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Design Optimization of a Wafer Dough Blade Using Artificial Neural Network and Monte-Carlo Simulation

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1. Introduction

Engineering design process generally includes the phases of task clarification, conceptual design, embodiment design, and detail design. Especially, during the last two phases, the design optimization has a significant role for research and development activities. The important challenge in the design optimization process is that there is usually no any analytical expression between design inputs (variables) and outputs (responses). This situation makes it more difficult to conduct the design optimization process when compared to the situations including analytical expressions. To overcome the challenge, the response surface methodologies that relies on the implementation of an optimization technique along with a response surface or surrogate model representing the experimental or simulated input-output data has been emerged [1, 2]. These methodologies are also known to be surrogate model-based optimization methodologies. The surrogate-based design optimization method has received an extensive attention in the recent years due to its CPU cost efficiency, and its practical usage [3-6].

To conduct the surrogate-based design optimization method, it could be suggested to follow three main steps that are the data sampling using design of experiment, constructing a surrogate model based on the sampled data points, and realizing the design optimization based on the surrogate model by using a specific optimization technique. There are several researches on the surrogate-based design optimization method in the literature. In the most of the research, the Latin hypercube sampling (LHS) to implement the Design of Experiment (DoE), and the Artificial Neural Network (ANN) and the Kriging model to build the surrogate model, are used. LHS, which relies on Monte Carlo Simulation (MCS), is more useful for complex design problems because of its less computational cost. Kriging model or method is known to be one of the most accurate techniques for fitting a model. ANN, which is another accurate and popular technique for building a surrogate model, have been still used for modelling nonlinear problems. From these aspects mentioned above, Zong et al. [7] present a design optimization of a nuclear main steam safety valve based on an E-AHF ensemble surrogate model. In the work, an optimized LHS and Computational Fluid Dynamics (CFD) simulations are performed. As an optimization technique, the k-sigma method is used. From other similar works, Meng et al. [8] propose an enhanced Collaborative Optimization (CO) method using LHS and the Kriging model. Luo et al. [9] implement the multidisciplinary optimization of an underwater vehicle based on dynamic surrogate model. The dynamic surrogate model is based on the radial basis function and LHS. The simulated annealing algorithm is used as as the optimization algorithm. Tang et al. [10] put forward an optimization method based on a dynamic adaptive surrogate model, which is applied to the drag reduction of the transonic supercritical airfoil and wing. For surrogate model and optimization method, Kriging model and evolutionary algorithms are used respectively. Lee et. al [11] introduce an experimental surrogate-based design optimization of wing geometry by utilizing Efficient Global Optimization (EGO) algorithm. Qiao et al. [12] propose a new surrogate model sequential refinement and optimization framework for design and optimization of dynamic systems. In this proposal, Kriging model is taken as a basis model. LHS is used for sampling. Nonlinear Programming (NLP) is used as optimization method. As a different work from the works mentioned above, Hu et al. [13] implement design optimization of air foil in ground effect based on free-form deformation utilizing ANN and Genetic Algorithm (GA). Herein, the ANN is used to build the surrogate model representing relationships between the design inputs and outputs. Also, the best design solution is validated with the result of the CFD simulation. As another different work, Lye et al. [14] put forward an algorithm for Partial Differential Equations (PDE) constrained optimization by combining the gradient based optimization algorithms and deep neural network.

From this literature review, it can be possible to see that implementing the Kriging model and ANN along with the sampling methods such as MCS or LHS for design optimization is proven to be efficient and effective for design problems. In this work, a systematic method to conduct the surrogate-based design optimization is proposed by utilizing ANN and MCS. To show its applicability, the design optimization of a wafer dough blade that is an important component in the food industry is carried out.

The rest of this work is presented as follows: In Section 2, the deterministic design optimization is explained. In Section 3, the flowchart of design optimization is described in a systematic manner. In Section 4, a case study is conducted to show the applicability of the systematic way for design optimization. In Section 5, the results of the case study are evaluated, and a discussion about the effectiveness of the proposed systematic optimization approach is presented.

