

# Application of Response Surface Methodology (RSM) as tool for the optimization of production processes in industries

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## Abstract:

The concept of Response Surface Methodology (RSM) was systematically exposed for possible adoption by Scientists, Engineers and Industries. RSM is an empirical model which employs the use of mathematical and statistical techniques in relating input variables otherwise known as factors to the response. RSM became very useful due to the fact that other methods available such as the full factorial model could be very cumbersome to use, time-consuming, inefficient, error prone and unreliable. In an effort to obtain an objective conclusion between the factors and the response, an experimenter needs to plan and design the experiments, and analyze the results. An approximation of the response in relation to the variables is otherwise known as RSM. Some few methods used as Design of experiments were reviewed. RSM concept and design types were highlighted; some scenario applications of RSM in various fields were cited for easy understanding and adoption by researchers. The study concluded that RSM is a highly beneficial tool for finding optimum conditions to and for developing mathematical models that predicts the output (response) which depends on the combinations of parameters level. It also gives the opportunity for studying the parameters which affect the response as well as to project the relative magnitude and interaction between them. The use of RSM technique is the best technique for process modification, optimization and experimental analysis.

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## 1. Introduction

To design, develop, improve and validate their products, processes, and operations, scientists, engineers, technologists, and manufacturing industries must carry out experimentation, data collection, data processing, and analysis [1]. The design of experiments (DOE) is a technique use to optimize product/process design and process operation, and limiting the effect of uncontrollable factors [2]. This technique is very helpful in determining the most desirable design of product, the best parameter combination of process and the most effective data collection plan. The optimization of process parameters by DOE provides the evaluation of the effect of individual independent parameters on the identified quality characteristics. A few methods used as Design of experiments are Full Factorial Design, Taguchi Method and Response Surface Method.

Full Factorial Design is an experimental design technique that takes all possible combination of each factor for studying the effect of each factor and the effects of interactions between factors on the response variable [3]. If there are k factors with 2 levels then the full factorial design has 2k runs. The full factorial design is a laborious and complex method since it requires a large number of experiments to be carried out by considering all possible control variable combinations.

Taguchi method was developed by Genichi Taguchi the father of quality engineering, who successfully integrated powerful applied statistical methods into engineering processes for achieving greater stability and quality [4]. Taguchi method is a powerful technique to optimize performance of the product or process. Taguchi's main purpose is to reduce the variability around the target value of product properties via a systematic application of statistical experimental design called robust design [5]. The advantages of the Taguchi method is that it emphasizes a mean performance characteristic value close to the target value rather a value within certain specification limits, thus improving the product quality. It is also straightforward and easy to apply to many engineering situations making it a powerful simple tool. It can be used quickly, narrow down the scope of a research project or identify problems in manufacturing process from data already in existence.

Taguchi method also allows for the analysis of many different parameters without a prohibitively high amount of experimentation [6]. However the Taguchi method also has limitations. Its main disadvantage is that the results obtained are only relative and do not exactly indicate what parameter has the highest effect on the performance characteristic value. Also since orthogonal arrays do not test all variable combinations, this method should not be used with all relationships between all needed variables. Another limitation

is that the Taguchi methods are offline and therefore inappropriate for a dynamically changing process such as simulation study. Furthermore, since Taguchi methods deal with designing quality rather than correcting for poor quality they are applied most effectively at early stages of process development.

Due to the shortcomings of these methods it becomes imperative in this work to review the applicability of the concept of RSM in many areas of scientific research, engineering and manufacturing industries. Response Surface Methodology (RSM) can be defined as a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several independent variables or factors and the objective is to optimize this response [7, 8].

Since first introduced by Box and Wilson in 1951 [9, 10], RSM has been widely used by scientists and engineers to find optimal parameter settings to improve process and equipment designs. RSM is known to play a pivotal role in new product design and development as well as in improving existing ones. With it, we can determine the optimum factor needed to produce the best result. RSM is a critical and very robust tool for data manipulation and analysis of research data to obtain a quality result or an improvement. It has major applications in the design, development, and, formulation of new products as well as in improving existing product design. Many researchers have conducted researches on the application of RSM in which the results of their findings have been used to develop a predictive model in several fields such as; tool life modeling, surface roughness prediction, for monitoring and functionality or health condition of electronic devices. RSM has also been applied in various experimental designs involving extraction process, food preservation, fermentation as well as other discipline of engineering [11].

