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Optimization design technique for reduction of sloshing by evolutionary methods

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Abstract

The oscillation of a fluid caused by external force, called sloshing, occurs in moving vehicles containing liquid masses, such as trucks, railroad cars, aircraft, and liquid rockets. This sloshing effect could be a severe problem in vehicle stability and control. Therefore, development of efficient and easy method to reduce sloshing effect is positively necessary.

In this study, optimization design technique for reduction of the sloshing using evolutionary method is suggested. Two evolutionary methods are employed, respectively, the artificial neural network (ANN) and genetic algorithm (GA). ANN is used for the analysis of sloshing and GA is adopted as optimization algorithm. The considered storage tank for fluid is a rectangular tank. The design variables are width and installation location of the baffle, and sloshing reduction coefficient by baffle is used as an object function in the optimization. As a result of this study, the optimal design for sloshing reduction is presented.

Keywords: Optimization design; Sloshing; Evolutionary methods; ANN; GA

1. Introduction

Storage tank structures with fluids have been of interest for a long time, because these have unique characteristics due to the interaction between fluid and structure. The interaction between fluid and structure, which causes the sloshing, could be a severe problem in vehicle stability and control [1]. Numerous studies have been conducted for reduction of sloshing so far. Baffles, floats and partitions are being used for that purpose, and baffles are the most widely used among these due to installation simplicity and high performance. However, baffles can change the modal characteristics of a structure and increase its total weight. And there exist many design variables having an effect on the sloshing; for example, size, interval, installation position, the number of baffles, and so on. There are some related studies on the reduction of sloshing in the literature, and studies on the sloshing using various methods have been reported by several researchers [2-13]. In many previous studies, the sloshing is simulated by using a simplified theoretical method by pendulum or spring-mass model [2]. However, this method has many errors and limitations of application by the large number of assumptions and simplifications in the modelling stage of the sloshing.

In this study, an optimization design technique for reduction of the sloshing by using an evolutionary method is suggested to overcome this defect. Artificial neural networks (ANN) and genetic algorithm

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(GA) are employed as an evolutionary optimization method [14, 15]. The principal reason of adopting evolutionary method as an optimization tool is to overcome the limitation of application and error of the conventional optimization technique by using a simplified theoretical method such as a pendulum of spring-mass model. The conventional gradient-based mathematical optimization technique requires gradient information of the object function and computational sensitivity. However, in a real engineering problem, the derivation of the object function and obtaining the gradient information is very complicated and difficult. The sloshing is also a complicated fluid-structural interaction phenomenon. Therefore in this study, a newly proposed evolutionary optimization algorithm is applied to the reduction of sloshing of the water in a rectangular tank with baffles under translational excitation. As a result of the optimal design, the optimized width and installation location of baffle are suggested. Especially, the validity of the optimized design for installation location of baffle is verified through a comparison with experimental results.

2. Verification of the sloshing analysis

2.1 Analysis model

A rectangular storage tank with baffles is considered as an analysis model. The length, height and width of the tank are 300 mm, 150 mm and 100 mm, respectively. Fig. 1 shows the dimensions and coordinate systems of the tank. The tank is filled with water at a height of 50 mm. To reduce the sloshing, a wing type baffle is installed and the tank is made of acrylic with a thickness of 5 mm.

The material properties of acrylic and water, which are applied for the sloshing analysis, are presented in Table 1 [16]. In the sloshing analysis, 2198 quad elements are used for tank regions and 5016 hex elements are used for fluid regions.

2.2 Verification of ALE analysis results

To use the ANN instead of the FEM analysis as analyzer in the optimization process, training of ANN for the design parameter is positively required. In this study, an ALE numerical analysis method is used to generate the patterns for the learning and test sets of the ANN. The ALE numerical analyses are performed by using the commercial explicit code MSC/Dytran [17, 18]. In this analysis, the ALE contact algorithm is used for the analysis of solid-fluid interaction effect.

