POLITYKA ENERGETYCZNA – ENERGY POLICY JOURNAL

2024 ✦ Volume 27 ✦ Issue 2 ✦ 89–104

DOI: 10.33223/epj/185719

Ivan Antonov Petrov[1]

Regression analysis of experimental data in a study of the performance of a flat flame burner

Abstract: The complex nature of the combustion process, which simultaneously obeys the laws of thermodynamics, heat transfer, aerodynamics and the chemical kinetics of oxidation reactions, makes numerical modelling very difficult and the experimental approach is currently playing a crucial role in their investigation. The modern highly developed theory of experimental design combines various analytical procedures that allow, with a minimum number of experiments, the obtaining of maximum information about the physical or technological processes under investigation, the properties of materials and phenomena. The ability to determine the influence of the main mode and design parameters on the geometrical characteristics of the flare is a prerequisite for effectively influencing the combustion process in order to intensify it. The present work is an introduction to the methods of planning and knowledge of multifactorial experiments, including: the preparation, conduct and processing of experimental results; mastering the methodology of experimental research; using the methods of mathematical statistics and regression analysis to plan experiments; developing the ability to analyze the object of study; correctly selecting the optimization parameter and the essential factors of the object of study; building an experiment planning matrix to obtain an adequate mathematical model of the object. The objective of this work is to propose an approach to study the effect of mode and design parameters, on the basic

✉ Corresponding Author: Ivan Antonov Petrov; e-mail: ivan.a.petrov@abv.bg

[1] Department of Mechanical Engineering, Manufacturing and Thermal Engineering; Technical University of Sofia, Faculty of Engineering and Pedagogy of Sliven, Bulgaria; ORCID iD: 0009-0007-9080-8722; e-mail: ivan.a.petrov@abv.bg

dimensions and shape of the gas flare, based on regression analysis of experimental data in the study of the performance of a flat flame burner.

KEYWORDS: factorial experiment, regression analysis, combustion, flat flame burner

Introduction

Gas fuel has widely been used as an energy carrier in industry in recent decades. There has been a continuous upward trend in its relative share. This is due to the requirements imposed by both energy efficiency and environmental protection legislation. A primary concern is the ability to actively influence the combustion process in order to manage it optimally. The optimization of combustion devices actually means the appropriate selection of the relevant mode and design parameters, on which both the efficiency of the use of the gaseous fuel and the amount of harmful emissions released into the environment depend. Structural, aerodynamic and physical factors have a determining influence on the combustion completeness and ignition conditions (Kostov et al. 2022; Makzumova et al. 2023).

Flat flame burners are widely used in industry due to their high uniformity of heating and complete combustion with low excess air coefficient. A characteristic feature (Fig. 1) is the possibility of creating a flat torch spreading radially on a refractory plate.

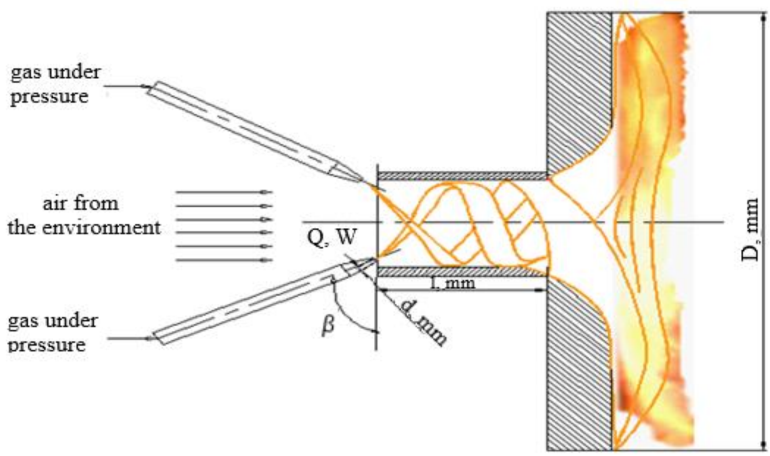

Fig. 1. Schematic of a flat flame burner

Rys. 1. Schemat palnika z płaskim płomieniem

The geometry of the flare is determined by a number of factors, the degree of influence of each of which is difficult to assess by a single-factor experiment. Estimation is further complicated by the fact that most of these factors influence each other. From previous experiments and data from the literature (Krystev 2021; Zlateva et al. 2020; Dostiyarov et al. 2022), it boils down to the determination of four main independent parameters that have a significant influence on the formation of a flat flame. These are:

- Angle of inclination of the gas nozzles – β. This characterizes the degree of rotation of the air flow and defines the conditions of heat and mass exchange in the flame.
- The diameter of the nozzle holes through which the gas fuel flows – d. This determines the fuel distribution in the air flow and thus the heat exchange characteristics of the flame.
- Heat load – Q. This determines the temperature regime.
- Length of the mixing chamber – l. This determines the residence time of the reacting components in the mixing section and the ignition intensity of the fuel-air mixture.

The method of the full factorial experiment allows obtaining a mathematical description of the studied process in a certain local region of the factor space. A full factorial experiment is an experiment in which all possible non-repeating combinations of the levels of the independent factors are realized. A full factorial experiment is applied 2^{K}, at two levels with four factors ($k = 4$). Sixteen trials were conducted, each of which was equally duplicated three times. This number of trials allows the assessment of the set of main effects together with their interaction effect (Madani et al. 2015).

The purpose of choosing this plan is to obtain as complete information as possible about the influence of the adopted factors on the diameter of the formed flat flame by minimizing the number of trials and respecting the requirements of rotatability and orthogonality of the corresponding matrix,.

In order to eliminate the influence of external factors, the experiments were conducted randomly over time. The use of this approach allows filtering out the influence of irrelevant factors and avoiding the accumulation of systematic error. The local area for the determination of the factors is established by a priori considerations. Each of the factors is varied at two levels.

Two-stage factorial experiments are excellent tools, providing a means by which the factors included in an experiment can be both assessed and tested for significance (González 1998).

