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Application of Design of Experiment (DOE) methods in materials engineering and construction

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ABSTRACT:
Design of Experiments (DOE) is a key tool for the efficient and accurate analysis of technological processes in materials and structural engineering. Unlike traditional single-factor approaches, DOE enables the simultaneous evaluation of multiple variables and their interactions on the mechanical properties of materials and structural elements, while also allowing for comprehensive process optimization. This paper presents the benefits of DOE methods and the basic experiment design phases, from defining the research problem to mathematical modeling and assessment of model fit. In the following section, selected types of DOE plans are discussed, and a literature review is presented that outlines their applications in materials and structural engineering, including welding processes and composite design. The literature analysis indicates that DOE is an effective method and tool for optimizing technological process parameters, predicting material properties, and improving existing processes, including techniques for joining metal structural components.

KEYWORDS:
DOE; regression models; ANOVA; full factorial designs; response surface methodology

1. Introduction

The development of new, innovative technologies for material production, processing, and joining processes necessitates the control of parameters in complex technological processes. The growing number of variables, their interactions, and hierarchy make the classic single-factor method insufficient for a complete understanding of the physical processes taking place. One variable at a time experiments are therefore unreliable, inefficient, time consuming, and often lead to falsely optimal parameters [1]. They do not enable effective optimization of the technological and structural processes under investigation. Consequently, the statistical methodology known as Design of Experiments (DOE) is gaining increasing importance. This method was developed in the 1920s by the British statistician Sir Ronald Fischer, primarily for agricultural purposes [1]. Nevertheless, it has found wide application in various fields of industry and science [2].

The purpose of DOE is to understand the simultaneous influence of multiple input factors on selected response parameters. DOE enables the optimization of technological processes and the development of effective predictive models by jointly evaluating the significance of factors, their optimal levels, and the interactions between them. This methodology is considerably more effective and precise than arbitrarily chosen test procedures, as it reduces the number of experiments required while maximizing the amount of information obtained and enabling reliable prediction of results. It is therefore a key tool supporting the development of modern technologies in materials and structural engineering. It is used, among other things, in the analysis of heat treatment parameters, chemical composition, and microstructure, as well as in assessing

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the impact of material joining process parameters and tool geometry on the mechanical properties and durability of the resulting joints. The DOE tool also supports the construction sector by enabling the assessment of the impact of material properties, geometry, support methods, and loading conditions on the behavior of structural elements.

2. Experimental Design Phases

In materials and structural engineering, experimental planning enables the systematic investigation of the influence of multiple input factors on selected process responses. In technological processes such as material joining or manufacturing, this approach allows for the identification of the most statistically significant parameters and their interactions, as well as for the optimization of technological processes with a minimal number of trials. Applying the DOE methodology requires following several sequential stages. Figure 1 presents a schematic diagram of the individual phases in the DOE procedure.

