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Research Article

The Application of the Design of the Experiment to Investigate the Stability of Special Equipment

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In experimental design theory, plans with two or three levels of influence are the most often employed. The total factor experiment includes $N = 2^k$ experiments with two levels of change in the influencing variables, and $N = 3^k$ experiments with three levels of change in the influencing factors. The 2^k plan, in particular, is often utilized throughout the early stages of research and even while conducting explorations with a high number of influencing variables. The number of influencing variables, for example, would be $k = 15$, and the number of experiments, $N = 2^{15} = 32768$. Not just on actual devices, but also in computer simulations, this is virtually impossible. As a result, the number of experiments must be reduced to a manageable amount. The method of influencing factors space reduction can be implemented in the following ways. (i) Preliminary influencing factor analysis is used to screen for influencing factors with no or little value, i.e., variables that have little or no impact on the objective function. (ii) Using partial plans (or, as the theory of experimental planning calls them, partial responses) when the number of variables remaining after screening for null factors is still very large. This article will discuss one method for doing a preliminary screening of the initial influencing factors in order to identify those that have either no influence at all or a small effect on the objective function that is the subject of the investigation.

1. Introduction

The design of experiments (DOE) is a subfield of applied statistics concerned with the design, execution, analysis, and interpretation of controlled experiments with the purpose of determining the variables that influence the value of a factor or set of factors [1–3]. The DOE is a highly flexible method for gathering and analyzing data, and it may be used in a broad variety of different types of scientific investigations. It makes it possible to play around with a large number of input factors in order to analyze how those variables affect a certain outcome (response). When the department of energy experiments with a single component at a time, it is possible that it may miss important interactions that can be discovered when they change many inputs at the same time. Either all of the possible permutations may be researched (known as a full factorial), or simply a subset of all of the permutations can be looked at (fractional factorial). An experiment that is well planned out and carried out has the potential to provide a wealth of information on the influence that one or more factors have on a response variable. In many studies, researchers would maintain some aspects of their experiment the same while changing the other aspects. This way of processing information, known as “one factor at a time” (OFAT), is, however, inefficient when compared to simultaneously adjusting the amounts of many factors.

The DOE serves as the basis for modern empirical research in terms of methodological considerations. It is a fresh approach to research that is now being used in a broad range of subfields within the scientific and commercial communities. The construction of an experiment strategy is the first step in the DOE’s investigation process. This strategy starts with the geographical identification of factors that will influence the experiment and continues with the design of experimental procedures. Establishing the impact factor space serves two purposes: the first is to identify the factors that have a significant influence on the researcher's objective function, and the second is to generate a conjugate set of the change levels for those variables. There are a number of methods that may be used in order to successfully separate factors that have a significant impact on the goal function. Among these methods are the following:

(i) Heuristic analysis [4, 5]: derived from the ancient Greek term for "to discover," is a method for discovery, learning, and problem-solving that uses rules, estimates, or informed guesses to arrive at a satisfying solution to a given situation. While this method of issue solving is not ideal, it may be very effective when applied to computer systems that demand an immediate response or timely alarm based on intuitive judgment.

(ii) Expert consultation method [6]: a consultation with a doctor or other specialist is a meeting in which they are invited to discuss a specific issue and get their recommendations. In science, consultation refers to the process of seeking advice from a physician or other specialist.

(iii) Rank correlation [7–9]: in statistics, a rank correlation is one of several statistics that quantify an ordinal association—the relationship between the rankings of different ordinal variables or between different rankings of the same variable, where "ranking" refers to the assignment of the ordering labels "first," "second," "third," and so forth to different observations of a particular variable. The rank correlation coefficient quantifies the degree of similarity between two ranks and may be used to determine the relationship's importance.

(iv) Manual or mechanical independent factor screening experiment [10–13]: this method can be used to screen influence elements in systems manually or with the help of a mechanical or computer-aided part.

(v) Continuous screening experiment [14–16]: a screening experiment is a set of experiments conducted with the goal of determining whether experimental factors have a significant impact on the outcome of the experiment. An experimental design is a thorough plan for a set of experiments that have been carefully planned so that the observed results will provide the information that has been sought.

