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A study on multi-objective optimal design of derrick structure: Case study

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Abstract

Engineering system problems consist of multi-objective optimisation and the performance analysis is generally time consuming. To optimise the system concerning its performance, many researchers perform the optimisation using an approximation model. The Response Surface Method (RSM) is usually used to predict the system performance in many research fields, but it shows prediction errors for highly nonlinear problems. To create an appropriate metamodel for marine systems, Lee (2015) compares the prediction accuracy of the approximation model, and multi-objective optimal design framework is proposed based on a confirmed approximation model. The proposed framework is composed of three parts: definition of geometry, generation of approximation model, and optimisation.

The major objective of this paper is to confirm the applicability/usability of the proposed optimal design framework and evaluate the prediction accuracy based on sensitivity analysis. We have evaluated the proposed framework applicability in derrick structure optimisation considering its structural performance.

Keywords: Multi-objective optimal design framework; Sensitivity analysis; Back-Propagation Neural Network (BPNN); Neuro-Response Surface Method (NRSM); Non-dominated Sorting Genetic Algorithm-II (NSGA-II); Derrick structure

1. Introduction

The optimal design of engineering systems is considered as a multi-objective optimisation problem, and the geometry of engineering systems severely affects its performance. For this reason, determining an optimal geometry is one of the challenging problems in the initial design stage. In recent years, system optimisation based on the performance using the commercial code is a method that was employed for engineering design problems (Ko et al., 2013; Jung et al., 2012).

The essence of optimisation design process is the performance analysis/evaluation according to the geometry modification. Generally, the performance analysis of the complex engineering system such as marine, aerospace, machinery system … etc. is time-consuming. To reduce the performance calculation time, many researchers try to predict the performance using approximation models (also known as response surfaces, or metamodels). These approximation models represent the relationship between inputs (design variables) and outputs (system's performance) (Hong et al., 2000; Mayers and Montgomery, 1995; Li et al., 2012). However, Response Surface Method (RSM) produces some errors in highly nonlinear problems (Sankaya and Gullu, 2014; Salman, 2014; Kahraman, 2009).

The optimal design problems of a marine system based on its performance involve highly nonlinear components, such as structural, hydrodynamic, vibration performances, etc.

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Many researchers tried to optimise the hull form using the parametric design method. Zhang (2008) researched hull form design using the parametric approach. They employed the Non-Uniform Rational B-Spline (NURBS) method to represent the hull form. Grigoropoulos and Chalkias (2010) tried to optimise the hull form in calm and rough water based on the parametric design method. Lee and Choi (2009) tried to optimise the hull form in terms of hydrodynamic performance using the form parametric design method. Park et al. (2015) tried to optimise hull form of SUEZMAX using optimisation techniques. The parametric design method for geometry representation is a useful technique for geometry optimisation based on performance.

Up to now, many relevant papers about optimisation based on system performance have been published. To predict the system performance, Shin (2007) employed the neuro-fuzzy algorithm to predict the wake distribution, Xu (2011) predicted the maritime safety using the Artificial Neural Network (ANN), and Lee et al. (2014a) tried the prediction for added resistance in waves using the Genetic Programming (GP). To optimise the shape based on performance, Kim et al. (2007) developed a framework to optimise the stern form based on CFD, Halder et al. (2017) studied multi-objective optimisation of blade sweep for a Wells turbine using CFD simulation, Yu et al. (2017) studied optimisation for bow hull form of a 66,000 DWT bulk carrier using the Particle Swarm Optimization (PSO) algorithm, and Chen et al. (2016) tried to optimise the hull form (10000TEU container ship) using CFD method. In the shape optimisation research, generally, CFD analysis was just a means of checking the performance of a design process, and it is very time-consuming. Therefore, optimisation becomes difficult/impossible using CFD tools because we need to check the system performances for a large number of alternative design cases. To examine alternative design cases and minimise the performance analysis time, a multi-objective optimal design framework that includes performance prediction and an optimisation process is essential.

To create an appropriate approximation model for marine system, Lee (2015) compares the prediction accuracy of the response surface generated by the RSM, the kriging method and the ANN method using two NLP problems and one user define problem, and subsequently proposes a multi-objective optimal design framework comprising two principal phases:

(1st Phase)

To predict the system performance, generate the response surface using the Artificial Neural Network (ANN) that is considered as a Neuro-Response Surface Method (NRSM) in the proposed framework.

(2nd Phase)

Optimise the system geometry in the generated response surface using NSGA- II.

By means of a case study of constraint optimisation problem, the effectiveness of the proposed optimal design methodology is verified in view of structural performances (Lee et al., 2016).

The remainder of this paper is organized as follows. Chapter 2 presents an optimal design framework based on the Neuro-Response Surface Method (NRSM), and Chapter 3 presents an example of derrick system optimisation problem considering its structure performance (Lee et al., 2016). Finally, Chapter 4 explains the conclusion and future research plan.