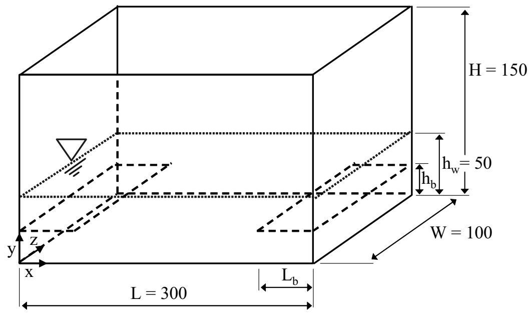


Fig. 1. The analysis model of rectangular tank partially filled with water (L_b = 30～150 mm, h_b = 35～55 mm).

Table 1. Mechanical properties of the acrylic and water [16].

Material	Mechanical Property	Unit	Value
Acrylic	Young's modulus (E)	GPa	3.003
	Poisson's ratio (ν)	-	0.3
	Density (ρ)	kg/m^3	1170
Water	Bulk modulus (K)	GPa	2.07
	Shear viscosity	s^{-1}	1.131×10^{-3}
	Density (ρ)	kg/m^3	1000

For effective optimization design, the proper objective function and design variables should be defined properly. As an object function of sloshing reduction optimization, the following parameters can be considered.

1) Force or moment induced by sloshing to tank, 2) Water height variation induced by sloshing, 3) Stress or strain induced by sloshing at tank.

Among these parameters, the first parameter is eliminated as an object function because the ALE method's validity for this parameter has not been verified in this study. The stress is also eliminated because of the limitations of the experimental device used in this study. Therefore, the water height variation is adopted as an object function for sloshing reduction optimization in this paper.

The experimental results and the ALE analysis results for the water height variation by sloshing of the tank under translational motion are compared in order to verify the validity of the ALE analysis used in this study. In the ALE numerical analysis, the water height variation is evaluated by the fraction of fluid element ($F_i(e_i)$) from the analysis results. For example, the fraction of a full filled fluid element is “1” and fraction of an empty fluid element is “0”. Using this principle, the water height at the specified time and horizontal location can be measured. In Fig. 2, y_i shows the height of i-th element and $F_i(e_i,t)$ shows the faction of the i-th element at specific time “t”. Therefore, the total water height (h) can be expressed as eq. (1) at specified time “t” and horizontal location. This concept is shown in Fig. 2.

$$h = y_1 \times F_1(e_1,t) + y_2 \times F_2(e_2,t) + \cdots + y_{i-1} \times F_{i-1}(e_{i-1},t) + y_i \times F_i(e_i,t) \tag{1}$$

Where, $0 \le F_i(e_i,t) \le 1, \quad i = 1,2,3,\cdots$

The experimental device to simulate the translational motion is developed and presented in Fig. 3. A slider-crank is used to convert the rotary motion of motor into the translation of rectangular tank. In the experiment, the maximum rotating speed of driving motor is 1800 rpm and final rotating speed through reduction gear is 45 rpm (0.75 Hz). The rotating speed and the water height are fixed at 31 rpm (0.51 Hz) and 50 mm, respectively, during the verification process of the ALE analysis. The water height of 50 mm is equal to 1/3 the total height of the tank.

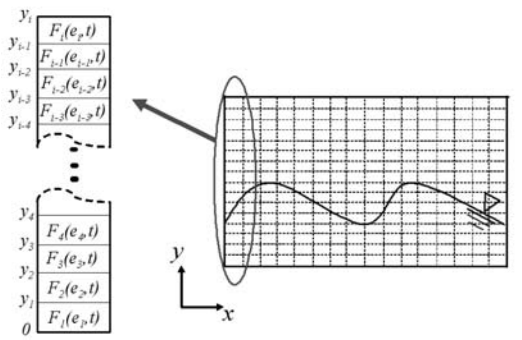


Fig. 2. Water height evaluation in the ALE analysis.

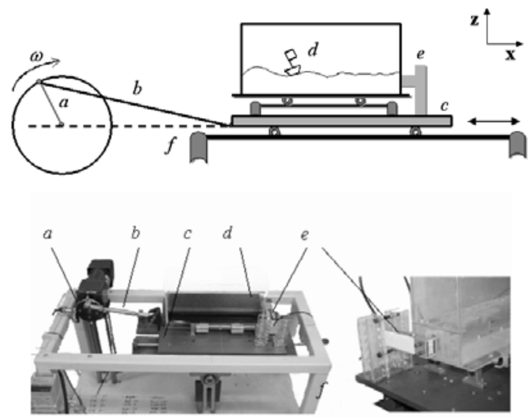


Fig. 3. Apparatus of experimental device for sloshing.

