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OPTIMIZATION OF OCTADECANOIC ACID CONVERSION TO STEAROYL LYSINE SURFACTANT APPLYING BOX BEHNKEN DESIGN

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ABSTRACT

Biodegradable surfactants can be obtained from natural lipo amino acids from renewable raw materials. Stearoyl lysine is an environmentally friendly surfactant and was synthesized by amidification reaction of octadecanoic acid and lysine. Evaluated for their reaction variables, such as catalyst ratio (A), substrate ratio (B), and solvent ratio (C), to the amount of octadecanoic converted to stearoyl lysine has been optimized using Box Behnken Design. Significantly, variables A, C, AC, BC, A^2, B^2, and C^2 had a significant effect on the response, namely the conversion of octadecanoic acid. However, the quadratic model needs to be reduced because the difference between the adjusted R-squared and the predicted R-squared is more than 0.2.

Keywords: octadecanoic acid, lysine, box-behnken design, quadratic model, optimization.

INTRODUCTION

Stearoyl lysine is a non-ionic surfactant with good application prospects due to its unique safety and performance. Stearoyl lysine surfactant is a type of surfactant of amino acids with polar head groups and hydrophobic tails connected by amide bonds. This surfactant can be applied to skincare formulas and cosmetics, and cleaning products [1,2] because it has good physicochemical properties and antimicrobial activity for the skin [3, 4]. Furthermore, Stearoyl lysine has attracted great interest because it is derived from renewable sources, is not harmful to the environment, and is also more biodegradable. In addition, it has been found that this class of surfactants exhibits lower toxicity when compared to conventional surfactants [5].

Protein-based surfactants are an excellent type of biodegradable and renewable candidate. Proteins are reacted with different fatty acids such as lauric acid, myristic acid, and palmitic acid to produce N-acyl products according to their respective characteristics. Amino acids are proteins that can be used for the manufacturing process [6, 7, 8].

Octadecanoic acid is a mixture of solid organic acids obtained from fatty acids, primarily octadecanoic acid (C18H36O2) and hexadecanoic (C16H32O2) in the form of a rigid solid, white or pale yellow, slightly odorless, and similar to waxy fat. Octadecanoic acid is incompatible with most metal hydroxides and may be incompatible with producing and oxidizing agents. Octadecanoic acid plays a role in providing consistency and hardness to soap and having the ability as a compatibilizer and has properties as a dispersant and lubricant. Octadecanoic acid has been widely used in synthesizing surfactants because octadecanoic acid can be obtained in large quantities from vegetable oil derivatives such as palm oil. In addition, vegetable oil is an economical material and is most often found. Lysine is one of the essential amino acids. Lysine is also one of the efficient amino acids in feed raw materials for protein sources, especially from vegetable ingredients. In addition, lysine is anti-bacterial and good for pharmaceutical and biomedical applications [1, 9, 10, 11].

Sodium methoxide or potassium methoxide has also been proposed as a catalyst. This catalyst is more soluble in methyl formate and gives a higher reaction rate. Under conditions of high pressure, the reaction temperature and catalyst concentration must be increased to achieve an acceptable conversion. The carbonylation reaction was carried out at a pressure of 45 bar, a temperature of 80oC and 2.5% sodium methoxide as a catalyst. About 95% of carbon monoxide, but only about 30% of methanol, is converted in this state. However, quantitative conversion of methanol to methyl formate can be achieved by recycling unreacted methanol [12, 13, 14].

The occurrence of competition between the formation of amides, esters, and amide esters which causes a decrease in the yield value of alkanolamide surfactants, is one of the problems in the manufacture of surfactants. So, the reaction conditions need to be regulated properly; one way is to optimize the reaction of the research variables using the Response Surface Method and Box Behnken Design [15, 16].

Box and Behnken are good designs for response surfaces because they allow for an estimation of the parameters of a quadratic model, construct sequential designs, detect model flaws, and use beams. The Box-Behnken design and other response surface designs (central composite, Doehlert matrix, and full three-level factorial design) have shown that the Box-Behnken Design and Doehlert matrix are slightly more efficient than the Central Composite Design but much more efficient than the three-tier factorial design. full [17, 18, 19].

MATERIALS AND METHODS

Materials

The Octadecanoic acid and sodium methoxide were purchased from Merck (Darmstadt, Germany) and

lysine was purchased from GNC (Pittsburgh, USA). Hexane, acetone, and all other chemicals and solvents used in this study were analytical grade.