2. Framework for optimum design based on NRSM

The proposed optimal design framework includes geometry representation, performance prediction, and optimisation. Fig. 1 illustrates the framework which is composed of three processes (Lee et al., 2014b):

(1st process: Definition of the geometry)

The framework defines the geometry of the structure using parameterisation. An orthogonal array table (Ross, 1996) is used to systematically generate design alternatives. The system performance prediction is more accurate when the range of design variables includes all possible design alternatives.

To check the interaction between the variables and the response, the generated design alternatives are divided into two sets:

Training data: used to generate the response surface and check the learning accuracy.

Test data: used to check the prediction accuracy.

(2nd process: Generation of response surface using NRSM)

The Multi-Layer Perceptron (MLP) is used to generate the response surface. It has three layers: an input layer, a hidden layer, and an output layer. The back-propagation algorithm (Robert, 1989) is used to train the neural network. The prediction accuracy of generated response surface is very important because the optimisation process is conducted on it. In order to construct the appropriate response surface, the best structure and the best number of learning cycles for the neural network are prepared and the prediction accuracy of the generated response surface is checked using Test data (1st process). Through this process, we can make an appropriate ANN structure for our problem. After generating the response surface, the performance of various design alternatives can be predicted easily and quickly.

(3rd process: Optimisation)

The optimisation process is conducted to generate the response surface. The NSGA-II (Deb, 2002) is used as a multi-objective optimisation algorithm.

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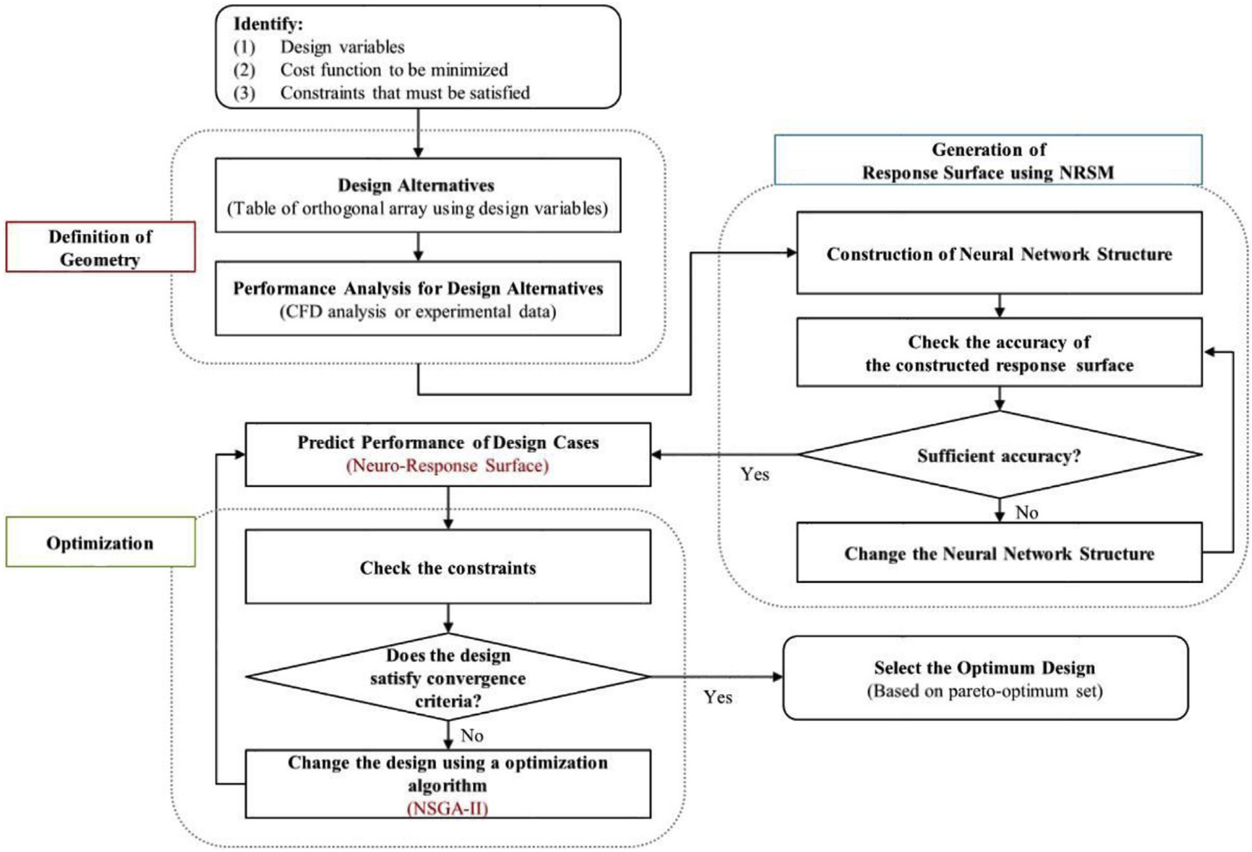

Fig. 1. Optimal design framework based on NRSM (Lee, 2015).