To obtain the velocity history for sloshing analysis, first the movement history of the experimental device’s slide is measured under movement with 0.51 Hz. Then, the obtained movement history is fitted by using a 6th-order polynomial equation. Finally, the velocity history can be obtained from differentiating the previous polynomial equation. The displacement and velocity history is shown in Fig. 4. The validity of the sloshing analysis in this study is verified by using this velocity history.

In the sloshing experiment, in order to measure the variation of free surface of water by external force directly, the use of an ultrasonic sensor was originally considered. But this type of sensor has too many observational errors such as low response time and resolution. So, in this study, the variation of free surface of water was directly measured. A camcorder was

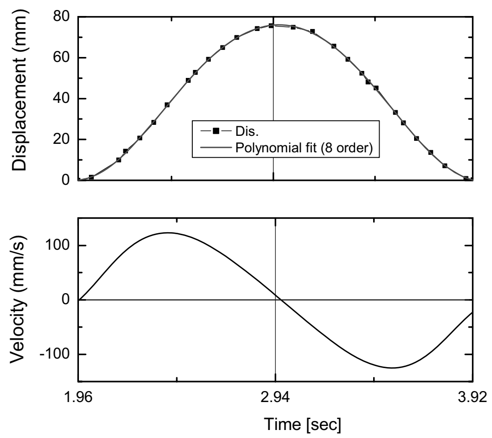


Fig. 4. Applied velocity history for verification of the validity of ALE analysis.

8 mm video camera

↓

Convert into digital video file through MPEG board

↓

Capture 24 picture every second through Adobe Premiere

↓

Measure water height through Tracer

Fig. 5. Procedure to measure water height.

used to capture the sloshing of water accurately. The taken image using camcorder was converted to "avi" format, then converted again to a figure file at regular intervals by using the Adobe Premiere program. Finally, using this figure file and the trace chase program, Tracer, the variation of surface of the water was measured. Fig. 5 shows this experimental procedure.

Fig. 6 shows a comparison between the experimental and the ALE results as the water height varies under the translational motion. The water height is measured from the centerline of the tank side wall. The y-axis shows the ratio of the sloshing water height to the original water height. The solid line is the result of the ALE analysis and the dotted line is the result of the experiment and some discrepancy is shown between the two lines. The major reason for this discrepancy is considered to be the observational error in the experiment etc. But, the period of water sloshing and the water height configuration in time history of the two results show good agreement in general. From these results, the ALE numerical method used in this study seems to have validity in the sloshing analysis.

3. Evolutionary optimization method

3.1 Analysis for creating training data of ANN

The ANN is used for the analysis of the sloshing in the optimization of baffle. The basic advantage of ANN lies in the fact that it is able to automatically map a relationship from the supplied input and output parameters [19]. Therefore, complicated relationships between various parameters can be found by the ANN. An ANN can be learned with the input of design variables and the network should map the object value itself. In this study, multi-layer perceptrons (MLP) are used because of their adaptable structure and to the definition of well-known learning algorithms. An MLP, as used in this study, consists of one input layer, two hidden layers and one output layer. The signals always propagate from the input to the output layer throughout the hidden layers. During the learning process, the interconnections and basis of the MLP are changed so to minimize the differences between the known and computed outputs. The use of nonlinear differentiable transfer functions in the MLP neural network allows the definition of the back-propagation learning rule by which the RMS between the known and computed output is minimized.