Factorial experiments helps to develop a statistical response model by performing the minimum number of well-chosen experiments and determining the optimal values of the process parameters. Factorial experiments are an empirical modelling technique used to evaluate the relationship between experimental variables and corresponding responses (Krishna Prasad and Srivastava 2009).

Data generated in this way is used to calibrate an empirical model, typically including first- or second-order terms, which is eventually refined to exclude unaffected factors and/or add higher -order terms (Montgomery 2013; Cenci et al. 2023).

Normalized first-order sensitivity coefficients are typically applied to combustion to provide a kinetic view of the model and its strengths and weaknesses relative to experimental data. If little is known about the uncertainty distribution of the input parameters then such first-order methods can provide a useful starting point for key parameter identification and model analysis. Input-output dependencies arising from the application of such sampling approaches are typically estimated using statistical methods. This may include calculating the expected value and variance of selected target outputs (Saltelli et al. 2000; Tomlin 2013).

Regression analysis is a statistical method for analyzing and modelling relationships between mass phenomena. It is a statistical method for investigating cause-effect and phenomenon-response relationships in processes and phenomena (Jamshidnezhad 2015). The main purpose of regression analysis is to represent in analytical form, in the form of a mathematical model, the studied correlation relationship. Therefore, this analysis is also called an analytical method for studying correlation dependencies (Ivanov et al. 2022; Denev et al. 2021; Kostov et al. 2021).

1. Materials and methods

Experimental design methodology refers to the use of practical and powerful statistical tools and techniques to develop efficient, balanced, and economical experimental designs that allow the experimenter to determine how controlled and uncontrolled factors relate to the outcome of the process (Antony 2023).

Developing predictive models to be used in model-based activities requires the identification of the model structure, specifically a set of model equations and model calibration, i.e., the precise estimation of model parameters from experimental data (Mihaluta et al. 2008; de Prada et al. 2019; Cenci et al. 2023).

However, it is imperative to develop a model whose factor interactions can be uniformly distributed over any number of desired levels to ensure the unbiased estimation of main effects. Analysis of variance, a diagnostic tool for regression analysis, is used in some cases to analyze the significance of factor interactions (Sathish Kumar et al. 2022; Hatami et al. 2015).

Direct measurements have played an invaluable role in the development and improvement of kinetic mechanisms over many years with the available techniques discussed in the literature (Pilling 2009; Tomlin 2013). In order to validate the optimized experiments, a desirability check is performed for all studies (Sathish Kumar et al. 2022; Antony 2014; Ansari et al. 2019).

Running a full factorial experiment involves determining the effects of variable controllable input factors (X_1, X_2, ..., X_n) on the corresponding varied output responses (Y_1, Y_2, ..., Y_n) of a process/system. These experimental design approaches are typically implemented by assigning all factors "k" to two levels, usually denoted by a high (+1 or simply +) and a low (–1 or simply –) level for each factor (Antony 2003; Montgomery 2013; Eriksson et al. 2008).

The experimental design chosen for this study is a 2^4 factorial experiment for four independent variables of gas nozzle inclination angle (X_1), gas nozzle diameter (X_2), burner heat load (X_3) and combustor length (X_4). Table 1 gives the ranges of variation of the factors (independent variables) and their values in a natural scale at the basic, upper and lower levels.

TABLE 1. Intervals for variation of factors

TABELA 1. Zakresy zmian wskaźników

Factors	X_1 β [°]	X_2 d [mm]	X_3 Q [kW]	X_4 l [mm]
Basic level (X_{i0})	45	0.8	70	230
Variation interval (ΔX_i)	15	0.1	20	80
Upper level ($x_i = +1$)	60	0.9	90	310
Lower level ($x_i = -1$)	30	0.7	50	150

The coded values of the factors (x_i) are associated with the naturel (X_i) by the dependence:

$$x_i = \frac{X_i - X_{i0}}{\Delta X_i} \tag{1}$$

After applying this dependency, we obtain:

$$x_1 = \frac{\beta - 45}{15} \tag{2}$$

$$x_2 = \frac{d - 0.8}{0.1} \tag{3}$$

$$x_3 = \frac{Q - 70}{20} \tag{4}$$

$$x_4 = \frac{l - 230}{80} \tag{5}$$

Table 2 shows the expanded matrix of the full factorial experiment 2^4 in a coded and natural scale after applying the dependence between the factors, and the experimental results, with the dependent variable $\overline{y}_u$, represents the gas flare diameter D. Here, a column of dummy variable is added x_0, taking in all experiments a positive value necessary to estimate the free term b_0 of the regression equation.

First-order plans are most often used in designing the experiment. These are those plans that allow an experiment to be conducted to determine the regression equation, which is a first-order polynomial. The minimum number of factor levels required is one greater than the order of the regression equation, for example, for a first-degree polynomial, the minimum number of factor levels is two.

The regression analysis was performed using the methodologies described by (Novik and Arsov, 1981; Degtyarev; Lyubimova and Sisykov 2017) and the sequence of experimental treatments in the particular case of equal duplicated trials is as follows:

✦ To determine the regression coefficients in this case, a model of the type:

$$\bar{y} = b_0 + \sum_{1\le i\le 4} b_i x_i + \sum_{1\le i\le j\le 4} b_{ij} x_i x_j + \sum_{1\le i\le j\le l\le 4} b_{ijl} x_i x_j x_l + b_{ijlm} x_i x_j x_l x_m \tag{6}$$

✦ After implementing the plan, sixteen equations with sixteen unknowns are obtained and from solving these equations, all sixteen coefficients are found of the regression equation. The coefficients are computed using the formulas:

$$b_0 = \frac{\sum_{u=1}^{N} x_{0u} \cdot \bar{y}_u}{N} \tag{7}$$

$$b_i = \frac{\sum_{u=1}^{N} x_{iu} \cdot \bar{y}_u}{N}, i = 1, \ldots, k \tag{8}$$

$$b_{ij} = \frac{\sum_{u=1}^{N} x_{iu} \cdot x_{ju} \cdot \bar{y}_u}{N}, \; i = 1, \ldots, k; j = i+1 \ldots, k \tag{9}$$

$$b_{ijl} = \frac{\sum_{u=1}^{N} x_{iu} \cdot x_{ju} \cdot x_{lu} \cdot \bar{y}_u}{N}, i = 1, \ldots, k; j = i+1, \ldots, k; \; l = j+1, \ldots k \tag{10}$$

$$b_{ijlm} = \frac{x_{iu} \cdot x_{ju} \cdot x_{lu} \cdot x_{mu} \cdot \bar{y}_u}{N}, i = 1, \ldots, k; j = i+1, \ldots, k; \; l = j+1, \ldots k; \; m = l+1, \ldots, k \tag{11}$$