2. Definition of deterministic design optimization

Design optimization can be usually classified as two groups: deterministic and stochastic design optimization. Stochastic design optimization has been used for design problems including random design variables or parameters. Due to its practical and effective usage, herein the deterministic design optimization is taken as a base method. In this work, all of design variables are assumed to be deterministic. The definition of a deterministic design optimization can be given as follow:

$$\left.\begin{array}{ll} Min/Max \;\; f(x) & \\ subject\,to: h_i(x) \le 0, & i = 1,\dots,n_{ineq} \\ \qquad\qquad g_j(x) = 0, & j = 1,\dots,n_{eq} \\ \qquad x^L \le x \le x^U & \end{array}\right\}. \tag{1}$$

3. The design optimization method followed

In this section, the design optimization method followed is explained in four steps by following the flowchart given in Fig. 1.

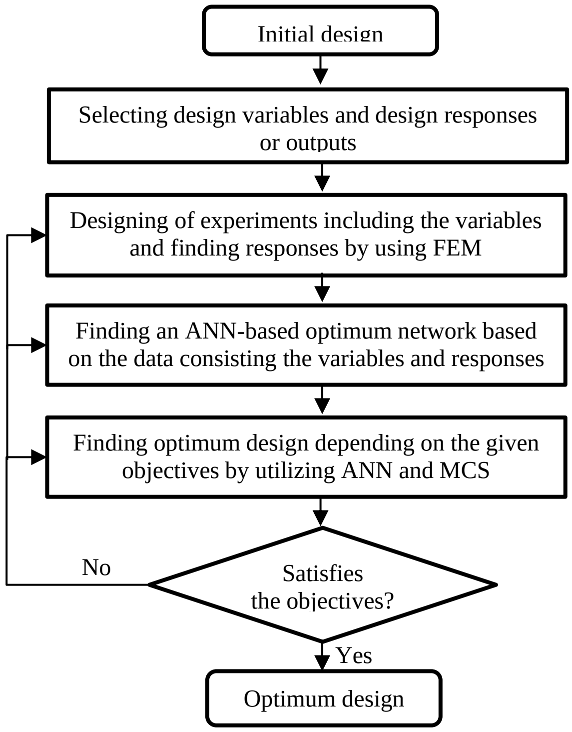

Fig. 1 The flowchart of the design optimization method followed

Step 1. First, a design problem is chosen. Second, the critical design variables or inputs of the design problem are determined by a designer or an engineer. Finally, the critical design responses or outputs corresponding to the design problem are identified to effectively govern the optimization process.

Step 2. In this step, the process of designing of experiment and finding the design responses by using FEM are realized. To that end, first, the ranges of design variables, such as the lower and upper values of the variables, are identified according to the constraints of the design problem. Second, the process of design of experiment is carried out by using the full factorial technique. Finally, the design responses corresponding to the design inputs are found by FEM simulations. Herein, SolidWorks Simulation is used for the finite element analysis of the design points.

Step 3. This step includes searching an ANN-based optimum network representing the relationships between the design variables and responses. For that purpose, the input-output design data is separated as train and test data, and thereafter several ANN networks are tested according to the criteria of R^2 (coefficient of determination). As a result, the ANN network having the highest R^2 value for both train and test data is chosen as an optimum ANN model.

Step 4. In the final step, an optimum design is found by following this way: first, the implementation of a large number of MCS realizations to generate of a large number of design input values; second, finding of the design responses corresponding to the design inputs through the optimum ANN model; and third, the optimum design is searched depending on an objective function defined. To validate the optimum design found based on the ANN model, the optimum design is analyzed via the FEM module of SolidWorks Simulation, and the two design responses are compared. If the relative difference between two responses is so high, then the number of MCS realizations is increased, or a new optimum ANN model is searched. All of these steps are repeated until the desired criteria are satisfied.

4. A case study

To explicitly show applicability of the proposed design optimization method, design optimization of a wafer dough blade was implemented. The design variables *DV*, fixed dimensions *F*, and their initial values are presented in Fig. 2. In this example, six design variables are considered as critical variables, which are also known to be design inputs. Other dimensions are assumed to be fixed. Herein, the mass of the design, maximum Von Mises stress on the design, and the surface area of one blade are determined to be the design responses or outputs. The main aim in the optimization process is to minimize the mass and stress for both cost efficiency and better strength, and to maximize the surface area for better mixing performance.

