Journal of Materials and Manufacturing (2022) 1: 31-37

Journal of Materials and Manufacturing

Design optimization of a robot arm using kriging modelling and genetic algorithm

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Abstract

In this work, the design optimization of a robot arm was conducted by following the Kriging-genetic algorithm method. The method followed has three main steps which are conducting design of experiment, building a response surface, and implementing design optimization. In this method, Latin Hypercube Sampling is used for conducting the design of experiments. Kriging modelling is used for constructing a response surface. As regard with the optimization technique, the multi-objective genetic algorithm is used to govern the optimization process. When the results of the method followed was compared with those of the FEM simulation, it was concluded that the method followed can give accurate and precise results for the design optimization. Moreover, at the result of the optimization process, a new robot arm having more strength and less weight was achieved. Also, the case study points out that the method of Kriging-Genetic algorithm can be effectively used in design optimization of mechanical components.

Keywords: Design optimization, robot arm, Kriging, genetic algortihm.

1. Introduction

Design optimization generally can be categorized as two types: deterministic and stochastic design optimization. Deterministic design optimization involves mean or nominal values specified for a design problem while stochastic design optimization focuses on the uncertainty in the design variables or parameters [1]. There are several up-to-date researches about the stochastic design optimization. The directions of these research can be given as reliability-based design optimization [2, 3], robust design optimization [4, 5], and reliability-based robust design optimization [1, 6]. Although the stochastic optimization provides designers with more realistic design solutions, this type of optimization has high computational costs [7]. Compared to the stochastic one, the deterministic design optimization is known to be more practical and efficient approach for design problems. Most of the up-to-date research about the deterministic design optimization have utilized the Response Surface Methodology (RSM) [8-10]. In this paper, the deterministic optimization is taken as a base approach. Herein, to implement the deterministic design optimization, RSM is followed. RSM follows three main steps: conducting the Design of Experiments (DoE), building a response surface, and implementing the design optimization. Within this work, the design optimization of a robot arm by using RSM consisting of

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DOI: 10.5281/zenodo.7107358
Received: 10 September 2022, Revised: 10 September 2022 and Accepted: 19 September 2022
ISSN XXX-XXXX.

Kriging modelling and Genetic Algorithm (GA), which is a well-known method in the literature, is carried out via ANSYS software. Herein the main aim is to show how to use the Kriging-GA method in a robot design.

The rest of this paper is organized as follows: In Section 2, the method of design optimization followed in this work is explained step by step. In Section 3, a case study is implemented to show how to apply the method of design optimization to a robot arm design problem. In Section 4, evaluations of the results, and a discussion about the superiority of the optimization method is given.

2. The followed Deterministic Design Optimization Method

This section includes the method of design optimization followed in this work is theoretically explained step by step as illustrated in the flowchart given in Figure 1.

In the first step, the lower and upper bounds of the design variables are specified, and sufficient number of design candidates are generated by utilizing a method of DoE. Within this work, Latin Hypercube Sampling (LHS) is used to generate different design inputs depending on the given ranges of the design variables. Finally, the design responses corresponding to design inputs are calculated via Finite Element Analysis (FEM).

In the second step, it is aimed to construct a response surface. To that end, several techniques, such as Artificial Neural Network (ANN) and Kriging modelling can be used. Kriging modelling has been mostly used for constructing a response surface. ANN also have been used for modelling nonlinear problems. Herein, Kriging modelling is chosen for constructing a response surface representing the relationships between the design inputs and their responses.

In the third step, the design optimization is carried out depending on aim-specific objectives by utilizing an optimization technique. The objectives can be determined according to the conditions of the design problem. As an optimization technique, the Genetic Algorithm (GA) is used to govern the multi-objective optimization in this work. When the optimum design found does not sufficiently satisfy the objectives, all of the process is repeated from first step to third step.