## 2. Fundamentals of RSM

The most extensive applications of RSM are in the particular situations where several input variables potentially influence some performance measure or quality characteristic of the process [12]. According to them, performance measure or quality characteristic is called the response. The input variables are sometimes called independent variables and are subject to the control of the scientist or engineer. They adopted a statistical modeling and developed an appropriate approximating model between the response  $y$  and independent variables  $\xi_1, \xi_2, \dots, \xi_k$ .

They developed a general relationship between the response and independent variables as given in equation (1)

$$y = f(\xi_1, \xi_2, \dots, \xi_k) + \varepsilon \quad (1)$$

Where according to them, the form of the true response function  $f$  is unknown and perhaps very complicated, and  $\varepsilon$  is a term that represents other sources of variability not accounted for in  $f$ . Usually  $\varepsilon$  includes effects such as measurement error on the response, background noise, the effect of other variables, and is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance  $2\sigma$ . Then

$$E(y) = \eta = E[f(\xi_1, \xi_2, \dots, \xi_k)] + E(\varepsilon) \\ = f(\xi_1, \xi_2, \dots, \xi_k) \quad (2)$$

The variables  $\xi_1, \xi_2, \dots, \xi_k$  in Equation [2] are usually called the natural variables, because they are expressed in the natural units of measurement, such as degrees Celsius, etc. In much RSM work it is convenient to transform the natural variables to coded variables  $x_1, x_2, \dots, x_k$ , which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables, the response function [2] will be written as in equation [3]

$$\eta = f(x_1, x_2, \dots, x_k) \quad (3)$$

Because the form of the true response function  $f$  is unknown, it is usually approximated. Successful use of RSM is critically dependent upon the experimenter's ability to develop a suitable approximation for  $f$ . In many cases, either a first-order or a second order model is used.

For the case of two independent variables, the first-order model in terms of the coded variables is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (4)$$

The form of the first-order model in Equation [4] is sometimes called a main effects model, because it includes only the main effects of the two variables  $x_1$ , and  $x_2$ . If there is an interaction between these variables, it can be added to the model easily as follows:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 \quad (5)$$

This is the first-order model with interaction. For the case of two variables, the second-order model is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 \quad (6)$$

This model would be useful as an approximation to a response surface in a relatively small region. The relationship of the independent variables and the response will be calculated by the second order polynomial equation.

$$Y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i=1}^k \sum_{j=1}^k \beta_{ij} x_i x_j \quad (7)$$

Where  $Y$  is the predicted response,  $\beta_0$  is the model constant,  $\beta_i$  is the linear coefficient,  $\beta_{ii}$  is the quadratic coefficient,  $\beta_{ij}$  is the interaction coefficient, and  $k$  is number of factors. The second-order model is widely used in response surface methodology.

### 2.1 Assumptions of RSM

According to Abdullahi, *et al.* [13] the assumptions of RSM are;

- The error term is assumed to distribute normally with zero mean and variance  $\sigma^2$ .
- The true response function  $f$  is unknown
- The experiment starts with a low order polynomial in some small region.

### 2.2 Advantages of Using Software to Design Experiments

Optimization of product attributes using software designs eschews trial and error experiments of the past and

saves the researcher both time and cost of executing researches [14]. Optimization of process variables has been the most reliable means of validation of product quality during product development and without using software, experiments cannot be satisfactorily optimized. The responses are usually modeled for easy prediction of results since not all possible levels of a given factor in an experiment must be tried during the execution of the work. Only statistical software that has design of experiment (DOE) such as Design Expert, Minitab, etc can be used to design and analyze RSM experiments.

Box-Behnken (B-B) and Central composite design (CCD) designs are two of the most common response surface methodology (RSM) models used.

### 2.3 Box-Behnken design (BBD)

The Box-Behnken design is an independent quadratic design in that it does not contain an embedded factorial or fractional factorial design. In this design the treatment combinations are at the midpoints of edges of the process space and at the center. These designs are rotatable (or near rotatable) and require 3 levels of each factor. Their primary advantage is in addressing the issue of where the experimental boundaries should be, and in particular to avoid treatment combinations that are extreme. The corner points and the star points are extreme points in terms of region in which experiment is done. The Box-Behnken design avoids all the corner points, and the star points. It has limited capability for orthogonal blocking compared to the central composite designs [7].