The experimental planning approach is the one that sees widespread use in the area of engineering. In particular, the disciplines that are associated with special weaponry and equipment. The following is a selection of published publications that make use of this methodology. Jagdale et al. [17] used the design of experiment (DOE) methodology in order to achieve optimal Tapentadol hydrochloride distribution using floating drug delivery. Tapentadol hydrochloride is a synthetic opioid that is used as an analgesic with a centrally acting mechanism. It is useful in treating pain in both clinical and experimental settings. Alipoor and colleagues [18] suggested a novel experimental design strategy based on reducing the predicted parameters' covariance matrix (D-optimal design). D-optimal design is independent of scanned quantities, unlike earlier techniques. Applying this approach to ADC imaging shows its stable performance for all input variables (imaged parameters, number of measurements, and range of b-values). Monte Carlo simulations reveal that the D-optimal design is more accurate and precise than current experiment design approaches. Hung and his co-workers [19] presented a novel method for combining light. An RGB light-mixing mechanism is made by applying the mechanism's design. Each RGB LED bulb type is put on the relevant coupler link of the three mechanisms. As a consequence of the relative motion produced by the coupling connection and output link as a result of a crank's rotation, RGB lamps may project light on the same plane to achieve color mixing. Tang and his research team [20] presented an enhanced PLC communication software based on PLC network connection communication. Read and write production data at varied time intervals through the shared link area, and use link location soft components as interactive handshake signals. The main station download module and slave station upload module is intended to fulfill the extensive range of data transmission interactions between master and slave stations, and the control system is implemented in an automated drum brake pad processing manufacturing line. Li et al. [21] introduced a system based on the two-phase natural circulation concept and is intended to remove long-term core residual heat after an accident so that the reactor is in a safe condition. The PRS steady-state characteristic test and transient start and run test were conducted on the ESPRIT integrated experiment bench. The findings of the experiment indicate that the PRS is capable of establishing natural circulation and releasing remaining heat from the first loop. Islam et al. [22] studied multiple response optimization for the removal of the organophosphorus pesticide quinalphos from an aqueous solution onto a low-cost material in an effort to overcome the disadvantages of univariate optimization. In this investigation, inexpensive adsorbents included used tea leaves, and the batch equilibration technique was used. Using a Box–Behnken design, a response model was created, and the desirability function was then utilized to optimize all influencing factors simultaneously in order to obtain the largest elimination percentage of quinalphos. Using the weight loss technique of measuring corrosion rate, Nkuzinna and colleagues [23] investigated the suppression of copper corrosion by acid extract of *Gnetum africana*. The suppression of copper corrosion by Gnetum africana was optimized using 23 factorial designs. In addition to investigating the interaction effects of temperature, inhibitory concentration, and reaction time, input components and output response were adjusted. At a temperature of 303 K, a reaction period of 24 hours, and an inhibitory concentration of 0.003 g/L, the optimal conditions for inhibiting copper corrosion by Gnetum africana were determined. Under the parameters of the experiment, it was possible to infer that the

Table 1: Table of signs of the first line of the planning matrix.

N	k	Alternatives to the first line of the plan's sign																	
		+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−	+	−
4	3	1	1	1															
8	7	3	1	1	2														
12	11	2	1	3	3	1	1												
16	15	4	1	1	1	2	2	1	3										
20	19	2	2	4	1	1	1	1	4	2	1								
24	23	5	1	1	1	2	2	2	2	1	1	1	4						
28	27	1	1	4	4	1	3	1	2	3	1	1	1	2	1	1			
32	31	1	4	1	1	1	1	3	1	2	3	5	2	2	1	1	2	1	
36	35	1	1	3	3	5	1	3	2	1	4	1	1	1	1	2	2	1	2

Where, N is the number of experiments; k is the number of influencing factors studied.

factorial design was sufficiently appropriate for the optimization of process variables and that Gnetum africana sufficiently prevented the corrosion of copper.

The process of developing and manufacturing weapons is a highly specialized field that requires the use of machinery that is both technologically advanced and very accurate. When it comes to the development of new weapon systems, a great deal of experimentation is necessary, which results in a substantial expenditure of financial resources. In order to save costs and cut down on the amount of time spent on the manufacturing process in the first place, the design of experiments is used to discover the parameters that have the biggest influence on the manufacturing process and the functioning of the weapon system. In this work, the theory as well as several examples that demonstrate the usefulness of this approach for determining the influence of nine different factors on the muzzle velocity of the warhead and the maximum pressure in the barrel of a machine gun are described. These examples demonstrate the usefulness of this approach by demonstrating how it can be used to determine these values. The authors will provide a comprehensive presentation on one of the aforementioned methodologies within the context of this article. It is a way of conducting an experiment that screens for independent factors.

The structure of this paper is organized as follows. Section 1 briefly presents some particular approaches used in the design of experiments as well as the main idea of this work. The theory of the proposed method is introduced in Section 2, where the independent factor screening experiment and an example are presented in detail. The example of applying the proposed theory related to the muzzle velocity of the warhead and the maximum pressure in the barrel of a PK machine gun is introduced in Section 3. Section 4 gives out some important comments as well as conclusions.

2. Theory of the Proposed Method

2.1. Independent Factor Screening Experiment. From a vast number of variables studied, an independent screening experiment was performed to separate the most important influencing elements. To do this, the Plackett–Berman saturation plan [24–26] is used, where the number of experiments (excluding parallel experiments) will be one unit larger than the number of factors studied, which is expressed as follows [27]:

$$N = k + 1, \tag{1}$$

Where, N denotes the number of experiments, and k denotes the number of influencing factors investigated.

Each of the examined influencing factors may experience varying degrees of change. However, in experimental planning theory, the most often utilized plans included two ($v = 2$) or three ($v = 3$) influencing factor change levels. The changing levels of the influencing factor may be quantitative (e.g., pressure, temperature, velocity, displacement) or qualitative (e.g., pyroxicillin and ballistic drugs, liquids such as oil or water).