Finally, the optimum structural design can be selected using the Pareto-optimum set generated by the proposed framework.

3. Case study

To verify the efficacy for the applicability/usability of the proposed framework, a derrick structure is used for a case study by considering its weight reduction while keeping its safety factor upper than 3. The accuracy of the framework results has been analysed using commercial software (ANSYS).

3.1. Formulation of optimisation problem

Eqs. (1)–(4) represent the optimisation formulation for the derrick structure, considering structural performance.

Find x_i, x_i = Design variables (i = 1, 2, 3, 4, 5, 6, 7) to minimize $f_1(x)$ = Steel weight (ton) to maximize $f_2(x)$ = Safety factor.

Using weighting factor, we can formulate the problem as one function to be minimized:

$$F(X) = (W_1 * f_1) + \left(W_2 * {}^1/_{f_2} \right) \quad (1)$$

where, W_j = Weighting factor (j = 1, 2).

Subject to

$$\mathrm{Min}\, x_i \le x_i \le \max x_i \quad (2)$$

(i = number of design variables)

$$f_1(x) \le \text{base design case} \quad (3)$$

$$f_2(x) \ge 3.0 \quad (4)$$

Derrick structure consists of 2 beam shapes (I-beam and Box beam). Fig. 2 shows the cross section area shape and main dimension.

Seven design variables are considered such as I-beam (Web thickness and Flange thickness) and beam thickness of Top box, Middle box and Bottom box (Table 1). Fig. 3 ((a) and (b)) shows the design model including the design variables.

3.2. Environmental conditions

Fig. 4 shows the environmental conditions and constraints for calculation. A, B, C, D, E mean the gravity (about 9.81 m/s2), acceleration of heave motion (about 3.73 m/s2), rotational velocity of roll and pitch motion (about 5.39e-3 rad/s), vertical loads (wind pressure) and fixed condition respectively. Fig. 5 and Table 2 show the loading conditions.

3.3. Definition of geometry

The proposed framework defines the shape of the structure by parameterisation. The generated geometries are used to generate the response surface. 18 sets of different design alternatives are generated using an orthogonal array table (L18

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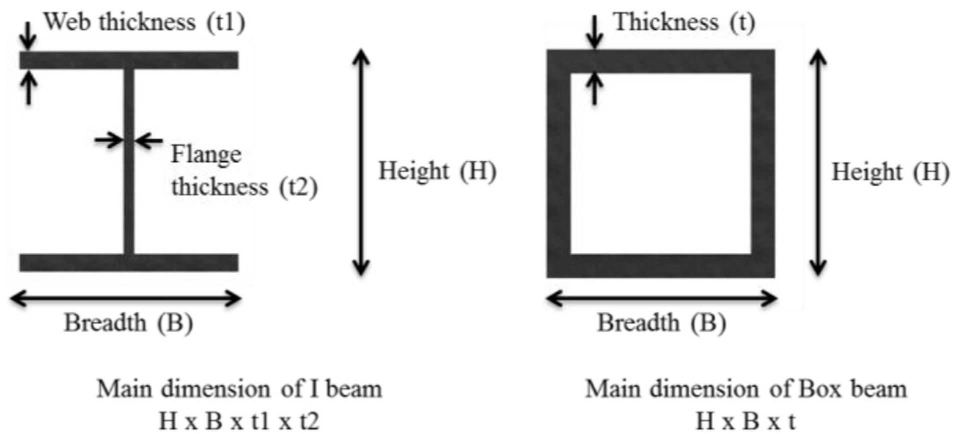

Fig. 2. Cross section area shape and main dimension of I-beam and Box beam.

Table 1
Design variables.

Breadth 750 mm (I-beam)	Web thickness	W1 (mm)
	Flange thickness	F1 (mm)
Breadth 500 mm (I-beam)	Web thickness	W2 (mm)
	Flange thickness	F2 (mm)
Top Box beam thickness		T (mm)
Middle Box beam thickness		M (mm)
Bottom Box beam Thickness		B (mm)

(21 × 32)) as shown in Table 3. Design no. 19 is considered as base design case. Table 4 shows the results of the performance analysis for steel weight and safety factor using the ANSYS. The safety factor is calculated as below:

$$\text{Safety factor} = \text{Yield stress}/_{\text{Maximum stress}} \quad (5)$$

In Eq. (5), yield stress is a material property while the maximum stress is calculated on the derrick system.

After performance calculations of the generated design cases, the response surface was generated using NRSM. Then, we predicted the performance of the design cases in a continuous response surface that was not directly computed. Fifteen sets of data were used to generate the response surface and four sets of data (Case 4, 8, 12, 16) to check its accuracy. To increase the learning rate for a neural network, all data was used as a normalized value between 0.5 and 1.