✦ The experimental variance is calculated and the uniformity of the variance series is checked by calculating the value of the Cochrane criterion or G-criterion:

$$S_y^2 = \frac{\sum_{u=1}^{N} S_{y_u}^2}{N} \tag{12}$$

$$S_{y_u}^2 = \frac{\sum_{g=1}^{n_u} \left(y_{ug} - \bar{y}_u \right)^2}{f_u} \tag{13}$$

$$G^* = \frac{S_{y_{umax}}^2}{\sum_{u=1}^{N} S_{y_u}^2} \tag{14}$$

where:

S_y^2 – dispersion of experience,
$S_{y_u}^2$ – dispersion for each trial in turn,
$S_{y_{umax}}^2$ – largest dispersion in the series,
y_{ug} – result of the g-th iteration of the u-th trial,
$\bar{y}_u$ – average of all n_u repetitions of the u-th trial,

N	–	number of trials,
f_u	–	the number of degrees of freedom in determining the u-th order variance $S_{y_u}^2$,
G^*	–	calculated value of the Cochrane criterion,
$G^* < G_{table}$	–	homogeneity of the dispersion series.

✦ The statistical significance of the coefficients of the regression equation was checked using the Steudent's criterion.
The dispersion of the coefficient estimates is calculated using the formula:

$$S_{b_i}^2 = \frac{S_y^2}{n_u \cdot N} \tag{15}$$

$$\Delta b_i = t_{\alpha;f_1} \cdot S_{b_i} \tag{16}$$

where:

S_{b_i}	–	mean squared error,
$t_{\alpha;f_1}$	–	t-criterion value,
f_1	–	the number of degrees of freedom,
α	–	level of significance,
Δb_i	–	confidence interval. Coefficients whose absolute value is equal to or greater than the confidence interval are statistically significant.

✦ The next stage of processing the experimental data is to test the hypothesis of the model adequacy using the Fisher's criterion or F-criterion:

$$F_{f_2;f_1}^* = \frac{S_{in}^2}{S_y^2} \tag{17}$$

$$S_{in}^2 = \frac{n \cdot \sum_{u=1}^{N} \left(y_u - \overline{y}_u\right)^2}{f_2} \tag{18}$$

where:

S_{in}^2 – dispersion of inadequacy,

F^* – calculated value of Fisher's criterion. The hypothesis of adequacy is accepted when the calculated value of the F-criterion is $F^* \leq F^{table}$.

2. Discussion

The numerical results shown in the summary in Table 2 after implementation of the full factorial experiment and considering the condition of statistical significance of the coefficients, the following regression equation is obtained:

$$\begin{aligned}\bar{y} = 367.63 - 41.75x_1 + 36.63x_2 + 11.25x_3 - 11.38x_4 - 12x_1x_2 - 8.13x_1x_3 \\ -7.75x_1x_4 - 16.75x_3x_4 - 5.38x_1x_2x_3 - 4.5x_1x_2x_4 + 5.25x_2x_3x_4\end{aligned} \quad (19)$$

After going from the coded to the natural scale, the equation takes the form:

$$\begin{aligned}D = 367.63 - 41.75\cdot\frac{\beta-45}{15} + 36.63\cdot\frac{d-0.8}{0.1} + 11.25\cdot\frac{Q-70}{20} - 11.38\cdot\frac{l-230}{80} - 12\cdot\frac{\beta-45}{15}\cdot\frac{d-0.8}{0.1} \\ - 8.13\cdot\frac{\beta-45}{15}\cdot\frac{Q-70}{20} - 7.75\cdot\frac{\beta-45}{15}\cdot\frac{l-230}{80} - 16.75\cdot\frac{Q-70}{20}\cdot\frac{l-230}{80} - 5.38\cdot\frac{\beta-45}{15}\cdot\frac{d-0.8}{0.1}\cdot\frac{Q-70}{20} \\ - 4.5\cdot\frac{\beta-45}{15}\cdot\frac{d-0.8}{0.1}\cdot\frac{l-230}{80} + 5.25\cdot\frac{d-0.8}{0.1}\cdot\frac{Q-70}{20}\cdot\frac{l-230}{80}\end{aligned} \quad (20)$$

After conversion, the following is obtained:

$$\begin{aligned}D = 182.86 - 16.46\beta + 301.8d - 54.32Q + 1.16l + 14.49\beta d + 0.122\beta Q \\ + 0.025\beta l + 0.51dQ - 0.66dl - 0.041Ql - 0.19\beta dQ - 0.04\beta dl + 0.037dQl\end{aligned} \quad (21)$$

Figure 2 gives a plot of the relative magnitude of the influence of the factors and their interactions, in which the value of each coefficient is denoted by the corresponding height of the bar.