In the first case, a total factor experiment of the following type is used [27–29].

$$n = v^{k} = 2^{k} \text{ experiments}, \tag{2}$$

in which, v denotes the number of times the investigated influencing factor has changed.

In the second instance, a total factor experiment of the following type is used [27–29].

$$n = v^{k} =^{3k} \text{ experiments}. \tag{3}$$

In this work, the first case will be considered in detail.

According to the documents [27, 28, 30, 31], this plan's planning matrix is defined by the following concepts

(i) To begin, the planning matrix's row count is a multiple of four. The reason for this is because of selecting all feasible combinations of two components' change levels when $v = 2$ equals four.

(ii) Secondly, the first row of the planning matrix is determined by searching up the number of investigated influencing variables k with known values in Table 1. From there, the number of experiments N will be generated, and the subsequent lines will be generated by moving all items in the preceding row one place to the right (or left) and permuting the final (or first) element to the first (or last) position. This process will be carried out $(N - 2)$ times in total.

(iii) Thirdly, the matrix's last row includes only <−1> or <-> elements (lower level of the element). The matrix has a dimension of $N.\,(N - 1) = N.k = k.(k + 1)$.

That is, the planning matrix has a row count of N and a column count of k.

(iv) Fourth, all influencing factors change at only two levels, i.e., the elements of the matrix will be <+1> (the upper level of the factor) or <−1> (the lower level of the factor).

Each number is represented by a separate cell in this table to indicate the number of matching signs ("+" or "–") in the first line, which starts with the first position of the planning matrix. For example, for $k = 3$, corresponding to $N = 4$, the first row of the planning matrix will have the form "+ – +". Similarly, with $k = 7$, which corresponds to $N = 8$, the first row of the planning matrix would look like this "+ + + – + ––," and so on. Finally, the first row of the planning matrix's common number of signs must equal k.

According to the abovementioned planning matrix principle, after determining the sign of the first line of the planning matrix, the signs of the subsequent lines of the planning matrix, from the second to the N^{th}, would be obtained in turn. As a result, the experimental planning matrix has been completed based on the number of known influencing variables k.

In a particular scenario [27, 28], if the number of studied influencing variables k differ from the values in Table 1, construct the planning matrix first using the value of known k, and then using the row in Table 1 that most closely approximates k. However, usually we choose the line whose value is greater than the value of the given k. If $k = 6$ is taken into account for the influencing variables under consideration (a value that is not included in Table 1), for example. In ways to construct the planning matrix, it is essential to choose the row in Table 1 with the value $k = 7$ as the starting point. That is, the sign of the planning matrix's first row will be the same as the sign of the row corresponding to $k = 7$ in Table 1. Then, we will have a plan for $N = 8$ experiments, which corresponds to $k = 7$, despite the fact that the number of influencing variables examined is only 6. Thus, an additional element is required in the last column of the matrix; this element is referred to as a pseudo-element. In this instance, an unsaturated experiment plan with two residual experiments and one dummy factor will be generated. Additionally, in the instance of the investigated influencing factors, $k = 6$, if we select a higher number, for example, $k = 11$ $(N = 12)$, we will get an unsaturated experiment plan with six residual experiments and five dummy factors.

2.2. Example

(i) The following is the shape of a planning matrix with $k = 3$ and $N = 4$ [27, 28]:

$$X = \begin{pmatrix} + & - & + \\ + & + & - \\ - & + & + \\ - & - & - \end{pmatrix}. \tag{4}$$

(ii) The planning matrix for $k = 7$ and $N = 8$ is as follows [27, 28]:

$$X = \begin{pmatrix} + & + & + & - & + & - & - \\ - & + & + & + & - & + & - \\ - & - & + & + & + & - & + \\ + & - & - & + & + & + & - \\ - & + & - & - & + & + & + \\ + & - & + & - & - & + & + \\ + & + & - & + & - & - & + \\ - & - & - & - & - & - & - \end{pmatrix}. \tag{5}$$

Following the determination of the experimental plan by the planning matrix, we will perform the experiment with the decided number of experiments N, as well as the values of the variables in each experiment, and the experimental results are recorded in tabular form as shown in Table 2 [27–29].

The regression model is constructed in the following manner. If there are k influencing factors in the experiment, each of which will vary at two levels, we will have a 2^k total factor experiment. Based on the experimental findings for the total factor in the form of 2^k, the linear regression equation is as follows [27, 28, 31, 32].

$$y = b_0 + \sum_{j=1}^{k} b_j x_j, \tag{6}$$

where y is the objective function of the research object; x_1, x_2, . . ., and x_k are the inputs in the experimental planning; b_0 is the mean value of the objective function at the center of the plan; b_j are the regression coefficients in the linear components of the model.

