Comparative Study and Analysis of Mathematical Models for Degree of Thermal Oxidation of Edible Oil as a Polynomial Function of Induction Temperature and Induction Time Developed by Statistical Software and Others Functions by Manual Transformations

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Abstract

This study was conducted for comparison of the Models developed for Degree of Thermal Oxidation of Blended Refined Edible Oil (80% sunflower and 20% Soya bean Oil) as a function of induction temperature and induction time by the use of statistical software and others by manual transformations. In this, different models developed for Peroxide Value of edible oil for different fixed time (0-120) minutes, within the Temperature range of 120 – 200 ^{0}C with interval of 10 ^{0}C and graphs have been plotted using Expert Design Software 8.0.

Keywords: *Peroxide value, Induction time, Induction temperature, Design Expert Software 8.0, R-Square, Hot Oven, Hot Plate, RSM*

1. Introduction

Mathematical modeling is an effective way of representing a particular process. It can help us to understand and explore the relationship between the process parameters. Mathematical modeling can help to understand and quantitative behavior of a system. Mathematical models are useful representation of the complete system which is based on visualizations. Mathematical modeling is an important method of translating problems from real life systems to conformable and manageable mathematical expressions whose analytical consideration determines an insight and orientation for solving a problem and provides us with a technique for better development of the system. Mathematical models in the field of oxidation of edible oils can enable the determination of temperature of edible oil which would lead to the least amount of oxidation as well as the induction or exposure time of the oil to the high temperature for the same desirable requirement of minimizing the oxidation of edible oil during processing using edible oils as a heating medium.

Mathematical models can enable the optimization of frying time and temperature to reduce the rancidity of frying oils.

In light of above considerations the study was conducted in order to attain the following objectives

1) To make comparative study of models developed by Statistical Software with others developed by manual transformation as the relationship of the Thermal oxidation as function of temperature and induction time of the frying oil.
2) To find out the best suited model for cooking process of the edible Oil.

Models can be developed by using statistical software as such or using transformation as required and the best suited model for particular process can be choosen by thorough analysis of the same.

<u>About the Software:-</u>

Design-Expert software (DX8) is a software (a Windows®-based program) for design of experiments (DOE) which can be used to optimize your product or process. It provides many powerful statistical tools, such as:

- Two-level factorial screening designs: Identify the vital factors that affect your process or product so you can make breakthrough improvements.
- General factorial studies: Discover the best combination of categorical factors, such as source versus type of raw material supply.
- Response surface methods (RSM): Find the optimal process settings to achieve peak performance.
- Mixture design techniques: Discover the ideal recipe for your product formulation.
- Combinations of process factors, mixture components, and categorical factors: Mix your cake (with different ingredients) and bake it too!

Design-Expert program offers rotatable 3D plots to easily view response surfaces from all angles. Use mouse to set flags and explore the contours on interactive 2D graphs. It numerical optimization function finds maximum desirability for dozens of responses simultaneously!

The concept of a *design space* is introduced as the set of all possible experiments or simulations that interest the analyst. This is the set that consists of all controllable variables set at all possible levels and associated dependent features of interest. Because the total design space is often prohibitively large, methods have been developed in the literature to efficiently explore it. In the case of response surface metamodels, design of experiments methods (often called response surface methods) are employed. Already popular in the chemical and industrial engineering communities, design of experiments is a statistical method used to "intelligently" determine which simulation or physical experiments should be run when resources are scarce.
Design of experiments relies on analysis of variance, or ANOVA, to choose a few points out of the full factorial set that efficiently provide information about the full response space. Metamodels may then be fit to these intelligently chosen data points using standard multiple regression methods resulting in a polynomial model that relates input parameters to output features. While these models are empirical in nature, they rely on the expertise of the experimenter for assignment of model input parameters and choice of appropriate output feature(s).
It is the empirical nature of response surface models that makes them well suited to nonlinear dynamics simulation and experiment, because higher order models may be used to relate input variables to response features. In addition to features derived from the frequency domain (which may be difficult to derive in nonlinear settings), response features may be derived from measured or simulated responses in the time domain. In fact, the number and types of response features used are limited only by the ingenuity of the experimenter.