Optimization of Stearoyl Lysine

The design matrix and the actual data of the octadecanoic acid conversion response for the optimization experiments are outlined in Table-1. The actual data were obtained by the following method. Octadecanoic acid was dissolved in hexane-isopropanol with lysine by refluxing at boiling point of hexane for four h, using a round bottom flask equipped with a water-cooled condenser and magnetic stirrer. Next, sodium methoxide (NaOCH3) catalyst is added with a ratio of 3% by weight percent; 5%; 7% of octadecanoic acid into a beaker glass. The reaction mixture was conducted at 60oC and 200 rpm. After the reaction time is reached, the mixture is separated from the catalyst by filtration, the solvent is evaporated, and the percent conversion of octadecanoic acid is calculated.

Design Expert 10 software is used for formulation and response design. Two groups of variables are used, namely fixed variables and independent variables. The reaction temperature and time were selected variables because they were considered less influential on the response. In contrast, the catalyst, substrate, and solvent ratios were used as changing variables because these three variables were considered to affect the response.

The optimization step using the Behnken Box begins by setting the lower and upper limits of each variable so that the amide yield response of each combination of variables can be known. So, in this study, the independent variables used in the experimental design are the catalyst ratio (A, 3-7 %w Catalyst/Acid), the substrate ratio (B, 2-4 M Lysine/Acid), and the solvent ratio (C, 1-3 Solvent/Acid).

RESULTS AND DISCUSSIONS

Optimum operating conditions for the independent variables were determined to obtain information on the maximum conversion gain of octadecanoic acid. The single response optimization of the experimental design was carried out, starting with first-order analysis (linear model). The significance value of the Lack of Fit (LOF) can be used to see the suitability of the order. In the first order, the results are expected to reject H0 or LOF so that the first order does not match. This is because the linear model is generally a straight line so the optimum point cannot be found [16].

However, if order 1 has a high LOF, it is necessary to use the steepest accent to find new experimental levels and then retry. If the analysis results using order one are not appropriate, then it can be continued on the analysis of order 2. The order 2 model is expected to have the proper LOF so that the correct setting is found to produce the optimum response. If the optimization results have been obtained, the residual assumptions will then be tested against the equation results for each response [18].

Table-2 shows the generated summary statistics model. It can be seen that the resulting adjusted R-squared is excellent, namely 0.9691. This indicates that the resulting model is perfect. In addition to looking at the p-value of the model, where the p-value is not more than the value of, it is necessary to look at the R2 value of a model. The value of R2 will be displayed in the form of a percent to make it easier to see the size of the influence of the independent variable on the measured parameters. The larger the R2 value of a model, the better the relationship between the variables.

On the other hand, the smaller the R2 value, the weaker the relationship between the variables [16, 19]. The value of the coefficient of determination (R2) generated by the model is 0.9134. This shows that a significant regression value has a good influence on the independent variables.

Table-3 shows the Analysis of Variance for the response surface quadratic model. It can be seen that the model F-value of 17.40 implies the model is significant because there is only a 0.29% chance that this large F-value occurs due to noise. Value of "Prob > F" less than 0.0500 indicates model terms are significant. A, C, AC, BC, A^2, B^2, C^2 are significant model terms. A value greater than 0.1000 indicates the model term is not significant.

The results in Table-3 also show that the combination of independent variables can achieve the optimal combination according to the response variable because the DF value is close to one. On the other hand, the combination of independent variables is difficult to reach the optimal point based on the response variable if the DF value is close to zero [16].

If the results of the analysis of variance show that there are many non-significant term models, it is necessary to reduce the model, to improve the quality of the resulting model. The R-squared of the model is 0.9691, then the Adj R-squared is 0.9134, and the Pred R-squared is 0.5049. The "Pred R-squared" of 0.5049 is not close to the "Adj R-squared" of 0.9134 as one might typically expect because the difference is more than 0.2. This shows a significant block effect or a possible problem with the model and data.

Model reduction for that can be considered, apart from the response transformation. The resulting adeq precision is 14,150. Model precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The resulting percentage is 14,150, which indicates that it is an adequate signal, and the model can be used to navigate the design space.

