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Determining Optimum Design Parameters of Foldable Product Using Response Surface Methodology and Genetic Algorithm

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Abstract

It is desired to optimize design parameters in any product development for achieving the appropriate efficiency level in any manufacturing industry. To select the best materials used, reduce cost, and increase a product's sustainability, an analysis of all design parameters must be conducted. Suitable design parameters and their optimum ranges provide the feasibility in developing a specific product. Response Surface Methodology (RSM) provides the opportunity of checking the parameters after considering optimization strategies, which results in improving the production process. In this study, the research aims to construct a 3D model and a mathematical equation on a foldable product to optimize the design parameters. A 2-level 3 factors small Central Composite Design (CCD) method is used for planning experimental trials, and the primary objective is to determine the optimal value for three design parameters, which are fold angle, length of the cycle, and height between seat and paddle in terms of the response which is "time required to fold the product". This paper directs attention towards response optimization to achieve minimum "time required to fold the product" using the desirability criteria of Response Surface Methodology (RSM) and the optimization approach of the Genetic Algorithm (GA). The optimum value of "time required to fold the product" is found to be 2.415 seconds with a combination of design parameters such as "fold angle" of 180˚, "length of the cycle" of 74.112 cm, and "height between seat and paddle" of 0.613 m using Response Surface Methodology (RSM). The Genetic Algorithm (GA) predicts the "time required to fold the product" is 2.39 seconds and design parameters of "fold angle" of 179.559˚, "length of the cycle" of 74.1 cm, and "height between seat and paddle" of 0.59 m. This similar sort of analysis can be implemented in different manufacturing industries for developing a specific product.

Keywords

RSM, GA, Desirability, Foldable Product, CCD

1. Introduction

The elimination of time-consuming functionality provides additional value along with providing the primary purpose of any product. The design phase in product development is to provide all items that have been considered in the measure and analysis phases [1]. In the design phase of any new product, the design parameters must be optimized to function appropriately within the least time for selecting low time-consuming functionality [2]. People working in product development have experienced significant changes in the design phase of a product development process. So, the design must be conducted and reviewed extensively for satisfying the customer during the design phase of a product development process.

This research study considers a foldable cycle with a foldability function consisting of the front fork and rear gear assembly with four small wheels. The front fork and rear gear assembly of the cycle are joined by a knuckle joint to fold the cycle. The foldable cycle is designed to fold the product into a compact form, facilitating transport and storage [3]. The cycle can be more easily carried into different places with the back four small wheels attached with the back seat of the cycle and more easily stored in a compact living place in folded condition. The two main wheels of the cycle remain side by side in the folded condition of the cycle. For making the folding operation more time-efficient, the time needed to fold the product requires to be minimized. Response Surface Methodology (RSM) can be conducted at the design phase of product development to compensate for this fact. RSM can be used for optimizing the design parameters, which affect the response named "time required to fold the product". RSM consists of mathematical and statistical techniques based on empirical models' fit to the experimental data obtained with experimental design [4] [5]. "Response Surface Methodology (RSM) establishes the relationships between several explanatory variables and one or more responses or outcomes" [6] [7]. The number of experiments required is affected by the Design of Experiment (DOE); hence it is essential to adopt an appropriate experimental design. Several experimental designs are available, including central composite design (CCD), Box-Behnken, Plackett Burman, full factorial. This 2-level small CCD is the most appropriate method for this study, which requires a sufficient number of experimental runs to provide a minimum error. The models developed were based on only a few experimental results [8] [9]. Regression is performed to an approximate empirical variable (response) based on a functional relationship between the estimated response function and one or more regressors or input variables [10]. RSM involves the following steps: 1) The postulation of the mathematical model [11]. 2)

Experimental design. 3) Estimation of test region (Coding) for independent variables. 4) Estimation of parameters in the postulated model. 5) Analysis of results by a) Checking the adequacy of the postulated model and the test for significance of individual variables by analysis of variance (ANOVA) [11]. b) The precision of prediction, *i.e.*, the estimation of confidence intervals [11] [12]. As this study intended to investigate all factors' effects and interactions, the small factorial design of experiments is used to find the optimum range of the design parameters.