Figures 3, 4, 5 and 6 show the variation of the flare diameter with the change of each of the selected independent factors. Figures 7, 8, 9 and 10 show the response surfaces and their plots obtained from the regression equation due to the influential interaction between the selected independent factors, fixing each of the factors at zero level: *d = 0.8; Q = 70; l = 230.*

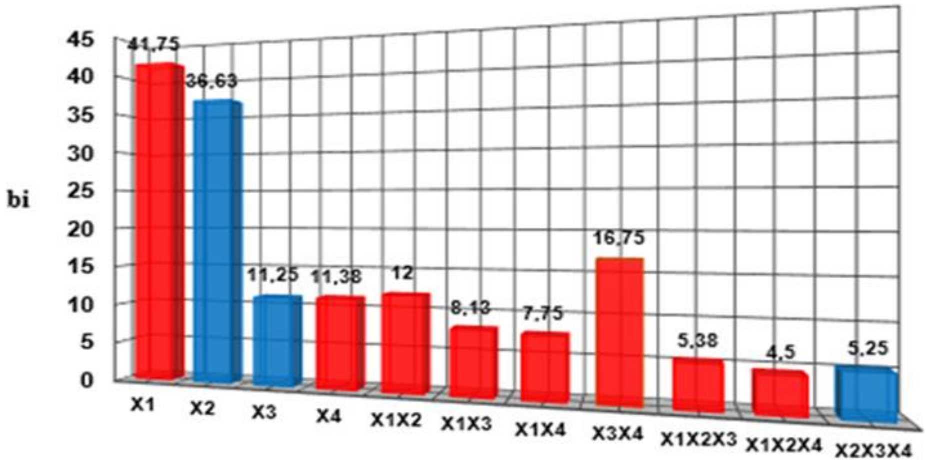

Fig. 2. The relative magnitude of the influence of factors and their interactions (red bars for negative coefficients and blue bars for positive coefficients)

Rys. 2. Względna wielkość wpływu czynników i ich interakcji (czerwone słupki dla współczynników ujemnych i niebieskie słupki dla współczynników dodatnich)

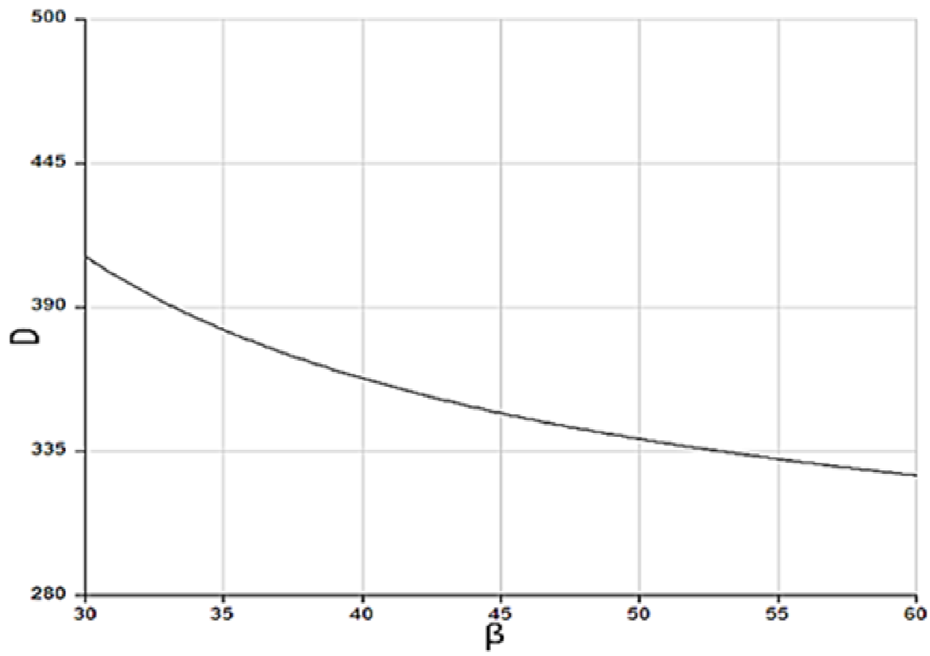

Fig. 3. Variation of the flare diameter D depending on the change of the gas nozzles inclination angle β

Rys. 3. Zmiana średnicy kielicha płomienia D w zależności od zmiany kąta nachylenia dysz gazowych β

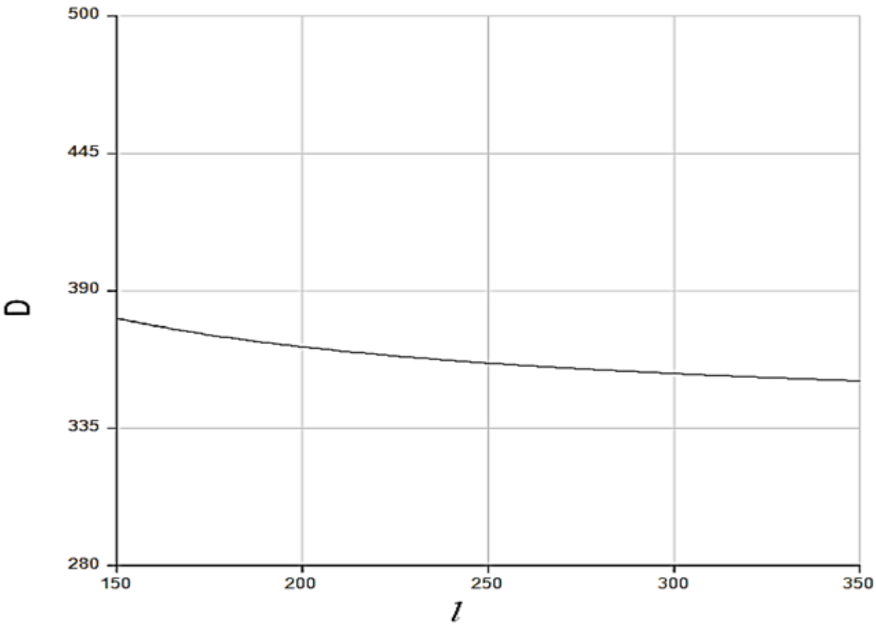

Fig. 4. Variation of the flare diameter D with the change of the mixing chamber length *l*

Rys. 4. Zmiana średnicy kielicha płomienia D wraz ze zmianą długości komory mieszania *l*

