**Research Article**

# Design of experiments optimization application in physics: a case study of the damped driven pendulum experiment

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**Abstract**

The design of experiment (DoE) approach developed for experiments requiring cost and time is applied in many disciplines. Unfortunately, the insufficient use of the DoE technique in physics led to the emergence of this study. This study aims to demonstrate the applicability of the DoE technique in the field of physics with a case study. The most widely used full factorial experimental design was used for the damped driven pendulum case study. Length (m), dumpling (Newton), and mass (kg) as independent and energy (joule) as dependent variables were defined in this study to apply the DoE approach. As a result of the statistical analyses in DoE, optimization models were created, and optimum values were obtained for the case study. The experiment performed was proved to be statistically significant and valid by calculating the R-square as 0.97. The value of the objective function is calculated as 4.058 (joule). The optimum values for length, dumping, and mass was calculated as 2.719 m, 2.485(Newton), and 2.895 kg, respectively. In conclusion, this study will contribute to the literature to guide the researchers who spend a lot of time in experimental labs and have problems with experiment costs.

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## INTRODUCTION

Natural sciences, engineering, and research and development work required to reach the main objective should improve performance to have the maximum desired outputs. To reveal the conditions in which the best results are obtained, the feature that determines the performance is determined, and the factors affecting this feature are examined. Experiments are then carried out (taking into account uncontrollable factors) to determine the effects of these factors on the performance-determining feature and find the most appropriate combination. The optimum indicator is determined by evaluating the performance indicator obtained as a result of the experiments. The experiments carried out within the framework of this approach can be perceived as the question asked to the system, and the results of the experiment can be perceived as the answer given by the system. This study has focused on demonstrating the applicability of the DoE technique in physics with a case study.

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Experimental studies play an important role in engineering, product, and process development. DoE was first developed in the 1920s by the famous British Statistician R. A. Fisher and his friends [1]. Fisher also developed the ANOVA technique, which is used to measure whether there are significant differences between the observed data groups' averages. Fisher said that the most appropriate way to arrange arithmetic is to analyze variance [2]. One of the experiment design's main objectives is to minimize experiment errors [3]. Data are central to experimental or observational studies. One of the main problems of experimental studies is the formulation of inferences. In experimental studies, the source of variables can be controlled or fixed for each test. But uncontrollable variables in observational studies may be recorded as data only [4]. There are many sub-techniques in DoE.

A factorial design is a statistical method used to determine which factors, among many factors, affect the results to what extent in experimental designs. The most basic and specific application area of this method is the two-stage factorial design [5]. In many experiments in which the 2k design is used, the factors and their effect are tested. Today, many statistical package programs are used to calculate this relationship, providing significant benefits in terms of time savings and accuracy. DoE techniques are a statistical approach and methods that can be used in all research and development activities, increase quality, reduce costs, strengthen the reliability of results, support and complement all other quality techniques. The advantages they bring in practice can be listed as increasing performance and quality, efficient use of resources, accelerating research and development activities, and being less sensitive to uncontrollable or difficult/costly factors that determine the product's quality characteristics and/or process [6].

Rakić et al., comparison of full-factorial design, central composite design, and Box-Behnken design in chromatographic method development for the determination of fluconazole and its impurities [7]. The central composite design (CCD), based on the Design of Experiment (DoE), was applied to obtain an optimized design of VTG vane geometry [8]. Savaşkan et al. examined the performance optimization example of thin hard ceramic coated (TiAlN and TiN) drill bits to reach the targeted optimum point, the effects of coating type, cutting speed, and feed rate, which are the most important factors in the industrial environment, were examined with the help of the Taguchi Experiment Design technique [6]. Rafidah et al. have applied both the Taguchi and full factorial design techniques to highlight the application and compare the Taguchi and full-factorial design processes used on surface roughness [9]. Veljković et al., in modelling biodiesel production, Box-Behnken compared facial center composite and full factorial design performances [10]. Kechagias et al. have examined Taguchi and the full factorial design comparatively for predicting machinability in turning a titanium alloy [11].