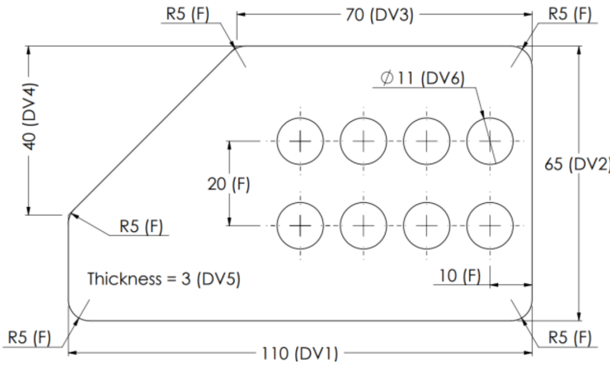

Fig. 2 The design variables and their initial values of one blade (*F*: Fixed dimension, *DV*: Design variable)

The design variables and responses to be used in the design optimization process are presented in Table 1.

To realize design of experiment prior to the finite element analysis, the ranges of the design variables are identified as given in the Table 2, and accordingly the full factorial technique is applied. At the result of the process of design of experiment, totally, a set of 324 design points including design variable values is obtained.

With the regard to the finite element analysis of the design, the boundary and loading conditions are established as presented in Fig. 3. A pressure of 0.015 MPa stemming from dough pressure occurred inside the vessel is applied to the four surfaces of the blade. The shaft center hole is fixed when the pressure is applied to the surfaces of the blade. Under the boundary and loading conditions, the finite element analysis of all of the design points is conducted via SolidWorks Simulation. Based on the conditions, the design response corresponding to each design point are found one by one.

Table 1

The design variables and responses to be used in the design optimization process

Variables/responses	Symbol
Distance, mm	*DV*1
Distance, mm	*DV*2
Distance, mm	*DV*3
Distance, mm	*DV*4
Thickness, mm	*DV*5
Diameter, mm	*DV*6
Mass, g	*DR*1
Stress, MPa	*DR*2
Surface area, mm^2	*DR*3

Table 2

The initial values and ranges of the design variables

Variable, mm	Initial value	Range
*DV*1	110	$90 \le DV1 \le 130$
*DV*2	65	$55 \le DV2 \le 75$
*DV*3	70	$70 \le DV3 \le 90$
*DV*4	40	$30 \le DV4 \le 40$
*DV*5	3	$3 \le DV5 \le 6$
*DV*6	11	$7 \le DV6 \le 12$

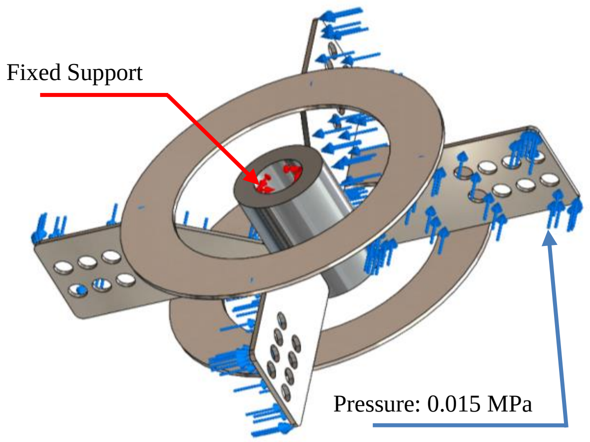

Fig. 3 The boundary and loading conditions for the finite element analysis of the design

To find the best promising ANN model, the set of 324 design points is separated as train and test data with the ratios of 70% and 30%, respectively. 97 of 324 the data set is used to test the ANN model, and the rest of the data set is used to train the ANN model.

The best promising ANN model is based on the algorithm of feed forward back propagation. The best ANN model found has three hidden layers, having 18, 24 and 16 neurons, respectively. In Fig. 4, the architecture of the best ANN model found in this work is presented. Moreover, the minimum R^2 value achieved during finding the optimum ANN model is 0.9656 for the testing of the stress data, which can be accepted to be a reasonably sufficient R^2 value for conducting the design optimization process. *R*2 values obtained for both the train and test data of the three design responses are denoted in Fig. 5. In this Figure, it can be clearly seen that there is a strong correlation between the observed data from FEM simulation and the predicted data by ANN model.