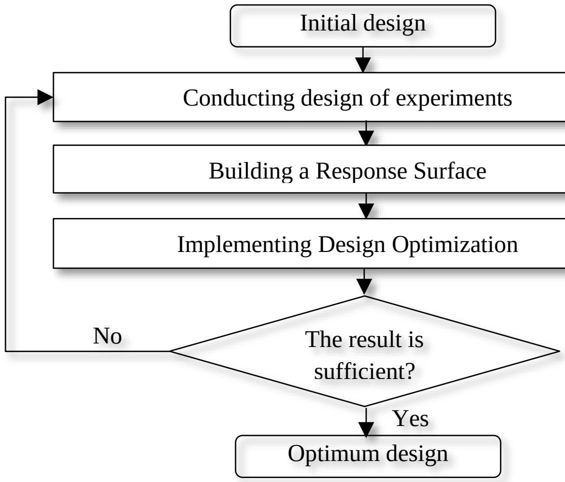


Figure 1. The flowchart of the design optimization method followed

3. A Case Study

In this section, a case study is implemented to show how to apply the method of design optimization to a robot arm design problem. It is assumed that the robot arm is assumed to move in a narrow space on the X-and

Z-axes (Figure 2). In addition to that, the design optimization of the robot arm is conducted based on the data achieved from the static analysis using FEM.

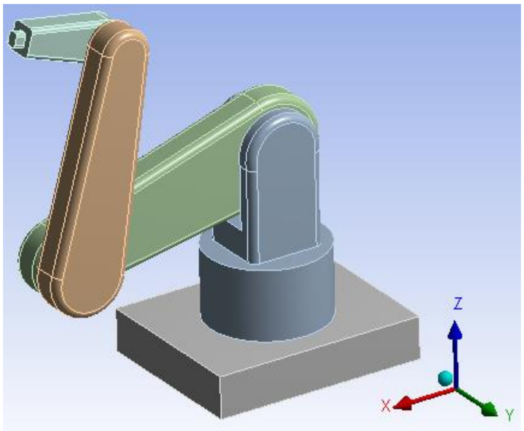


Figure 2. The robot arm to be optimized.

Design variables of the robot arm to be used in design optimization are presented in Figure 3. Totally, three design variables (thicknesses) were used in the optimization process. Other dimensions were assumed to be fixed to evaluate the robot arm at the same position. As regards to the design responses, three design outputs or responses, which were maximum Von-Mises stress, maximum total deformation and mass, were considered.

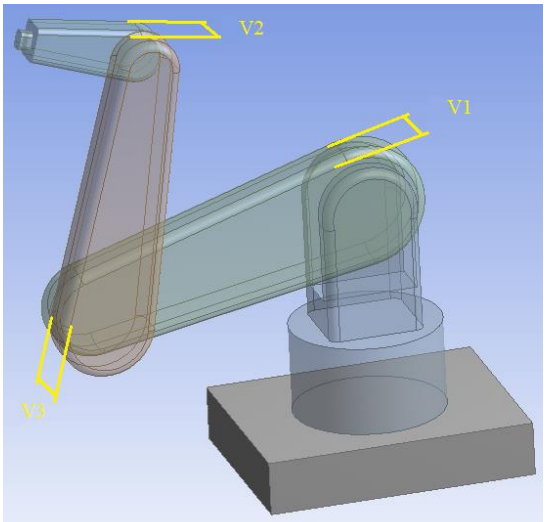


Figure 3. Design variables of the robot arm to be used in design optimization.

Prior to the DoE along with the FEM process, the initial design is needed to be analyzed to find the design responses for the first situation in the design process. For that aim, first, the boundary and loading conditions for the finite element analysis of the arm were determined (Figure 4). The base of the robot arm is considered to be fixed support, and a force with Fx=1500 N and Fy=1500 N is applied to the end effector.