The microencapsulation of lutein extracted from marigold flowers (Tagetes erecta L.) was determined using full-factorial design [12]. Salvati and Serra have made linear modelling of compressive stress and strain of EPS packaging material using the full-factorial DoE [13]. Jung et al. studied numerical research on melting the circular fin PCM system using CFD and full-factorial design [14]. Capetillo and Ibarra have used the full-factorial DoE and optimization in multiphase injector modelling for automotive SCR systems [15]. Kechagias et al. have conducted a case study in Experimental Design Comparison with full and fractional factors for estimating Shear Forces in turning titanium alloy [16]. Wahab et al. applied the full-factorial design to improve the conversion of phosphogypsia to calcium carbonate [17]. Dalvi et al. have used full-factorial design for optimization, development, verification of the RPHPLC method, and the technique indicating stability for tamsulosin and dutasteride [18]. Chan et al. have studied the optimization of weld coating parameters using a full-factorial of DoE [19]. Chen et al. have tried to reduce multiple differential BGA and differential integrated crosstalk noise (ICN) between pairs using the DoE method [20]. Politis et al. have used the DoE in pharmaceutical development [21]. Wilkens Flecknoe-Brown and Van Hees have performed a sensitivity analysis on micro-scale combustion calorimetry for polyurethane foam using full-factorial design methodology [22].

Meischl et al. have applied the full-factorial design in spelling with the Gaussian peak fitting function to determine the cleaning efficiency of solid-phase extraction of rosemary extracts [23]. Melo et al., the effect of Portland cement inclusions in hybrid glass fibre reinforced composites based on a full-factorial design [24]. Teja and Damodharan (2018) used the DoE Approach for the full-factorial model for particle size optimization of $2^3$ methotrexate-Loaded Chitosan Nanocarriers. De Olveira et al. have researched short fiber reinforced composites through full-factorial design [25]. Akkuş & Yaka have implemented the turning process's optimization by using the taguchi method (Akkuş & Yaka, 2018). The solid lipid nanoparticles were optimized with $2^2$ factorial designs for skin application studied cytotoxicity in NIH3T3 fibroblasts [27]. Afzali-Naniz and Mazloom have evaluated the effect of micro and nano-silica on self-compacting lightweight concrete using full-factorial design [28]. Grine and Benhamza have modelled nanofluids' effective thermal conductivity using full-factorial design analysis [29]. Anika et al. have made an application using DoE to determine the optimum design parameters of the portable workstation [30].

This study consists of four sections. General information about DoE methodology and literature research, including studies using this method in different disciplines, are included in the first part of the study. The second part comprises mathematical and design operations on DoE methodology. In the third part of the study, there is a case

study involving the DoE method. The advantages of using the DoE method in physics were discussed in the conclusion part of the study.

## DESCRIPTION OF THE METHODOLOGY

The working principle of DoE is to measure independent variables' effect on dependent variables according to a design. The DoE approach consists of 3 main stages: design, statistical, and optimization phases (see Fig. 1). The



**Figure 1.** The flowchart of the DoE Approach.

identification of the experiment planned to be designed is the first step of these phases. The next step is to decide which design of the DoE to use. Determining dependent and independent variables in quality and quantity is the next step in the DoE. The dependent variable(s) is (are) defined as the objective function(s), and independent variables are expressed as constraints in the optimization phase.

The level of the specified input variables is created in DoE. Thus, the number of experiments to be carried out is revealed. The levels of factor can be discrete or continuous. Levels are also expressed as textual (high/low) or numerical (1.00, 2.00, 3.00). The experimental design for two-level factors is described in Eq. (1):

$$2^f \tag{1}$$

where $f$ represents the number of factors; for example, the total number of experiments without replication for three factors with two levels is calculated as 8. This count takes into account all combinations for the experiment. The experimental design for three-level factors is expressed in equation 2.

$$3^f \tag{2}$$

These formulas are valid for the full factorial design method of DoE. In this study, the full-factorial design method of DoE was used. The full-factor experiment design for three factors with two levels is shown in Table 1.

