MULTIFACTORIAL EXPERIMENT SIMULATOR: AN ANDROID APP TO TEACH THE EXPERIMENTAL DESIGN

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Abstract - This article presents the problems associated in generating examples for the experimental design. The android app Multifactorial Experiment Simulator (MES) is presented in this document which simulates a multi-factorial process. This app can be used by an individual or by a teacher in a classroom to learn or teach the optimization techniques in the area of experimental design. Also, an example of finding optimal parameters is presented.

Keywords - Experimental Design, Experiment Simulator, Android App

I. INTRODUCTION

The experimental design topic is part of the curriculum for undergraduate students of engineering and biological sciences [1]–[4]. Its objective is to minimize the cost of the experiments in finding optimal value. Various optimization technique are applied to achieve it [5]. A bad design may lead in a wasting time, money and the material [6].

Statistics is the core part in an experimental design algorithm. Teaching these topics is effective with the help of examples [7]. Students also develop insight by solving a large number of examples [8], [9].

Generating examples to teach Experimental design is not always possible because:

- A multi-factorial experiment requires a lot of materials which is costly.
- Each experiment consume certain amount of time and it is not feasible to conduct many experiments to collect data in one class time.

The authors of [10] observed the growth in mobile usage in education and research area. Efforts are put to prepare curriculum with smartphones as a integral part of it [11]. Authors of this article identify the importance of engaging students with smart device in the classrooms.

In this article, an android-based educational tool for simulating experiments is proposed, which takes into account factor limits selected by the user. Teachers may adopt this educational tool in order to generate numerical examples, and to highlight all characteristics of experimental design. Moreover, the proposed educational tool allows teachers to evaluate the knowledge acquired by students during a course, and to implement problem-based learning. In this pedagogy, a student learns the topic while solving a problem given by the teacher.

The paper has the following structure. Section 2 describes a multi-response model. The mathematical function C_4 of [12] is employed in the android studio to develop a mobile application, is presented in

Section 3. The implementation of the proposed function is mentioned in Section 4. Section 5 describes the algorithm that generates an experiment of a multi-factorial process. Section 6 shows an application used to implement this algorithm. The paper ends with some concluding remarks.

II. MULTI-RESPONSE MATHEMATICAL MODEL

A numerical example for an experimental design is generated through a multi-response mathematical model that represents the physical process. This model consist of a set of static functions that map the factors to the responses, and it is given by

$$y_j = f_j(x_1, x_2, x_3, ..., x_n) + \xi_j$$
 (1)

where y_j , $j \in \{1,2,3,\ldots,m\}$ are responses, x_i , $i \in \{1,2,3,\ldots,n\}$ are factors, f_j , , $j \in \{1,2,3,\ldots,m\}$ are nonlinear functions mapping the n factors to the m responses, and ξ_i , $i \in \{1,2,3,\ldots,m\}$ are zero mean random noise. All factors, x_i , are constrained by upper and lower limits. Numerical examples should produce unique optimal responses, y_i^M , for the set of factors.

The algorithm developed in this paper uses a single response mathematical model, which is described by a proposed function presented in the next section. Several functions of this kind are used to mimic a multi-response system, since a set of m singe response systems can represent a multi-response system.

III. IMPLEMENTATION OF THE PROPOSED FUNCTION

A scaled version of the proposed function C_4 in [12] is given by

International Journal of Advances in Science Engineering and Technology, ISSN(p): 2321 –8991, ISSN(e): 2321 –9009 Vol-7, Iss-1, Spl. Issue-2 Mar.-2019, http://iraj.in

(8)

(9)

(12)

