperature is M) and (NaOH-concentration, is M) and (Incubation-time is M) then (MOPE is H) (1)

Fig. 6 IF-THEN linguistic rule

3.3 Simulation of Experimental Design

In this optimization work, we have implemented 20 IF-THEN rules as depicted in Fig. 5. Evolution of the logical conjunction AND and OR has been done by using min and max operators. Min and max operators are utilized for suggestion and collection technique, individually, whose general form is If (first input parameter) is A1 AND (second input parameter) is $A_2, \cdots$ AND (mth input parameter) is A_m THEN (output parameter) is B, where $A_1, \cdots, A_m$ are the linguistic values of the respective input variable and B linguistic values of output variables. The last step is the defuzzifications step which is the interaction to changes over the fluffy yield of the induction motor to fresh esteem utilizing participation capacities are finished by the centroid strategy. Predicted values obtained by stimulation of the proposed model,T2FLC, T1FLC, and RSM [15] are given in Table 4 and plotted in Fig. 10.

From the data set of output and input variable, Table 4, three dimension surface plot is developed in T2FLC environment to investigate the variation of solubilization % of POME to interactive effect of the independent variable which is in the experimental range . All the generated surface plots are depicted in Figs. 6, 7, and 8. From Figs. 6, and 7, it is observed that NaOH concentration is considered being the most important factor among the three. The solubilization % increases gradually on the increase in alkali concentration in the process. According to some writing, expansion in the convergence of antacid increments the solubilization in different interaction like saponification and balance of various acids framed from the debasement of specific materials[8]. According to Fig. 8, the effect of incubation time on solubilization % is more dominate on temperature. At lower temperatures, more incubation time is required to attain higher % of solubilization Fig. 9.

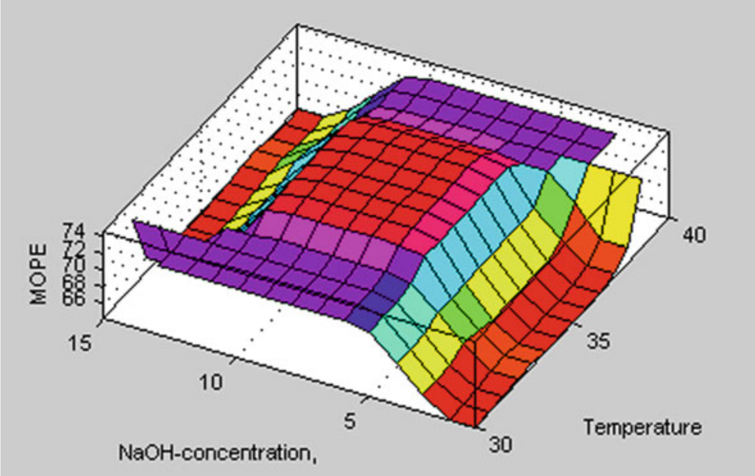

Fig. 7 Surface contour plot of COD solubilization% on NaOH concentration and temperature

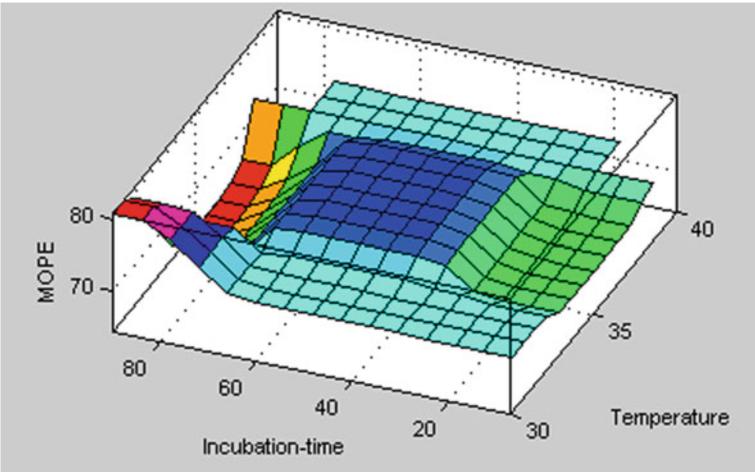

Fig. 8 Scatter plot between predicted values from T2FLC model and actual values of COD solubilization %

4 Results and Discussion

For every input, the proposed model is stimulated to obtain output results. Experimentally, getting the result is termed as actual value, and data obtained by stimulating the independent data set in the T2FLC model is termed as predicted values. The expectation capacity of the created model is determined by utilizing the test information in the prepared information and looking at the real qualities and anticipated qualities. In