A total of 8 experiments are required according to the full factorial design of 3 factors with 2 levels shown in Table 2. However, the experiments carried out in DoE must be repeated at least 2 times to express a statistical significance. This repetition process is called replication. So, a general expression is formed with the following formula for the number of tests to be performed in an experiment;

$$l_f \times n \tag{3}$$

where $f$, $l$, and $n$ represent the number of factors, the number of levels of factors, and the number of replications of the experiment, respectively. DoE analyzes whether the independent variables express statistical significance (relevance) on the dependent variables in the second phase of the DoE approach. If one or more independent variables do not affect the dependent variable, these variables are removed from the design. The model is made up again and analyzed statistically.

The DoE also expresses the relationship between the two variables as a regression equation to demonstrate input variables' effect on output variables. The basic or the first-order regression equation does not take into account the relationship between independent variables. However, DoE usually considers the interaction of independent variables to create the second-order equation and measures the
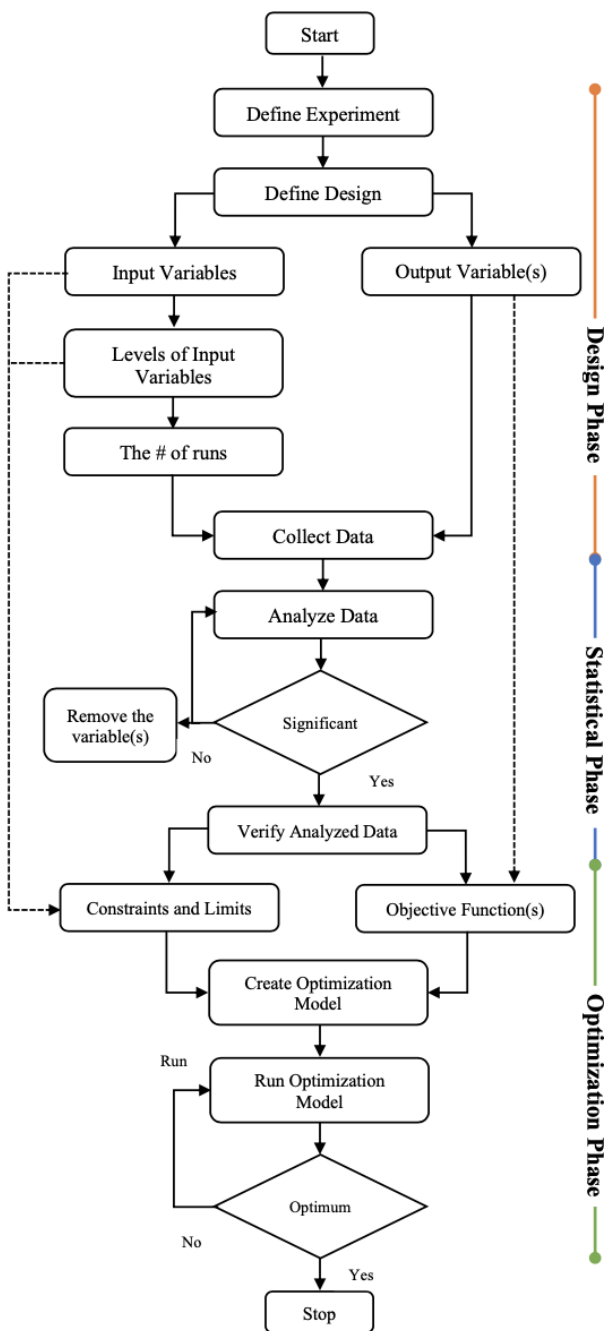
**Table 1.** Full Factorial DoE of three factors with two levels

| Run | Inputs | | | Output Response |
|-----|--------|--------|--------|-----------------|
|     | Factor 1 $(x_1)$ | Factor 2 $(x_2)$ | Factor 3 $(x_3)$ | |
| 1.00 | 1.00 (Low) | 1.00 (Low) | 1.00 (Low) | $y_1$ |
| 2.00 | 1.00 (Low) | 1.00 (Low) | 2.00 (High) | $y_2$ |
| 3.00 | 1.00 (Low) | 2.00 (High) | 1.00 (Low) | $y_3$ |
| 4.00 | 1.00 (Low) | 2.00 (High) | 2.00 (High) | $y_4$ |
| 5.00 | 2.00 (High) | 1.00 (Low) | 1.00 (Low) | $y_5$ |
| 6.00 | 2.00 (High) | 1.00 (Low) | 2.00 (High) | $y_6$ |
| 7.00 | 2.00 (High) | 2.00 (High) | 1.00 (Low) | $y_7$ |
| 8.00 | 2.00 (High) | 2.00 (High) | 2.00 (High) | $y_8$ |