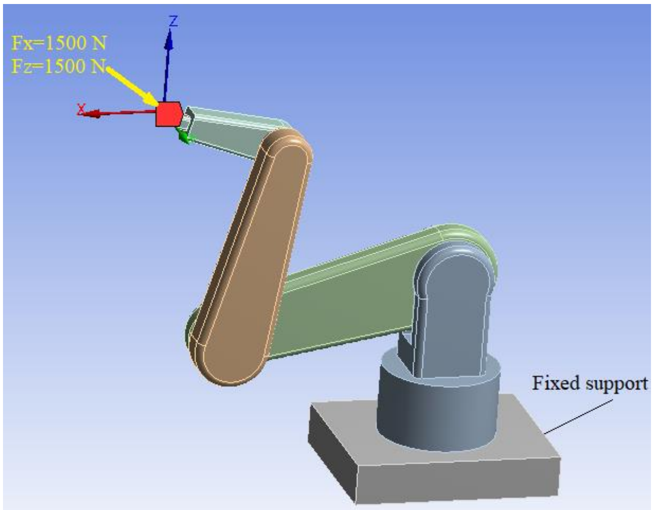
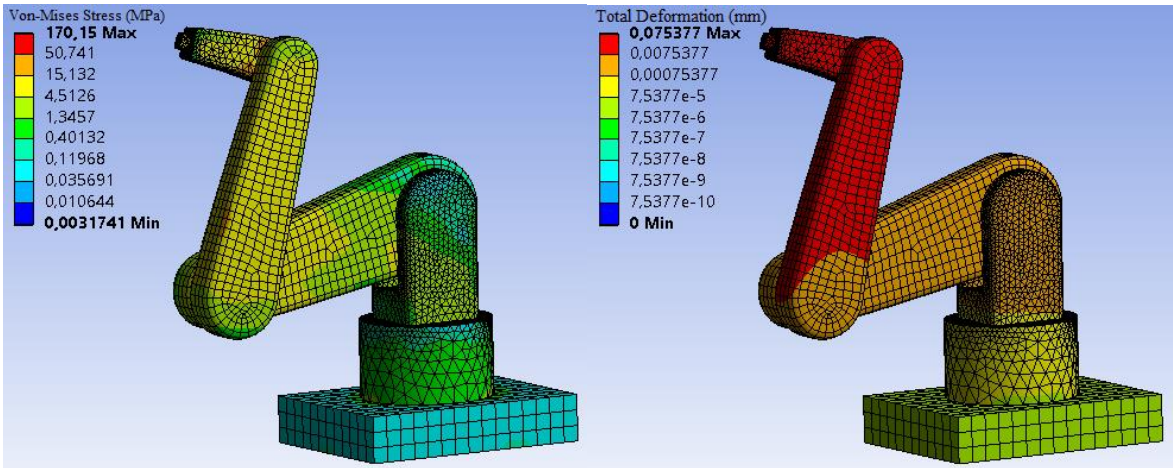


Figure 4. Boundary and loading conditions for the finite element analysis of the arm

Based on the boundary and loading conditions, static analysis of the arm was conducted. At the result of the finite element analysis, the Von-Mises stress and total deformation distribution of initial design are demonstrated in Figure 5. The maximum stress occurred on the initial design was found to be 170.15 MPa, and the maximum total deformation of the design was found to be about 0.08 mm. Also, the mass of the initial design was found to be 11.94 kg.



a) b)

Figure 5. The results of finite element analysis of initial design: a) Von-Mises stress distribution, b) total deformation distribution.

Prior to the DoE process, the lower and upper bounds of the design variables should be determined. The initial values of the design variables and their ranges specified are presented in Table 1. In this design, the lower and upper bounds for all of variables were assumed to 15 mm and 28 mm, respectively.

Table 1. The initial values of the design variables, and their ranges specified.

Design variables (symbol)	Initial Value	Ranges
Thickness (mm) (*V1)*	25	$15 \leq V1 \leq 28$
Thickness (mm) (*V2)*	20	$15 \leq V2 \leq 28$
Thickness (mm) (*V3)*	25	$15 \leq V3 \leq 28$

A set of 50 design candidates was generated using LHS when the DoE process was carried out depending on the given ranges of the design variables. After that, the design responses corresponding to design inputs were calculated via Finite Element Analysis (FEM).

In the second step of the optimization process, the best promising response surface was constructed by utilizing Kriging modelling. The learning accuracy of the response surface is presented in Table 2. From the Table, the coefficients of determination for all of the design responses are sufficiently high values. Also the root mean square errors for all of the design responses are sufficiently low values. It can be said that the Kriging model is an accurate model to account for the relationships between design variables and responses.

Table 2. The learning accuracy of the Kriging model

Learning criteria	Maximum Von-Mises stress	Maximum total deformation	Mass
Coefficient of determination	0.99	0.99	0.99
Root mean square error	4.6573E-06	6.631E-10	6.232E-15

In the third step, the design optimization was implemented by utilizing the Kriging model and multi-objective GA. The GA parameters used in the optimization process were 300 initial samples, 80 iterations, 300 samples of per iteration, and 814 evaluations. The optimum design found by the GA process must be validated by comparing the result of Kriging-GA process with that of the FEM simulation. This comparison is presented in Table 3. According to the Table 4, all of response values has low differences for two methods. It means that the method of Kriging-GA can give accurate and precise results for the design optimization.