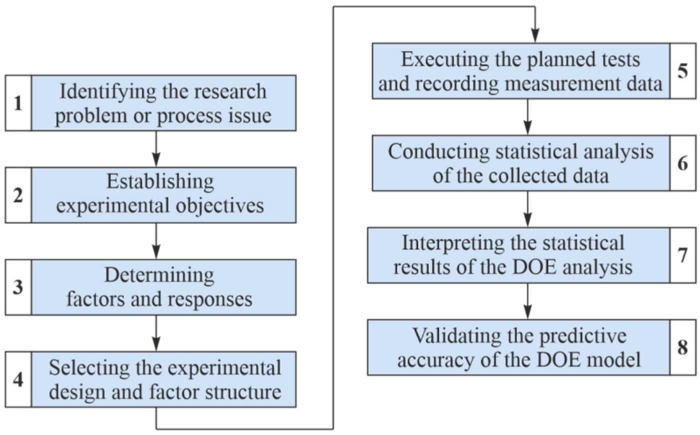


Fig. 1. Experimental Design Phases

A key step in experiment planning is the precise identification of the research problem. This stage defines the specific element of the technological process that requires improvement, optimization, or in which technical issues occur. It provides the foundation for all subsequent stages of the experiment, and the clarity and accuracy of the problem formulation directly affect the reliability and validity of the interpretation of results. Closely related to this is the next step, which defines the precise experiment objectives. At this stage, the dominant factors and their interactions are identified, and the goals related to optimizing process parameters are formulated. The third step consists of determining the factors (independent variables) influencing the process and the responses (dependent variables) to be measured. Additionally, the budget and timeline for the experimental work are established. The next step is to select an appropriate experimental design and determine the factor structure. This involves determining the number of levels for each independent variable, the type of interactions to be analyzed, and the type of experimental design. The variables in a DOE (the number of factors, levels, and the method of their selection) most often depend on available resources and the type of research being conducted [2]. Once the experimental design is appropriately tailored to the research problem, planned trials of all factor combinations included in the DOE plan are carried out and output data is collected. Tests should be conducted under controlled conditions, and results should be collected precisely. This ensures adequate data quality for further statistical analyses. These analyses involve processing and evaluating the data, determining the influence of individual independent variables (factors) and their interactions on the dependent variables (responses). Tools such as ANOVA (analysis of variance), regression models, main effects analysis, and residual analysis are used for this purpose. Together, these methods enable the assessment of model fit and the identification of statistically significant relationships.

The results of the statistical analysis are then translated into practical conclusions regarding the analyzed technological process. Interpretation of the results reveals the significance of factors and which interactions are key. It also shows how the way parameters are changed affects the output results. This connects mathematical analyses with real world technological processes. This stage, therefore, transforms large data sets into concise, precise conclusions.

The resulting predictive model is verified by conducting an experiment using optimal parameters and conditions obtained in the model and validating the results against the predicted values. Obtaining similar results confirms the reliability of the DOE model and its usefulness in optimizing technological processes.

3. Selected types of experimental designs

Choosing the right experimental design is crucial in the DOE method, as it determines the number of trials necessary, the range of possible responses, and how the results will be interpreted. Many experimental designs are available, varying in complexity and the range of relationships examined. Their selection depends primarily on the study's objective, the number of factors, and the available resources. The use of DOE in process improvement can lead to increased process efficiency, reduced process variability, and lower process costs [3]. The most common types of experimental designs include: Full Factorial Designs [4, 5] and Fractional Factorial Designs [6]; Response Surface Methodology (RSM), including Central Composite Design (CCD) and Box-Behnken Design (BBD) [7, 8]; Taguchi Orthogonal Arrays [9] and Mixture Designs. The remainder of this chapter focuses on the characteristics and overview of the applications of Full Factorial Designs and Response Methodology.

3.1. Full Factorial Designs

Full Factorial Designs (FFD) are the most classic tools used in DOE methodology, distinguished by their comprehensive and robust approach. They consider all possible combinations of independent factor levels, allowing for a complete analysis of the impact of each factor on the dependent variable. They enable the assessment of both main effects and interactions between factors. A typical experimental design assumes that each input factor can take one of two values (a low level (–) or a high level (+)). Combining all possible settings of these factors results in a full two-level factorial design. If k factors are considered, each at two levels, then 2^k experimental runs are required.

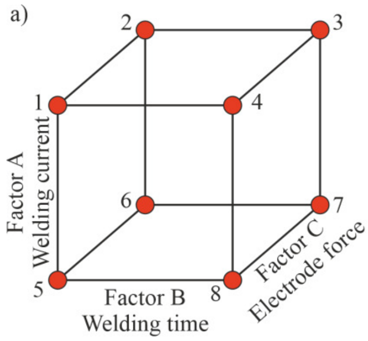
The full two-level factorial design for three factors (2^3) is presented using an example research problem concerning the effect of resistance welding parameters on the strength of steel joints. Three input (independent) factors were assumed:

- Factor A – welding current [kA],
- Factor B – welding time [s],
- Factor C – electrode force [kN].

For each factor, two levels were defined: a low level (–), corresponding to the lower limit of the parameter range, and a high level (+), corresponding to the upper limit of the parameter under consideration. Coding the factor levels according to the (–) and (+) designations yields a table of the full factorial design 2^3.