2. Materials and Methods

Oil was purchased from the market as refined blended oil (80% sunflower oil and 20% soyabean oil) of composition as shown in Table I.

TABLE I Approx. Composition of Oil.

Contents	Qty. per 100g
Energy	900
Carbohydrate (g)	0
Protein (g)	0
Fat (g)	100
- Saturated fatty acids (g)	10
- Monounsaturated fatty acid (g)	26
- Polyunsaturated fatty acid (g)	64
- Omega-6 [n-6] (g)	63
- Omega-3 [n-3] (g)	1
- Trans fatty acid (g)	0
Total Essential fatty acids (g)	53
Cholesterol (mg)	0
Vitamin E (mg/I.U*)	50/50
Moisture (g)	0.987
Peroxide value (meq) at 28 ^{0}C	19.8
AntiOxidant TBHQ (mg)	12

2.1 Preparation of samples
The oil was first heated on hot plate in 500 ml beaker filled to 290ml, to reach the required temperature and then

incubated in hot baking oven to maintain the temperature of the oil for required time intervals.

2.2 Sample Collection (refer Annexure I)

*Assumptions

a) Surface area exposed to atmosphere is constant or same.

b) No mixing or agitation.

2.3 MEASUREMENT OF OXIDATION

2.3.1 Peroxide Value (PV) Analytical method. (refer Annexure II)

2.4. Statistical Analysis

The experimental data obtain using the previous procedures were analyzed by the response surface regression procedure using the following higher-order polynomial equations: like, $y = \beta 0 + \sum \beta_i x_i + \sum \beta_{ii} x^2{}_i + \sum \beta_j x_j + \sum \beta_{jj} x^2{}_j + \sum \beta_{ij} x_i x_j$, where y is the response, xi and xj are the uncoded independent variables (factors), and $\beta 0$, β_i & β_j, β_{ii} & β_{jj} and β_{ij} are intercept, linear, quadratic, and interaction constant coefficients, respectively. Design Expert software package 8.0 was used for regression analysis, analysis of variance (ANOVA) and developing of models of different forms by transformation (linear and of higher order) based on above mentioned principles of forming a functions. Confirmatory experiments were carried out to validate the equations using the combinations of independent variables which were not part of the original experimental design but were within the experimental region. Various models were compared for the best fit summary and there R^2 values were compared to choose the best appropriated model for particular data design and selected runs.

Some functions or model were developed by performing manual transformation and finding out the constant values using statistical software.

Model Reduction

Because it has been emphasized that metamodels may be used with reduced data sets, a review of traditional model reduction methods follows so that the advantages and disadvantages of response surface metamodels may be seen. Model reduction methods have been used in conjunction with structural dynamics problems for many years.

Hemez and Masson provide a review of exisiting model reduction methods in their 2002 LANL Technical Memo, "Model Reduction Primer". In this paper the authors emphasize that there are two families of model reduction methods, direct reduction methods and component mode synthesis, or sub-structuring. Direct reduction methods involve reducing matrices to a subset of actual degrees of freedom in order to improve computational efficiency. Sub-structuring methods, most commonly applied in larger systems, are integrated from numerous subsystems that are condensed at their interfaces. Sub-structuring allows individual components to be analyzed separately and may be implemented on problems of unlimited size, given current computational capabilities.