This paper is organized as: Section 2 describes the methodology and design parameters. Section 3 shows the 3D model and design of experiments analysis, and Section 4 interprets the research results. Section 5 presents the conclusion and recommendations.

2. Methodology

A response is obtained at different level settings to which the design parameters are set for experimental work. The optimum value of a response depends on the setting range of all design parameters. Any input to the process is a factor which can be set to the desired value or can be selected from the available options. On the other hand, any output from a process is a response [13]. The general equation for the experimental factorial design is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{12} X_1 X_2 + \varepsilon \quad (1)$$

where Y is the level of the measured response, β_0 is the intercept, β_1, β_{12} are the regression coefficients. X_1, X_2 and X_3 stand for the main effects. $X_1 X_2$, $X_2 X_3$ and $X_3 X_1$ are the interaction between the main effects. X_1^2, X_2^2 and X_3^2 are the quadratic terms of the independent variables used to simulate the designed sample space [14]. In this article, the response is the time required to fold the product. The response depends on the fold angle, length of the cycle, and the height between seat and paddle. The fold angle depends on the folding mechanism of the cycle. The folded (15˚) and unfolded (180˚) conditions are illustrated in **Figure 1**.

Small factorials designed experiment consists of all possible combinations of levels for design parameters [15]. CCD is an experimental design used in RSM

(a) (b)

Figure 1. (a) Unfolded (180˚) condition and (b) Folded (15˚) condition of the product.

for developing a second-order model for the response [16]. Central Composite Design (CCD) with 3 factors was applied to investigate the foldable cycle's response. CCD consists of 3 parts, such as factorial points, center points, axial points. A total of 15 experimental runs (small CCD) are sufficient to calculate the second-order polynomial regression model's coefficient for three variables. In this study, 15 experimental runs, including 5 similar experimental runs for the center points and 2 experimental runs for checking the optimum value for the response outside of the given range of input design parameters. The process of the foldability of the product is illustrated in Figure 2. The list of the design parameters, along with their levels, is represented in Table 1.

3. Design Analysis

3.1. Experimental Layout

The times are measured for different experimental runs of design parameters and recorded as a response for this study. The experimental layout is illustrated in Table 2.

3.2. Pareto Plots

The main effect of plots or Pareto plots is a plot of the mean response values at each level of design parameters. One can use this plot to compare the relative strength of the effects of various design parameters [17]. In this study, the Pareto plot is used to determine which design parameters significantly affect the response. Pareto plots for the response of the product are presented in Figure 3.

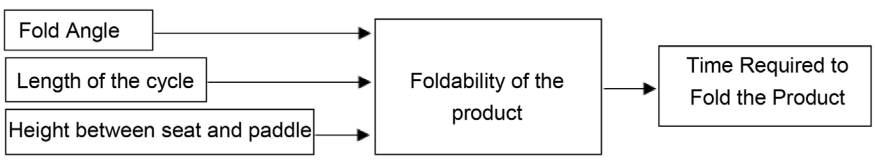

Figure 2. The schematic diagram for the foldability of the product.

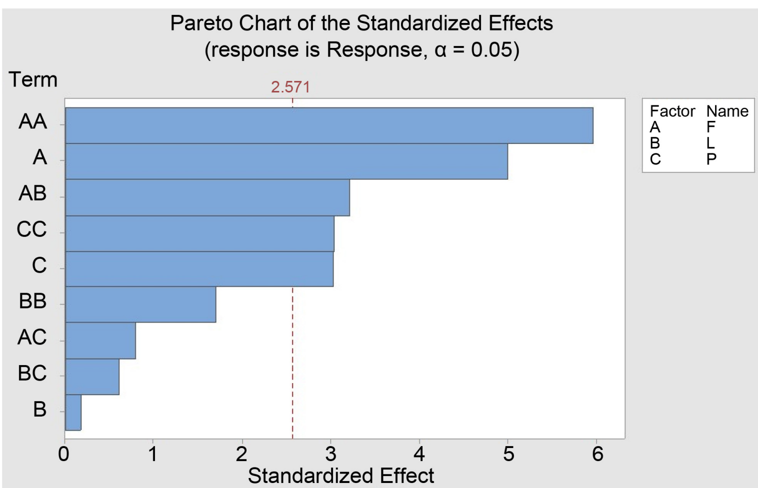

Figure 3. Pareto plot for response.

