Title:
Efficient Sizing Optimization using ANN Instead of FEM

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Introduction:
Structural optimization is a type of optimal design problem in which the shape of a structure is determined to minimize or maximize the objective function by using the evaluation characteristics such as weight, stiffness, and natural frequency as the objective function and the shape of the structure as the design variables. Structural optimization can be roughly classified into three types: sizing optimization [2], shape optimization [4], and topological optimization [1], depending on how the shape of the structure is represented and what is treated as a design variable.

In sizing optimization, an optimization problem is formulated using the evaluation characteristics of the structure, e.g., weight, stiffness, and maximum stress, as objective functions while the design dimensions that define the shape of the structure, e.g., beam length and height, plate thickness, and cross-sectional area, as design variables, and mechanical or geometric conditions as constraints, and optimization is performed using an optimization algorithm such as steepest descent, GA or PSO. Shape optimization derives the optimal shape of a structure using its outer shape as design variables. To be more specific, the coordinates of the nodes on the boundary of the finite element model representing the initial shape of the structure are used as design variables, and the optimal shape is explored by combining the finite element method, sensitivity analysis method, and mathematical optimization algorithm. Topology optimization is a method of simultaneously optimizing the shape and form of the structure by replacing the problem of finding the optimal shape of the structure with the problem of placing materials in a fixed design domain. Each method has its own characteristics, or advantages and disadvantages, and is used in different ways depending on the situation.

In this research, sizing optimization is focused among the three methods. Sizing optimization treats the dimensions, which define the shape of the structure, as optimization variables, which is similar to the way of defining the shape in general 3D CAD that adopts parametric modeling, and thus has a high affinity with 3D CAD. In fact, several commercial 3D CADs [3] provide the function of sizing optimization. On the other hand, in sizing optimization, as the number of design variables increases, the number of iterations to reach the optimal solution increases rapidly. In order to evaluate the objective function and constraint conditions for each iteration and each design proposal, an analysis using techniques such as the finite element method is required, and each analysis requires a certain amount of time. Therefore, there is a limit to the size of the design problem or the number of design variables that can be optimized in a practical amount of computation time. To overcome this limitation and to handle more design variables within a practical computation time, an efficient sizing optimization method using artificial neural networks is investigated. An artificial neural network, a method of machine learning, requires a large amount of training data to train the network, but once training is completed, inference can be performed in a small amount of time. In the proposed method, networks with the values of the design variables as inputs and the values of the objective function and constraint conditions as outputs are trained in advance using training data collected by using commercial FEM software. During the calculation of sizing optimization, the trained networks evaluate design proposals instead of FEM. The collection of training data using FEM software takes a lot of time, but the time required to evaluate design proposals using the trained networks during sizing optimization becomes almost negligible. Therefore, if the number of evaluations of design proposals performed until reaching the optimal solution in sizing optimization is greater than the number of training data required to train the networks, the total calculation time can be reduced. In order to be applicable to more diverse design problems, the proposed method can handle both continuous values such as dimensions and discrete values such as the number of ribs. In the case study, the proposed method is applied to the optimal design of an aircraft wing.

Proposed method:

The proposed method consists of the following four steps:

Step1: Sampling the design proposals
Step2: Collection of training data
Step3: Training the networks
Step4: Sizing optimization using ANN

Step 1: Sampling the design proposals

The design variables for optimization are selected from the dimensions that define the shape of the structure to be optimized, their upper and lower limits are determined, and combinations of the values of the design variables, or design proposals, are sampled from the design space for the required number of training data. In order to sample design alternatives as uniformly as possible from the design space, Latin hypercube sampling (LHS) is used.

Step 2: Collection of training data

The design proposals sampled in Step 1 are analyzed using FEM software to collect training data.

Step 3: Training the networks

The ANN with the values of the design variables as inputs and the values of the objective function and constraint conditions as outputs is created and trained using the training data collected in Step 2.

Step 4: Sizing optimization using ANN

Sizing optimization is performed by evaluating the design proposal using the networks trained in Step 3. Any optimization algorithm can be used for sizing optimization, such as the steepest descent, PSO, or GA.

Case study:

In order to confirm the effectiveness of the proposed method, it is applied to the design of an aircraft wing.