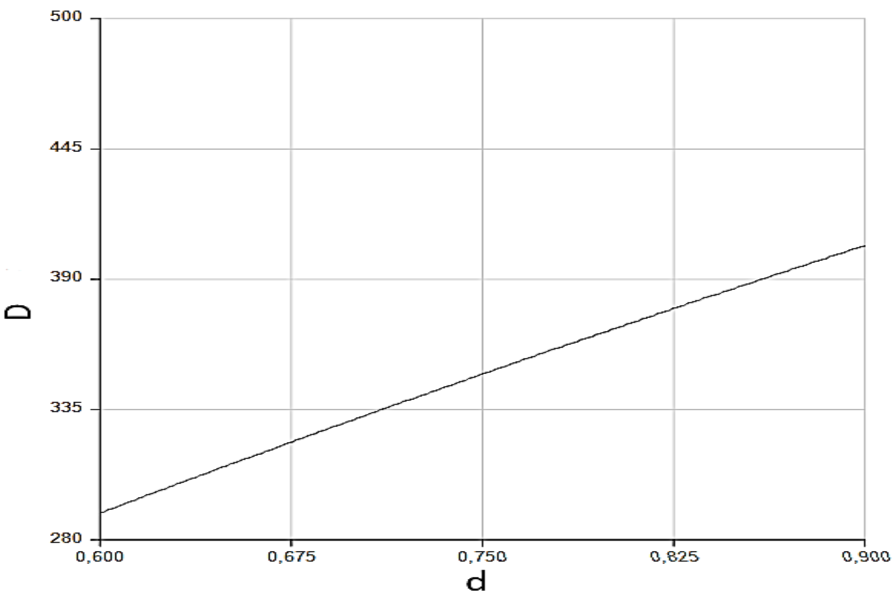

Fig. 5. Variation of the flare diameter D depending on the variation of the gas nozzle orifice diameter *d*

Rys. 5. Zmiana średnicy kielicha płomienia D w zależności od zmiany średnicy otworu dyszy gazowej *d*

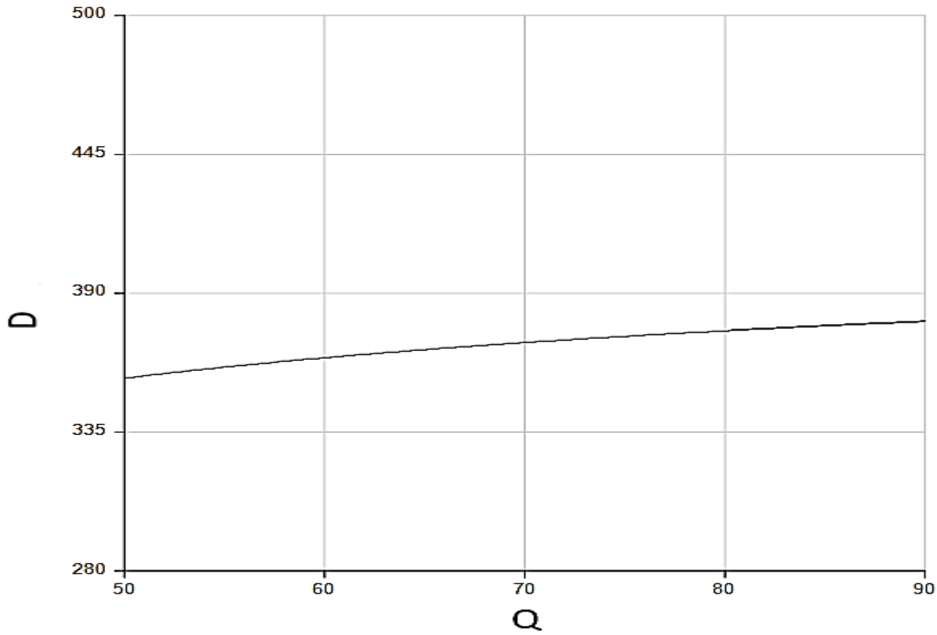

Fig. 6. Variation of the flare diameter D with the change of the heat load *Q*

Rys. 6. Zmiana średnicy kielicha płomienia D wraz ze zmianą obciążenia cieplnego *Q*