In this study, ANN is used in order to analyze the sloshing characteristics of a rectangular tank with baffles with the variation of design parameters. The variable training rate is applied to improve convergence on the ANN. The ANN used in this study is shown in Fig. 7. The inputs of the ANN are baffle design variables, namely, the baffle width and installation height and the output is sloshing reduction coefficient (β). The sloshing reduction coefficient is defined as follows:

$$\beta = \frac{\sigma_{unbaffled} - \sigma_{baffled}}{\sigma_{unbaffled}} \tag{2}$$

Where, σ is $\sqrt{\frac{\sum d_N^2}{N}}$ and $\sum d_N^2$ means the summation of the square for standard deviation of

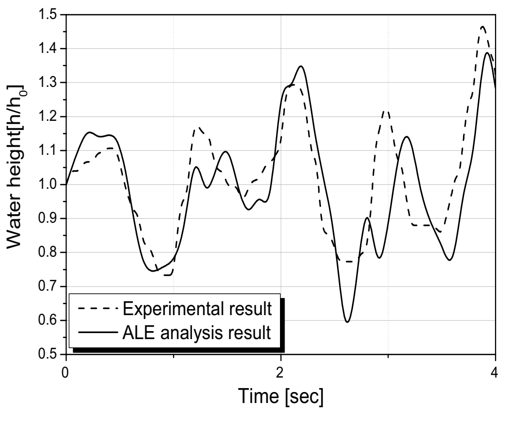


Fig. 6. Comparison of the experimental and the ALE results for water height variation under sloshing.

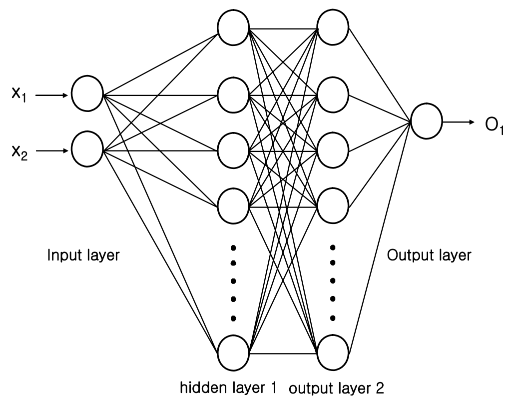


Fig. 7. Multilayer perceptron artificial neural network for sloshing reduction optimization of the rectangular tank.

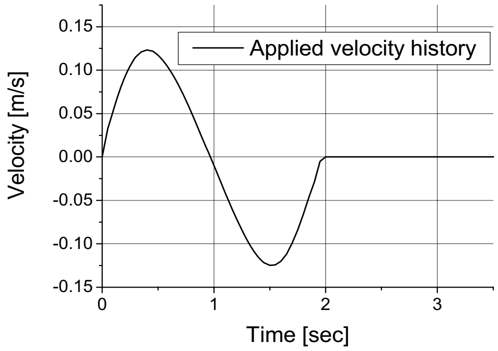


Fig. 8. Velocity history applied in sloshing reduction optimization of the rectangular tank.

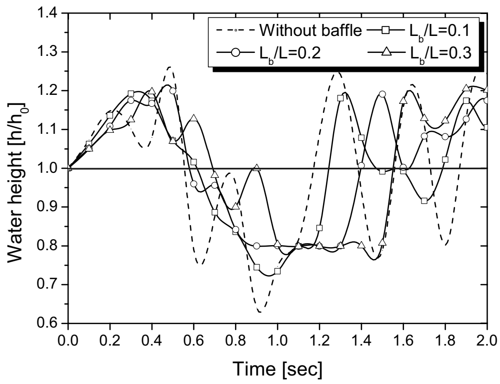


Fig. 9. Water height variation measured at the wall of tank for various baffle width (L_b/L = 0.1, 0.2, 0.3, h_b/h_w = 0.7).

water height variation at the left wall of a rectangular tank. "N" means the number of measurement times. In this paper, water height variations during 1.9 sec are measured with interval of 0.1 sec for the evaluation of baffle performance.

Structure and fluid coupling analysis using the ALE is conducted in order to create the training data of the ANN. Applied external force condition is shown in Fig. 8. This velocity history is applied in the direction of length of the rectangular tank. The dimension of the rectangular tank is 300*150*100 mm and the height of water is fixed at 50 mm. The baffle shape and the tank material properties are equal to those of the analysis model of the previous chapter.

