Review on Optimization of Biodiesel Production through Various Statistical and Computational Tools

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Abstract— The enhancement of biodiesel production can best be obtained by applying statistical and computational techniques. The present work described the various research works on optimization techniques applied to biodiesel production. It is observed that for maximum biodiesel production firstly RSM approach is applied and if biodiesel yield is still less than 90 % (by weight) computational techniques must be recommended.

Key words: Statistical approach, Biodiesel production, RSM, ANN, GA

I. INTRODUCTION

Different optimization techniques have been carried out for enhancing the biodiesel production by various researchers [Silitonga et al., 2013; Dhingra et al., 2013a; Dhingra et al., 2013b; Dhingra et al., 2014a; Dhingra et al., 2014b; Dhingra et al., 2014c; Dhingra et al., 2014d; Dhingra et al., 2016a; Dhingra et al., 2016b] such as response surface methodology, Taguchi, GA, ANN etc. Out of these techniques, RSM is a useful technique in predicting the optimal trans-esterification process parameters [Chen et al., 2008; Abdullah et al., 2009; Jeong and Park, 2009; Silva et al., 2011; Abuhabaya et al., 2013]

As a thumb rule, the classical method for determining optimal biodiesel production process is by varying one process parameter while keeping others at a constant level. This practice is time consuming, needs large number of experiments and the results are not accurate and reproducible. In such practice, interaction effect between the variables is not taken in consideration. In recent times, response surface methodology (RSM), a good statistical experimental design tool, has proved its worth and is now commonly used in optimization experiments of similar processes to provide a fast and efficient way to understand and identify the significant process variables, thereby saving time and maintaining key information on each component. It includes factorial design and regression analysis that helps in evaluating significant variables and plotting them simultaneously against each other to evaluate the interaction and their effects on each other simultaneously.

Sheih et al. (2003) utilized lipase based catalyst for the optimization of soybean biodiesel production in the presence of methanol through response surface methodology (RSM) based on central composite rotatable design (CCRD). An optimum biodiesel conversion of 92.2 % in trans-esterification process was observed at 3.4:1 molar ratio of methanol to soybean oil, 0.9 BAUN (Batch Acidolysis Units), 5.8 % water content, 36.5°C temperature in 6.3 hours.

Izadifar (2005) applied artificial neural network (ANN) to predict total trans- isomer content (produced during vegetable oil hydrogenation) as well as oleic acid, linoleic acid, linolenic acid content using multi-layer back propagation training algorithms. The eight variables (reaction temperature, H_2 pressure, catalyst concentration, mixing rate, iodine value and initial unsaturated fatty acid contents) were considered as inputs to ANN model. The neural model was trained, tested and evaluated from various experimental data obtained from pilot-plant hydrogenation reactor and using these data the network generalization was evaluated. Comparison of actual and predicted results showed the authenticity of predicted neural model.

Ghadge and Rehman (2006) evaluated optimum trans-esterification process parameters for mahua (madhua indica) oil using response surface methodology. Firstly the pre-treatment process was done to mahua oil (to decrease the free fatty acid) and then trans-esterification process was performed at various experiments suggested by CCRD of RSM. The FFA value was reduced to less than 1 % at 60°C reaction temperature, 0.32 v/v methanol to oil ratio, 1.24 % v/v H_2SO_4 catalyst and 1.26 hours reaction time. The maximum conversion of biodiesel was achieved at 0.25 v/v methanol to oil ratio and 0.7 % KOH (as an alkaline catalyst).

Bouaid et al. (2007) experimentally investigated high oleic sunflower oil (HOSO), high and low erucic Brassica carinata oils (HEBO and LEBO) for optimization of biodiesel production with ethanol in the presence of an acid (H_2SO_4) or alkaline (KOH) catalyst. Factorial design and response surface methodology approach were used for the required purpose. The model was found to be of second order for LEBO process in order to adequately study the biodiesel conversions as a function of temperature and catalyst concentration. The best result was found to be at 32°C with 5:1 ethanol/oil molar ratio and 1.5 % of KOH for HEBO and HOSO while 20°C with 6:1 ethanol/oil molar ratio and 1.5 % of KOH for LEBO.