(13)

$$f(x) = F(r,s) := F_1 + \frac{F_2}{n} \left[\prod_{i=1}^n e^{-r_i^2} \right] \left[\sum_{j=1}^n e^{-ss_j^2} \right] + K_R \xi$$

$$(2)$$

$$F_1 := F_L + \alpha F_I \Xi$$

$$F_2 := \frac{(1 - 2\alpha)F_I(1 + \Xi)}{2}$$

$$F_I := (F_U - F_L)$$

$$\Xi := 0.5(\xi + 1)$$

$$r := Pz$$

$$s := Qz$$

$$z_i \coloneqq \frac{K_D(x_i - x_i^M)}{x_i^I}$$

$$x_i^I := x_i^U - x_i^L \tag{10}$$

$$x_i^M := x_i^L + \beta x_i^I + (1 - 2\beta) x_i^I \Xi$$
 (11)

$$0 < \alpha < 0.5$$

$$0 < \beta < 0.5$$

where $i\in\{1,2,3,\ldots,n\}$, $x,r,s\in\Re^n$, ξ is a random variable such that $E(\xi)=0$ and $|\xi|\le 1$, with E(.) the expected value notation. Moreover, Ξ is a random variable with the properties $E(\Xi)=0.5$ and $0\le\Xi\le 1$. On the other hand $[F_L,F_U]$ is the function range, and K_R is a factor that introduces noise into the system. Parameter K_D is a difficulty factor; the higher its value, the harder it is to reach the optimum value. In addition, x_i^M are the optimal factors where function f reaches its maximum value, x_i^L and x_i^U are lower and upper limits of the i^{th} factor respectively, α and β are padding constants that limit the maximum value of the function f within the desired region.

It is worth mentioning that function F(r,s), shown in (2), preserves all the mathematical properties of function C_4 . Moreover, multiplying function F_2 in (4) by a negative number inverts the peak of function F(r,s).

Next section presents an algorithm that implements the proposed procedure.

IV. ALGORITHM

The objective of the algorithm is to generate experimental results by simulating a multi-factorial process. Teacher gives the parameters required by the multi-factorial process such as upper and lower limits of the factors, and students perform experiments at different factors. The algorithm generates responses

for the given x_i , $i \in \{1, 2, 3, ..., n\}$ factors using the equations and inequalities shown in equations (2) to (13).

Figure 1 shows the flowchart of the proposed (3)gorithm. The teacher should define the values of α , β , F_L , F_U , K_D and K_R , where α and β (4)hould be less than 0.5. Based on our experience, It is recommended to use $\alpha = \beta = 0.2$, and $K_D = 5$. It (5) is important to mention that this algorithm can be (6)hoplemented in any programming language.

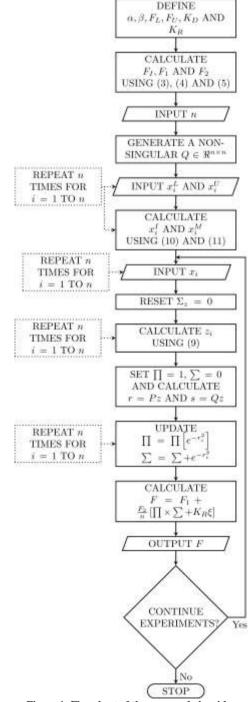
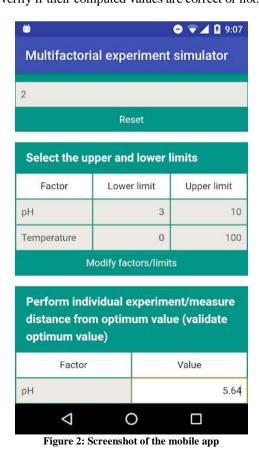


Figure 1: Flowchart of the proposed algorithm

V. APPLICATION

The triad of JavaScript (JS), Hypertext Markup Language (HTML) and Cascading Style Sheets (CSS) is used to create the application presented at the web page [13]. JS is used to implement the algorithm discussed in the previous section. This application is then wrapped into an android app [14], which lets the students to use the app offline.

Master students of the Biological Sciences Faculty. Universidad Autónoma de Coahuila, are instructed to use this application. Figure 3 and 3 show the screenshots of the web-application and mobile app respectively. It is employed by students in the classroom, at homework, and in projects related to the learning of Response Surface Methodology (RSM). Students are asked to perform experiments on this application by opening it in the web browser with the objective of maximizing the response of a biological process with n factors. The graphic user interface allows performing multiple experiments at once, where a student can paste factorial information and copy the model response to the clipboard. The factors computed by the students, are compared with the optimal ones in order to evaluate the student's performance. It is worth mentioning that the optimal values are not shown in the graphic user interface. The application contains a distance tool, which measures the distance between the estimated values to the optimal ones, thus students can use this tool in order to verify if their computed values are correct or not.