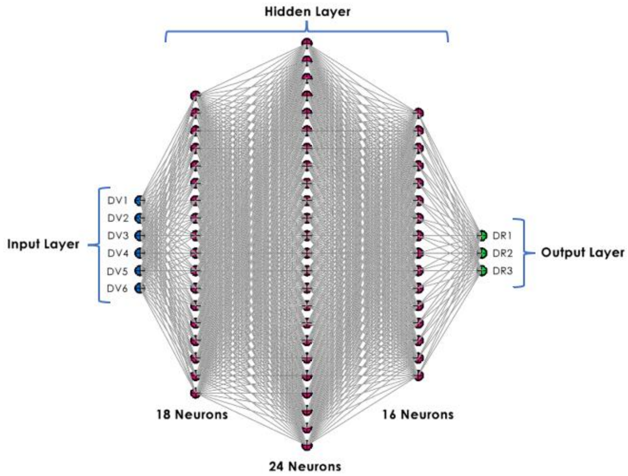

Fig. 4Architecture of the best ANN model found

To find the optimum design, first, an objective function is defined as follows:

$$\left.\begin{aligned} &Max \quad f(DR) = \frac{DR3 \cdot 0.05}{(DR1 \cdot 0.65 + DR2 \cdot 0.30)} \\ &subject\,to: 90 \le DV1 \le 130, \\ &\qquad 55 \le DV2 \le 75, \\ &\qquad 70 \le DV3 \le 90, \\ &\qquad 30 \le DV4 \le 40, \\ &\qquad 3 \le DV5 \le 6, \\ &\qquad 7 \le DV6 \le 12, \end{aligned}\right\}. \tag{2}$$

In this definition, the design responses (*DR*1, *DR*2 and *DR*3) are assumed to have importance percentages of 65%, 30% and 5%, respectively. Accordingly, it is aimed to maximize the objective function. After the objective function and constraints are constructed, MCS with 2,000,000 realizations are conducted. Thereafter, the optimum values of the design variables corresponding to the maximum objective function achieved are found. However, it is required to compare the design responses found based on the ANN-MCS model, and those obtained from SolidWorks Simulation in order to ensure that the best design is accurate.

In Table 3, the comparison of the design response results predicted by ANN-MCS and the results analyzed by SolidWorks Simulation is given. As seen in the Table 3, there is a good agreement between the response results of the ANN-MCS method and those of the FEM-Simulation so that the ANN-MCS model is sufficiently accurate to predict the true responses.

To clearly see the exact improvements on the initial design, it is required to compare the values of design responses of both initial design and optimum design. The comparison is presented in Table 4. From this Table, it can be concluded that a significant decrease in the maximum stress (nearly 66%) is obtained whereas there is a reasonable difference in both the mass and surface area.

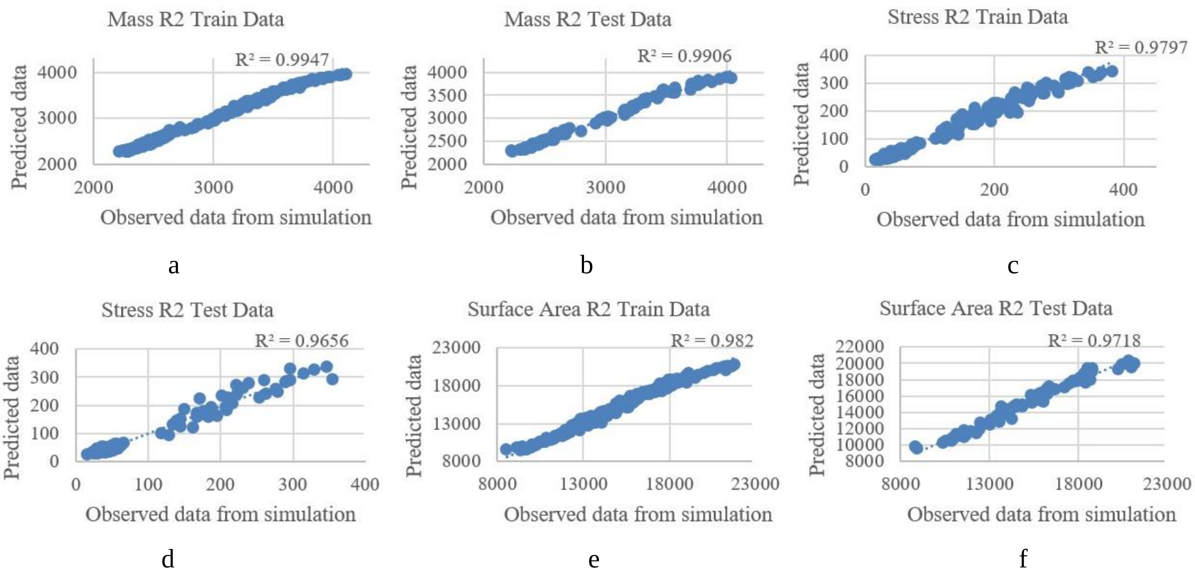

Fig. 5 *R*2 values obtained for both the train and test data of three design responses: mass (a, b); stress (c, d) and surface area (e, f), respectively