Kumar and Bansal (2007) examined seven neural network architectures, three training algorithms along with ten different sets of weight and biases to predict various properties (flash point, fire point, viscosity and density) of diesel-soybean biodiesel blend (prepared from trans-esterification with methanol in the presence of alkaline catalyst). The results showed that an architechture 2-7-4 with Lavernberg-Marquardt (LM) training gave the best estimation of properties for diesel-biodiesel blend.

Bezerra et al. (2008) studied the various optimization techniques along with their applications to achieve the required objectives. Symmetrical experimental designs (three level factorial, Box-Behnken, Central Composite and Doehlert Designs) were compared in terms of their characteristics and efficiency. Applications of these techniques in analytical chemistry, utilization of artificial neural networks for modeling and multi-objective optimization through desirability functions in RSM were also presented. Chen et al. (2008) applied RSM on acid oil in the presence of methanol with lipase based catalyst for predicting optimum biodiesel production.

Domingos et al. (2008) experimentally investigated trans-esterification of Raphanus sativus (L. Var.) crude oil by applying response surface methodology. The biodiesel yield of 99.10 % was obtained at optimum values of input process parameters of 38°C reaction temperature, 11.7:1 ethanol to oil molar ratio and 0.6 wt. % NaOH concentration. The second optimum condition yielded 94.5 % biodiesel and required 50 % less ethanol and 90 % less catalyst consumption. Also Yuan et al. (2008) applied the same technique (RSM) for the optimum conversion of high FFA waste rapeseed oil to biodiesel.

Abdullah et al. (2009) investigated K/SBA 15 as catalyst in the trans-esterification of palm oil with methanol by utilizing central composite design of RSM. The biodiesel yield of 93 % was obtained at optimum conditions of 70°C reaction temperature, 11.6 mol/mol methanol to oil ratio, 3.91 wt. % catalyst loading and 5 hours reaction time. Also catalyst loading and reaction time were the significant factors in the production of biodiesel.

Halim et al. (2009) suggested optimum biodiesel yield from waste cooking palm oil at two important reaction variables (packed bed height and substrate flow rate) by utilizing central composite design of response surface methodology. The maximum biodiesel yield (FAME) of 80.3 % was obtained at 10.52 cm packed bed height and 0.57 ml/min substrate flow rate. The mass transfer effect in the packed bed reactor was also studied and the results showed that the FAME yield model was mass transfer controlled. Jeong and Park (2009) utilized same approach for optimum conversion of castor oil to biodiesel using methanol in trans-esterification process.

Rajendra et al. (2009) applied hybrid ANN-GA for predicting best pre-treatment process parameters in order to bring down the free fatty acid (FFA) levels of oil mixture (mahua and simarouba). Acid pre-treatment followed by main base trans-esterification reaction was developed to enhance biodiesel yield at a reaction temperature of 60°C. Biodiesel conversion of more than 90 % was observed by gas chromatography (GC). The important fuel properties were also found to be closer to commercial diesel and biodiesel standards.

Fahmi and Cremaschi (2012) developed ANN model for the optimization of biodiesel synthesis plant i.e., the one that gives the minimum net present sink. Various data were trained through ANN to reduce the computational cost of solving the resulting disjunctive programming through surrogate models. The total net present sink of about $41 million was obtained with difference of less than one percent from the results obtained by simulator. Shahbaz et al. (2012) examined glycerol removal in the production of biodiesel by the use of artificial neural networks (ANNs). Training was done on Lavenberg-Marquardt (LM) optimization method at feed forward neural network with 4 hidden neurons. The results from ANN were in agreement with actual one and an average deviation of 6.46 % was observed.

II. Conclusion

The biodesel production can be enhanced by first applied RSM approach and if the biodiesel yield is less than 90 % (by weight) other techniques like ANN, GA etc. helps to achieve the desired enhancement of biodiesel yield. Therefore it is concluded that statistical and computational techniques are most effective method to enhance the biodiesel production at optimum combination of trans-esterification process parameters.

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