3.4. Generation of response surface using NRSM

The number of hidden layers was changed from 1 to 10. Using six hidden layers gave a better result in view of prediction result (Training and Test data). Therefore, the final structure and the number of learning cycles are 7(input neuron) - 6(hidden neuron) - 2(input neuron) and 6400 respectively (Fig. 6). Fig. 7 shows the error convergence in the learning process of the neural network. The error convergence (0.0004) occurs at approximately 6238 iterations.

The error is defined in Eqs. (6) and (7). The error value between the output of the network (d_j) and the actual value (y_j) is used. L is the number of output neurons.

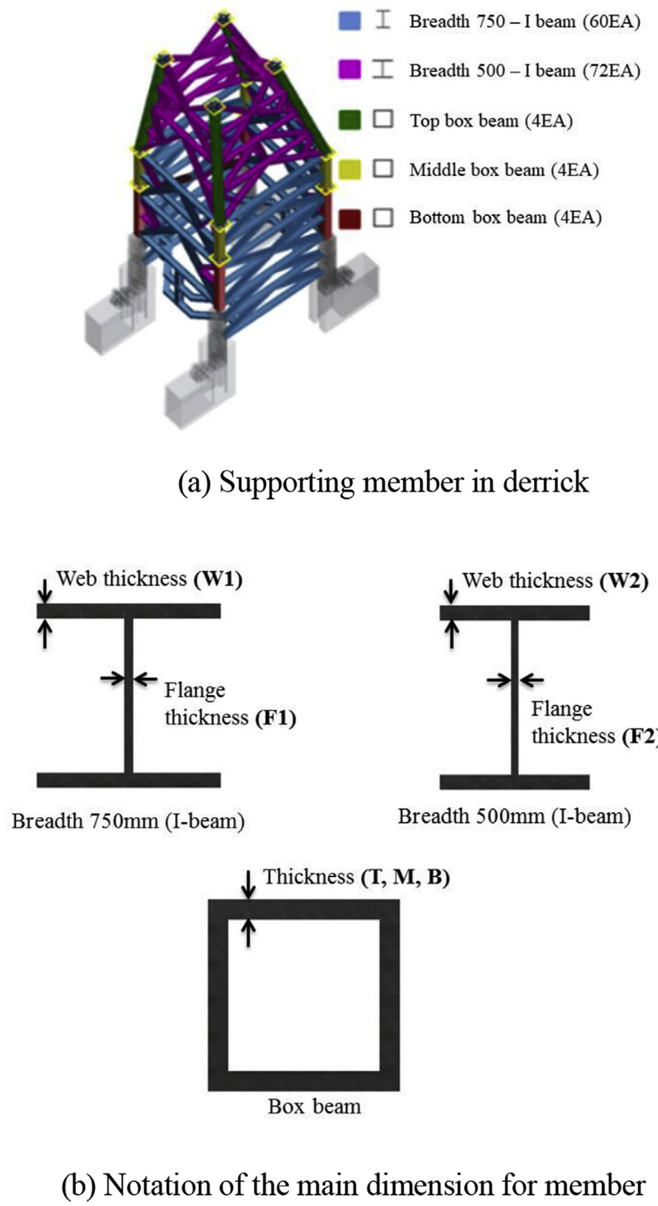

Fig. 3. Design model and design variables.

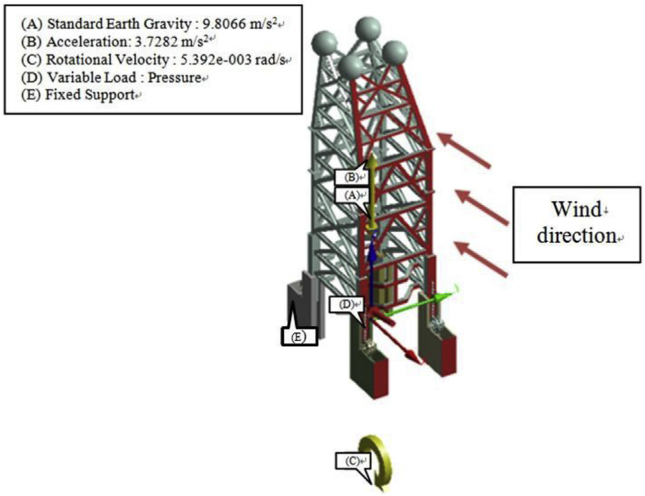

Fig. 4. Environmental conditions and constraints.