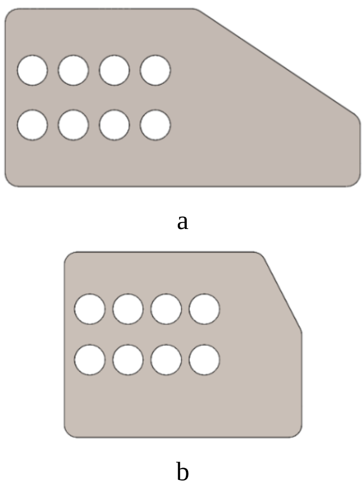

Fig. 6 Solid models of the blade: for initial design (a) and for optimum design (b)

Table 3

Validation of the followed method of design optimization

Design response	Optimum design, ANN-MCS	Optimum design, FEM	Accuracy,%
*DR*1, g	2527.2	2553	-0.01
*DR*2, MPa	52.4	49.6	0.06
*DR*3, mm^2	14668.3	14502.5	0.01

Table 4

Comparison of the values of design responses of both initial design and optimum design

Symbol	Initial design	Optimum design	Difference,%
*DR*1, g	2510.380	2553	+0.10 ↑
*DR*2, MPa	144.7000	49.6	-0.66 ↓
*DR*3, mm^2	14839.47	14502.5	-0.02 ↓

The values of design inputs of both initial design and optimum design are presented in Table 5. From the Table, it is possible to see the differences between the values of design inputs. The input values of optimum design should be rounded up to the nearest values for manufacturing cost.

To show the visual difference between initial and optimum designs, the solid models of the initial and optimum designs are illustrated in Fig. 6. From these solid models, the optimum design has more strength than the initial design because the welding length of the optimum design is larger than that of the initial design.

Table 5

The values of inputs of initial and optimum design

Symbol	Initial design	Optimum design
*DV*1	110	93.2495
*DV*2	65	73.0456
*DV*3	70	77.1656
*DV*4	40	31.3457
*DV*5	3	4.0232
*DV*6	11	11.9794

5. Conclusions

In this work, the design optimization of a wafer dough blade was realized by following a method combining ANN and MCS, which has four steps. For that purpose, the best ANN model having R^2 values greater than 0.96 for both the testing and training process of the model was found. Based on the ANN model, MCS with 2,000,000 realizations were conducted by assigning design inputs values depending on their specified ranges, and by getting design responses corresponding to the inputs. After the MCS process, the variable values of the optimum design were found subject to the aim-specific objective function. Also, to ensure accurate values of the best design found via ANN-MCS method, the responses found based on the ANN-MCS model, and the responses obtained from SolidWorks Simulation were compared. From this comparison, it can be said that there is a good agreement between the response results of the ANN-MCS method and those of the FEM-Simulation. When the results of the initial and optimum designs were compared, there was a significant decrease in the maximum stress (nearly 66%) whereas there was a reasonable low difference in both the mass and surface area. With the followed method within this paper, it can be possible to take into account the experimental data instead of analytical data in a design problem. Moreover, the followed method provides engineers with a practical and systematic way to find the optimum design during engineering design process. In the future, it can be possible to improve the method followed, especially in large-scale design problems, by using Latin Hypercube Sampling to decrease the period of design optimization process.

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DESIGN OPTIMIZATION OF A WAFER DOUGH BLADE USING ARTIFICAL NEURAL NETWORK AND MONTE-CARLO SIMULATION

S u m m a r y

In this work, a systematic method to conduct the surrogate-based design optimization is proposed by utilizing Artificial Neural Network and Monte Carlo Simulation. To show its applicability, the design optimization of a wafer dough blade that is an important component in the food industry is carried out. In the optimization problem, design variables or inputs are totally six variables including distances, diameter and thickness, and design responses or outputs are the blade mass, the maximum stress occurred on it, and its surface area. When the results of the initial and optimum designs are compared, there is a significant decrease in the maximum stress (nearly 66%) whereas there was a reasonable low difference in both the mass and surface area. Thanks to the proposed method, it can be possible to take into account the experimental data instead of analytical data in a design problem. Moreover, the followed method provides engineers with a practical and systematic way to find the optimum solution for even nonlinear problems needs to be solved during engineering design process.

Keywords: design optimization, wafer dough blade, Monte-Carlo simulation, artificial neural network.

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