Table 1. Design parameters with their levels and labels.

Factors	Labels	Low Level	High Level
Fold Angle	F (degree)	15˚	180˚
Length of the cycle	L (cm)	50	110
Height between seat and paddle	P (m)	0.5	0.8

Table 2. Experimental layout.

Run	Factor 1: F (Degree)	Factor 2: L (cm)	Factor 3: P (m)	Response (second)
1	97.5	80	0.862132	5.88
2	15	50	0.5	11.02
3	97.5	80	0.65	5.6
4	97.5	80	0.437868	5.198
5	97.5	122.426	0.65	5.68
6	97.5	80	0.65	5.29
7	180	50	0.8	3.29
8	97.5	37.5736	0.65	5.79
9	15	110	0.8	10.98
10	214.173	80	0.65	1.38
11	12.1726	80	0.65	11.56
12	97.5	80	0.65	5.559
13	97.5	80	0.65	5.58
14	180	110	0.5	3.33
15	97.5	80	0.65	5.12

It can be interpreted that fold angle (F) and length between seat and paddle (P) significantly affect the product's foldability. Other factors, including the interaction between fold angle (F) and the length of the cycle (L), show a noticeable impact on the response.

According to the fit and summery tests, the quadratic model was suggested. The fitted response model for foldability of the product was found to be as:

$$\begin{aligned}\text{Response} = {} & 21.95483 - 0.072337F - 0.120214L - 20.55898P \\ & + 0.000106F*L - 0.003143F*P + 0.054628L*P \\ & + 0.000114F^2 + 0.000457L^2 + 13.92510P^2\end{aligned} \quad (2)$$

3.3. Effect of Design Parameters on the Response

From the experimental results, it is found that the length of the cycle tends to have minimal effect on the response for a specified range of design parameters. The interaction between (P) along with fold angle (F) and length of the cycle (L) also offers less significant effects over response. The response is found to increase with increasing value of fold angle.

Figure 4 shows the effect of fold angle (F) versus length of the cycle (L) for a

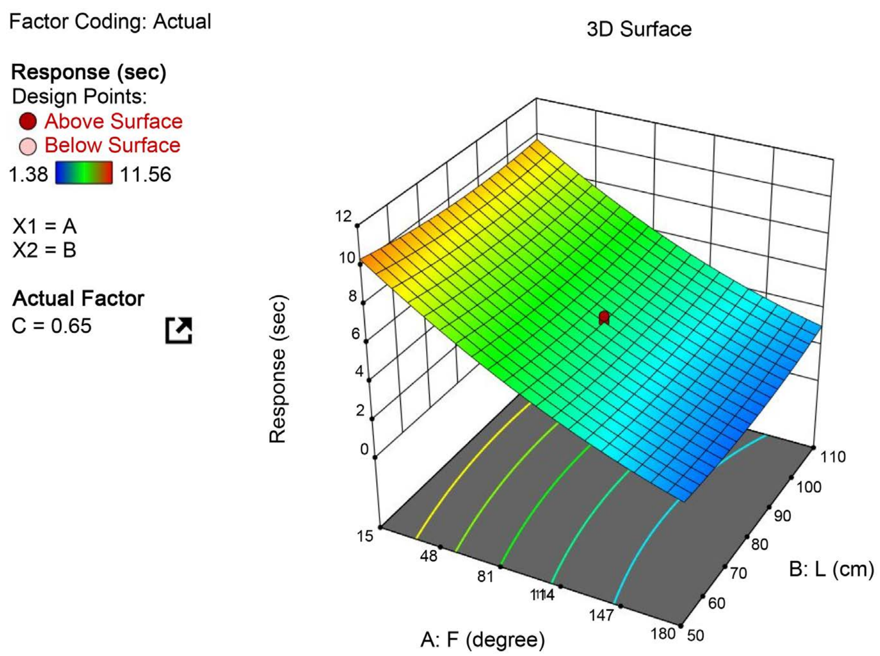

Figure 4. Effect of fold angle (F) vs. length of the cycle (L). (Response as a function of fold angle (F) and length of the cycle (L) for "0.65" level value of the height between seat and paddle (P) during the experimental run).