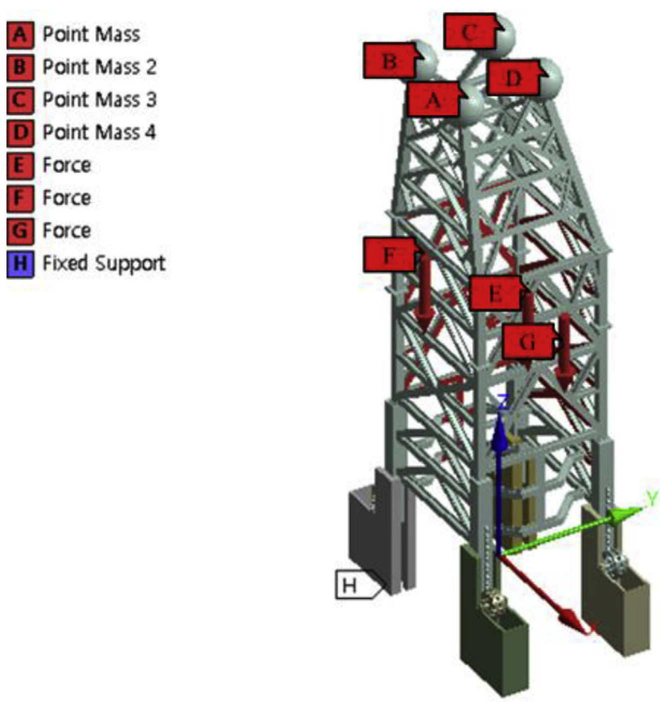

Fig. 5. Loading conditions.

Table 2
Loading conditions.

	HC, TDM and etc.	Pipe and etc.	Total
Weight	1030 ton	600 ton	1630 ton
Mark (Fig. 5)	A, B, C, D	E, F, G	–

$$e_i(n) = d_j(n) - y_j(n) \quad (6)$$

$$E(n) = 1/2 \sum L_{j=1} e_j^2(n) \quad (7)$$

Table 3
Design variables.

Case	Design variables							Remark
	W1	F1	W2	F2	T	M	B	
1	25	40	20	30	80	80	80	–
2	25	50	25	40	90	90	90	–
3	25	60	30	50	100	100	100	–
4	30	40	20	40	90	100	100	Test data
5	30	50	25	50	100	80	80	–
6	30	60	30	30	80	90	90	–
7	35	40	25	30	100	90	100	–
8	35	50	30	40	80	100	80	Test data
9	35	60	20	50	90	80	90	–
10	25	40	30	50	90	90	80	–
11	25	50	20	30	100	100	90	–
12	25	60	25	40	80	80	100	Test data
13	30	40	25	50	80	100	90	–
14	30	50	30	30	90	80	100	–
15	30	60	20	40	100	90	80	–
16	35	40	30	40	100	80	90	Test data
17	35	50	20	50	80	90	100	–
18	35	60	25	30	90	100	80	–
19	35	60	30	50	100	100	100	base design

Table 4
Results of performance analysis.

Case	Steel weight (ton)	Safety factor
1	1279.337	2.249
2	1439.202	2.746
3	1597.343	3.203
4	1390.810	2.431
5	1478.803	2.784
6	1491.352	3.126
7	1398.747	2.306
8	1460.352	2.728
9	1560.115	3.136
10	1393.590	2.390
11	1423.310	2.756
12	1498.982	3.195
13	1401.650	2.502
14	1440.041	2.717
15	1526.360	3.203
16	1420.795	2.328
17	1486.953	2.823
18	1511.466	3.174
19	1630.613	3.536

Table 5 shows the prediction accuracy of the generated response surface for 15 cases in the training data. The structure of the neural network is appropriate because all of the error values are below 3 percent (Table 6).

Table 7 and Table 8 show the prediction accuracy of the generated response surface and errors for the test data. Analysis of the results in Table 8 shows that there are still prediction errors (up to 5%). However, to determine the performance in a limited time, the NRSM can give reasonable results for the initial design stage.

3.5. Optimisation

Table 9 and Fig. 8 show the parameters for NSGA-II and the pareto-optimum sets as the final result of the framework.

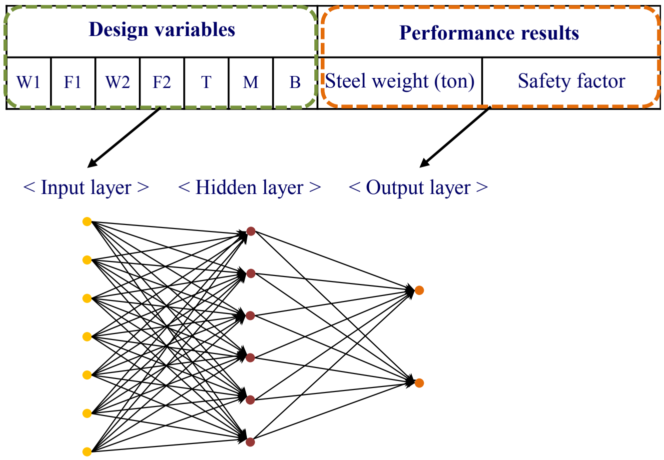

Fig. 6. Structure of the neural network.

Table 5
Analysis results for training data set.