The RSM equation for optimizing the three variables A, B, and C on the octadecanoic acid conversion response follows. The final equation in terms of coded factor is:

Acid conversion = +76.92 +0.86*A -0.25*B +1.89*C -0.66*AB +1.27*AC +1.46*BC +2.74*A2 +1.39*B2 +3.05*C2

The equation in terms of coded factors will then be used to make predictions regarding the response for each level of each factor. As a given default, +1 is the code for the high levels, and -1 is the code for the low levels. The negative sign in the equation indicates an inverse relationship with the expected response. Meanwhile, the final equation in terms of actual factors is:

Acid conversion = +123.75938 -6.70875*A -9.85750*B -17.86500*C -0.32875*AB +0.63375*AC +1.45500*BC +0.68563*A2 +1.39000*B2 +3.05500*C2

Where A is the catalyst ratio (%w Catalyst/Acid), B is the substrate ratio (M Lysine/Acid), and C is the solvent ratio (Solvent/Acid). In the above equation, the levels have been written in the original units for each factor. After the regression model is generated, a normal probability plot test is needed. Uninormality is needed to find out whether data can be said to be normally distributed or not. The normality of the distribution of data must be met if a parametric statistical analysis is carried out, such as this multiple linear regression analysis.

Table-1. Matrix design and actual data of octadecanoic acid conversion response.

Run	A-Catalyst Ratio	B-Solvent Ratio	C-Subtrate Ratio	R1-Conversion (%)
1	5	2	1	81.42
2	7	3	3	87.50
3	3	4	2	81.37
4	5	4	3	84.22
5	3	3	1	80.47
6	3	2	2	80.32
7	7	4	2	80.47
8	5	4	1	77.77
9	7	2	2	82.05
10	5	3	2	76.92
11	3	3	3	81.95
12	5	3	2	76.92
13	5	2	3	82.05
14	5	3	2	76.92
15	7	3	1	80.95

Table-2. Model summary statistics.

Source	Standard Deviation	R- Square	Adjusted R-Square	Predicted R- Square
Linear	2.72	0.2997	0.1088	-0.1238
2 FI	2.85	0.4424	0.0242	-0.3891
Quadratic	0.85	0.9691	0.9134	0.5049
Cubic	0.00	1.0000	1.0000	

Table-3. ANOVA for response surface quadratic model for stearoyl lysine synthesis.

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob>F
Model	112.92	9	12.55	17.40	0.0029
A-Catalyst Ratio	5.88	1	5.88	8.16	0.0356
B-Substrate Ratio	0.51	1	0.51	0.70	0.4408
C-Solvent Ratio	28.54	1	28.54	39.58	0.0015
AB	1.73	1	1.73	2.40	0.1822
AC	6.34	1	6.43	8.91	0.0306
BC	8.47	1	8.47	11.74	0.0187
A^2	27.77	1	27.77	38.51	0.0016
B^2	7.13	1	7.13	9.89	0.0255
C^2	34.46	1	34.46	47.79	0.0010
Residual	3.61	5	0.72		
Lack of Fit	3.61	3	1.20		
Pure Error	0.000	2	0.000		
Cor Total	116.53	14			

Figure-1 shows this normality test for externally studentized residuals. The technical use of this normality test is carried out on the residual value in the regression model and not using the value of each research data. The normality of the residuals can be done by looking at the resulting plot points [16]. The results of the normality test in Figure-1 conclude that the plot points are located around the diagonal line, which means the data is normally distributed.

The plot of externally studentized residuals against the predicted conversion is shown in Figure-2. Figure-2 is used to check for constant error, and it can be seen that the resulting points are random and do not form a certain pattern. This is in line with Figure-1, which shows that the residual values are normally distributed.

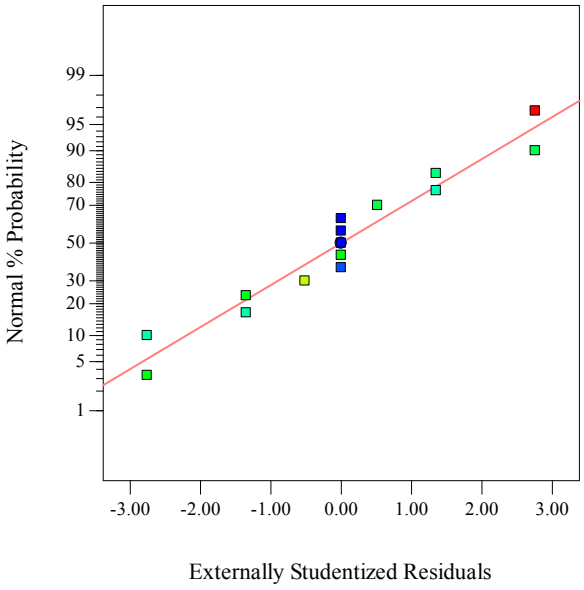

Figure-1. A plot of normality test on externally studentized residuals.