In the case study, the wings of Hawker Tempest, Mitsubishi A6M Zero, and Kawasaki Ki-45 Toryu, fighters used in World War II, are used as design targets because of the ease of collecting documents. From a structural point of view, an aircraft wing is roughly composed of three elements: ribs, spar, and skin. Based on the drawings available in the literature, wing models of these aircraft, which consist of three elements, were created. Ribs and spars usually have an I-shaped cross section, but they were simplified to a rectangular cross section. All structural elements are modeled by shell elements. In actual aircrafts, there are cutouts in these structural elements due to the presence of devices inside the wings and moving surfaces such as ailerons and flaps, but these are not considered in this case study. Fig. 1 shows the created models. As for design variables, the thickness of the ribs, spars, and skins, the length of the ribs, and the number of ribs are treated. For the thickness, as also shown in Fig. 1, all the structural elements are divided into 9 groups, and the thickness is configured for each group. The range of thicknesses is shown in Tab. 1. For the rib length, the rib length of the original fuselage is considered to be 100%, and the rib length is expressed as X% of that length. All ribs are divided into 5 groups as shown in Fig. 2 and rib length is configured for each group. The range of rib lengths is shown in the Tab. 2. The number of ribs varies from 26 to 29, with 27 as the initial value. The total number of design variables is 15: 9 for thickness, 5 for rib length, and 1 for the number of ribs.

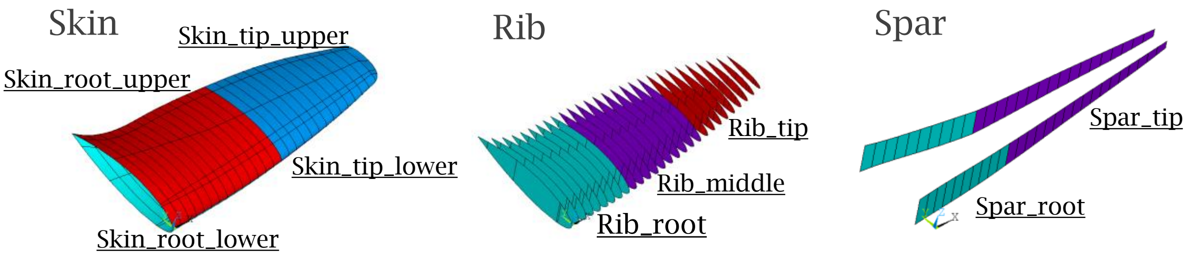

Fig. 1: Wing model and design variables concerning thickness.

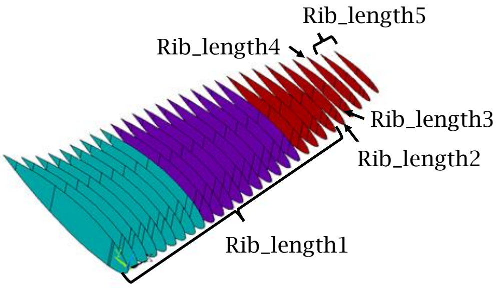

Fig. 2: Design variables concerning rib length.

	Min (mm)	Initial (mm)	Max (mm)
Skin_root_upper	0.8	1	2
Skin_tip_upper	0.5	1	1.5
Skin_root_lower	0.8	1	2
Skin_tip_lower	0.5	1	1.5
Rib_root	3	8.9	10
Rib_middle	3	8.9	10
Rib_tip	3	8.9	10
Spar_root	30	55.7	60
Spar_tip	10	24.8	25

Tab. 1: The range of thicknesses.

	Rib length1	Rib length2	Rib length3	Rib length4	Rib length5
Max	105%	102%	101%	101%	102%
Min	98%	99%	99%	98%	95%

Tab. 2: The range of rib length.

As for the number of training data, in order to discuss the effect of the number of training data on the inference accuracy and optimization results, the proposed method was run while varying the number of training data from 1000 to 20000. As for the objective function and constraint conditions of sizing optimization, the total weight was used as the objective function, while the maximum stress and natural frequency were used as constraints. In order to collect these values of the design proposals sampled in Step 1, ANSYS was used for modeling and analysis. As for ANN, 3 networks with 15 design variables as input and weight, maximum stress, and natural frequency as output respectively were created and trained. In order to discuss the effect of network configuration on the inference accuracy and optimization results, networks with three or four hidden layers were tested in addition to the standard networks with one hidden layer. Similarly, networks with different number of nodes in the hidden layers were tested. In training, 70% of the training data was used as training data, 15% as cross-validation data, and 15% as test data. As for sizing optimization, PSO was used as the optimization algorithm.