Case	Desired values (ANSYS)		Prediction values (NRSM)	
	Steel weight	Safety factor	Steel weight	Safety factor
1	0.500	1.000	0.500	0.992
2	0.728	0.752	0.720	0.746
3	0.953	0.591	0.962	0.587
5	0.784	0.736	0.782	0.728
6	0.802	0.615	0.799	0.607
7	0.670	0.966	0.665	0.965
9	0.900	0.612	0.893	0.612
10	0.663	0.919	0.656	0.919
11	0.705	0.747	0.698	0.751
13	0.674	0.861	0.666	0.868
14	0.729	0.764	0.724	0.771
15	0.852	0.591	0.850	0.601
17	0.796	0.721	0.797	0.724
18	0.830	0.600	0.833	0.604
19	1.000	0.500	0.979	0.501

To select the final optimum design among the pareto-optimum set, we used a weighting factor. 0.5 is the weighting factors of both Steel weight and Safety factor. The black point (Steel weight(X): 0.7626, Safety factor(Y): 0.52) is the selected optimum design (Fig. 8).

3.6. Sensitivity analysis of the weighting factor

To analyse the weighting factor effects on the objective functions, three different set of the weighting factor was considered (Table 10). Table 11 shows the design variables of each design case. The design variable of F1 (Flange thickness; Breadth 750 mm) and T (Top Box beam thickness) have a great effect on the performance (Table 11).

Table 12 shows the performance results of selected design case. According to weighting factors, the performance values make a good prediction. Table 13 shows the prediction errors between proposed framework and commercial code (ANSYS) result. The prediction error is below 10% (Table 13).

To optimise the system geometry based on its performance, proposed framework is considered as useful design method such as save the calculation time for performance analysis and examine widely the alternative design cases.

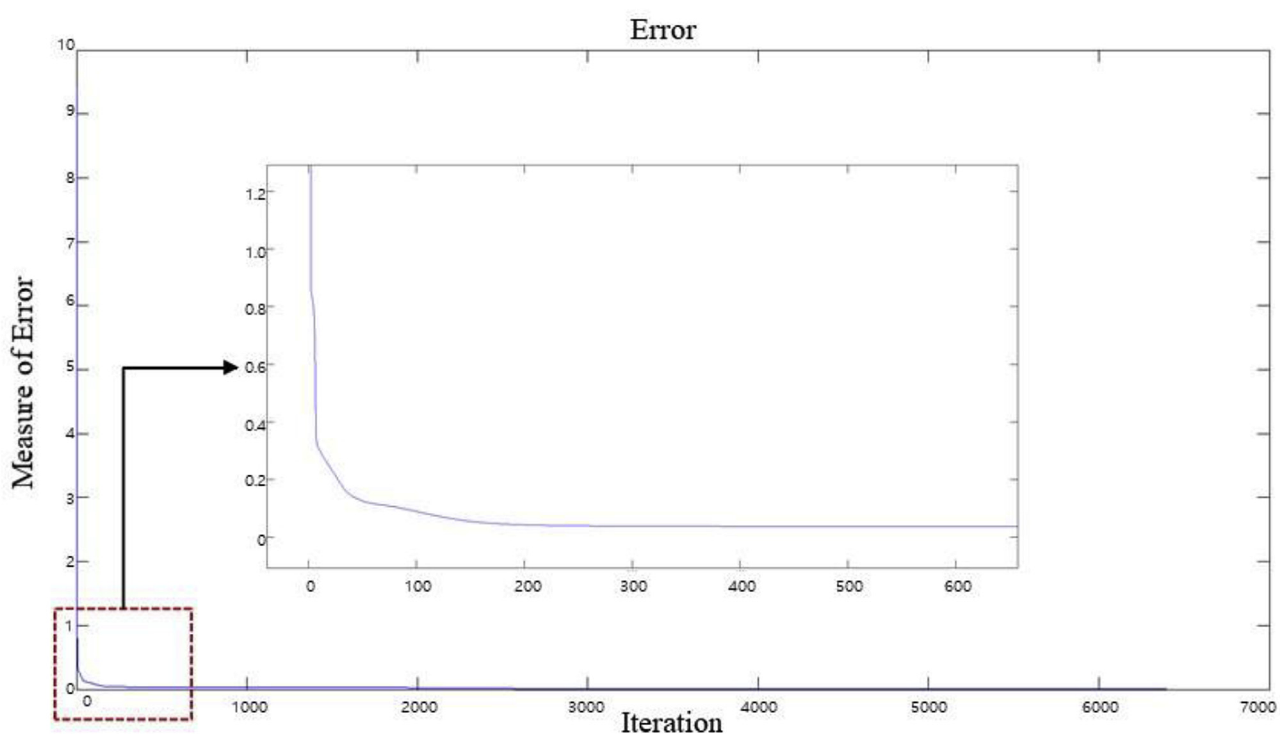

Fig. 7. Measure of error.

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Table 6
Error of training data set.