C Select number of factors Select the upper and lower limits Pactor Leaver Hmit Upper limit Factor s Factor s ☼ Perform individual experiment/measure distance from optimum value (validate optimum value) Partne Value Factori Factor s Calculate respons Response= 315.43551574906843 @ Perform bulk experiments To perform bulk experiments, paste your excel data here. Save results to eliphoard

Figure 3: Screenshot of the web-application

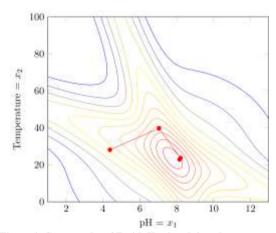


Figure 4: Contour plot of F with K_R =0 and the other constants given in Section 5 superimposed with the RSM results.

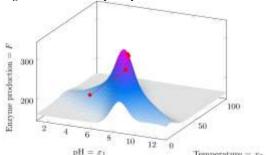


Figure 5: Surface plot of F with K_R =0 and the other constants given in Section 5 superimposed with the RSM results.

International Journal of Advances in Science Engineering and Technology, ISSN(p): 2321 –8991, ISSN(e): 2321 –9009 Vol-7, Iss-1, Spl. Issue-2 Mar.-2019, http://iraj.in

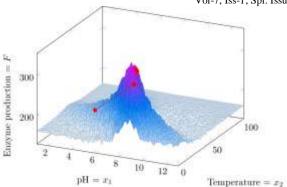


Figure 6: Surface plot of \$F\$ with the constants given in Section 5 superimposed with the RSM results.

As an example of an experiment, consider a biological process with two factors, which are pH and temperature that takes values between 1 to 13 and 0 to 100° Celsius, respectively. Let x_1 and x_2 the factors pH and temperature, respectively, and let $f(x_1, x_2)$ the enzyme production that will be maximized. The lower and upper limits of these factors are $x_1^L = 1$, $x_1^U = 13$, $x_2^L = 0$, and $x_2^U = 100$ as shown in Fig. 7. The scaled version of function C_4 , described in equations (7) to (18), uses the parameters: n = 2, $\alpha = \beta = 0.2$, $F_1 = 100$, $F_U = 600$, $K_D = 5$, $K_R = 0.1$, $x_1^L = 1$, $x_1^U = 13$, $x_2^L = 0$, and $x_2^U = 100$, $P = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} , \quad Q = \begin{bmatrix} 2.128 & 0.675 \\ 0.675 & 1.452 \end{bmatrix} ,$ $F_1 = 160.498$, $F_2 = 167.908$, $x_1^I = 12$, $x_2^I = 100$, $x_1^M = 7.784$, and $x_2^M = 23.606$. Figure 8 shows the surface plot of $f(x_1, x_2)$. Moreover, s 9 and 10 show, respectively, the contour and surface plots of the function $f(x_1, x_2)$ when it is not corrupted by the noise term ξ , i.e., $K_R = 0$. In this experiment, the Response Surface Methodology estimates the optimal values of x_1 and x_2 , and the results of each iteration are superimposed over these plots.

CONCLUSIONS

This article presented a computed educational tool, designed in HTML, CSS, and JavaScript, in order to generate random processes with factors provided by a

teacher. It is based on a novel single response, unique peak multivariable mathematical function, denoted as C_4 . This function mimics a multi response physical process designed for experiments, it is adapted to generate experimental data for a selected range of factors, and its gradient is not proportional to the distance from the optimal point. Students that learn the topic of Response Surface Methodology use the proposed education tool in order to perform experiments with the objective of maximizing the response of a biological process with factors. This educational tool can be used for showing the performance of other optimization algorithms that can maximize the response of a process, such as the Taguchi methods.

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