Results and discussion

Due to the limitation of the paper, the results of Mitsubishi A6M Zero are shown here as an example. Tab. 3 shows the number of hidden layers, the number of nodes in the hidden layers, the number of training data, and the average error with the lowest average error for the obtained networks that infer maximum stress, natural frequency, and weight. Here, the hidden layer configuration of 50_60_50_5 means that the network has four hidden layers, and each hidden layer has 50, 60, 50, and 5 nodes. Fig. 3 shows the effect of the number of training data on mean error of the networks that infer maximum tress. By increasing the number of training data, the average error decreases. The required number of training data depends on how much accuracy is required. Next, the optimal solution derived using the learned ANN and PSO and the analytical results of the optimal solution using ANSYS are shown in Tab. 4. This result shows that the weight and natural frequency can be inferred with great accuracy, but the maximum stress has an error of several percent in the optimal solution. It is dangerous if the maximum stress is inferred to be lower than it should be.

	Configuration of hidden layer	Training data	Training time (s)	Average error (%)
Maximum stress	50_60_50_5	14000	844	0.79
Natural frequency	30_40_30	7000	412	0.73
Weight	20_30_20_10	11000	374	0.0046

Tab. 3: Obtained ANNs that infer maximum stress, natural frequency, and weight.

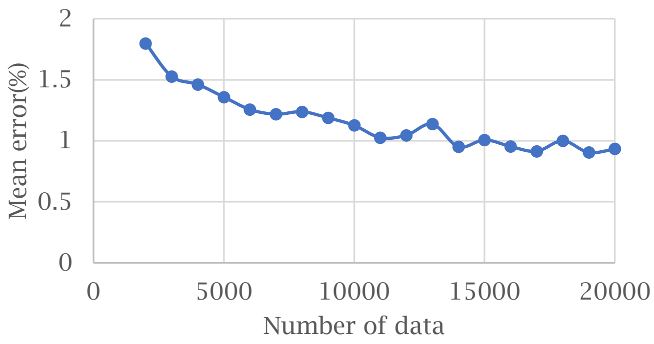

Fig. 3: Effect of the number of training data on mean error.

	ANN		FEM		Error		
The number of inference	Maximum stress (Mpa)	Weight (Kg)	Maximum stress (Mpa)	Weight (Kg)	Maximum stress (%)	Weight (%)	Natural frequency (%)
105016	6.1	786.6	6.33	786.7	3.62	0.0107	0.58

Tab. 4: Result of sizing optimization.

As for the calculation time, 14000 training data were used to train the network to infer the maximum stress, while 100000 inferences were made to reach the optimal solution in sizing optimization using ANN. The collection of a training data, in other words, the analysis of a design proposal using ANSYS, takes an average of 144 seconds. This means that it takes about 560 hours to collect 14,000 training data. On the other hand, training the networks and optimization using the learned networks and PSO both require only a few minutes, thus the time required is almost negligible. Even in conventional sizing optimization, most of the computational time is occupied by the analysis executed during the iterative computation. If sizing optimization was performed without ANN and 100000 analyses were performed during that process, the sizing optimization would take 4000 hours.

To summarize, it was found that while the proposed method succeeds in significantly improving the efficiency of sizing optimization, inference errors are unavoidable and thus this needs to be to be further investigated.

Conclusion:

In this study, an efficient sizing optimization method using artificial neural networks is investigated in order to handle more design variables within a practical computation time. In the proposed method, in order to reduce the calculation time required for the analysis for evaluating design alternatives performed during sizing optimization, the networks for inferring the objective function and constraint conditions from the design variables are trained in advance, and the learned networks are used during sizing optimization. A large amount of training data is required to train the network, but as shown in the case study, if the number of evaluations of design proposals performed during sizing optimization is larger than the number of required training data, the total calculation time can be reduced. It was also found that if the networks used to the sizing optimization for the similar products were available, the computational efficiency could be further improved by fine tuning.

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