Case	Error (%) = [(Desired value−Prediction values)/Desired values] × 100	
	Steel weight (ton)	Safety factor
1	0.1%	0.8%
2	1.0%	0.7%
3	1.0%	0.7%
5	0.3%	1.0%
6	0.4%	1.3%
7	0.7%	0.2%
9	0.7%	0.0%
10	0.9%	0.0%
11	1.0%	0.4%
13	1.2%	0.8%
14	0.6%	0.9%
15	0.2%	1.8%
17	0.2%	0.5%
18	0.3%	0.7%
19	2.1%	0.1%

Table 7
Analysis results for test data set.

Case	Desired values (ANSYS)		Prediction values (NRSM)	
	Steel weight	Safety factor	Steel weight	Safety factor
4	0.659	0.897	0.658	0.924
8	0.758	0.759	0.751	0.721
12	0.813	0.593	0.806	0.616
16	0.701	0.953	0.688	0.930

Table 8
The error of test data set.

Case	Error (%) = [(Desired value−Prediction values)/Desired values] × 100	
	Steel weight (ton)	Safety factor
4	0.2%	3.0%
8	0.8%	5.0%
12	0.8%	3.8%
16	1.9%	2.4%

Table 9
NSGA-II parameter.

Parameter	Value
Population size	100
Generation	1000
Crossover	30%
Mutation	2%

3.7. Analysis of optimum design

The improvement in standards of performance evaluation was analysed, as shown in Table 14, where all criteria for the optimum design case (Set 1) are satisfied such as steel weight that decreased about 10% comparing with base design case and safety factor that increased about 3.8% comparing with the required safety factor.

Fig. 9 shows the result of structure analysis. The maximum stress is 1.1238e2 (MPa).

3.8. Discussion

The effectiveness of the proposed framework through multi-objective optimisation problem was confirmed by a derrick weight minimisation while considering a given safety factor: more than 3.

In the initial design stage, the shape of various design alternatives considering their performances can be checked in a reduced analysis time using the proposed framework. We considered that optimal design framework presents the starting design point and save the time for optimal design using existing experimental or calculation data based on commercial codes in the initial design stage. However, the proposed framework shows some errors for extrapolation design problems. To increase the prediction accuracy of extrapolation design alternatives, we can add some experimental or calculation data using commercial codes into pre-existing data, or set the range of design variables including all possible design alternatives in the proposed framework (1st stage: generation of geometry).

4. Conclusion

The major objective of this research is to confirm the applicability/usability regarding multi-objective problems. The proposed framework is composed of three parts: definition of geometry, generation of an appropriate metamodel, and optimisation process. To reduce the time for performance prediction and minimize the prediction errors, the metamodel is generated based on the backpropagation neural network (BPN). The optimisation process is done for the generated metamodel by Non-dominated Sorting Genetic Algorithm-II (NSGA-II). The detailed results are as follows.

I. Through a case study on the optimal structure of a derrick, we confirmed the applicability/usability of the proposed framework for multi-objective NAOE optimisation problems.
II. Through sensitivity analysis of the weighting factor, we can check the prediction accuracy of structure performance.
III. The proposed framework is considered as a useful engineering system optimisation design tool in the initial design stage:
   - Save the performance analysis time in the optimisation process
   - Widely check the alternative design cases.

Evaluations of the appropriate approximation model for each problem and their application to various optimisation problems considering actual design constraints will be conducted in future work.