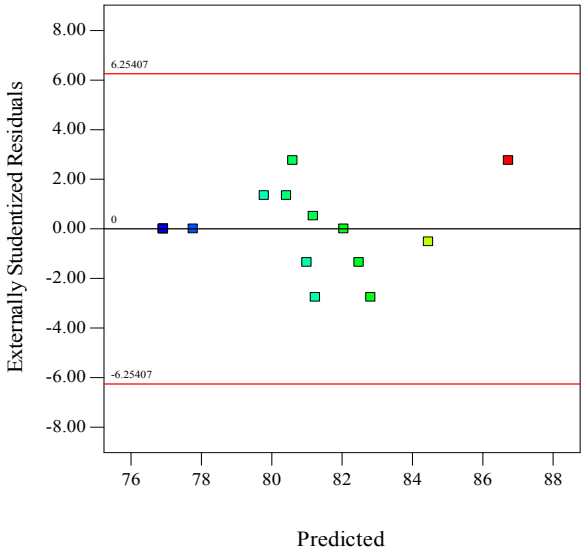

Figure-2. A plot of externally studentized residuals against predicted conversions.

The plot of externally studentized residuals was also observed for the run numbers, as shown in Figure-3. 15 run numbers were executed, and this plot it shows that the residual values are random and do not form a specific pattern. So the assumption of the residual versus run can be accepted to strengthen the resulting regression model [16].

Figure-4 is the output of the normality test between the predicted conversion and the actual conversion. Based on Figure-4, it can be seen that the plotting points contained in this figure follow a diagonal line. So this is also the basis for deciding that the predicted value generated from the regression model will be in line with the actual conversion value generated from the experiment.

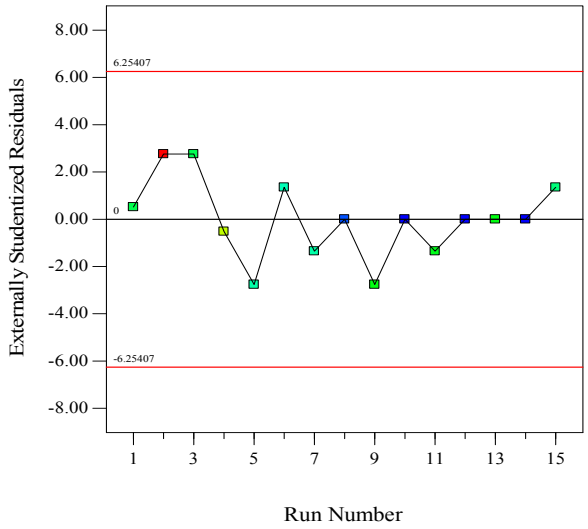

Figure-3. A plot of externally studentized residuals against the run number that is run.

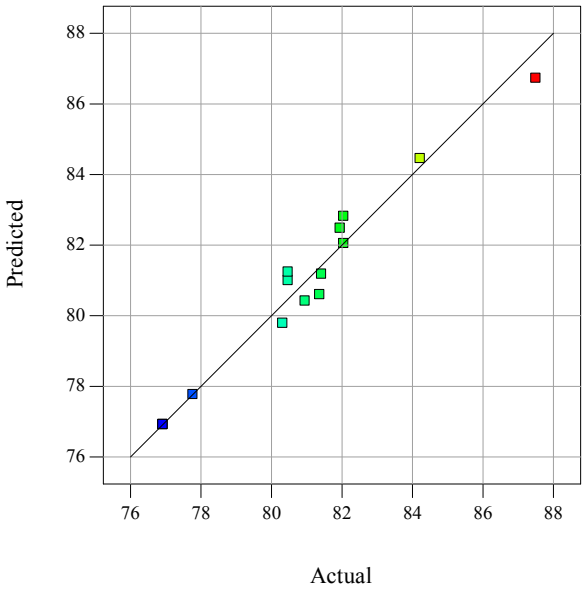

Figure-4. A plot of normality test output between predicted conversion and actual conversion.