constant height between seat and paddle (P) of 0.65 m. The surface plot has been developed based on the regression model developed using the experimental data. It is understood from the surface plot that the increase in fold angle (F) at the lower height between seat and paddle (P) increases the possibility of finding an acceptable response. Whereas at any length of the cycle (L) and lower height between seat and paddle (P) (less than 0.65 m), an acceptable response can be observed. So, for the most acceptable response, the fold angle (F) should be higher (closer to 180˚) at a lower height between seat and paddle (less than 0.65 m).

3.4. Optimization by Coupling RSM with GA

The objective of the optimization is to achieve a lower response in experimental runs. This can be achieved efficiently by adjusting design parameters with the help of an appropriate numerical optimization method. For this, minimization of response must be formulated in the standard mathematical format as below:

Find: F (fold angle), L (length of the cycle), P (height between seat and paddle)

Minimum: Time required to fold the product (F, L, P)

Within ranges: ($F_{\min} \le F \le F_{\max}$), ($L_{\min} \le L \le L_{\max}$), ($P_{\min} \le P \le P_{\max}$)

The ranges of design parameters in optimization have been selected based on the developed RSM model ranges [18]. The GA mechanics is simple, involving copying binary strings and the binary strings' swapping [8]. The simplicity of operation and computational efficiency are the two main attractions of the GA approach [8]. The GA solves optimization problem iteratively based on the biological evolution process in nature. The solution procedure of an optimization problem with GA begins with a set of parameter values or "chromosomes" (usually in the form of bit strings), which are randomly generated or selected [19] [20]. The entire set of these chromosomes comprise a "population" [21]. The chromosomes evolve during several iterations or "generations" [21] [22]. New generations called "offspring" are generated using the "crossover" and "mutation" technique [21]. "Crossover involves splitting two chromosomes and then combining one-half of each chromosome with the other pair" [21]. "Mutation involves flipping a single bit of a chromosome. The chromosomes are then "evaluated" using specific "fitness" criteria, and the best ones are kept while the others are discarded" [21]. "This process repeats until one chromosome has the best fitness and is taken as the best solution to the problem" [21].

MATLAB 2018a Toolbox for GA is used to develop the GA program (MathWorks Incorporation, 2018). The critical parameters in GA are such as "the size of the population" (80), "mutation", "number of generations", "crossover friction" (0.8). The developed RSM models for response prediction (Equation (2)) were used as fitness functions for the GA. The corresponding optimum design parameters are given in **Table 3**.

3.5. Interaction between the Design Parameters

The study of the response surface and contour graphs provides an approach for optimizing foldability efficiency and identifying the interaction between the design parameters [23]. "The contour plots are sagacious to measure various design parameters (independent), which affect the response with the marked feasible region and optimum point" [24]. The contour graph is given in **Figure 5**.

Figure 6 is a perturbation plot, which illustrates the effect of all the design parameters at the center point in the design space, and **Figure 7** represents the predicted vs. actual plots. However, it is often seen in a practical situation that even though the main factors have little or little impact on the variability of a response, the interaction between those factors significantly impacts that [25].

4. Results and Discussion

Table 4 shows the DESIGN EXPERT software that suggests the design parameters obtained after single response optimizations and ten possible solutions.

In solution 1, *i.e.*, the shown values of design parameters, it is 89.8% likely to

Table 3. The best design condition was found in GA for the experiment.

Parameters	Optimized Values
Fold Angle, F (Degree)	179.559
Length of the cycle, L (cm)	74.1
Height between seat and paddle, P (m)	0.59
The time required to fold the product (sec) (GA prediction)	2.39

Table 4. Values of design parameters for the optimization of response.