As presented in [33, 34], one gets:

$$b_j = \frac{\partial y}{\partial x_j}. \tag{7}$$

The regression coefficients, in other words, reflect the degree of the variables' impact, while their signs indicate the direction of that influence. They are computed using the least squares method [10, 27, 28, 30, 31, 34]:

$$b_j = \frac{1}{N} \sum_{i=1}^{N} x_{\text{ij}} y_i. \tag{8}$$

The mean value of the objective function at the center of the plan is determined by the following expression [10, 27, 28, 30, 31, 34]:

$$b_0 = \frac{1}{N} \sum_{i=1}^{N} y_i. \tag{9}$$

The statistical significance of the b_j coefficients in the regression equation is then determined. When analyzing the experimental data, consider the regression coefficients b_j, their standard deviation estimates S_{b_j}, and the confidence ranges for each of them. If the following criteria are met, the influencing factor is statistically significant [10, 27, 28, 30, 31, 34]:

$$\left|b_j\right| \geq t_{\text{th}} (1 - \alpha, \nu).S_{b_j}, \tag{10}$$

Table 2: Experimental data and measured experimental results.

Number of experiments	The level of change of factors				Values of objective functions			
	Z_1	Z_2	...	Z_n	y_1	y_2	...	y_n
1								
2								
...								
N								

Where, $t_{\text{th}}(1-\alpha,\nu)$ denotes the critical value of the Student's distribution [35–38] with a significance level of and n denotes the number of degrees of freedom ν. S_{b_j} is the estimate of the standard deviation for the j^{th} regression coefficient.

3. The Example of Applying the Proposed Theory

This section considers an example in which the effect of nine distinct variables on the warhead's muzzle velocity and the maximum pressure in the barrel of PK machine gun is examined [39]:

Among the variables examined are the following:

(i) $Z_1 = p_0$—warhead thrust pressure;
(ii) $Z_2 = \varphi_1$—Slukhovski's coefficient;
(iii) $Z_3 = L_d$—barrel length (length of bullet moving in the barrel);
(iv) $Z_4 = f$—the force of the powder gun;
(v) $Z_5 = J_k$—final momentum of the drug gas;
(vi) $Z_6 = \theta$—process index;
(vii) $Z_7 = \alpha$—cumulative quantity of the drug gas;
(viii) $Z_8 = \gamma$—weight density of drug dose;
(ix) $Z_9 = \Delta$—stuffing density.

The following Table 3 lists the values of the components corresponding to the higher level (+1) and the lower level (−1).

Some of the hypotheses are used as follows:

(i) the levels of change are determined from the condition of 10% of the value of the factor at the center of the plan;
(ii) the proposed model is linear;
(iii) the confidence level $p = 0.975$ is selected; i.e., significance level $\alpha = 0.025$ is used.

The question posed is as follows. Filter the variables to see which ones have the most effect on the warhead's velocity and the maximum pressure in the barrel of PK machine gun.

Solution:

Step 1. the computation takes into account nine influencing factors as well as two objective functions $y_1 = v_o$ and $y_2 = p_m$.

Step 2. The influencing factors are encoded as follows [27, 28, 40]:

$$\begin{aligned}
&x_j = \frac{Z_j - Z_j^0}{\Delta Z_j}; \Delta Z_j = \frac{\overline{Z}_j - \underline{Z}_j}{2},\\
&x_j = +1 \Leftrightarrow Z_j = \overline{Z}_j\,(\text{upper limit}),\\
&x_j = -1 \Leftrightarrow Z_j = \underline{Z}_j\,(\text{Lower limit}),\\
&x_j = 0 \Leftrightarrow Z_j = Z_j^0\,(\text{the value of factors at the center of the plan}),
\end{aligned} \tag{11}$$

where $j = 1\div 9$. Then, they are calculated as:

$$\begin{aligned}
\Delta Z_1 &= \frac{\overline{Z}_1 - \underline{Z}_1}{2};\\
\Delta Z_2 &= \frac{\overline{Z}_2 - \underline{Z}_2}{2};\\
\Delta Z_3 &= \frac{\overline{Z}_3 - \underline{Z}_3}{2} =; \Delta Z_4 = \frac{\overline{Z}_4 - \underline{Z}_4}{2};\\
\Delta Z_5 &= \frac{\overline{Z}_5 - \underline{Z}_5}{2} =; \Delta Z_6 = \frac{\overline{Z}_5 - \underline{Z}_5}{2};\\
\Delta Z_7 &= \frac{\overline{Z}_7 - \underline{Z}_7}{2};\\
\Delta Z_8 &= \frac{\overline{Z}_8 - \underline{Z}_8}{2};\\
\Delta Z_9 &= \frac{\overline{Z}_9 - \underline{Z}_9}{2},\\
x_1 &= \frac{\overline{Z}_1 - \underline{Z}_1^0}{\Delta Z_1} = \frac{Z_1 - 30}{3};\\
x_2 &= \frac{Z_2 - Z_2^0}{\Delta Z_2} = Z_2 - \frac{1.055}{0.01};\\
x_3 &= \frac{Z_3 - Z_3^0}{\Delta Z_3} = \frac{Z_3 - 4}{0.4};\\
x_4 &= \frac{Z_4 - Z_4^0}{\Delta Z_4} = \frac{Z_4 - 1}{0.1};\\
x_5 &= \frac{Z_5 - Z_5^0}{\Delta Z_5} = \frac{Z_5 - 0.81}{0.081};\\
x_6 &= \frac{Z_6 - Z_6^0}{\Delta Z_6} = Z_6 - \frac{0.221}{0.0267};\\
x_7 &= \frac{Z_7 - Z_7^0}{\Delta Z_7} = \frac{Z_7 - 1}{0.1};\\
x_8 &= \frac{Z_8 - Z_8^0}{\Delta Z_8} = \frac{Z_8 - 1600}{160};\\
x_9 &= \frac{Z_9 - Z_9^0}{\Delta Z_9} = \frac{Z_9 - 0.554}{0.0609};
\end{aligned} \tag{12}$$

Table 3: The true values of the influencing factors correspond to the range of change's upper and lower limits.