The geometric interpretation and the matrix of the considered factorial design are presented in Figure 2. The axes of the cube correspond to the individual factors, while the vertices represent all eight combinations of the low (–) and high (+) levels of each parameter.

a)



b)

Factor levels

Trial	A	B	C
1	+	−	−
2	+	−	+
3	+	+	+
4	+	+	−
5	−	−	−
6	−	−	+
7	−	+	+
8	−	+	−

Fig. 2. a) Geometric interpretation of a full factorial design 2^3, b) matrix of a full two-level factorial design

A literature review indicates that full factorial designs are used in materials and structural engineering to investigate the influence of several process parameters and their interactions on the properties of joints or other structural elements. This allows for the capture of nonlinear relationships that often determine strength or microstructural characteristics. In [4], the effects of joint shear strength parameters and weld interface thickness were investigated using a full factorial design. The study focused on diffusion welded joints between CoCrNi and SUS 304 stainless steel, fabricated to obtain combinatorial properties suitable for cryogenic applications. The authors conducted a full factorial design with two factors (welding temperature and setting time). Analysis of variance (ANOVA) revealed that welding temperature had a dominant effect on joint shear strength. The interaction between welding temperature and setting time, however, proved insignificant. Weld interface thickness was also shown to be strongly related to both parameters and exhibited a strong interaction between these independent factors. The full factorial design enabled the development of regression models with prediction errors of 7 % - 15 %, which in turn made it possible to define a safe range of optimal process parameters.

In [10], the weldability of ferritic ductile cast iron using the shielded metal arc welding (SMAW) process was investigated with two types of consumables under eight combinations of process parameters. A 2^3 full factorial experimental design was employed to systematically evaluate the effects of welding conditions (preheat and cooling conditions), consumable type, and their interactions on weld quality and tensile strength. Preheating proved to be the most dominant factor influencing joint strength. In the case of the E7018 electrode, the preheating and cooling conditions and their interaction were particularly important. In this case, the factorial design also provided a tool enabling precise modeling of technological relationships leading to improved joint quality.

A full factorial design was also used in work [5], the influence of friction stir welding (FSW) parameters on impact strength was analyzed. Four input factors were assumed: tool speed (rpm), feed rate (mm/min), displacement (mm/min), and welding time (min) at two levels each, and sixteen experimental runs were performed. The full factorial design (FFD) approach made it possible to identify the optimal parameter combination that produced the highest impact strength. The analysis confirmed that thermomechanical parameters and their interactions play a key role in the FSW process. The most influential factors were the tool rotational speed and feed rate. An appropriate combination of parameters led to improved mechanical properties, confirming the usefulness of DOE methods in optimizing friction welding processes. As the number of factors increases, the number of required combinations increases exponentially, making such a large number of runs inefficient. In such cases, a fractional factorial design or a Plackett–Burman design (PBD) may be a more suitable choice.

3.2. Response Surface Methodology

Response Surface Methodology (RSM) is one of the leading DOE methods. It is a set of mathematical and statistical methods used to analyze, model, and optimize multivariate processes [11]. RSM is based on planned experiments (Design of Experiments) and assumes that the influence of input variables on the responses can be determined using fitted polynomial regression models. Their effects can be expressed as nonlinear parameters. RSM accounts for main effects and interactions between factors. This allows for the capture of complex nonlinear relationships and the determination of parameter combinations that lead to a minimum or maximum of the studied response. In materials and structural engineering, it enables the construction of accurate predictive models for technological process parameters or material properties. It allows for the performance of ANOVA to assess the statistical significance of factors and their interactions. For example, it is possible to examine the impact of input parameter interactions on joint characteristics, achieving practical results. Relationships are visualized in the form of response surface graphs and contours that indicate the direction of change. In practice, RSM also enables the optimization of processes in order to obtain maximum or minimum values of selected properties and parameters. It is widely used in the literature, particularly in materials engineering, in joining processes, where the simultaneous influence of multiple parameters on a nonlinear response requires considering not only the main effects but also the interactions between independent factors.

Common experimental designs used in RSM are Central Composite Design (CCD) and Box--Behnken Design (BBD). In [7], regression models were developed using a Box–Behnken design within the RSM framework to analyze the effects of various variables (mineral additives) and their interactions on the mechanical properties and water resistance of gypsum composites. The results showed that the strength and water resistance of cementitious composite materials are influenced by both individual factors and the relationships between them. The developed regression models were used to optimize the composition. Analysis of variance and assessment of the quality of fit showed that the polynomial models used were characterized by good data representation.