3. Result

Different Models Designed

3.1 Data for 150-200 ^{0}C by Design Expert Software 8.0
Model 1 : PV=+4397.89048
-100.79774* temp
-1.29626 * time
+0.027467 * temp * time
+0.86555 * temp^2
-0.015728 * time^2
-2.30942E-004 * temp^2 * time
+2.89746E-004 * temp * time^2
-3.29389E-003 * temp^3
-8.42163E-005 * time^3
-9.28019E-007 * temp^2 * time^2
+6.11508E-007 * temp^3 * time
+1.23026E-007 * temp * time^3
+4.68333E-006 * temp^4
+2.21595E-007 * time^4

R^2 =0.8876

3.2 Data for 150-200 ^{0}C by Design Expert Software 8.0
Model 2 : PV =
-51554.03370
+1527.51936 * temp
-27.63804 * time
+0.76710 * temp * time
-18.05071 * temp^2
-0.20239 * time^2
-7.75883E-003 * temp^2 * time
+3.60195E-003 * temp * time^2
+0.10635 * temp^3
-2.01307E-004 * time^3
-1.97779E-005 * temp^2 * time^2
+3.37010E-005 * temp^3 * time
-5.35095E-008 * temp * time^3
-3.12435E-004 * temp^4
+1.37842E-006 * time^4
+3.48010E-008 * temp^3 * time^2
+3.21863E-009 * temp^2 * time^3

-5.32366E-008 * temp^4 * time
-3.95827E-009 * temp * time^4
+3.66071E-007 * temp^5
-1.54709E-009 * time^5

R^2 =0.9108

3.3 Data for 150-200 ^{0}C by Design Expert Software 8.0
For level -1 - +1
Model 3: PV =
+0.75
+1.23 * A
+0.61 * B
+1.42 * A * B
-2.47 * A^2
+4.16 * B^2
+0.22 * A^2 * B
-1.38 * A * B^2
-5.15 * A^3
-0.70 * B^3
+1.73 * A^2 * B^2
-6.26 * A^3 * B
-0.95 * A * B^3
+3.49 * A^4
-10.21 * B^4
+1.96 * A^3 * B^2
+0.43 * A^2 * B^3
-1.25 * A^4 * B
-1.28 * A * B^4
+3.57 * A^5
-1.20 * B^5
-1.65 * A^3 * B^3
-3.73 * A^4 * B^2
+0.22 * A^2 * B^4
+6.30 * A^5 * B
+2.28 * A * B^5
+8.86 * B^6

R^2 = 0.9345

3.4 Data for 120-200 ^{0}C by Design Expert Software 8.0
Model 4 : PV =
-6119.63756
+195.65958 * temp
-9.72281 * time
+0.28518 * temp * time
-2.48540 * temp^2
-0.028874 * time^2
-2.90276E-003 * temp^2 * time
+2.90389E-004 * temp * time^2
+0.015683 * temp^3
+1.01597E-004 * time^3
+1.06674E-006 * temp^2 * time^2
+1.20925E-005 * temp^3 * time
-3.68070E-006 * temp * time^3
-4.91394E-005 * temp^4
+1.43304E-006 * time^4
-8.08004E-009 * temp^3 * time^2
+1.23021E-008 * temp^2 * time^3
-1.75383E-008 * temp^4 * time
-1.67440E-009* temp * time^4
+6.11284E-008 * temp^5
-2.92268E-009 * time^5
R^2 = 0.6747

3.5 Data for 150-200 ^{0}C by Manual Transformation and Design Expert Software 8.0 (refer Annexure III)
Model 5 : PV=2233.80 * Temp $^{-3.51530}$ * time $^{0.12862}$
R^2 = 0.4881

3.6 Data for 150-200 ^{0}C by Manual Transformations and Design Expert Software 8.0 (refer Annexure III)
Model 6 : PV= 16364.18 * (0.9590) ^{Temp} * (0.99191) ^{time}
R^2 = 0.3591

3.7 Data for 150-200 ^{0}C by Manual Transformations and Design Expert Software 8.0 (refer Annexure III)
Model 7 : PV= 1/ (-1.26206 + 0.012626*temp + 3.91481E-004 * time)