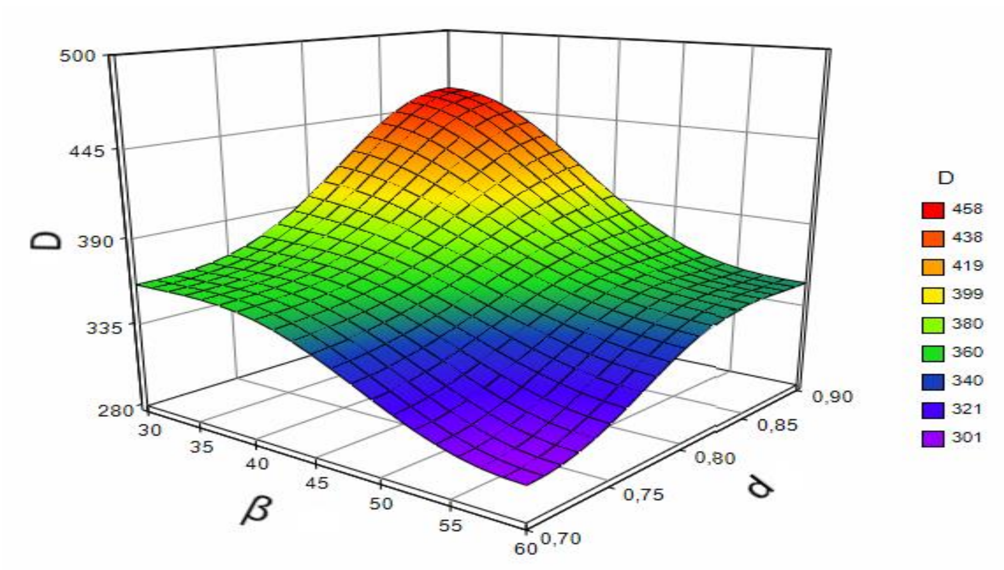

Fig. 7. Fixed factors: $Q = 70$; $l = 230$

Rys. 7. Stałe współczynniki: $Q = 70$; $l = 230$

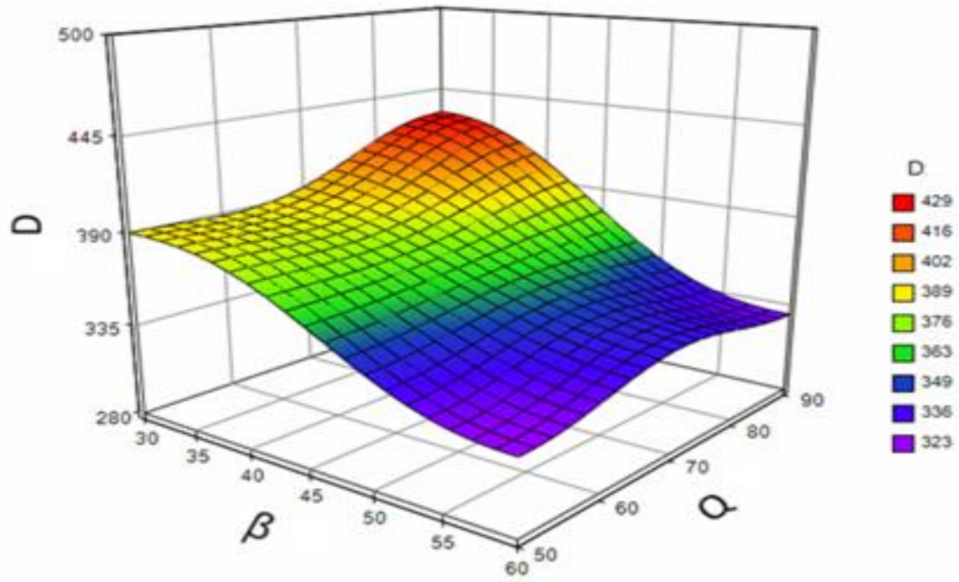

Fig. 8. Fixed factors: $d = 0.8$; $l = 230$

Rys. 8. Stałe współczynniki: $d = 0,8$; $l = 230$

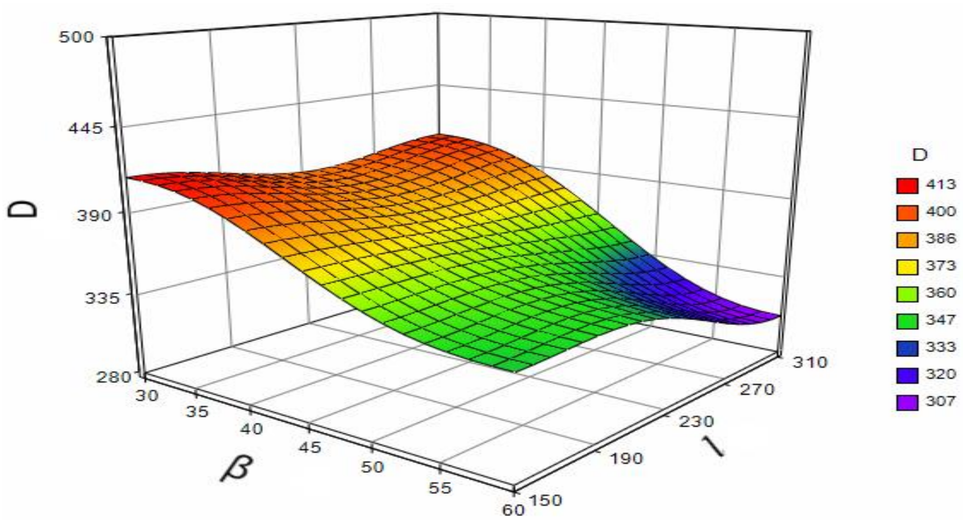

Fig. 9. Fixed factors: $d = 0.8$; $Q = 70$

Rys. 9. Stałe współczynniki: $d = 0,8$; $Q = 70$

TABLE 2. Full factorial experiment results 2^4

TABELA 2. Wyniki pełnego eksperymentu czynnikowego 2^4

No	x_0	x_1	x_2	x_3	x_4	x_1x_2	x_1x_3	x_1x_4	x_2x_3	x_2x_4	x_3x_4	$x_1x_2x_3$	$x_1x_2x_4$	$x_1x_3x_4$	$x_2x_3x_4$	$x_1x_2x_3x_4$	y_{u1}	y_{u2}	y_{u3}	$\overline{y}_u$	$S^2_{y_u}$
1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	+1	320	300	295	305	175
2	+1	–1	+1	+1	+1	–1	–1	–1	+1	+1	+1	–1	–1	–1	+1	–1	476	456	466	466	100
3	+1	+1	–1	+1	+1	–1	+1	+1	–1	–1	+1	–1	–1	+1	–1	–1	302	282	262	282	400
4	+1	–1	–1	+1	+1	+1	–1	–1	–1	–1	+1	+1	+1	–1	–1	+1	335	353	362	350	189
5	+1	+1	+1	–1	+1	+1	–1	+1	–1	+1	–1	–1	+1	–1	–1	–1	342	352	332	342	100
6	+1	–1	+1	–1	+1	–1	+1	–1	–1	+1	–1	+1	–1	+1	–1	+1	465	440	430	445	325
7	+1	+1	–1	–1	+1	–1	–1	+1	+1	–1	–1	+1	–1	–1	+1	+1	288	293	313	298	175
8	+1	–1	–1	–1	+1	+1	+1	–1	+1	–1	–1	–1	+1	+1	+1	–1	372	362	352	362	100
9	+1	+1	+1	+1	–1	+1	+1	–1	+1	–1	–1	+1	–1	–1	–1	–1	379	389	384	384	25
10	+1	–1	+1	+1	–1	–1	–1	+1	+1	–1	–1	–1	+1	+1	–1	+1	492	502	482	492	100
11	+1	+1	–1	+1	–1	–1	+1	–1	–1	+1	–1	–1	+1	–1	+1	+1	350	355	330	345	175
12	+1	–1	–1	+1	–1	+1	–1	+1	–1	+1	–1	+1	–1	+1	+1	–1	407	417	397	407	100
13	+1	+1	+1	–1	–1	+1	–1	–1	–1	–1	+1	–1	–1	+1	+1	+1	390	365	358	371	283
14	+1	–1	+1	–1	–1	–1	+1	+1	–1	–1	+1	+1	+1	–1	+1	–1	423	425	439	429	76
15	+1	+1	–1	–1	–1	–1	–1	–1	+1	+1	+1	+1	+1	+1	–1	–1	265	285	290	280	175
16	+1	–1	–1	–1	–1	+1	+1	+1	+1	+1	+1	–1	–1	–1	–1	+1	340	324	308	324	256
$\sum_{u=1}^{16} x_u \cdot \overline{y}_u$	5,882	–668	586	180	–182	–192	–130	–124	–60	–54	–268	–86	–72	6	84	–22	Cochrane criterion: f_u=2; N=16; a=0.05 G*=0.15; $G^{table}_{0.05;2;16}=0.322$ Conclusion: the dispersion series is homogeneous.				
b_i	367.63	–41.75	36.63	11.25	–11.38	–12	–8.13	–7.75	–3.75	–3.38	–16.75	–5.38	–4.5	0.38	5.25	–1.38					
$t_{0.05;32}$; Δb_i=3,86	sig.	sig.	sig.	sig.	sig.	sig.	sig.	sig.	insig.	insig.	sig.	sig.	sig.	insig.	sig.	insig.	Fisher criterion: a=0.05.				
																	f_1;f_2	F^*	$F^{table}_{0.05;4;32}$	model	
Model: $= b_0 - b_1x_1 + b_2x_2 + b_3x_3 - b_4x_4 - b_{12}x_1x_2 - b_{13}x_1x_3 - b_{14}x_1x_4 - b_{34}x_3x_4 - b_{123}x_1x_2x_3 - b_{124}x_1x_2x_4 + b_{234}x_2x_3x_4$																	32; 4	1.57	2.69	adequate	