Fig. 9 shows the sloshed water height variation with respect to time. The water height variation is calculated by ALE analysis at the wall of the rectangular tank as the baffle width(L_b) varies: 30, 60, 90 mm, respectively, with the installation height of baffle is fixed at 35 mm. In this figure, the water height

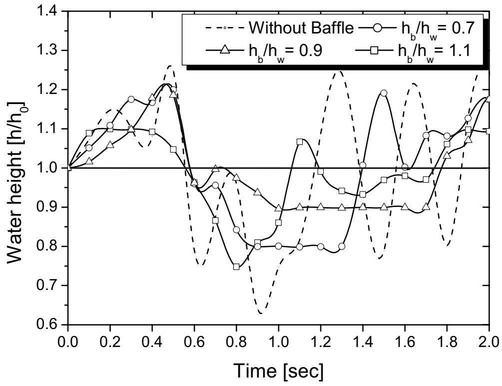


Fig. 10. Water height variation measured at the wall of tank for various baffle installation height (h_b/h_w = 0.7, 0.9, 1.1, L_b/L = 0.2).

"1.0" means no oscillation of water and therefore no sloshing. As the baffle width increases, the water height variation becomes smaller. The lowest water height variation is seen for the largest baffle width of 90 mm. Fig. 10 shows the water height variation calculated by the ALE with the variation of installation height of baffle (h_b) : 35, 45, 55 mm, and fixed baffle width of L_b=60 mm, respectively. The best performance, in this case, is seen when the baffle height is L_h=45 mm. This means a little submerged installation condition of the baffle for water.

3.2 Learning of the ANN

All the characteristics of design parameters need to be included in the ANN learning data in order to maximize the efficiency of the learning. A learning example consists of a set of values for the input neurons and the corresponding value for the output neurons.

In this study, 15 input-output pairs (patterns) are prepared carefully to reflect all the aspects that the network needs to learn and are shown in Table 2. In Table 2, the inputs of the ANN are baffle installation height and width, which are the design variables of sloshing reduction optimization of the baffle. For the prevention of convergence at the local optimization value, the normalized input by regularization function is applied in the learning of the ANN and optimization. The following regularization function is used to generate normalized inputs of the ANN.

$$X_i = \frac{x_{ri} - x_{ri\,\min}}{x_{ri\,\max} - x_{ri\,\min}}, \quad i = 1, 2 \qquad (3)$$

Table 2. ANN training data of rectangular tank with baffle for the sloshing analysis.

Patterns	Baffle Location [Unit : mm]	Baffle Width [Unit : mm]	Reference Output*
1	35 (0.00)**	30 (0.00)	0.1737
2	35 (0.00)	60 (0.25)	0.1766
3	35 (0.00)	90 (0.50)	0.1475
4	35 (0.00)	120 (0.75)	0.1366
5	35 (0.00)	150 (1.00)	0.1139
6	45 (0.50)	30 (0.00)	0.2769
7	45 (0.50)	60 (0.25)	0.4630
8	45 (0.50)	90 (0.50)	0.5796
9	45 (0.50)	120 (0.75)	0.7569
10	45 (0.50)	150 (1.00)	0.7205
11	55 (1.00)	30 (0.00)	0.3448
12	55 (1.00)	60 (0.25)	0.4177
13	55 (1.00)	90 (0.50)	0.4269
14	55 (1.00)	120 (0.75)	0.4394
15	55 (1.00)	150 (1.00)	0.4189

Where, $x_{r1\min} = 35\ mm$, $x_{r1\max} = 55\ mm$

(*Installation height of baffle*)

$x_{r2\min} = 30\ mm$, $x_{r2\max} = 150\ mm$

(*Width of baffle*)

The output of ANN is the sloshing reduction coefficient (β) for each learning pattern. The larger value of sloshing reduction coefficient represents the larger reduction of sloshing; therefore, the sloshing reduction coefficient can be an indicator for the level of sloshing efficiently. In this study, the water variation by sloshing from 0 to 1.95 sec is studied. The main issue of the application of ANN is the accuracy according to the structure of that. So, in this study, the accuracy of ANN by number of hidden layers node is evaluated. The number of hidden layers node is 4, 6, 8, 10, 12 and 14, respectively. From the evaluation results, the case of hidden layers node number 8 shows the best learning performance. Therefore, 2-8-8-1(No. of input layers node - No. of 1st hidden layers node - No. of 2nd hidden layers node - No. of output layers node) structural ANN is applied in the sloshing reduction optimization of the rectangular tank.