R^2 = 0.2037

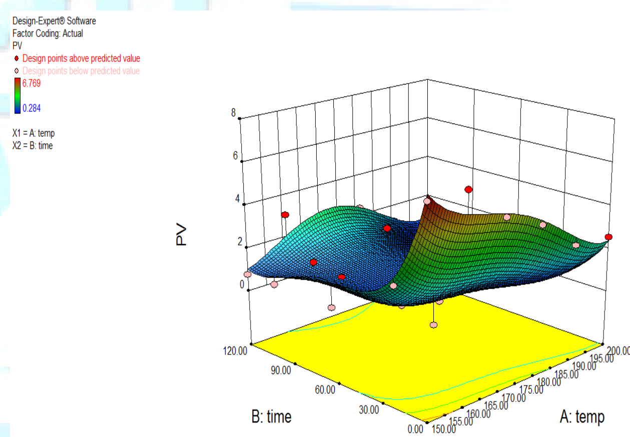

Fig. 1. Showing Model graph (3D) for peroxide values (PV(meq/kg)), temperature (^{0}C) and time (minute) for Model 1. Design Points above predicted values.

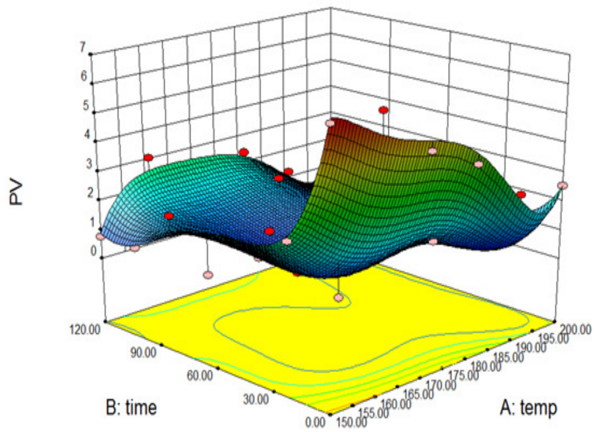

Fig. 2 Showing Model graph (3D) for peroxide values (PV(meq/kg)), temperature (^{0}C) and time (minute) for Model 2. Design Points above predicted values.

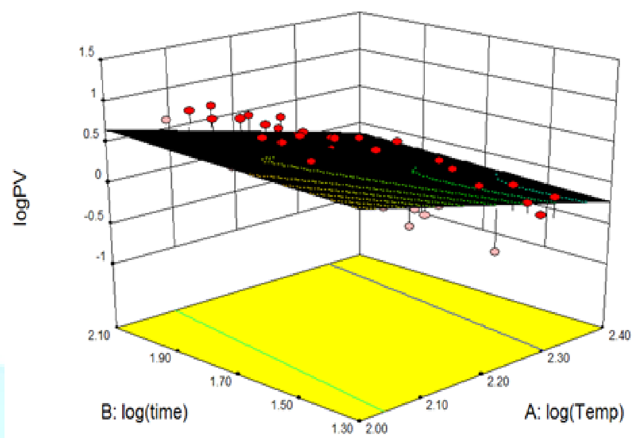

Fig. 5. Showing Model graph (3D) for log of peroxide values (PV(meq/kg)), log of temperature (^{0}C) and log of time (minute) for Model 5. Design Points above predicted values.

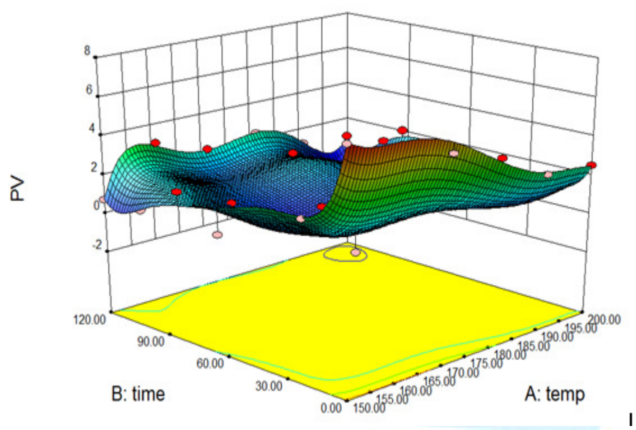

Fig. 3. Showing Model graph (3D) for peroxide values (PV(meq/kg)), temperature (^{0}C) and time (minute) for Model 3. Design Points above predicted values.