Input factors	The value of factors at the center of the plan	Upper limit ("+")	Lower limit ("-")
Z_1, MPa	30	33	27
Z_2	1.055	1.065	1.045
Z_3, times of caliber	4.00	4.40	3.60
Z_4, MJ/kg	1.00	1.10	0.90
Z_5, MPa.s	0.81	0.891	0.729
Z_6	0.2210	0.2486	0.1934
Z_7, dm^3/kg	1.00	1.10	0.90
Z_8, kg/m^3	1600	1760	1440
Z_9, kg/dm^3	0.554	0.6149	0.4931

Table 4: The experimental planning matrix.

Number of experiments	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}
1	+	+	−	+	+	+	−	−	−	+	−
2	−	+	+	−	+	+	+	−	−	−	+
3	+	−	+	+	−	+	+	+	−	−	−
4	−	+	−	+	+	−	+	+	+	−	−
5	−	−	+	−	+	+	−	+	+	+	−
6	−	−	−	+	−	+	+	−	+	+	+
7	+	−	−	−	+	−	+	+	−	+	+
8	+	+	−	−	−	+	−	+	+	−	+
9	+	+	+	−	−	−	+	−	+	+	−
10	−	+	+	+	−	−	−	+	−	+	+
11	+	−	+	+	+	−	−	−	+	−	+
12	−	−	−	−	−	−	−	−	−	−	−

Step 3. Determine the type of the experimental planning matrix [34]:

According to the theory stated above and based on Table 1, we will select an experimental plan of form $N = 12$ (because $k = 9$ does not correspond to Table 1, we must choose $k = 11$ and $N = 12$) and conduct a computational experiment using the system of equations corresponding to the internal projection algorithm problem. The planning matrix will be created in accordance with the concepts outlined above in Table 1. Table 4 summarizes this experimental planning matrix.

As can be observed, this planning matrix has eleven components, nine of which are actual factors and two of which are pseudo-elements. This is described in the following manner. When estimating the repeatable variance of an objective function, experimental data is used to establish the confidence ranges for the planned regression coefficients to be used. With regard to outdoor experiments, this is accomplished via the addition of additional experiments to the design at regular intervals or even in the center. Because of the impact of hidden variables, it is impossible to have identical values of the objective function in two parallel experiments. However, if there are experiments conducted to calculate this impact, it will be completely removed. So, in order to estimate the variance, it is required to either regenerate or randomize the mathematical model that is the subject of the researcher to add factors known as pseudo-factors whose numbers range from $(k + 1)$ to the number of factors in the original model $(N - 1)$. Because $k = 9$ and $N = 12$ are present in the case under discussion, it is feasible to add two pseudo-factors in the plan: Z_{10} and Z_{11}, respectively. It is possible to raise the number of dummy elements to six by selecting a plan of the type $N = 16$. There are only two scenarios in which the impact of these pseudofactors will be zero, and there are no interactions and the measurements are perfectly precise. That is not always feasible, however, and in this case, it is possible to utilize the coefficients b_{10} and b_{11} to calculate the assessment of the recurrent variance of the objective function [34], as shown in the following example:

$$S_y^2 = \frac{N}{N - (k + 1)} \sum_{j=k+1}^{N-1} b_j^2 = \frac{12}{2}\left(b_{10}^2 + b_{11}^2\right) = 6\left(b_{10}^2 + b_{11}^2\right). \tag{13}$$

In the absence of parallel experiments, the variance of the regression coefficients is calculated as follows [1]:

$$S_{b_j}^2 = \frac{S_y^2}{N} = \frac{1}{N - (k + 1)} \sum_{j=k+1}^{N-1} b_j^2 = \frac{1}{2}\left(b_{10}^2 + b_{11}^2\right). \tag{14}$$

Step 4. Conduct experiments [27–32]:

The experimental plan is determined by the planning matrix in Table 4, and the number of experiments is set at 12. The factor values for each experiment are given in Table 5.

Step 5. Determine the regression model to use [27–32]:

The regression model is a linear model expressed as equation (6).

Table 5: Experimental data and outcomes.