Solution	Factor 1: *F* (Degree)	Factor 2: *L* (cm)	Factor 3: *P* (m)	Response (second)	Desirability	
1	**180.000**	**74.112**	**0.613**	**2.415**	**0.898**	**Selected**
2	180.000	74.296	0.613	2.415	0.898	
3	180.000	73.842	0.613	2.415	0.898	
4	180.000	74.269	0.614	2.415	0.898	
5	180.000	74.544	0.613	2.415	0.898	
6	179.998	74.505	0.614	2.415	0.898	
7	180.000	73.388	0.615	2.415	0.898	
8	180.000	73.422	0.613	2.415	0.898	
9	179.999	74.429	0.609	2.415	0.898	
10	180.000	75.033	0.610	2.415	0.898	

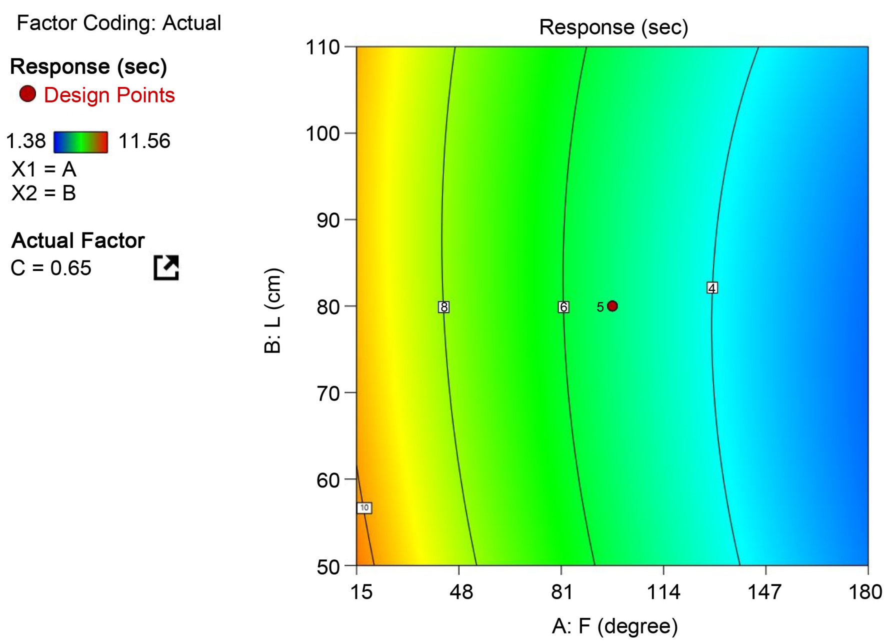

Figure 5. Contour Graph as a function of fold angle and length of the cycle.

get the Response = 2.415 sec. "Any other combination of the design parameters will either be statistically less reliable or give poor results of at least one response" [26]. However, these solutions could be used to achieve the possible values of the response. From Table 3 and Table 4, it is clear that RSM provides an optimum value of 2.415 sec, where GA predicts the optimum value is 2.39 sec.

The above design parameters will allow "minimum folding time", which will be achieved by combining the selected design parameters to develop its design and development phases.