### 2.4 Central composite design (CCD)

Central composite designs consist of three types of design points: factorial points, star (or axial) points, and center points. In the usual orientation and scaling, the factorial points are a  $2^k$  factorial design of at least resolution V with levels  $\pm 1$ ,  $2k$  axial points (Star points) two on each of  $k$  axes. The star points have each factor in turn at its high and low level ( $\pm \alpha$ ), ( $\alpha$  distance  $\pm \alpha$  from the center of the design) and the other factors at their middle level (zero). Coding of variables in the range of (-1 to +1) is done according to the following equation:

$$xi = \frac{(Xi - X_{cp})}{\Delta Xi} \quad (8)$$

For  $i = 1, 2, 3, \dots, k$

Where  $x_i$  is the dimensionless value of an independent variable,  $X_i$  is the real value of an independent variable,  $X_{cp}$  is the real value of an independent variable at the central point, and  $\Delta X_i$  is the step change of variable  $i$ .

When  $\alpha = 1$ , the designs cover a cuboidal region and are sometimes called face-centered cube designs; when  $\alpha = k^{1/2}$  the designs are spherical, but to make the precision of the model predictions equal on a sphere,  $\alpha$  must be equal to the fourth root of the number of factorial points. Designs that yield equally precise predictions in all directions are called rotatable designs (A rotatable design exists when there is an equal prediction variance for all points a fixed distance from the center, 0); the prediction variance of a rotatable design is a function only of the distance of the prediction point from the center of the design region [15, 16, 17]. The center

points represent replicate terms and provide good and independent estimate of the experimental error. According to Tan and Shahidi [17] the center points are points with all levels set to coded level 0; the midpoint of each factor range and this is repeated twice.

Considering these points, the number of experiments designed by CCD will be as given in equation [9] [18]

$$N = k^2 + 2k + n \quad (9)$$

Where  $N$  is the total number of experiments,  $k$  is the number of factors to be studied and  $n$ , the number of replicates.

The CCD is formulated on the basis of the factorial designs adding the star points and the central point, and three types of different structures can be used: the central composite circumscribed (CCC) central composite inscribed (CCI) and face-centered central composite design (CCF). CCC designs provide high quality predictions over the entire design space, but require factor settings outside the range of the factors in the factorial part. The design points describe a circle circumscribed about the factorial square. CCI designs use only points within the factor ranges originally specified, but do not provide the same high quality prediction over the entire space compared to the CCC. CCF designs provide relatively high quality predictions over the entire design space and do not require using points outside the original factor range. However, they give poor precision for estimating pure quadratic coefficients [20, 17]. Both the CCC and CCI are rotatable designs, but the CCF is not [20].

Recently, optimization studies have also used central composite rotatable design (CCRD) and face central composite design (FCCD).

### 3. Optimization of biodiesel production

RSM (full factorial) was used by Uket and Ugwu [21] for the production of biodiesel from orange seed oil using raw and thermal clay as catalyst which identified the various design points as being numerical and discrete. The process optimization was performed by varying five factors, each at two different levels. The process parameters: methanol to oil molar ratio (mol/mol), catalyst concentration (weight %), reaction time (minutes), temperature ( $^{\circ}\text{C}$ ) and agitation speed (revolution per minutes, rpm) were the independent variables (input), while the biodiesel yield (vol/vol) was the dependent variable (response) in the optimization process. The designed matrix, 3D (three dimensional) surface plots, contour plots and analysis of variance (ANOVA), was achieved using the Design Expert Software (version 12.0), the optimum biodiesel yield was predicted and experimented to ascertain the interactive effects of parameters. The correlating regression coefficient indicated the satisfactory performance of the model for the raw and thermal clay. The experimental/actual maximum optimal biodiesel yield for the biodiesel production from the orange seed oil using raw and thermal clay as catalyst was 79.53 and 94.58% v/v while the predicted biodiesel yield was 79.55 and 92.98% v/v. The set of conditions that caused these positive effects were established at Time of 150 minutes, Temperature  $65^{\circ}\text{C}$ , methanol /sample molar ratio of 12:1, catalyst concentration of 3.0 wt. % and agitation

speed at 300 rpm respectively. The results show agreement between the actual and predicted biodiesel yield.

The biodiesel production process for the transesterification of soybean oil with ethanol was optimized by the application of factorial design <sup>24</sup> and response surface methodology. The combined effects of temperature, catalyst concentration, reaction time and molar ratio of alcohol in relation to oil were investigated and optimized using response surface methodology (RSM). Optimum conditions for the production of ethyl esters were obtained and were experimentally validated. They concluded that RSM is a good optimization tool [22].