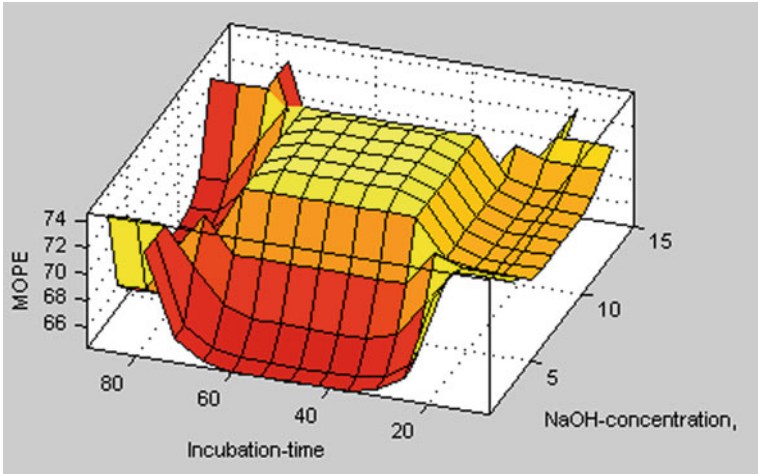

Fig. 9 Surface contour plot of COD solubilization % on incubation time and NaOH concentration

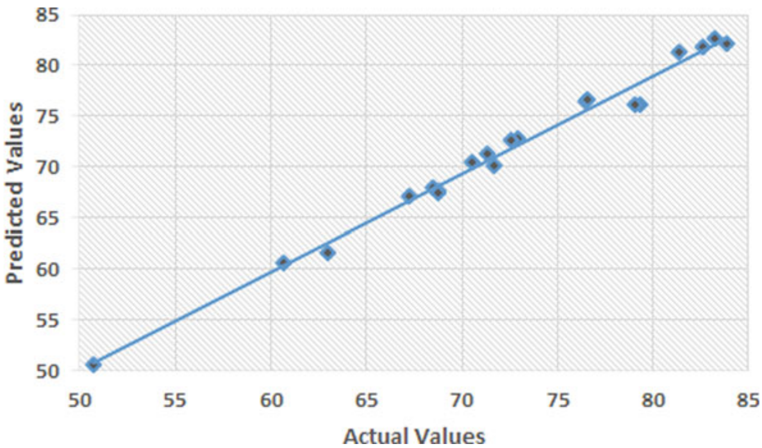

Fig. 10 Surface contour plot of COD solubilization % on temperature and incubation time

actual various predicted data set for COD solubilization depicted in Fig. 8 and Fig. 9. From the figure, it is observed that the predicted data set is obtained from T2FLC distributed near the straight line. For the measurement of the prediction capability, the statistical parameter is used. The statistical parameters are the root mean square error (RMSE), the determination coefficient (R^2), mean absolute percentage error (MAPE), and mean absolute error(MAE). All the statistical parameters are calculated by using Eq. (10), Eq. (11), Eq. (12), and Eq. (13), respectively, where n is the quantity of information designs in the informational index, y_{pred_i} demonstrates the anticipated worth, i is specific information point, and y_{act_i} is the real worth (which is depicted in Fig. 11).

Table 4 Statistical data analysis for T2FLC and T1FLC and RSM

FIS	RMSE	R^2	MAPE	MAE
T2FLC	0.104	0.991	4.703	0.072
T1FLC	0.056	0.953	3.965	0.039
RSM	0.051	0.923	3.121	0.032

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_{\mathrm{pred}_i} - y_{\mathrm{act}_i})^2} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{\mathrm{pred}_i} - y_{act_i})^2}{\sum_{i=1}^{n} y_{\mathrm{act}_i}^2} \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|(y_{\mathrm{pred}_i} - y_{\mathrm{act}_i})|}{y_{\mathrm{pred}_i}} \times 100\% \tag{12}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_{\mathrm{pred}_i} - y_{\mathrm{act}_i}| \tag{13}$$

The superiority of the proposed model can be predicted by analyzing the outcome of the statistical parameter. The closer the value R^2 to 1 and the smaller the value of RMSE, MAPE, and MAE, the greater the accuracy of the proposed model. The prediction capability of all the intelligent computing methods like RSM, T1FLC, and T2FLC is compared in terms of this statistical parameter, R^2, RSME, MAPE, and MAE. The outcome of all the parameters of all intelligent computing methods is given in Table 3 and Fig. 11.