The learning results of 15 patterns are shown in Table 3. Learning of the ANN is conducted until the training error reaches below 0.00001 and it takes approximately ten minutes for a personal computer (Pentium-4 CPU, 1.024GB RAM) to reach that value. The results are very close to the exact solutions within the limits of defined error.

Table 3. Learning results of the ANN for the sloshing of storage tank.

Patterns	Baffle Installation Location [Unit : mm]	Baffle Width [Unit : mm]	Reference Output*	ANN Structure 2-8-8-1	ANN Structure Error (%)
1	35 (0.00)**	30 (0.00)	0.1737	0.1737	0.0
2	35 (0.00)	60 (0.25)	0.1766	0.1766	0.0
3	35 (0.00)	90 (0.50)	0.1475	0.1475	0.0
4	35 (0.00)	120 (0.75)	0.1366	0.1366	0.0
5	35 (0.00)	150 (1.00)	0.1139	0.1139	0.0
6	45 (0.50)	30 (0.00)	0.2769	0.2769	0.0
7	45 (0.50)	60 (0.25)	0.4630	0.4630	0.0
8	45 (0.50)	90 (0.50)	0.5796	0.5796	0.0
9	45 (0.50)	120 (0.75)	0.7569	0.7569	0.0
10	45 (0.50)	150 (1.00)	0.7205	0.7205	0.0
11	55 (1.00)	30 (0.00)	0.3448	0.3448	0.0
12	55 (1.00)	60 (0.25)	0.4177	0.4177	0.0
13	55 (1.00)	90 (0.50)	0.4269	0.4269	0.0
14	55 (1.00)	120 (0.75)	0.4394	0.4394	0.0
15	55 (1.00)	150 (1.00)	0.4189	0.4189	0.0

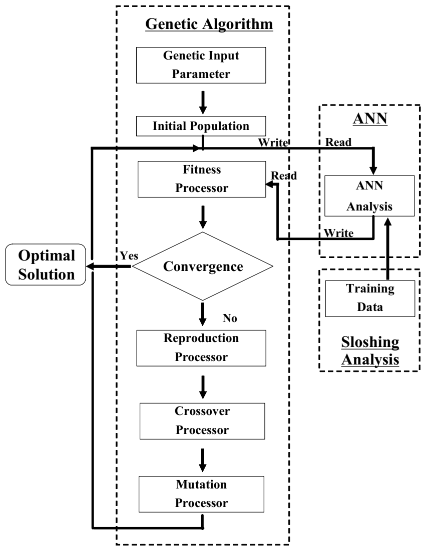


Fig. 11. Flow chart of the sloshing reduction optimization using ANN and GA.

3.3 The genetic algorithm

In this study, the Genetic Algorithm(GA) is employed as an evolutionary optimization method. The GA is an optimization algorithm in which the stochastic search algorithm is based on biological principles: selection, cross-over and mutation. One of the GA's characteristics is the multiple points' search, which discriminates the GA from the other random search methods [14]. Each string corresponds to a candidate of the optimal result in the search space and many similar results can be seen in the previous GA's search. A population consists of several strings. The GA typically begins with a randomly generated initial population of strings. Each string is transformed into a fitness value to obtain a quantitative measure. Based on the fitness value, the strings undergo genetic operations. The goal of genetic operations is to find a set of parameters that search an optimal solution to the problem or to reach the limited generations. In this study, a real coded GA with four decimal places and dynamic mutation are employed for an accurate and fast search for the optimal solution by using ANN. Dynamic mutation allows a search with equal probability at the initial generation number and a local search according to generation number.

A flow chart of the sloshing reduction optimization used in this study is shown in Fig. 11. ANN and GA are employed as an evolutionary optimization method. The ANN is used to analyze the sloshing and the genetic algorithm is adopted as an optimization algorithm. In creation of the ANN learning data, the ALE numerical method is used to obtain the sloshing analysis results. If the average object function value converges to the best object function value, the optimization process is finished.