RSM method was used by Ghorbani, *et al.* [23] for optimization of biodiesel production process in order to give maximum biodiesel yield. Also, RSM based on CCD was found suitable approach for simultaneous study of effects of process variables on the biodiesel production. There was a good correlation between predicted and tested responses which introduced RSM as a powerful technique to model the biodiesel yield. Moreover, the optimum values of the variables affecting the process were also determined by application of factorial design and response surface methodology.

The transesterification process for production of neem oil methyl ester has been analyzed for getting lower viscosity by use of statics and mathematics which can optimize the process parameters in very short time by using optimization method [24]. Central composite design (CCD) and response surface methodology (RSM) were utilized to determine the best operating condition for both esterification and transesterification process. The optimum condition for esterification process is 16.832 cSt against 1:9 alcohol to oil molar ratio, 10 minutes reaction time and 3ml H<sub>2</sub>SO<sub>4</sub> catalyst concentration.

A central composite design (CCD) was used to optimize the two major influential reaction variables: catalyst and methanol amount towards purity and yield of methyl esters. The analysis of variance (ANOVA) indicated that the catalyst has a positive influence on purity but negative on the yield. Meanwhile, the methanol/oil mass ratio showed a positive effect on both purity and yield. Using CCD, the optimum reaction conditions were found to be 4.9 wt. % of catalyst and 0.54:1 methanol/oil mass ratio. The prepared catalyst is capable of being reused under the suggested optimal conditions [25].

A central composite design (CCD) consisting three factors (solvent composition, temperature and time of extraction) at five levels was used to study the solvent extraction of neem oil from its seed using n- hexane and ethanol. Neem oil yield, pH, refractive index, acid value, iodine value and saponification value were evaluated as the responses. Forty-two experimental runs resulted from the CCD with a minimum oil yield of 12% and maximum of 41%. Response surface methodology was used to analyze the results of the CCD of the extraction processes. The optimum values for yield, pH, refractive index, acid value, iodine value and saponification values from the surface plots were determined respectively. The maximum predicted percentage yield was 43.48% at solvent composition of 80.77% n- hexane, 34.93°C and 6 hours duration of extraction. The five validation experiments had optimum oil

yield range between 32.85% and 37.20% while their accompanying quality characteristics were not significantly different from the simulated values [26].

An experimental design was used by Ramyadevi, *et al.* [27] to optimize protein partitioning from shrimp waste using polyethylene glycol(PEG)/sodiumcitrate aqueous two-phase systems (ATPS). Four factors, like PEG's molecular weight, pH, addition of sodium chloride and tie line length affecting the protein partitioning were studied. To build the mathematical model and minimise the number of experiments for the design parameters, response surface methodology (RSM) with a central composite design was defined based on the conditions found for the highest partitioning by preliminary tests. The best conditions of partitioning were achieved and maximum percentage yield of protein from shrimp was extracted. Central composite design allowed a thorough analysis of the factors that influence the partition of protein in aqueous two phase systems, leading to the definition of the conditions that maximise the recovery yield.

The degradation of methyl orange, using fenton reaction was studied and optimised using central composite design as a RSM. The effects of various experimental parameters in this reaction were investigated using the central composite design. 28 experiments, with 4 factors and five levels for each factor were design. The factors (or variables) were: the initial concentration of Fe (II), the initial concentration of H<sub>2</sub>O<sub>2</sub>, the initial concentration of oxalate and the reaction time. A full-quadratic polynomial equation between the percentage of dye degradation (as response) and the studied parameters was established. After removing the non- significant variables from the model, response surface method was used to obtain the optimum conditions. In addition, the results of extra experiments showed that these optimised values can be used for real samples and lead to a high value for the response [28].

Response surface methodology (RSM) was applied for the determination of optimum conditions on both esterification and transesterification step biodiesel production technique from crude palm oil. Crude palm oil biodiesel obtained from RSM met the ASTM biodiesel standard in term of methyl ester content. The optimum conditions for biodiesel production were determined with the aid of the central composite design (CCD). The percentage of fatty acid methyl ester content (FAME) from this optimized condition was 96.57 % [29].

The influence of key parameters like reaction temperature, reaction time, catalyst concentration and methanol/oil molar ratio on biodiesel was determined by Onukwuli, *et al.* [30]. These process parameters were optimized using response surface methodology (RSM) and analysis of variance (ANOVA). The significance of the different process parameters and their combined effects on the transesterification efficiency were established through a full factorial central composite design. The results obtained are in good agreement with published data for other vegetable oil biodiesel as well as various international standards for biodiesel fuel. An optimum yield of 96% was achieved with optimal conditions of methanol/oil molar ratio, 6:1; temperature, 55 °C; time, 60 min; and catalyst concentration, 0.6%. This investigation has shown that



cotton seed oil from Nigeria can be used to produce biodiesel.