5 Potential Application and Challenges

As per some literature, the solubilization process is considered to be beneficial for improving the anaerobic digestion rate and production of methane [8, 45]. Higher the generation of methane, more is the production of renewable energy. The biggest obstruction faced by the palm oil mill all over the world is a continuous threat to the ecosystem. The extensive treatment system is the traditional method widely used for pre-treatment POME. There are a couple of regions that value abuse in

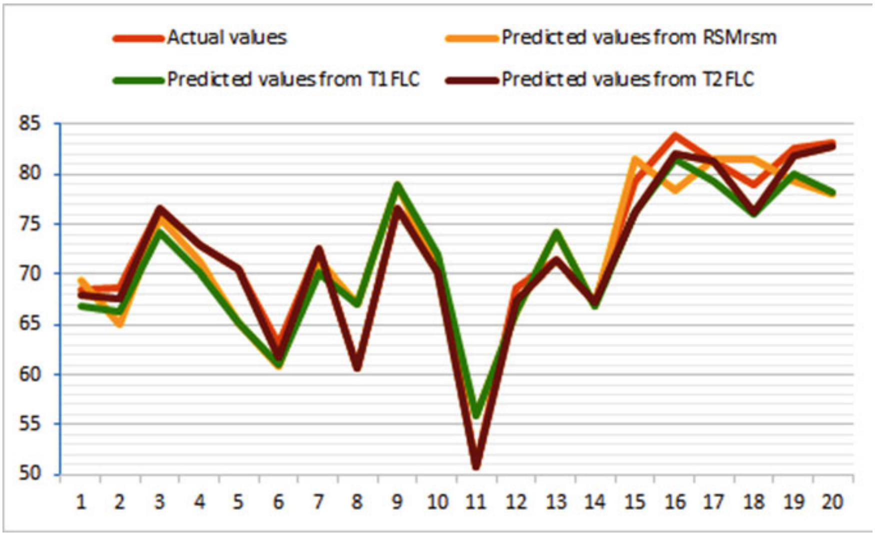

Fig. 11 Trajectory of actual value and predicted value evaluated from various soft computing techniques

Table 5 COD solubilization of POME

Data Set	Input			Output			
	Temperature	NaOH	Time	Experimental	RSM	T1FLC	T2FLC
1	30	4	24	68.48	69.4	66.81	68.01
2	30	4	72	68.74	65.05	66.28	67.6
3	30	12	24	76.51	75.6	74.19	76.51
4	30	12	72	72.9	71.24	70.2	72.9
5	40	4	24	70.55	65.29	65.29	70.55
6	40	4	72	62.98	60.92	61.01	61.72
7	40	12	24	72.61	71.49	70.1	72.61
8	40	12	72	60.67	67.12	67.12	60.67
9	36	8	48	76.59	78.89	78.89	76.59
10	43.4	8	48	71.67	70.4	71.97	70.1
11	35	1.27	48	50.7	55.82	55.82	50.7
12	35	14.73	48	68.77	66.25	66.25	67.5
13	35	8	7.64	71.37	74.27	74.27	71.37
14	35	8	88.36	67.23	66.93	66.93	67.23
15	35	8	48	79.36	81.5	76.22	76.2
16	35	8	48	83.85	78.34	81.5	82.1
17	35	8	48	81.33	81.5	79.29	81.33
18	35	8	48	79.03	81.5	76.1	76.2
19	35	8	48	82.64	79.3	80.1	81.81
20	35	8	48	83.22	78.1	78.2	82.7

this coordinated POME treatment approach as per Loh. et al. [46]. At first, the reduction of the leading wastewater stream obtains from the milling process in the palm oil plant. Secondly, in light of overseeing POME employing biogas catch and usage, preferential treatment of POME for the decrease of undesirable constituents, for example, hydrogen sulfur, in the biogas is delivered that will act as a corrosive agent for some machinery. Consequently, thermo-alkali-treatment could end up being a potential pre-treatment to improve anaerobic processing of POME and improve methane yield.

6 Conclusions

It is essential to minimize the pollution rate and to increase the solubilization % to stabilize the palm oil business model and too wide up the spectrum of its industrial profitable application. In this paper, Mamdani interval type-2 fuzzy logic inference approach which has three inputs and one output is used to predict the solubilization %. The influence of the independent parameters, reaction time, NaOH concentration, and temperature is investigated on the output parameter. The influence of the input parameter on output does not follow the trend which was traced by T2FLC techniques in an efficient way for developing the inferences train so that different sorts of procedure conditions could be anticipated. From the predicted data set (Table 4), third dimension surface plots are developed to study the variation of output concerning the interactive effects of inputs (Figs. 5, 6, and 7). From the graphical analysis, it is concluded that NaOH concentration is a more influencing parameter above all. For the validation of the performance efficiency of the T2FLC model, some of the statistical analyses like R^2, RMSE, MAPE, and MAE are evaluated and given in Table 3. In this paper, the developed model, T2FLC, is compared with other soft computing techniques such as RSM and T1FLC. The R^2 value of T2FLC is 0.991 which is the closest approach to 1 in comparison with other two, RSM and T1FLC, whose R^2 is 0.923 and 0.953, respectively. It is concluded that the prediction efficiency of the T2FLC model considers being effective and accurate. If the developed mathematical model is applied in palm oil mill effluent, it will prove to be beneficial for the engineers to set the independent parameters promptly to get the desired % of solubilization. The prediction of the % of solubilization during the effluent treatment phase will help the farm to evaluate the yield of the methane Table 5.

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