**Note**: $x_1$, $x_2$, and $x_3$ denote the input factors and $y_1$, $y_2$, $y_3$, $y_4$, $y_5$, $y_6$, $y_7$, and $y_8$, symbolize the result of responses.

independent variables' effect on the response variable. The first-order (or linear regression equation) and second-order equation are formulated as follows:

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \in \qquad (4)$$

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \left( \sum_{i=1}^{n} a_{ii} x_i^2 \right) + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j \qquad i < j \qquad (5)$$

where $x_i$ and $x_j$ are the design variables, $a_i$, $a_{ii}$, $a_{ij}$ are the tuning constraints, $a_0$ is the regression coefficient of the equation, and $\epsilon$ is random error. The blue **circle** in Eq. (5) indicates that this equation is nonlinear. According to Eq. (6), the equation of the second-order design for three factors is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 \\ + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 \qquad (6)$$

where $y$ represents the response variable, $\beta_0$, denotes the model constant; $x_1$, $x_2$, and $x_3$ symbolizes independent variables; $\beta_1$, $\beta_2$, and $\beta_3$ characterizes linear coefficients; $\beta_{12}$, $\beta_{13}$, and, $\beta_{23}$ represent cross-products coefficients and $\beta_{11}$, $\beta_{22}$, and $\beta_{33}$ are the quadratic coefficients.

There are two crucial parts, objective function, and constraints, in the optimization phase, the DoE's last step. The generated regression equation and the independent

variables' levels represent the objective function and constraints, respectively. These parts come together to form an optimization model. The objective functions have two aspects, maximum and minimum, in optimization models. For example, while the amount of energy produced is desired to be maximum, the amount of energy spent should be minimal. However, the limits created by the constraints should not be exceeded to achieve optimum function values. The optimization model is expressed mathematically as follows:

$$Z_{max/min} \qquad a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j \qquad i < j \qquad (7)$$

*Subject to*

$$l_{low} \leq x_i \leq l_{high}$$

where $Z_{max/min}$ represents the purpose function. $l_{low}$ and $l_{high}$ denote the lower limit and the upper limit of the constraints.

JMP Pro (version 15.0) statistical software was used to apply the method proposed in this study for the numerical case study.

## CASE STUDY: THE DAMPED DRIVEN PENDULUM EXPERIMENTS

This case study was made to demonstrate that the DoE approach is easy to use for physics experiments. DoE saves both cost and time and enables analysis of experiments according to a design. Thus, this study will contribute to the literature to guide the researchers who spend a lot of time in experimental labs and have problems in terms of experiment costs.

The data obtained from the damped-driven pendulum experiments were applied in DoE for this study. The pendulum must have the driving force to be exposed to friction exploitation. In this experiment, the drive width and friction coefficient are set to zero. Gravity is considered constant for all experimental scenarios. The Runge-Kutta algorithm approach was used for this experiment.