From Figure-4, it can be seen that the smaller the difference in the acquisition between the prediction conversion data and the actual data, the better the resulting equation and vice versa if the deviation of the predicted data is farther away, the resulting equation is not good. The lower the standard deviation number, the closer the data is to the average, whereas the standard deviation value is higher than the width of the data variation range. So it can be concluded that the equation model generated through statistical methods is acceptable because the resulting deviation is slight.

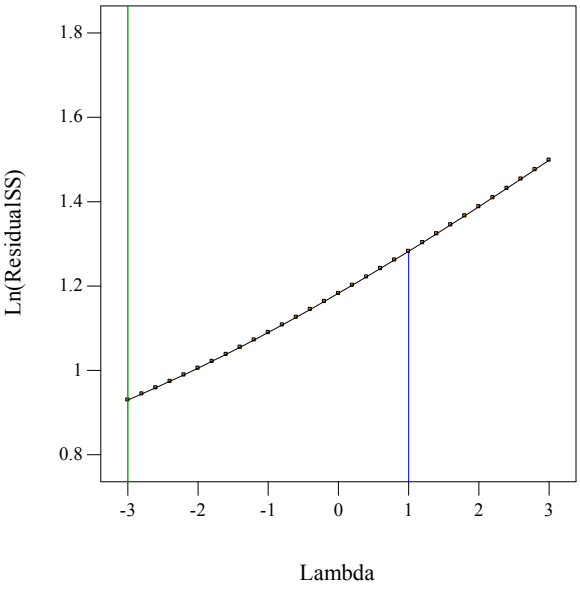

Figure-5. Box-Cox plot for power transforms.

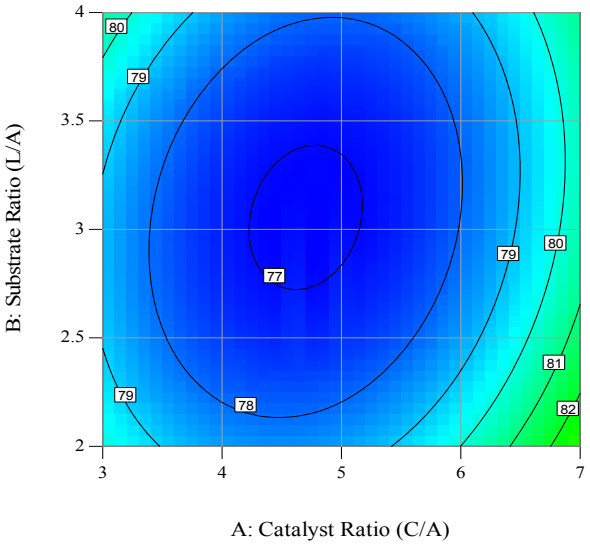

Figure-6. Conversion plot of octadecanoic acid on the interaction of catalyst ratio and substrate ratio in a fixed solvent 2.

Figure-5 shows a Box-Cox plot to determine if the transformation is appropriate. In Figure-5, the x-axis plot represents the values for the data transformation. The y-axis represents the estimated standard deviation of the transformed values after being standardized. In the Box-Cox transformation, if the value is 1, this indicates that original data should be used [16]. Therefore, if it is found that the confidence interval for the optimal includes 1, it can be concluded that the transformation is not required. If the value is not 1, it is necessary to transform the data using the Box-Cox transformation to be similar to a normal distribution.

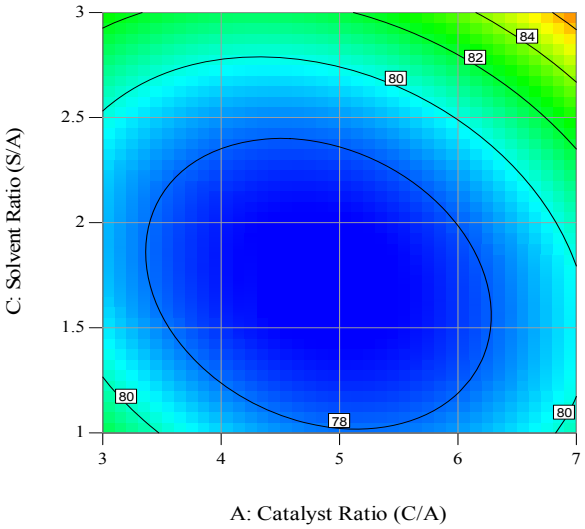

Figure-7. Conversion plot of octadecanoic acid on the interaction of catalyst ratio and solvent ratio on a fixed substrate 3.