Response Surface Methodology was also applied in [8], where Cold Metal Transfer (CMT) welding of various high-strength Al and Mg alloys was analyzed. As in the previous paper, the authors chose the Box-Behnken design to reduce the required experimental runs while providing adequate data for second-order polynomial regression models. Using RSM, they optimized CMT parameters (wire feed speed, welding speed, and arc length correction) to maximize tensile strength and weld metal hardness. Polynomial regression models were used to create parametric mathematical models, the suitability of which was assessed using Anova. The prediction error rate of the parametric mathematical models describing tensile strength and weld metal hardness for Al/Mg joints was less than 1 % at the 95 % confidence level.

In [12], RSM was used to optimize the parameters of rotary friction welding (RFW) of low--alloy steel pipes. The method allowed the development of empirical dependencies between the responses, such as tensile strength, yield strength, notch tensile strength, elongation and notch strength ratio and the investigated process factors (rotation speed, friction pressure, and forging pressure). The optimal process parameters were established, ensuring improved tensile properties of rotary friction welded joints. The RSM method also enabled the visualization of process areas in the form of contour maps and three-dimensional response surfaces. This allowed for the identification of areas of maximum joint strength, as well as the nonlinear nature of the influence of independent factors on the response.

In the analyzed works, Response Surface Methodology is an effective tool for building reliable predictive models and for determining process parameters, confirmed by additional experiments.

4. Conclusions

The literature review conducted in this paper indicates that Design of Experiment (DOE) is an effective and highly precise tool for designing research and optimizing technological processes in materials and structural engineering. The use of DOE allows for the simultaneous consideration of multiple variables influencing processes, the mechanical properties of materials, and the behavior of structural elements. It also allows for the consideration of interactions between factors, which distinguishes it from traditional single-factor methods where such effects remain undetected. By using approaches based on full factorial designs and response surface methods, among others, the number of necessary trials can be significantly reduced while maintaining the efficiency and precision of the information obtained.

An analysis of scientific publications indicates that DOE is a particularly useful tool for optimizing metal welding processes, including rotary friction welding, Cold Metal Transfer welding, shielded metal arc welding, resistance spot welding (RSW), and joining heterogeneous materials. It enables the development of precise predictive models for strength, hardness, microstructure, and joint quality parameters. DOE can also be used to design concrete and composite mixtures by enabling the determination of optimal component proportions.

The research conducted in the analyzed studies confirmed that DOE enables the generation of predictive models that are highly consistent with the results of experimental validations. This demonstrates the usefulness of experiment planning methods for predicting complex phenomena in technological processes. These methods not only facilitate understanding the mechanisms involved but, above all, enable the identification of important parameters and their interactions, as well as the presentation of specific engineering conclusions and further recommendations. Precise control of input variables in relation to the obtained output responses is crucial for achieving repeatable and effective results in technological processes.

Further development of DOE, combining it with numerical modeling and with the support of artificial intelligence, including machine learning, may in the future be a key element of intelligent design of technological processes in materials and construction engineering.

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Zastosowanie metod planowania eksperymentu (DOE) w inżynierii materiałowej i konstrukcyjnej

STRESZCZENIE:
Desing of Experimental (DOE) jest jednym z kluczowych narzędzi w efektywnej i precyzyjnej analizie procesów technologicznych w inżynierii materiałowej i konstrukcyjnej. W porównaniu do tradycyjnych analiz jednoczynnikowych, daje przede wszystkim możliwość jednoczesnej oceny wielu zmiennych oraz ich interakcji na właściwości mechaniczne materiałów oraz elementów konstrukcyjnych, a także możliwość pełnej optymalizacji procesów. W pracy przedstawiono korzyści wynikające z wykorzystywania metod DOE oraz podstawowe fazy projektowania eksperymentu, od zdefiniowania problemu badawczego po modelowanie matematyczne i ocenę jakości dopasowania. W dalszej części omówiono wybrane rodzaje planów DOE oraz dokonano przeglądu literatury, pokazującego ich zastosowanie w inżynierii materiałowej i konstrukcyjnej, w tym w procesach spawania, zgrzewania oraz przy projektowaniu kompozytów. Przeprowadzona analiza literatury pokazuje, że DOE stanowi skuteczne podejście i narzędzie do optymalizacji parametrów procesów technologicznych, przewidywania właściwości materiałowych oraz ulepszania istniejących już procesów, w tym metod łączenia metalowych elementów konstrukcyjnych.

SŁOWA KLUCZOWE:
DOE; modele regresyjne; ANOVA; pełne projekty czynnikowe; metodologia powierzchni odpowiedzi