Three independent and single dependent variables were defined in this study to apply the DoE approach. Damping is the only driving force that is determined as an independent variable. The other independent variable is defined as bob mass. The third independent variable is selected as the length of the rope to which the bob is tied. The type of energy that occurs in a simple pendulum without friction is defined as mechanical energy. Total mechanical energy is calculated as the sum of kinetic energy and potential energy. As the pendulum swings back and forth, there is a constant shift between kinetic energy and gravitational potential energy. However, changes in the mechanical energy values obtained in each scenario are observed. In this study, mechanical energy is defined as only one independent
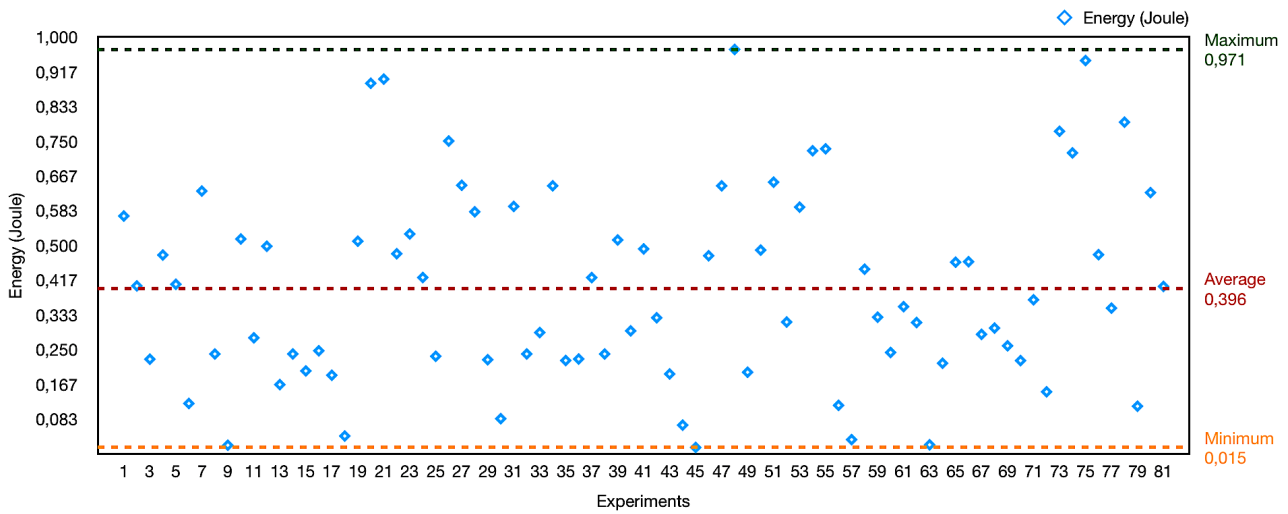
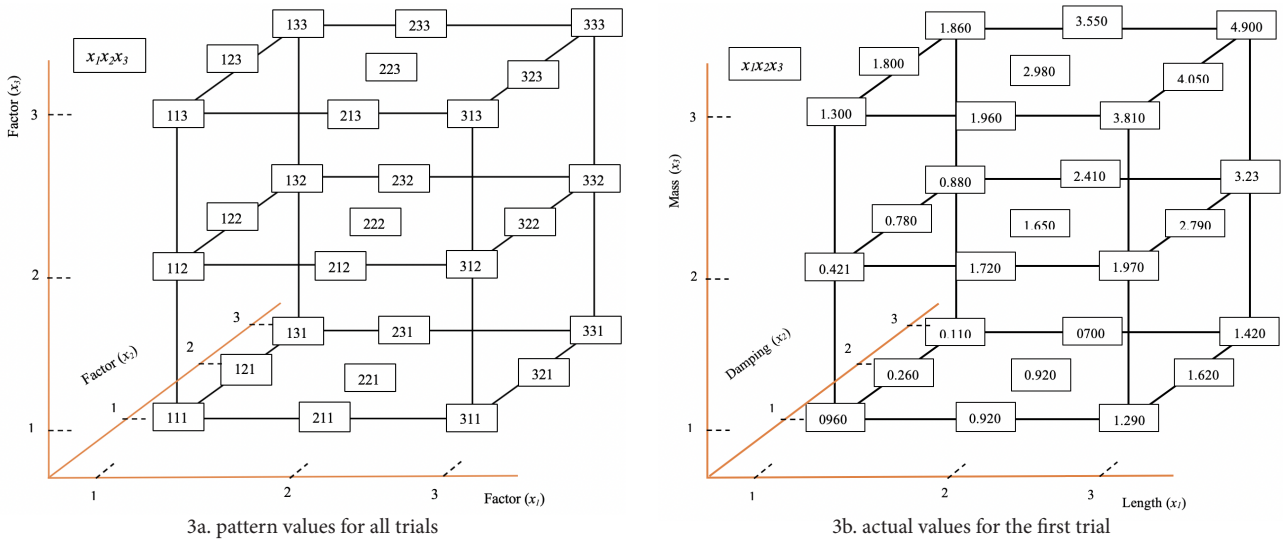**Figure 2.** Data for independent variables, Energy (Joule)



3a. pattern values for all trials

3b. actual values for the first trial

**Figure 3.** The combination of the trials in the $3^3$ design

variable. The dependent variable data are presented in Fig. 2 with descriptive statistics data such as maximum, minimum, and average value.