Conclusion

Based on the results of the regression analysis, the values of the regression coefficients and their confidence intervals, an adequate mathematical model of the studied process was obtained. The adequacy of the mathematical model was confirmed as a result of statistical hypothesis testing using Fisher's criterion with a significance level of 0.05. From the analysis, it can be seen that of the independent variables selected as factors, the gas flare geometry is strongly influenced by the inclination angle of the gas nozzles, to a lesser extent by the diameter of the gas nozzles and the interaction between them as well as the interaction between the heat load and the length of the mixing chamber. The influence of the heat load, the mixing chamber length and the interaction between the different factors is only weak. Any considerations about the direction and magnitude of the influence of the studied factors on the gas flare diameter can only be expressed for their intervals of variation chosen in the work. In accordance with the planning matrix and the resulting regression equation, appropriate levels of the factors can be selected at which to obtain the desired gas flare geometry.

References

Ansari et al. 2019 – Ansari, E., Menucci, T., Shahbakhti, M. and Naber, J. 2019. Experimental investigation into effects of high reactive fuel on combustion and emission characteristics of the Diesel – Natural gas Reactivity Controlled Compression Ignition engine. *Applied Energy* 239, pp. 948–956, DOI: 10.1016/j.apenergy.2019.01.256.

Antony, J. 2003. *Design of Experiments for Engineers and Scientists*. (1st ed.), Amsterdam: Butterworth Heinemann.

Antony, J. 2023. Design of Experiments in the service industry: a critical literature review and future research directions. *Design of Experiments for Engineers and Scientists* (*Third Edition*), pp. 233–248, DOI: 10.1016/B978-0-443-15173-6.00005-6.

Antony, J. 2014. 6. Full Factorial Designs. *Design of Experiments for Engineers and Scientists* (*Second Edition*), pp. 63–85, DOI: 10.1016/B978-0-08-099417-8.00006-7.

Centi et al. 2023 – Cenci, F., Pankajakshan, A., Facco, P. and Galvanin, F. 2023. An exploratory model-based design of experiments approach to aid parameters identification and reduce model prediction uncertainty. *Computers & Chemical Engineering* 177, DOI: 10.1016/j.compchemeng.2023.108353.

Degtyarev, D.A. A step-by-step methodology for conducting a multifactorial experiment. [Online] http://manyfactors.ru [Accessed: 2024-04-05].

Denev et al. 2021 – Denev, I., Ivanov, I. and Atanasov, K. 2021. Experimental Study of the Air Exchange in Livestock Building. *2021 6th International Symposium on Environment-Friendly Energies and Applications* (*EFEA*), Sofia, Bulgaria, pp. 1–6, DOI: 10.1109/EFEA49713.2021.9406239.

de Prada et al. 2019 – de Prada, C., Pantelides, C.C. and Pitarch, J.L. 2019. Special Issue on "Process Modelling and Simulation". *Processes* 7(8), DOI: 10.3390/pr7080511.

Dostiyarov et al. 2022 – Dostiyarov, A., Beloev, H., Anuarbekov, M. and Iliev, I. 2022. Numerical modelling biogas combustion in the novel burner. *2022 8th International Conference on Ener-*

gy Efficiency and Agricultural Engineering (*EE&AE*), Ruse, Bulgaria, pp. 1–4, DOI: 10.1109/EEAE53789.2022.9831416.

Eriksson et al. 2008 – Eriksson, L., Johansson, E., Kettaneh-Wold, N., Wikström, C. and Wold, S. 2008. *Design of Experiments*. (3rd ed.), Umeå: MKS Umetrics AB.

González, A.G. 1998. Two level factorial experimental designs based on multiple linear regression models: a tutorial digest illustrated by case studies. *Analytica Chimica Acta* 360(1–3), pp. 227–241, DOI: 10.1016/S0003-2670(97)00701-0.

Hatami et al. 2015 – Hatami, M., Cuijpers, M.C.M. and Boot, M.D. 2015. Experimental optimization of the vanes geometry for a variable geometry turbocharger (VGT) using a Design of Experiment (DoE) approach. *Energy Conversion and Management* 106, pp. 1057–1070, DOI: 10.1016/j.enconman.2015.10.040.

Ivanov et al. 2022 – Ivanov, I., Kostov, K., Atanasov, K., Denev, I. and Krystev, N. 2022. Analysis of the air exchange in livestock building through the computational fluid dynamics. *EUREKA: Physics and Engineering* (3), pp. 28–39, DOI: 10.21303/2461-4262.2022.002349.

Jamshidnezhad, M. 2015. 1. Introduction. *Experimental Design in Petroleum Reservoir Studies*, pp. 1–8, DOI: 10.1016/B978-0-12-803070-7.00001-6.