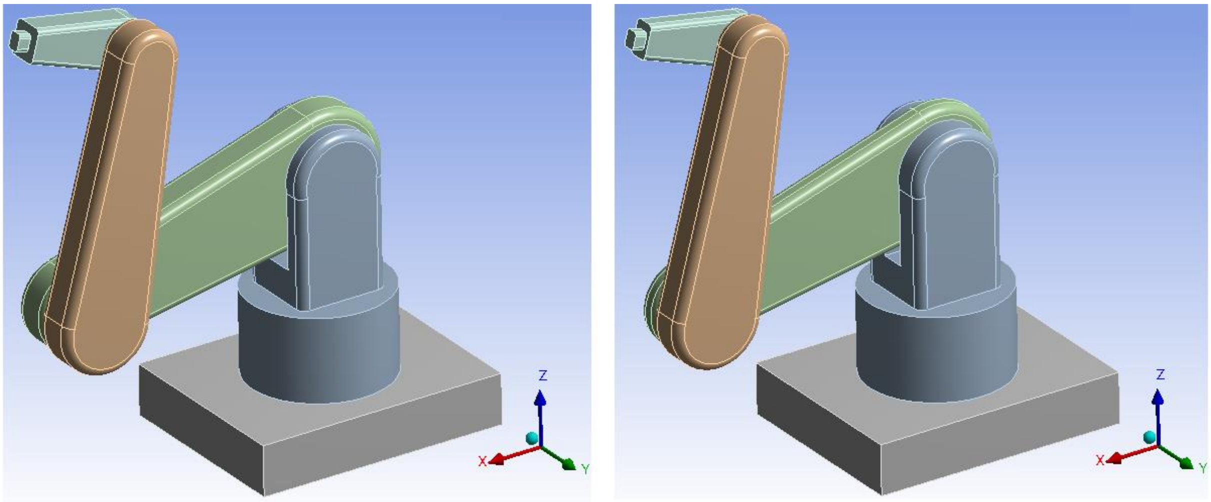
Table 3. Validation of the method of design optimization with FEM simulation.

Method	Design responses		
	DR1	DR2	DR3
Kriging-GA	152.76	0.08	11.06
FEM Simulation	149.12	0.08	11.06

To see the differences between initial and optimum design responses, a comparison between them was made as given in Table 4. From this comparison, there are significant improvements in two responses which are maximum stress and mass. At the result of the optimization process, a new robot arm having more strength and less weight was achieved. Also, the geometric models of initial design and optimum design are illustrated in Figure 6 to show visual differences between initial and optimum design.

Table 4. Comparison of initial and optimum design responses

Design responses	Initial design	Optimum design	Difference (%)
Maximum stress (MPa) (*R1*)	170.15	152.76	-10.22
Total deformation(mm) (*R2*)	0.08	0.08	~0
Mass(kg) (*R3*)	11.94	11.06	-7.37



a) b)

Figure 6. Geometric models of initial design (a) and optimum design (b).

4. Conclusion

In this work, the design optimization of a robot arm was conducted by following the Kriging-GA method. Herein, it is assumed that the robot arm is assumed to move in a narrow space on the X-and Z-axes. In addition to that, the design optimization of the robot arm is conducted based on the data achieved from the static analysis using FEM. Totally, three design variables (thicknesses) were used in the optimization process. Other dimensions were assumed to be fixed to evaluate the robot arm at the same position. As regards to the design responses, three design outputs or responses, which were maximum Von-Mises stress, maximum total deformation and mass, were considered. The Kriging model constructed was an accurate model to account for the relationships between design variables and responses because it had relatively high coefficients of determination, and low root mean square errors. When the results of Kriging-GA process were compared with those of the FEM simulation, it was concluded that the method of Kriging-GA can give accurate and precise results for the design optimization. Moreover, at the result of the optimization process, a new robot arm having more strength and less weight was achieved. Also, the case study points out that the method of Kriging-GA can be effectively used in design optimization of mechanical components. In the future, the comparison of performances of the different response surface techniques can be investigated, and most promising techniques or methods can be applied to the complex design optimization problems.

Author Contribution Statement

Murat Mayda conducted all of the works in this paper.

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