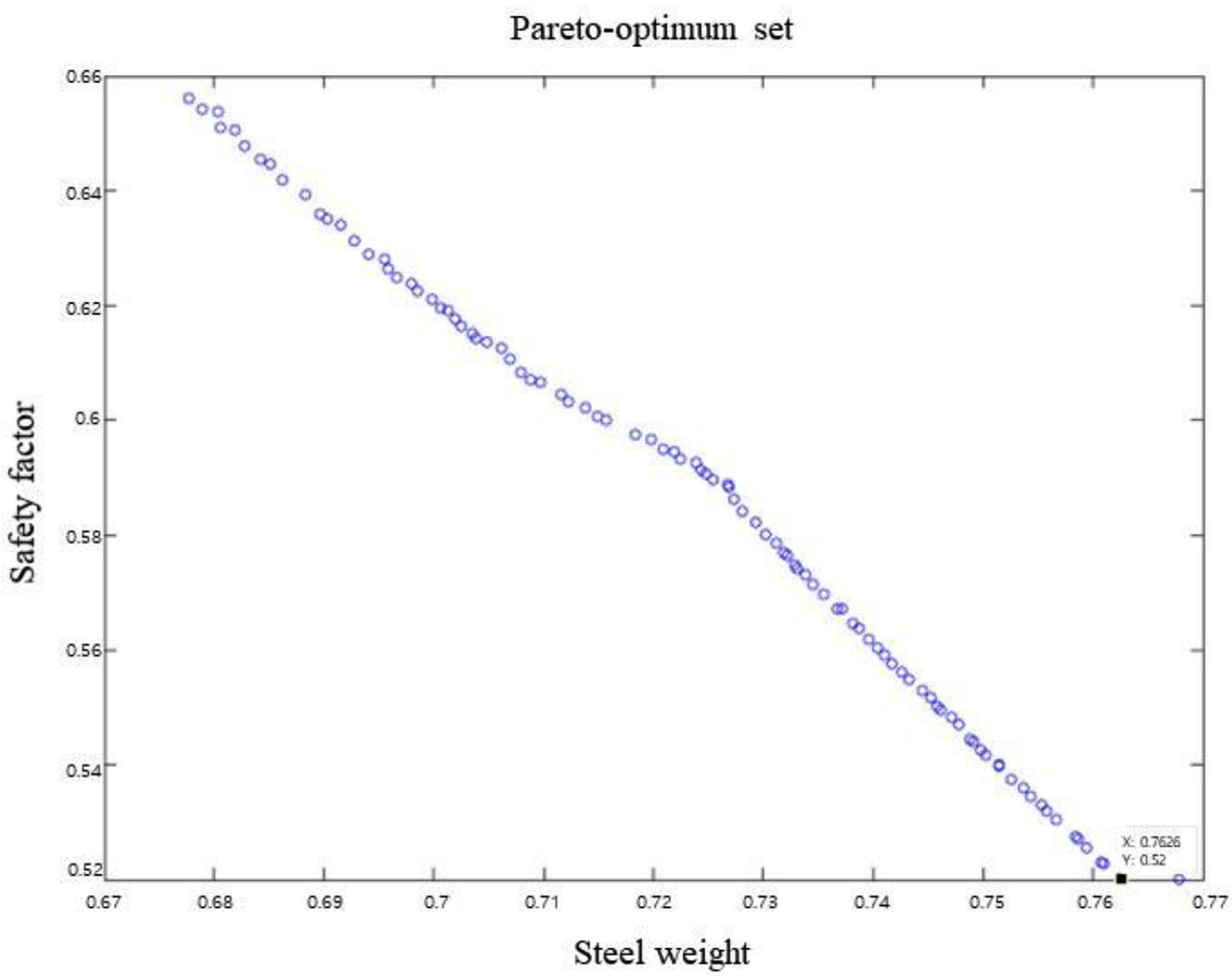

Fig. 8. Pareto-optimum set.

Table 10
Weighting factor effects.

Objective function	Weighting factor		
	Set 1	Set 2	Set 3
Steel weight (ton)	0.5	0.7	0.4
Safety factor	0.5	0.3	0.6

Table 11
Design variables for optimum design cases.

Design variables for optimum design case							
No.	W1	F1	W2	F2	T	M	B
1	25	58.277	20	30	100	100	80
2	25	57.296	20	30	80	99.996	80
3	25	58.151	20	30	100	100	80

Table 12
Analysis of results between desired value and prediction value.

No.	Results based on NRSM framework		Results for ANSYS calculation	
	Steel weight (ton)	Safety factor	Steel weight (ton)	Safety factor
1	1463.848	3.457	1472.944	3.114
2	1404.157	3.000	1426.711	3.076
3	1462.664	3.446	1472.045	3.106

Table 13
Prediction error.

Prediction error [(NRSM Framework−ANSYS Calculation)/NRSM Framework]		
No. of Set	Steel weight (ton)	Safety factor
1	0.62%	9.92%
2	1.60%	2.53%
3	0.64%	9.87%

Table 14
Improvement of performance evaluation criteria.

Improvement (%) = [(Base model−Optimisation model)/Base model] × 100	
Steel weight (ton)	Safety factor (Upper than 3.0)
10% (Decrease)	3.8% (Increase)

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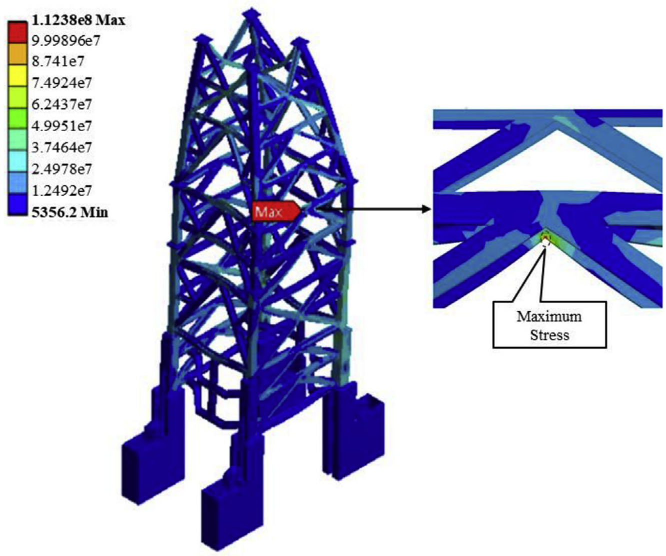

Fig. 9. Structure analysis of optimum design.

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