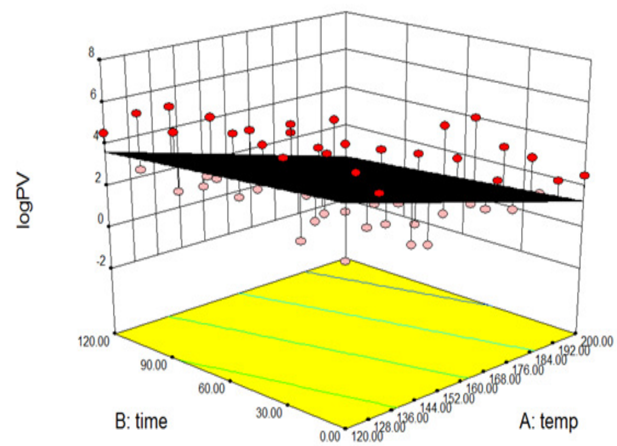

Fig. 6.Showing Model graph (3D) for log of peroxide values (PV(meq/kg)), temperature (^{0}C) and time (minute) for Model 6. Design Points above predicted values.

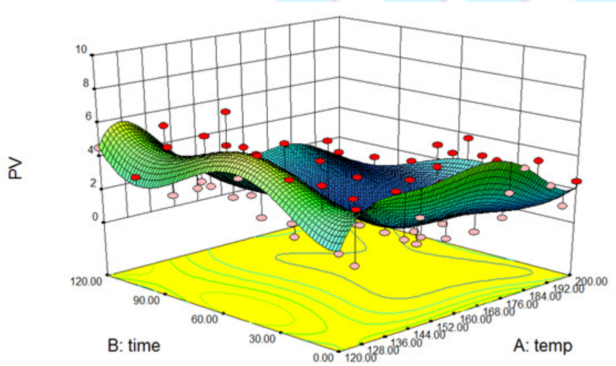

Fig. 4. Showing Model graph (3D) for peroxide values (PV(meq/kg)), temperature (^{0}C) and time (minute) for Model 4. Design Points above predicted values.

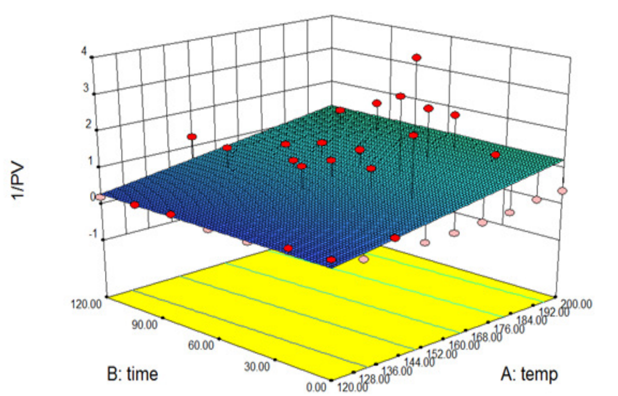

Fig. 7. Showing Model graph (3D) for inverse of peroxide values (1/PV(kg/meq)), temperature (^{0}C) and time (minute) for Model 7. Design Points above predicted values.