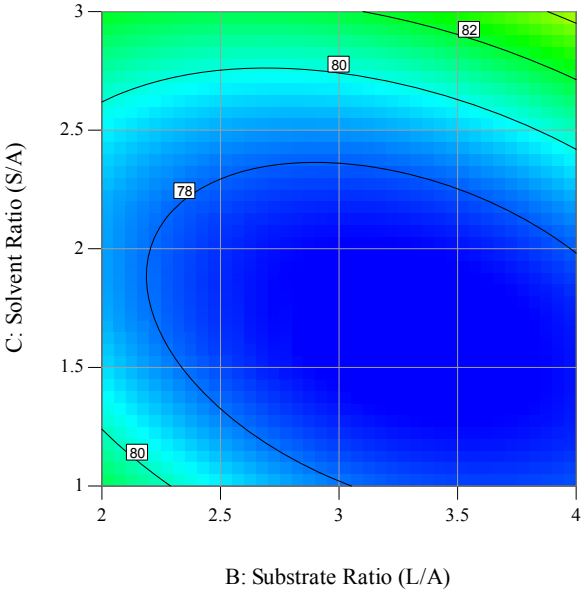

Figure-8. Conversion plot of octadecanoic acid on the interaction of substrate ratio and solvent ratio on a fixed catalyst 5.

Interaction Effect on the Contour Plot

The interaction between the three variables on octadecanoic acid conversion is observed in the contour plots of Figures 6, 7, and 8. In Figure-6, the contours of the interaction between A and C are observed. The middle of A=5 and B=3 will reduce the fatty acids converted to amides. The best results for this interaction were observed using A=7 and minimum B, or B=4 and minimum A. In these two conditions, the converted fatty acids reached >80%.

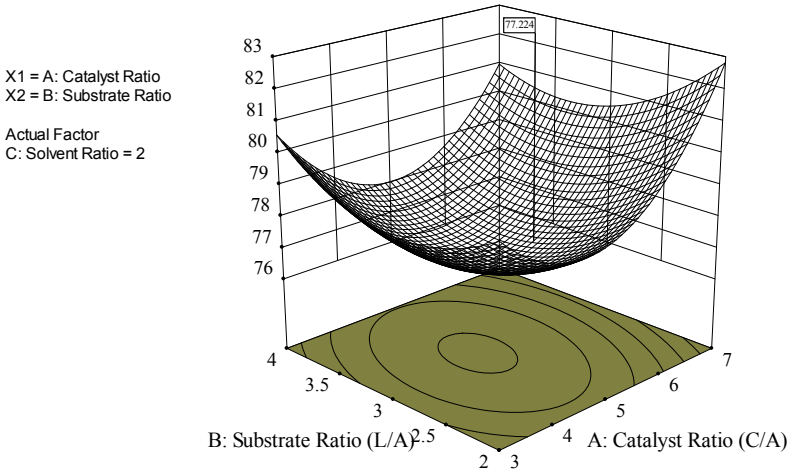

Figure-9. Surface plot of octadecanoic acid conversion on the interaction of catalyst ratio and substrate ratio in a fixed solvent 2.

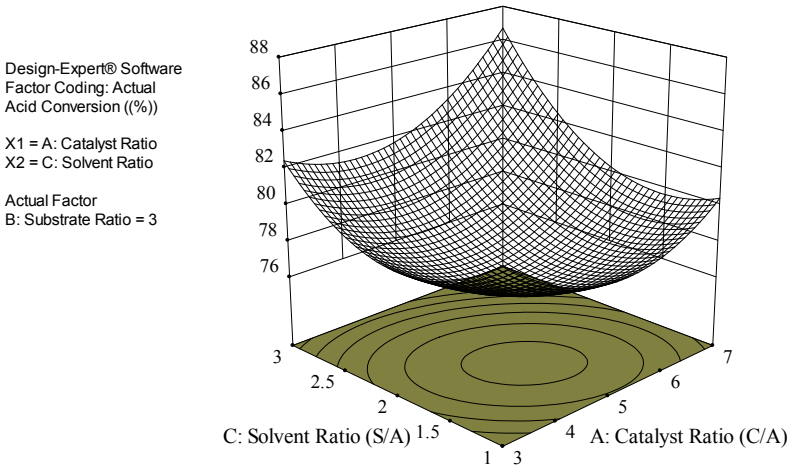

Figure-10. Surface plot of octadecanoic acid conversion on the interaction of catalyst ratio and solvent ratio on a fixed substrate 3.