Three levels were determined for each of the three independent factors. Three repetitions were performed for the experiments. A total of 81 experiments were carried out for the full factorial experiment design. Many combinations result in more superficial repetition behaviour. In the experiments, approximately one minute was waited for the bob to settle in the loop. The data were obtained by releasing the damped pendulum at an initial angle of $90^0$ without resting. According to the full-factorial experiment design, the graphic design of this experiment is visualized in Fig. 3. Fig. 3a contains the pattern data corresponding to the 3-level (stepped) sequence of 3 independent variables,

while Fig. 3b shows the actual data for the first replication corresponding to the pattern data.

In a full factorial experiment design, experiments are performed according to a certain order or combination. The experiment conducted for this study was done according to the experimental layout shown in Tab. 2. Thus, considering the time and cost aspects, it aimed to make the experiment according to a certain plan. It was ensured that the number of unnecessary experiments to be made was eliminated. It is facilitated for experimenters to experiment in a certain order with such a design.

The second stage includes statistical analysis in DoE. The statistical analysis of the results obtained is performed after the dependent variable(s), the independent variable(s), levels of the independent variables, and replication

**Table 2.** Full factorial design for damped driven pendulum experiments

| Run | Pattern | Input Variables | | | Output Variable | | |
|---|---|---|---|---|---|---|---|
| | | Length (m) | Damping (Newton) | Mass (kg) | Energy$_1$ (Joule) | Energy$_2$ (Joule) | Energy$_3$ (Joule) |
| 1.00 | 111 | 1.00 | 1.00 | 1.00 | 0.960 | 0.988 | 0.440 |
| 2.00 | 112 | 1.00 | 1.00 | 2.00 | 0.421 | 0.490 | 1.026 |
| 3.00 | 113 | 1.00 | 1.00 | 3.00 | 1.300 | 0.910 | 1.025 |
| 4.00 | 121 | 1.00 | 2.00 | 1.00 | 0.260 | 0.300 | 0.450 |
| 5.00 | 122 | 1.00 | 2.00 | 2.00 | 0.780 | 0.710 | 1.315 |
| 6.00 | 123 | 1.00 | 2.00 | 3.00 | 1.800 | 1.520 | 1.230 |
| 7.00 | 131 | 1.00 | 3.00 | 1.00 | 0.110 | 0.150 | 0.300 |
| 8.00 | 132 | 1.00 | 3.00 | 2.00 | 0.880 | 0.740 | 1.380 |
| 9.00 | 133 | 1.00 | 3.00 | 3.00 | 1.860 | 1.700 | 2.350 |
| 10.00 | 211 | 2.00 | 1.00 | 1.00 | 0.920 | 1.240 | 0.950 |
| 11.00 | 212 | 2.00 | 1.00 | 2.00 | 1.720 | 1.900 | 1.080 |
| 12.00 | 213 | 2.00 | 1.00 | 3.00 | 1.960 | 2.340 | 2.070 |
| 13.00 | 221 | 2.00 | 2.00 | 1.00 | 0.920 | 1.010 | 0.880 |
| 14.00 | 222 | 2.00 | 2.00 | 2.00 | 1.650 | 1.600 | 2.195 |
| 15.00 | 223 | 2.00 | 2.00 | 3.00 | 2.980 | 2.920 | 2.900 |
| 16.00 | 231 | 2.00 | 3.00 | 1.00 | 0.700 | 0.680 | 1.260 |
| 17.00 | 232 | 2.00 | 3.00 | 2.00 | 2.410 | 2.360 | 1.955 |
| 18.00 | 233 | 2.00 | 3.00 | 3.00 | 3.550 | 3.810 | 3.660 |
| 19.00 | 311 | 3.00 | 1.00 | 1.00 | 1.290 | 0.930 | 0.980 |
| 20.00 | 312 | 3.00 | 1.00 | 2.00 | 1.970 | 2.480 | 2.095 |
| 21.00 | 313 | 3.00 | 1.00 | 3.00 | 3.810 | 3.580 | 3.765 |
| 22.00 | 321 | 3.00 | 2.00 | 1.00 | 1.620 | 1.180 | 1.670 |
| 23.00 | 322 | 3.00 | 2.00 | 2.00 | 2.790 | 3.120 | 3.025 |
| 24.00 | 323 | 3.00 | 2.00 | 3.00 | 4.050 | 4.070 | 4.280 |
| 25.00 | 331 | 3.00 | 3.00 | 1.00 | 1.420 | 1.650 | 2.105 |
| 26.00 | 332 | 3.00 | 3.00 | 2.00 | 3.230 | 3.550 | 3.710 |
| 27.00 | 333 | 3.00 | 3.00 | 3.00 | 4.900 | 4.890 | 4.765 |