4. Discussion

For Model 1-3 Design type performed was Central composite. Although the ratio of upper limit to the lower limit for the response was greater than 10 and usually transformation is done in such case, but performing transformation did not benefited the result, and so no transformation was performed for the final output. Two Factors were induction time and induction temperature, minimum and maximum values for former were 0 minute, 120 minute and for latter were 150, 200 ^{0}C. Peroxide value (meq/kg) was taken as response. And analysis was of polynomial forms.

For Model 4-7 Induction time data was same but the induction temperature data was form 120-200 ^{0}C.

For Model 5-7 Manual transformations were performed.

4.1 Order for **Model 1**. was quartic type polynomial. It had 27 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity, here in case of model 1 it was 5 such point. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 1, the adjusted R-square is 0.8294, predicted R-square is 0.6827, standard deviation is 0.65 and R-square is 0.8876. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 1 the F-value of 15.23 implies the model is significant. For model 1 the "Adeq-pricision" measures signal to noise ratio of 17.572 which is greater than 4 and so desirable. Fig. 4.20 Shows the Optimization goal, ranges and solution for the optimized result of peroxide values, induction time, induction temperature and desirability for Model 1.

4.2 Order for **Model 2**. was Fifth order type polynomial. It had 21 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 2, the adjusted R-square is 0.8258, predicted R-square is 0.5830, standard deviation is 0.65 and R-square is 0.9108. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 2 the F-value of 10.72 implies the model is significant. Value of Prob>F less than 0.0500 indicates model terms are significant, values greater than 0.1 are not significant. For model 2 the "Adeq-pricision" measures signal to noise ratio of 14.255 which is greater than 4 and so desirable. Fig. 4.26 Shows the Optimization goal, ranges and solution for the optimized result of peroxide values, induction time, induction temperature and desirability for Model 2. Here for model 2, Predicted R-square is not as close to Adjusted R-square this may indicate a large block effect as a possible problem with the model or data. For such reason model reduction or transformation etc is to be considered.

4.3 Order for **Model 3**. was Sixth order type polynomial. It had 15 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 3, the adjusted R-square is 0.8215, predicted R-square is 0.2454, standard deviation is 0.66 and R-square is 0.9347. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 3 the F-value of 8.26 implies the model is significant. For model 3 the "Adeq-pricision" measures signal to noise ratio of 12.528 which is greater than 4 and P value <0.0001 so desirable. Fig. 4.32 Shows the Optimization goal, ranges and solution for the optimized result of peroxide values, induction time, induction temperature and desirability for Model 3. Here for model 3, Predicted R-square is not as close to Adjusted R-square this may indicate a large block effect as a possible problem with the model or data. For such reason model reduction or transformation etc is to be considered.

4.4 Order for **Model 4**. was Fifth order type polynomial. It had 82 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 4, the adjusted R-square is 0.5954, predicted R-square is 0.5235, standard deviation is 1.24 and R-square is 0.6747. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 4 the F-value of 8.50 implies the model is significant. For model 4 the "Adeq-pricision" measures signal to noise ratio of 9.146 which is greater than 4 and P value <0.0001 so desirable. Here for model 4, Predicted R-square is close to Adjusted R-square this indicate the model or data is significant, for such reason model reduction or transformation etc., is not usually required.

4.5 Order for **Model 5**. was first order Linear type by manual transformations of power function. It had 51 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 5, the adjusted R-square is 0.4680, predicted R-square is 0.4290, standard deviation is 0.27 and R-square is 0.4881. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 5 the F-value of 24.31 implies the model is significant. For model 5 the "Adeq-pricision" measures signal to noise ratio of 13.991 which is greater than 4 and P value <0.0001 so desirable. Here for model 5, Predicted R-square is close to Adjusted R-square this indicate the model or data is significant, for such reason model reduction or transformation etc., is not usually required. The model was manually transformed to linear form to calculate the constant terms and then back converted.