The number of experiments	Change in influencing factors									Values of objective functions	
	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	y_1 (m/s)	y_2 (MPa)
1	33	1.065	3.60	1.10	0.891	0.2486	0.90	1440	0.4931	636.7	179.6
2	27	1.065	4.40	0.90	0.891	0.2486	1.10	1440	0.4931	579.8	129.4
3	33	1.045	4.40	1.10	0.729	0.2486	1.10	1760	0.4931	728.3	299.7
4	27	1.065	3.60	1.10	0.891	0.1934	1.10	1760	0.6149	791.2	338.9
5	27	1.045	4.40	0.90	0.891	0.2486	0.90	1760	0.6149	682.6	191.2
6	27	1.045	3.60	1.10	0.729	0.2486	1.10	1440	0.6149	829.4	556.4
7	33	1.045	3.60	0.90	0.891	0.1934	1.10	1760	0.4931	578.3	138.1
8	33	1.065	3.60	0.90	0.729	0.2486	0.90	1760	0.6149	711.7	329.8
9	33	1.065	4.40	0.90	0.729	0.1934	1.10	1440	0.6149	781.6	411.2
10	27	1.065	4.40	1.10	0.729	0.1934	0.90	1760	0.4931	724.5	268.4
11	33	1.045	4.40	1.10	0.891	0.1934	0.90	1440	0.6149	812.6	318.7
12	27	1.045	3.60	0.90	0.729	0.1934	0.90	1440	0.4931	618.9	185.3

Table 6: Calculated values of regression coefficients.

Objective functions	Regression coefficients b_j								
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
$y_1 = v_0$	1.9	−2.05	12.0	47.5	−26.1	−11.6	8.47	−3.53	61.9
$y_2 = p_m$	0.62	−2.68	−9.1	48.0	62.9	2.12	33.4	−19.7	78.8

$$y = b_0 + \sum_{j=1}^{k} b_j x_j. \tag{15}$$

Step 6. Calculate the free regression coefficient b_0 [27–32]:

(i) for the objective function $y_1 = v_o$

According to equation (9) and Tables 4 and 5, the value of b_0 is calculated in the following way:

$$b_0 = \frac{1}{N}\sum_{i=1}^{N} y_i = \frac{1}{12}\left(y_1 + y_2 + y_3 + y_4 + y_5 + y_6 + y_7 + y_8 + y_9 + y_{10} + y_{11} + y_{12}\right). \tag{16}$$

(ii) For the objective function $y_2 = p_m$

According to equation (9) and Tables 4 and 5, the value of b_0 is also defined as follows:

$$b_0 = \frac{1}{N}\sum_{i=1}^{N} y_i = \frac{1}{12}\left(y_1 + y_2 + y_3 + y_4 + y_5 + y_6 + y_7 + y_8 + y_9 + y_{10} + y_{11} + y_{12}\right). \tag{17}$$

Step 7. Determine the free regression coefficient b_j [27–32]:

(i) for the objective function $y_1 = v_o$

According to equation (8) and Tables 4 and 5, the linear regression coefficients b_j and calculation results are listed in Table 6:

$$\begin{aligned} b_1 &= \frac{1}{N}\sum_{i=1}^{N} x_{1i} y_i = \frac{1}{12}\left(y_1 - y_2 + y_3 - y_4 - y_5 - y_6 + y_7 + y_8 + y_9 - y_{10} + y_{11} - y_{12}\right), \\ b_2 &= \frac{1}{N}\sum_{i=1}^{N} x_{2i} y_i = \frac{1}{12}\left(y_1 - y_2 + y_3 - y_4 - y_5 - y_6 + y_7 + y_8 + y_9 - y_{10} + y_{11} - y_{12}\right). \end{aligned} \tag{18}$$

Other factors are calculated similarly

$$b_9 = \frac{1}{N}\sum_{i=1}^{N} x_{9i} y_i = \frac{1}{12}\left(y_1 - y_2 + y_3 - y_4 - y_5 - y_6 + y_7 + y_8 + y_9 - y_{10} + y_{11} - y_{12}\right). \tag{19}$$

(ii) For the objective function $y_2 = p_m$

According to equation (8) and Tables 4 and 5, the linear regression coefficients b_j are calculated, in which, the method is exactly identical as before. The computation results are given in Table 6.

The computed values of the regression coefficients b_j for both objective functions are given in Table 6, and the accompanying graphs in Figures 1 and 2 illustrate the values in a visually appealing manner.

Step 8. Determine the statistical significance of the regression coefficients b_j [34]:

The values b_{10} and b_{11} for both objective functions are utilized to determine the statistical significance of the regression coefficients b_j.

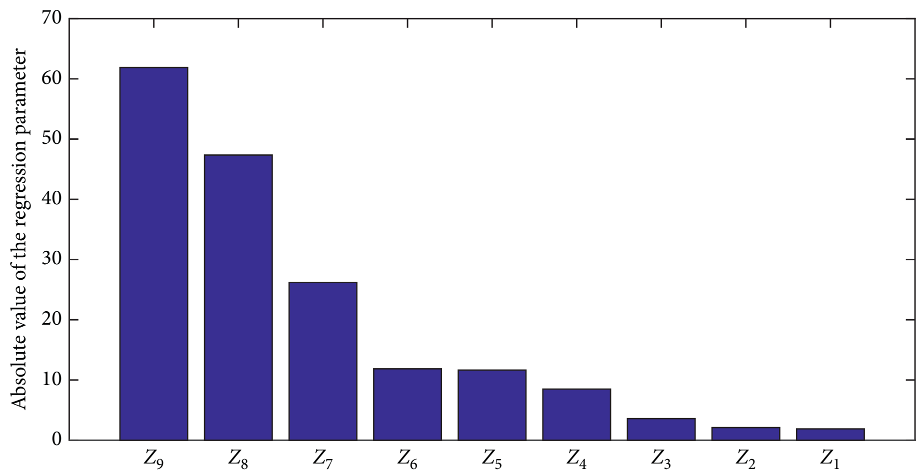

FIGURE 1: The regression coefficient of factors affecting speed v_o in descending order of absolute value.