are determined for an experiment. Statistical data of the experiment conducted for this study are given in Tab. 3.

The independent variables of length, mass, and dumping have a statistically significant effect on the output variable energy. Likewise, the results of the interactions of these independent variables with each other were found to be effective on the output variable. The fact that all three factors are important in this experiment means that no factor is excluded from the experiment. In this study, three different parameters, f-test, t-test, and p-value, were taken into account to measure statistical analysis consistency. In addition, the experiment performed is statistically significant and valid by calculating R-square ($R^2$) as 0.97. $R^2$ is a statistical term used to determine the accuracy and consistency of a statistical model. With the calculation of this term, you will have information about the reliability of your statistical analysis. $R^2$ is defined as the percentage of variation of the output variable of the statistical model. Thus,

$R^2$ provides the opportunity to compare with the regression model errors by using the mean of the output variable for modelling the data, especially in statistical analysis models that require a regression model.

As a result of the statistical analysis of DoE, the following regression equation has been formed in which all variables are taken into account. This equation also constitutes the optimization model's objective function, which is the third part of DoE.

To maximize

$$y_{Energy} = 1.9005 + 0.9543x_1 + 0.3223x_2 + 0.9747x_3 \\ + 0.2058x_1x_2 + 0.4313x_1x_3 + 0.3069x_2x_3 \quad (8) \\ - 0.1282x_1x_2x_3$$

In the optimization model developed for this study, the direction of the objective function must be maximum. However, the limits of some constraints affect the objective

**Table 3.** Analysis of Variance for the damped driven pendulum experiments

| Term | Notation | t Ratio | F Ratio | P Value | Prob>\|t\| Prob > F | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|---|
| Length | $x_1$ | 29.38 | 863.432 | 0.0001 | <.0001 | 0.889 | 1.019 |
| Dumping | $x_2$ | 9.940 | 98.8515 | 0.0002 | <.0001 | 0.258 | 0.388 |
| Mass | $x_3$ | 30.01 | 900.724 | 0.0001 | <.0001 | 0.910 | 1.039 |
| Length*Dumping | $x_1 * x_2$ | 5.170 | 26.7737 | 0.0002 | <.0001 | 0.126 | 0.285 |
| Length*Mass | $x_1 * x_3$ | 10.84 | 117.602 | 0.0003 | <.0001 | 0.352 | 0.511 |
| Dumping*Mass | $x_2 * x_3$ | 7.720 | 59.5320 | 0.0050 | <.0001 | 0.228 | 0.386 |
| Length*Dumping*Mass | $x_1 * x_2 * x_3$ | −2.63 | 6.93130 | 0.0103 | 0.0103 | −0.225 | −0.031 |