The optimization of Biodiesel production from waste cooking oil using transesterification reaction with solid or heterogeneous catalyst at laboratory scale studied by Supardon, *et al.* [31] using RSM. The selected process parameters are temperature ranged from 318 K to 333 K, molar ratio of methanol to oil from 4:1 to 8:1, mass ratio of catalyst to oil from 3% to 5% and rotation speed at optimum biodiesel yield was produced at 600 rpm.

Response Surface Methodology (RSM) was used for the optimization of Biodiesel production by reacting oil (mahua oil) with alcohol in present of base catalyst (KOH) by trans-esterification process in an oscillatory baffled reactor (OBR) by Dube and Mishra [32]. For the optimization of biodiesel production, various parameters have to be considered such as oil/alcohol ratio, temperature, reaction time, catalyst, nature of catalyst (homogeneous, heterogeneous), and type of process (single, two-step process). The optimum conditions achieved for the biodiesel production are 92.7 ml mahua oil with 1:12 methanol/oil molar ratio, 0.4wt of catalyst and 10 minutes reaction time

A study mainly focused on improving biodiesel experimental production using ethanol and investigating the influence of main operating parameters (ethanol–oil molar ratio, catalyst concentration and stirring speed) on biodiesel yield was carried out using Response Surface Methodology (RSM) [33]. The optimization of the produced biodiesel was carried out through three factors: Face-Centered-Composite Design (FCCD), building a mathematical model and statistical analysis. Results show that the experimental results agree with the predicted values; they are close to unity with the  $R^2$  value (0.9924), indicating the correctness of the model. The optimal conditions of catalyst concentration (1.62 wt%), stirring speed (200 rpm) and molar ratio of ethanol to oil (12.9:1) were obtained, resulting in a biodiesel efficiency of 89.75%. The model was also experimentally validated, achieving about 90% biodiesel yield.

A study was conducted by Cebeci and Köker [34] to remove hexavalent chromium (Cr (VI)), a highly toxic and soluble anionic heavy metal with molecular weight beyond the retention capability of standard UF membranes and achieve their retention through the incorporation of polymers and polymer- Surfactant complexes within the UF membrane. Experimental studies were conducted using CCD of RSM to determine optimal removal and permeate flux values as well as to unveil the relationship between the studied factors and the resulting responses. Results revealed that 100% of the Cr (VI) species were removed from wastewater in the chitosan- based polymer- enhanced ultrafiltration (PEUF) study.

Carboxy methyl cellulose (CMC), Curcumin (Cur) and grapheme oxide (GO) were used by Salimbahrami, *et al.* [35] to prepare a novel bio composite film (CMC-Cur-GO). ACCD under RSM was employed to optimize the films in terms of water vapor permeability (WVP) and swelling percent (SP). Results show that compared to pure CMC film, the tensile strength, elongation at break and young's

modulus of CMC-Cur-GO were significantly improved by up to 75%, 41% and 23% respectively ( $p < 0.05$ )

A review of recent research on the utilization of response Surface Methodology (RSM) in the fermentation process to effectively optimize and model a wide variety of microbial products was carried out by Breig and Luti [36]. In addition to discussing the usefulness of using this method, they also reviewed the current information and the hypothetical concepts as well as the main steps for the application of RSM in microbial cultures. The study also attempted to show the recent implementing studies as well as the challenges that may occur on using RSM as an effective technique to develop the performance of industrial microbial strains.

#### 4. Challenges

First, when preliminary approximations of parameters have to be outlined from verified optimum, the researches have to transfer to the optimal area through steepest descent technique to supply the excellent combinations of parameters. Another challenge is the narrow experimental range.

#### 5. Conclusion

RSM has many advantages when compared to classical methods. It requires fewer runs of experiments to understand the effects of all the factors and the optimum combination of all factor input. RSM requires less time, removes trial by error and ensure high quality results. Having presented in this chapter the huge applications of RSM in various fields of research, it can be concluded that RSM is a great research tool for product design, development and process optimization. RSM is a highly beneficial tool for finding optimum conditions to as well as for constructing mathematical models that predicts the output variable (response) depending on the combinations of parameters level. In addition, it gives the opportunity to study the parameters which affect the response as well as to project the relative magnitude and interaction between them. The use of RSM technique is the best technique for process modification, optimization and experimental analysis.

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