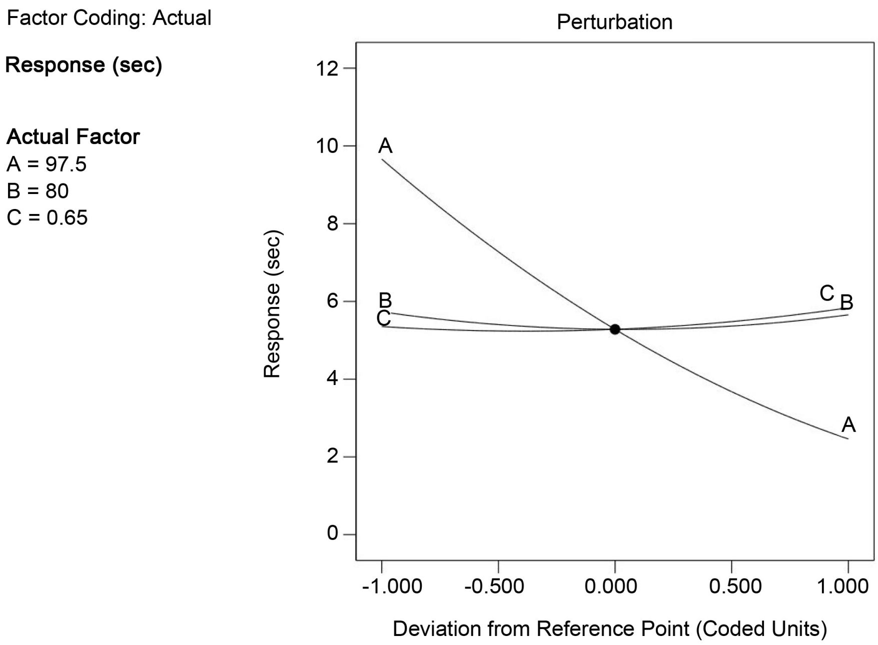

Figure 6. Perturbation graph for the response.

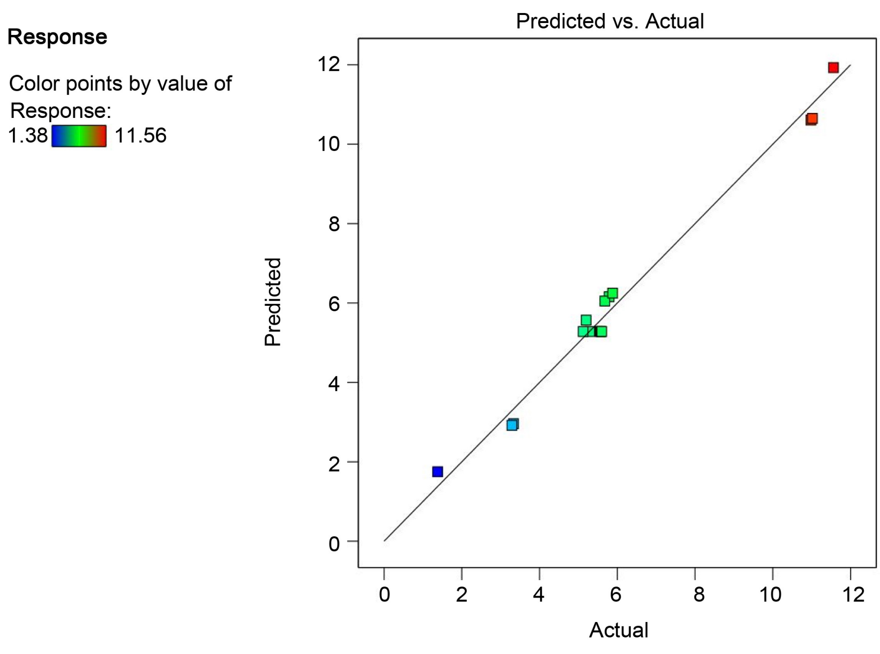

Figure 7. Predicted vs. Actual graph.

5. Conclusions

The interactions of the parameters are assessed on the grounds that quality attributes should ideally be added substance (*i.e.*, no collaboration exists among the quality qualities) and monotonic (*i.e.*, each factor's impact on robustness must be a predictable way, in any event, when the settings of variables are changed), however, it is regularly found in a pragmatic circumstance that despite the fact that the fundamental elements have close to nothing or little effect on the changeability of a reaction, the cooperation between those elements essentially impacts that. In this study, a foldable product is considered whose folding process is subjected to improvement using RSM and GA. The main objective is to determine the optimum time required to fold the cycle, predicting some future modifications of the folding mechanism. The following recommendations are for future works:

- Experimentation can be done using a more comprehensive set of design parameters.
- Other responses like stress analysis, materials density can be considered for model development.
- Finite Element Analysis (FEA) may be used to make the production process more reliable.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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