Kostov et al. 2021 – Kostov, K., Ivanov, I. and Atanasov, K. 2021. Development and analysis of a new approach for simplified determination of the heating and the cooling loads of livestock buildings. *Eureka: Physics and Engineering* (2), pp. 87–98, DOI: 10.21303/2461-4262.2021.001310.

Kostov et al. 2022 – Kostov, K.V., Denev, I.N. and Krystev, N.Y. 2022. Research of the combustion process in the initial mixing section of the injection gas burner. *Polityka Energetyczna – Energy Policy Journal* 25(3), pp. 21–34, DOI: 10.33223/epj/152805.

Krishna Prasad, R. and Srivastava, S.N. 2009. Electrochemical degradation of distillery spent wash using catalytic anode: Factorial design of experiments. *Chemical Engineering Journal* 146(1), pp. 22–29, DOI: 10.1016/j.cej.2008.05.008.

Krystev, N. 2021. Multiplying the Effect of Nitrogen Oxides Reduction Under Vortex Burner Conditions at Gas Fuel Injection. *2021 6th International Symposium on Environment-Friendly Energies and Applications* (*EFEA*), Sofia, Bulgaria, pp. 1–4, DOI: 10.1109/EFEA49713.2021.9406255.

Kumar et al. 2022 – Sathish Kumar, T., Vignesh, R., Ashok, B., Saiteja, P., Jacob, A., Karthick, C., Jeevanantham, A.K., Senthilkumar, M. and Muhammad Usman, K. 2022. Application of statistical approaches in IC engine calibration to enhance the performance and emission Characteristics: A methodological review. *Fuel* 324(B), DOI: 10.1016/j.fuel.2022.124607.

Lyubimova, O.N. and Sisykov, V.V. 2017. *Construction and checking regression models when processing the results of factorial experiments*.

Madani et al. 2015 – Madani, S., Gheshlaghi, R., Mahdavi, M.A., Sobhani, M. and Elkamel, A. 2015. Optimization of the performance of a double-chamber microbial fuel cell through factorial design of experiments and response surface methodology. *Fuel* 150, pp. 434–440, DOI: 10.1016/j.fuel.2015.02.039.

Makzumova et al. 2023 – Makzumova, A.K., Sarakeshova, N.N., Dostiyarov, A.M. and Iliev, I.K. 2023. Study of the aerodynamics of air flow in burners using the Comsol Multiphysics software. *IOP Conference Series: Earth and Environmental Science* 1234(1), DOI: 10.1088/1755-1315/1234/1/012014.

Mihaluta et al. 2008 – Mihaluta, M., Martin, P. and Dantan, J.Y. 2008. Manufacturing process modelling and simulation. ICME, Italy, 7 p., hal-00999479f [Online] https://hal.archives-ouvertes.fr/hal-00999479 [Accessed: 2024-03-23].

Montgomery, D.C. 2013. *Design and Analysis of Experiments*. (8th ed.), New Jersey: Wiley.

Novik, F.S. and Arsov, Y.B. 1981. *Experiment planning in metals technology*. Sofia: State Technical Publishing House.

Pilling, M. 2009. From elementary reactions to evaluated chemical mechanisms for combustion models. *Proceedings of the Combustion Institute* 32(1), pp. 27–44, DOI: 10.1016/j.proci.2008.08.003.

Saltelli et al. 2000 – Saltelli, A., Scott, M. and Chen, K. (Eds.) 2000 – *Sensitivity Analysis*. Chichester: Wiley.

Tomlin, A. 2013. The role of sensitivity and uncertainty analysis in combustion modelling. *Proceedings of the Combustion Institute* 34(1), pp. 159–176, DOI: 10.1016/j.proci.2012.07.043.

Zlateva et al. 2020 – Zlateva, P., Penkova, N. and Krumov, K. 2020. Analysis of combustion efficiency at boilers operating on different fuels. *2020 7th International Conference on Energy Efficiency and Agricultural Engineering* (*EE&AE*), Ruse, Bulgaria, pp. 1–4, DOI: 10.1109/EEAE49144.2020.9278784.

Ivan Antonov Petrov

Analiza regresji danych eksperymentalnych w badaniu wydajności palnika z płaskim płomieniem

Streszczenie

Złożony charakter procesu spalania, który jednocześnie podlega prawom termodynamiki, wymiany ciepła, aerodynamiki i kinetyce chemicznej reakcji utleniania, sprawia, że modelowanie numeryczne jest bardzo trudne, a podejście eksperymentalne odgrywa obecnie kluczową rolę w ich badaniach. Nowoczesna, wysoko rozwinięta teoria projektowania eksperymentów łączy w sobie różne procedury analityczne, które pozwalają przy minimalnej liczbie eksperymentów uzyskać maksimum informacji o badanych procesach fizycznych lub technologicznych, właściwościach materiałów i zjawiskach. Umiejętność określenia wpływu trybu głównego i parametrów konstrukcyjnych na charakterystykę geometryczną płomienia jest warunkiem skutecznego oddziaływania na proces spalania w celu jego intensyfikacji. Niniejszy artykuł stanowi wprowadzenie do metod planowania i wiedzy o eksperymentach wieloczynnikowych, obejmujące: przygotowanie, prowadzenie i przetwarzanie wyników eksperymentów; opanowanie metodyki badań eksperymentalnych; wykorzystanie metod statystyki matematycznej i analizy regresji do planowania eksperymentów; rozwijanie umiejętności analizy przedmiotu studiów; prawidłowy dobór parametru optymalizacyjnego i istotnych czynników przedmiotu badań; zbudowanie macierzy planowania eksperymentu w celu uzyskania odpowiedniego modelu matematycznego obiektu. Celem artykułu jest zaproponowanie podejścia do badania wpływu trybu i parametrów projektowych na podstawowe wymiary i kształt pochodni gazowej, w oparciu o analizę regresji danych eksperymentalnych w badaniu wydajności palnika z płaskim płomieniem.

Słowa kluczowe: eksperyment czynnikowy, analiza regresji, spalanie, palnik o płaskim płomieniu