4.6 Order for **Model 6**. was first order Linear type by manual transformations of power function. It had 60 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 6, the adjusted R-square is 0.3377, predicted R-square is 0.2916, standard deviation is 1.55 and R-square is 0.3591. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 6 the F-value of 16.81 implies the model is significant. For model 5 the "Adeq-pricision" measures signal to noise ratio of 12.823 which is greater than 4 and P value <0.0001 so desirable. Here for model 6, Predicted R-square is close to Adjusted R-square this indicate the model or data is significant, for such reason model reduction or transformation etc., is not usually required. The model was manually transformed to linear form to calculate the constant terms and then back converted.

4.7 Order for **Model 7**. was first order Linear type manually by transformations of inverse function. It had 60 lack of fit and recommended is minimum 3 lack of fit, And so ensure a valid lack of fit test. Lower standard error is better and the basis is 1.0. Ideal VIF is 1.0 and VIF greater than 10 causes for alarm indicating coefficient are poorly estimated due to multicollinearity. Ideal Ri-square is 0.0 and higher values mean the terms are co-related with each other possibly leading to poor model, in such case factor design space (FDS) better fit. For model 7, the adjusted R-square is 0.1771, predicted R-square is 0.1364, standard deviation is 0.66 and R-square is 0.2037. Since aim is for maximum predicted, adjusted R-square and minimum PRESS and standard deviation so the quartic form of model i.e., model 1 best suit for the design. For model 7 the F-value of 7.67 implies the model is significant. For model 5 the "Adeq-pricision" measures signal to noise ratio of 7.325 which is greater than 4 and P value <0.0001 so desirable. Here for model 7, Predicted R-square is close to Adjusted R-square this indicate the model or data is significant, for such reason model reduction or transformation etc., is not usually required. The model was manually transformed to linear form to calculate the constant terms and then back conversion done to inverse function .

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5. Conclusion

Among all the seven models Model 1 developed by Design Expert Software was found to the most sound after thorough analysis of all of them as discussed and those formed by manual transformations didn't work well with low value of R^2.

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References

[1] Allen, D.M., 1971, "Mean Square Error of Prediction as a Criterion for Selecting Variables," Technometrics, 13, 469-475.

[2] Allen, D.M., 1974, "The Relationship Between Variable Selection and Data Augmentation and a Method for Prediction," Technometrics, 16, 125-127.

[3] Box, G. E. P. and N.R. Draper, 1987. "Empirical Model-Building and Response Surfaces," Jon Wiley & Sons, New York.

[4] Blaine, R. L., Lundgren, C. J. and Harris, M. B., "Oxidative Induction Time – A Review of DSC Experimental Effects," in this volume.

[5] G. Litwinienko & T. Kasprzycka-Guttman, *Thermochim. Acta*, 1998, 319, 185.

[6] Hassel, R.L., Thermal Analysis: An Alternative Method of Measuring Oil Stability, *J. Am. Oil Chem. Soc. 53*:179–181 (1976).

[7] J.H. Sharp, Reaction kinetics, in: Mackenzie (Ed.), Differential Thermal Analysis, 1972 p. 47.

[8] J. Van Gerpen, B. Shanks, and R. Pruszko, D. Clements & G. Knothe, *Biodiesel Production Technology*,

[9] J.C.O. Santos, I.M.G. Dos Santos, A.G. De Souza, S. Prasad & A.V. Santos, *J. Food Sci.*, 2002, 67, 1393.

[10] Khuri, A.I. and J.A. Cornell, 1996. "Response Surfaces," 2nd edition, Marcel Dekker. New York.

[11] L.M.S. Freire, T.C. Bicudo, R. Rosenhaim, F.S.M. Sinfro^Nio, J.R. Botelho & J.R. Carvalho Filho, *J. Therm. Anal. Cal.*, **2009**, 96, 1029.

[12] Min D.B., Boff J.F., (2001). Lipid oxidation of edible oil. In: *Food lipids*, Akoh C., Min D.B. (Eds). New York: Marcel Dekker, pp 335-363.