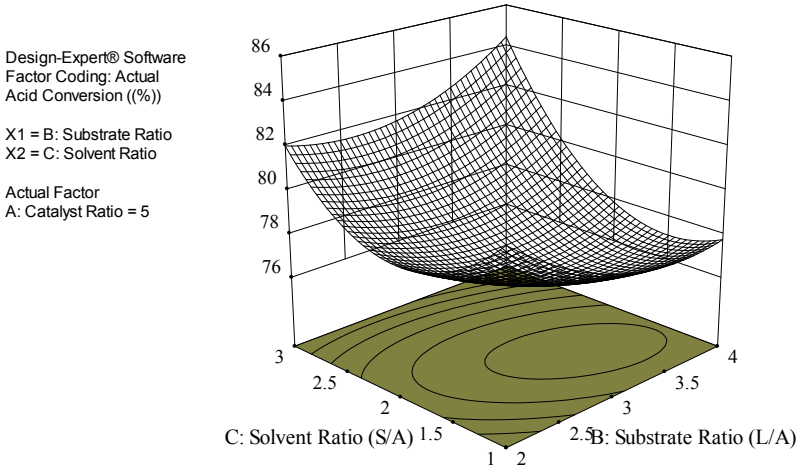

Figure-11. Surface plot of octadecanoic acid conversion on the interaction of substrate ratio and solvent ratio on a fixed catalyst 5.

Changes in the conversion of fatty acids on the interaction of A and C are shown in Figure-7. This contour illustrates that the best conversion is obtained when A and C are used at a maximum value of +1. A>7% and C>2.5, a fatty acid conversion field of >85% will be found. At the center point value 0, the minimum fatty acid conversion field was also observed. From both Figures 6 and 7, it is observed that the best A value is 7%, where the conversion of fatty acids to amides will reach more than 80%.

The interaction between B and C, and its effect on the converted fatty acids, is observed in Figure 8. The contour of this plot is quite interesting because it turns out that the selection of B in all ranges, either -1, 0, or +1, will result in a higher conversion of fatty acids. high, if C > 2.5 is used. This contour concludes that the effect of B is not significant in increasing conversion, wherein the entire range B will get low results if C is low.

Interaction Effect on the Surface Plot

The interaction effect between variables A, B, and C was also observed using the response surface. The three-dimensional graphs in Figures 9, 10, and 11 are surface shapes of the interactions between variables on the fatty acid conversion response. The surface response results are simpler to use because the data trend is very clearly visible through the resulting surface profile. Figure-9 shows the surface response to changes in the converted fatty acids, the result of the interaction between A and B. From this response, it can be seen that at the center point, a valley will be formed, which indicates the minimum response to the selection of the best-predicted value. The highest surface was observed at the maximum use of A or B maximum.

The surface response, the result of the interaction between A and C, is shown in Figure-10. The same surface trend was observed where the center point would produce a minimum valley in the fatty acid conversion. Optimal fatty acid conversion can be obtained if the highest variables A and C are set from the existing range. This indicates that the selected range can be widened until the best value/point is found, resulting in higher weak acid conversion.

A slightly different surface response is found in Figure-11. In this interaction between B and C, it turns out that variable C is more significant in increasing fatty acid conversion. It is characterized by a sloping surface at all changes in the value of B. However, the best conversion is still found if the maximum B and C are used. From Figures 9, 10, and 11, it can be concluded that variables A and C are more significant in increasing fatty acid conversion than variable B.

CONCLUSIONS

Stearoyl lysine is of great interest in novel surfactants research because of its environmentally friendly character. Catalyst ratio, substrate ratio, and solvent ratio are considered to affect the octadecanoic acid conversion response compared to temperature and reaction time. The contour plot of the relationship between catalyst ratio, substrate ratio, and the solvent ratio has also been observed. Of the three, the substrate ratio is the variable that is most capable of increasing octadecanoic acid conversion. Combining the three variables can also achieve an optimal combination of the conversion response, with the DF value close to one. And the F-value model of 17.40 shows the model is significant.

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REFERENCES

[1] Colomer A., Pinazo A., Garcia M.T., Mitjans M., Vinardell M.P., Infante M.R., Martinez V. and Perez L. 2012. pH-sensitive surfactants from lysine:

assessment of their cytotoxicity and environmental behavior. Langmuir. 28: 5900-5912.