**Status:** to determine the individual and interactive effects of the factors that could affect the responses and statistical significance ($p \leq 0.05$), *at the margin of statistical significance
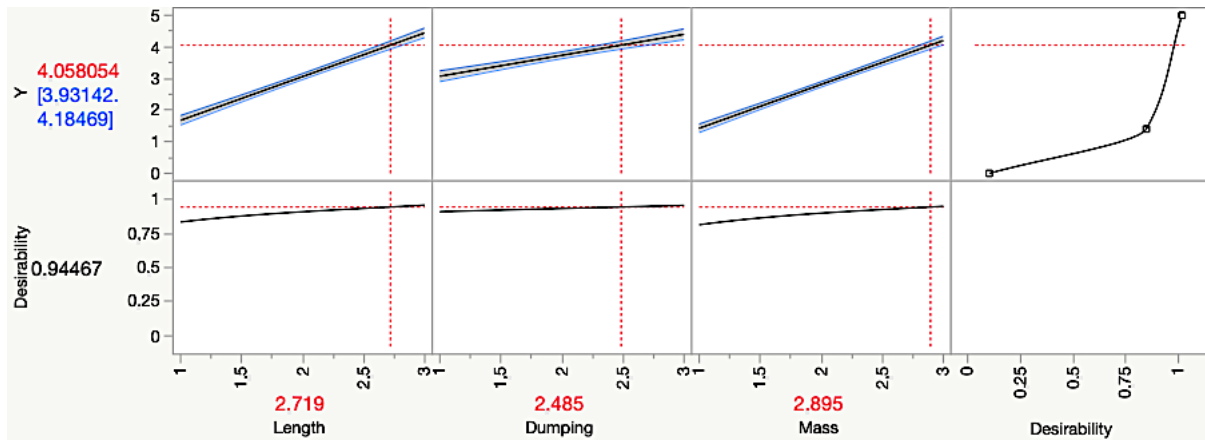


**Figure 4.** optimum data for decision variables, objective function and desirability value.

function reaching its maximum value. The limitations of length, mass, and dumping constraints are given in Eq. (9).

Subject to

$$l_1 \leq x_i \leq u_i, i = \{length, dumping, mass),$$
$$u_l = 3$$
$$l_l = 1 \quad\quad (9)$$
$$x_i \geq 0$$

where $x_i$ refers to the decision variable type. $l_i$ and $u_i$ denote the lower limit and the upper limit of the constraints.

According to the optimization model, the value of the objective function is calculated as 4.058 (joule). The optimum values for length, dumping, and mass were calculated as 2.719 m, 2.485(Newton), and 2.895 kg, respectively. These optimum values were obtained according to the desirability value, which measures the optimization model and checks its validity. This value ranges from 0 to 1. It is emphasized that the closer the desirability value is to 1, the more consistent and valid the optimum results. In this study, the

desirability value is relatively high, and it was calculated as 0.945. Fig. 4. contains optimum data for decision variables, objective function and desirability value.

## CONCLUSION

The design of experiment (DoE) ensures that an experiment is designed to obtain valid, reliable, effective and efficient results to easily show that the experiment is affected by changing the degrees or levels of more than one variable in an experiment. On the basis of the DoE technique, it is suggested how the design of the experiment will form before an experiment is conducted. Significantly, the DoE approach developed for experiments requiring cost and time is applied in many disciplines. This study aims to demonstrate the applicability of the DoE technique in the field of physics with a case study. Many experiments in the field of physics require both cost and time. A fixed cost is required for the materials and equipment needed for the Damped Drive Pendulum Test. There are types of costs in an experiment that include a fixed cost as well as a variable cost. These cost types arise from time, material and

long-term analysis. For example, in this type of experiment selected for this study, besides the fixed cost, savings in the cost of the experiment was achieved credits to the time and savings obtained during the analysis process. Thus, it provides both convenience and cost savings in maintaining applicability with the experiment designed for experimenters. Otherwise, it is not possible to get accurate and valid results in a short time from the results obtained from the experiments. The most commonly used full-factorial design was used in the DoE for the case study. The inputs variables were analyzed not only individually but also interactively. A different scenario was observed to be important for each output of the study. As a result of the statistical analyses in DoE, optimization models were created, and optimum values were obtained for the case study. Consequently, this study demonstrates that the DoE approach is easy to use for physics experiments. Thus, this study will contribute to the literature to guide the researchers who spend a lot of time in experimental labs and have problems with experiment costs.

## DATA AVAILABILITY STATEMENT

No new data were created in this study. The published publication includes all graphics collected or developed during the study.

## CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## ETHICS

There are no ethical issues with the publication of this manuscript.

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