[13] Mandel, J., The Statistical Analysis of Experimental Data, Dover Publications, New York, 1964, pp. 81-84.

[14] P. Simon & L. Kolman, *J. Therm. Anal. Cal.*, **2001**, 64, 813.

[15] R.O. Dunn, "Effect of temperature on the oil stability index (OSI) of biodiesel", Energ Fuel. 2008; 22(1): 657- 62.

[16] Simon P., Kolman L. (2001) DSC study of oxidation induction periods, *Journal of thermal Analysis and Calorimetry,* 64, 813-820.

[17] Tan, C.P., and Y.B. Che Man, DSC Analysis for Monitoring the Oxidation of Heated Oils, *Food Chem. 67*:177–184 (1999).

[18] Triola, M. F., Elementary Statistics, Addison-Wesley Publishing Co., Reading MA, 1992, p. 84.

Annexure I

Sample collection

Firstly, Samples (30 ml) were collected in the brown color bottle within the temperature range of 120-200 ^{0}C with interval of 10 ^{0}C for 0-120 minutes of induction time with the interval of 20 minute. And so the number of sample was 9*7=63. And there peroxide values were measured.

Secondly, Samples (30 ml) were collected in the brown color bottle within the temperature range of 125-195 ^{0}C with the interval of 10 ^{0}C for 0-60 minutes of induction time with the interval of 15 minute. And so the number of sample was 8*5=40. And there peroxide values were measured.

As such total number of samples collected was (63+40)=103.

Annexure II

Mesurement of Peroxide Value

Procedure

i) Approx. 3.0g of the sample was transfered, accurately weighed, into a 250 ml conical flask.

ii) 25 ml of the appropriate solvent mixture (glacial acetic acid: chloroform, 1:2) and 1 ml saturated potassium iodide solution freshly prepared was added.

iii) Was Allowed to react for 60 sec. and shaking thoroughly during this period. Then 35 ml of distilled water was added.

iv) Then was titrated with 0.001 N sodium thiosulphate solution using 0.5 ml 1%starch solution as indicator.

v) During the titration shaked until the blue color disappeared.

vi) Blank titration was carried under the same conditions.

Calculations

S=titration of sample.

B=titration of blank.

SW=weight of sample taken.(gm)

N=normality of sodium thiosulphate used.(0.001)

PV=peroxide value (meq/kg)

$$PV = (S\text{-}B)*N*1000/SW$$

Annexure III

Manual transformations

Power equation in Terms of Actual Factors

$PV=K*Temp^{A} * time^{B}$

logPV=logK+A*log(Temp)+B*log(time)

logPV =
+7.71146
-3.51530 * log(Temp)
+0.12862 * log(time)

logK=7.71146
K=2233.80
A= -3.51530
B=0.12862
Therefore,

$PV=2233.80 * Temp^{-3.51530} * time^{0.12862}$

Final Equation of power in Terms of Actual Factors

$PV=K* A^{Temp} * B^{time}$

logPV=logK + Temp*logA+time*logB

logPV =
+9.70285
-0.041873 * Temp
-8.12679E-003 * time

logK=9.70285, logA= -0.041873, logB= -8.12679E-003

K=16364.18
A=0.9590
B=0.99191

Therefore,
$PV=16364.18 * (0.9590)^{Temp} * (0.99191)^{time}$

Final Equation of inverse in Terms of Actual Factors

$$PV=\frac{1}{K+ A*temp + B*time}$$

1/PV=K + A*temp + B*time

1/PV =
-1.26206
+0.012626 * temp
+3.91481E-004 * time

K= -1.26206
A=0.012626
B=3.91481E-004

Therefore,
PV= 1/(-1.26206 + 0.012626*temp + 3.91481E-004 * time)

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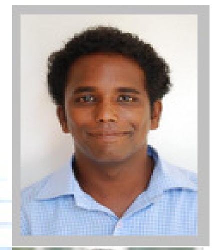

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