[2] Perez L., Pinazo A., Pons R. and Infante M. 2014. Gemini surfactants from natural amino acids. Advances in Colloid and Interface Science. 205: 134-155.

[3] Liu K.J., Liu K.M. and Chang H.M. 2007. Biocatalytic synthesis of palmitoyl vanillyamide in supercritical carbon dioxide through amidation of vanillyamine hydrochloride and palmitic anhydride by lipase. Food Chemistry. 102: 1020-1026.

[4] Pinazo A., Manresa A., Marques A.M., Bustelo M., Espuny M.J. and Perez L. 2016. Amino acid-based surfactants: new antimicrobial agents. Journal of Colloid and Interface Science. 228: 17-39.

[5] Teixeira R.S., Cova T.F.G., Silva S.M.C., Oliveira R., Araújo M.J., Marques E.F., Pais A.C.C. and Veiga F.J.B. 2014. Lysine-based surfactant as chemical phermeation enhancers for dermal delivery of local anesthetics. International Journal of Pharmaceutics. 474: 212-222.

[6] Madhumanchi S., Chakrabarti P.P., Bhamidipati V.S.K.R. and Rachapudi P.B.N. 2016. Preparation and surface active properties of coconut and sunflower protein-based diethanolamides. Biomass Conversion and Biorefinery. 6(4): 377-383.

[7] Ananthapadmanabhan K.P. 2019. Amino-acid surfactants in personal cleansing. Tenside Surfactants Detergents. 56(5): 378-386.

[8] Azarmi R. and Ashjaran A. 2015. Type and applicaytion of some common surfactant. Journal of Chemical and Pharmaceutical Research. 7(2): 632-640.

[9] Soo E.L., Salleh A.B., Basri M., Rahman R.N.Z.R.A. and Kamaruddin K. 2003. Optimization of the enzyme-catalyzed synthesis of amino acid-based surfactants from palm oil fractions. Journal of Bioscience and Bioengineering. 95(4): 361-367.

[10] Infante M.R., Pérez L., Pinazo A., Clapés P., Morán M.C., Angelet M., García M.T. and Vinardell M.P. 2004. Amino-acid based surfactant. Journal of Chimie. 7: 583-592.

[11] Dettori L., Jelsch C., Guiavarc'h Y., Delaunay S., Framboisier X., Chevalot I and Humeau C. 2018. Molecular rules for selectivity in lipase-catalyzed acylation of lysine. Process Biochemisry. 74: 50-60.

[12] Masyithah Z., Swasono A.W.P., Sianturi P.D.E., Leanon R., Wirawan W. and Riyadi R. 2020. Modeling and optimization of alkyl polyglucoside surfactants from fatty alcohol by response surface methodology. ARPN Journal of Engineering and Applied Sciences. 15(12): 1313-1318.

[13] Takassi M.A., Hashemi A., Rostami A. and Zadehnazari A. 2016. A lysine amino acid-based surfactant: application in enhanced oil recovery. Petroleum Science and Technology. 34: 1521-1526.

[14] Wang X., Han Z., Chen Y., Jin Q., Wang X. 2016. Scalable synthesis of oleoyl ethanolamide by chemical amidation in a mixed solvent. J Am Oil Chem Soc. 93: 125-131.

[15] Masyithah Z., Hutagalung A., Alfizah D., Sinaga E.K. and Ginting A. 2021. Catalytic amide formation of n-stearoyl lysine from carboxylic acid in mix solvent: analysis of the response surface. ARPN Journal of Engineering and Applied Sciences. 16(1): 37-44.

[16] Montgomery, D.C. 2013. Design and analysis of experiments. 8th edition. John Willey & Sons.

[17] Masyithah Z., Syukri M., Haryanto B. and Ginting A. 2021 A systematic studi of the variables that control the synthesis of n- acyl l-lysine from hexadecanoic acid in a stirred tank reactor. ARPN Journal of Engineering and Applied Sciences. 16(17): 1720-1730.

[18] De Lima C.J. B., Coelho L.F. and Contiero J. 2010. The use of response surface methodologyin optimization of lactic acid production: focus on medium supplementation, temperature and ph control. Biotechnology. 48(2): 175-181.

[19] Oguz P. and Colak M. 2013. Use of experimental Box-Behnken design for the estimation of interactions between harmonic currents produced by single phase loads. International Journal of Engineering Research and Application. 3(2): 158-165.