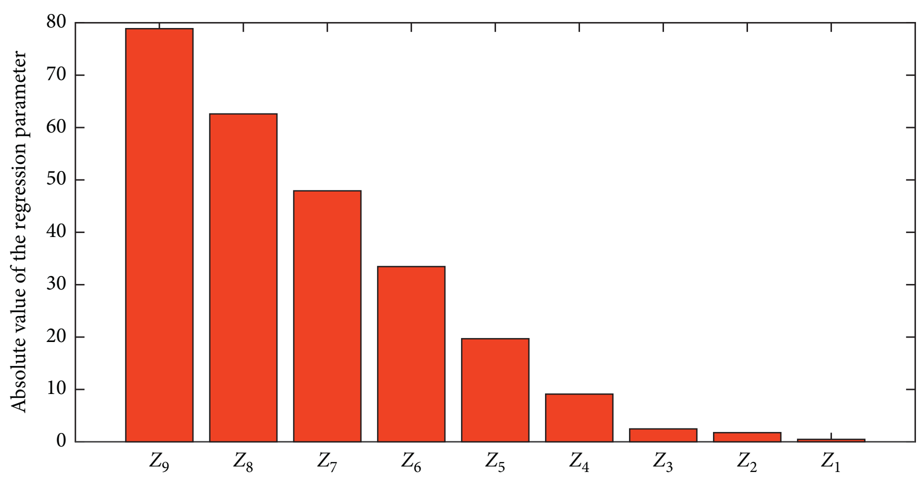

FIGURE 2: The regression coefficient of factors affecting pressure p_m in descending order of absolute value.

(i) For the objective function $y_1 = v_0$:

According to equation (8) and Tables 4 and 5, one gets:

$$\begin{aligned} b_{10} &= \frac{1}{N}\sum_{i=1}^{N} x_{10i} y_i = \frac{1}{12}(y_1 - y_2 + y_3 - y_4 - y_5 - y_6 \\ &\quad + y_7 + y_8 + y_9 - y_{10} + y_{11} - y_{12}), \\ b_{11} &= \frac{1}{N}\sum_{i=1}^{N} x_{11i} y_i = \frac{1}{12}(y_1 - y_2 + y_3 - y_4 - y_5 - y_6 \\ &\quad + y_7 + y_8 + y_9 - y_{10} + y_{11} - y_{12}). \end{aligned} \tag{20}$$

(ii) For the objective function $y_2 = p_m$

According to equation (8) and Tables 4 and 5, which are identical to the preceding, one obtains the following values: $b_{10} = 11.93$ and $b_{11} = 11.24$.

According to equations (12) and (13), one obtains the following result:

$$\begin{aligned} S_{y_1}^2 &= 6\left(b_{10}^2 + b_{11}^2\right) = 6\left[(-0.783)^2 + (-0.25)^2\right] = 4.056, \\ S_{y_2}^2 &= 6\left(b_{10}^2 + b_{11}^2\right) = 6\left(11.93^2 + 11.24^2\right) = 1611.96, \\ S_{b_j}^2(y_1) &= \frac{1}{2}\left(b_{10}^2 + b_{11}^2\right) = \frac{1}{2}\left[(-0.783)^2 + (-0.25)^2\right] = 0.338, \\ S_{b_j}^2(y_2) &= \frac{1}{2}\left(b_{10}^2 + b_{11}^2\right) = \frac{1}{2}\left(11.93^2 + 11.24^2\right) = 134.33, \\ S_{b_j}(y_1) &= \sqrt{S_{b_j}^2(y_1)} = \sqrt{0.338} = 0.581, \\ S_{b_j}(y_2) &= \sqrt{S_{b_j}^2(y_2)} = \sqrt{134.33} = 11.59. \end{aligned} \tag{21}$$

As a result, the correlations between the coefficients b_j define the importance of the coefficients:

(i) for $y_1 = v_o$ and equation (10), [34]:

$$\left|b_j\right| \geq 0.581 t_{\text{th}} (1 - \alpha, \nu). \quad (22)$$

(ii) For $y_2 = p_m$ and equation (10), [34]:

$$\left|b_j\right| \geq 11.59 t_{\text{th}} (1 - \alpha, \nu). \quad (23)$$

When we choose a confidence level of $p = 0.975$, that is, when we choose a significance level $\alpha = 0.025$ and a degree of freedom $\nu = 2$ (corresponding to the number of pseudo-factors), we may consult the Student's distribution's table of critical values [35, 37, 38, 41]. In addition, the critical value of the Student's distribution can be directly calculated using Mathcad software, one obtains t_{cr} $(0.975;\ 2) = 4.303$. Therefore, the following cases are calculated as:

(i) For $y_1 = v_0$

$$\left|b_j\right| \geq 0.581 t_{\text{th}} (0.975; 2) = 4.303 \times 0.581 = 2.5. \quad (24)$$

(ii) For $y_2 = p_m$,

$$\left|b_j\right| \geq 11.59 t_{\text{th}} (0.975; 2) = 4.303 \times 11.59 \approx 50. \quad (25)$$

As a consequence of comparing these findings with the estimated outcomes b_j given in Table 6, we have determined the following conclusions:

(i) for the objective function $y_1 = v_0$, all influencing factors except the first and second are important, namely the factors Z_3, Z_4, Z_5, Z_6, Z_7, Z_8, and Z_9, as shown in Figure 1.

(ii) Only the fifth and the ninth components (the fourth factor is nearly significant) are important for the objective function $y_2 = p_m$, i.e., Z_5 and Z_9. This is explained by the wide dispersion of the ejection mean pressure value under the circumstances of the experiment, i.e., the objective function's regeneration variance is enormous.

Therefore, to further screen without missing factors, in this case, it is more reasonable to reduce the confidence probability level to $p = 0.95$, i.e., choose the significance level $\alpha = 0.05$ then $t_{cr} (0.95; 2) = 2.92$ and for the objective function $y_2 = p_m$ this will be:

$$\left|b_j\right| \geq 11.59 t_{\text{cr}} (0.95; 2) = 2.92 \times 11.59 = 33.8. \quad (26)$$

Then, as shown by the accompanying chart in Figure 2, the factors Z_4, Z_5, Z_7, and Z_9 will be important. As a result, two more factors have been chosen: Z_4 and Z_7.

Step 9. Determine the regression model

Thus, according to equation (6), the linear regression model of the objective functions considered in the above example will have the following forms.

(i) For the objective function $y_1 = v_0$:

$$y = v_0(x) = 706.3 + 12x_3 + 47.5x_4 - 26.1x_5 - 11.6x_6 + 8.47x_7 - 3.53x_8 + 61.9x_9. \quad (27)$$

(ii) For the objective function $y_2 = p_m$

$$y = p_m(x) = 278.89 + 48x_4 + 62.9x_5 + 33.4x_7 + 78.8x_9. \quad (28)$$

4. Conclusions

In this article, the theory of the design of the experiment was developed, and then, it was applied to a particular case in order to determine the stability of the weapon. The following are some major quantitative conclusions that may be drawn:

(i) as a result of independent analysis and screening, the most significant influencing factors from the nine investigated influencing factors that concurrently impact the goal functions of cannon speed and maximum pressure have been identified and are being used in the design of the gun.

(ii) For a particular example, there are just seven factors that have a substantial impact on the speed and only four factors that have a considerable impact on the maximum pressure. In this case, if the experiment is carried out in accordance with the global experiment technique in the form of 2^k, the total number of experiments that must be carried out is $N = 2^k = 2^9 = 512$.

(iii) Because of the independent factor screening technique, the number of experiments is now $N = 2^k = 2^4 = 16$ after screening for factors, which includes sixteen experiments plus twelve screening experiments for a total of twenty-eight experiments after screening for factors.

The fact that the application examples are not very comprehensive is one of the things that holds this effort back. The reason for this is that the parameters associated with weapons, particularly special weapons, are a contentious matter relating to copyright. However, the authors believe that on the basis of these observations, more experiments are going to be carried out in order to define the exact model of the objective functions that are going to be explored. At that moment, there were far fewer experiments being conducted than there had been before. This is of the utmost importance in the event that lengthy and pricey tests are required in the course of the design and development of military systems.

Nomenclature

Symbols

N: Number of experiments

k: Number of influencing factors

v:	Influencing factor change levels
<->:	Lower level of the element
<+1>:	Upper level of the element
Z_i:	Level of change of factors
y_i:	Values of objective functions
b_0:	Value of the objective function at the center of the plan
b_j:	Regression coefficients in the linear components of the model
t^{th}:	Critical value of the Student's distribution
n:	Degrees of freedom
S_{b_j}:	Estimate of the standard deviation
j^{th}:	Regression coefficient
p_0 [MPa]:	Warhead thrust pressure
φ_1:	Slukhovski's coefficient
L_d [s]:	Length of the bullet moving in the barrel
f [MJ/kg]:	Force of the powder gun
J_k [MPa.s]:	Final momentum of the drug gas
θ:	Process index
α [dm^3/kg]:	Cumulative quantity of the drug gas
γ [kg/m^3]:	Weight density of drug dose
Δ [kg/dm^3]:	Stuffing density
DOE:	Design of experiments
OFAT:	One factor at a time.

Data Availability

There are no data supporting the findings of the study.

Conflicts of Interest

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

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