4. Sloshing reduction optimization

The optimization formulation to reduce the sloshing by baffle is represented as,

Maximize $f(x)$,

$f(x)$ =Sloshing reduction coefficient (β)

$$x_{r1l} \le x_{r1} \le x_{r1h}$$
$$x_{r2l} \le x_{r2} \le x_{r2h}$$

Where, $f(x)$ is sloshing reduction coefficient(β)as an object function, x_{r1} and x_{r2} are baffle installation height and width as design variable, respectively.

The selection method and control parameters of the GA for optimization are as follows:

- Real coded GA,
- Selection method = Roulette wheel selection,
- Population size=20, Crossover rate=0.8,
- Mutation rate=dynamic mutation=0.2,
- Generation number=200,

Table 4. Optimization results of the sloshing reduction problem.

Optimized baffle installation height, $x_1(L_h)$	43.5 mm (h_b/h_w=0.870)
Optimized baffle width, $x_2(L_b)$	118.5 mm (L_b/L=0.395)
Optimum value, $f(x)$	0.8034
Optimum value by ALE analysis for the optimized baffle design	0.7597

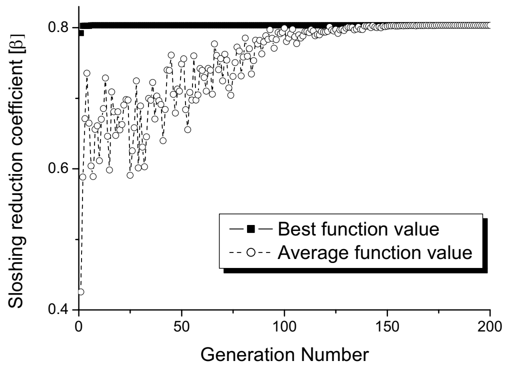


Fig. 12. History of best object function value and average object function value against GA generation

The optimization result is summarized in Table 4. The optimum baffle installation height and baffle width is 0.870(43.5 mm) and 0.395(118.5 mm), respectively. Especially, the optimum baffle installation height is seen at a little submerged point from the free surface of water.

The predicted object function value by evolutionary optimization method and calculated object function value for optimum baffle design is 0.8034 and 0.7597, respectively. This discrepancy is due to the error of ANN. In conclusion, a sloshing reduction of 76 % could be achieved for a rectangular tank under translational excitation by the suggested optimization technique.

Fig. 12 shows the history of the best object function value and average object function value against GA generation. The best object function value is quickly converged on the maximum value at initial generation; however, the average object function value is converged after generation number of 160.

Especially, the validity of the optimized design for the baffle installation location is evaluated through a

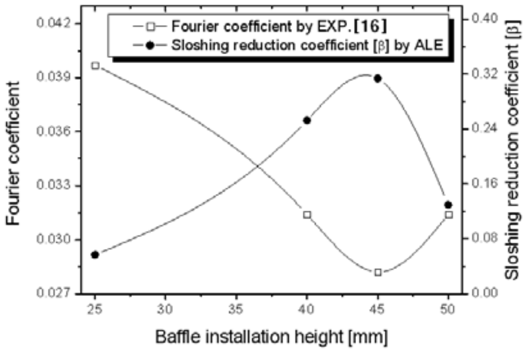


Fig. 13. Characteristic of the sloshing reduction according to baffle installation height under translational excitation for baffle width 20 mm.

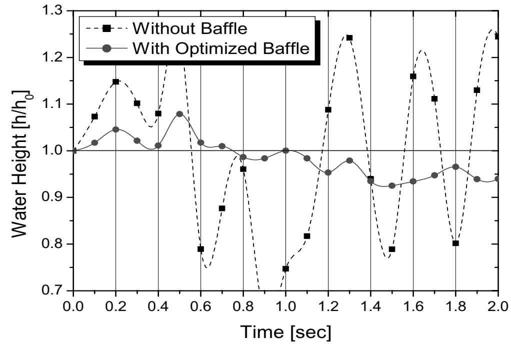
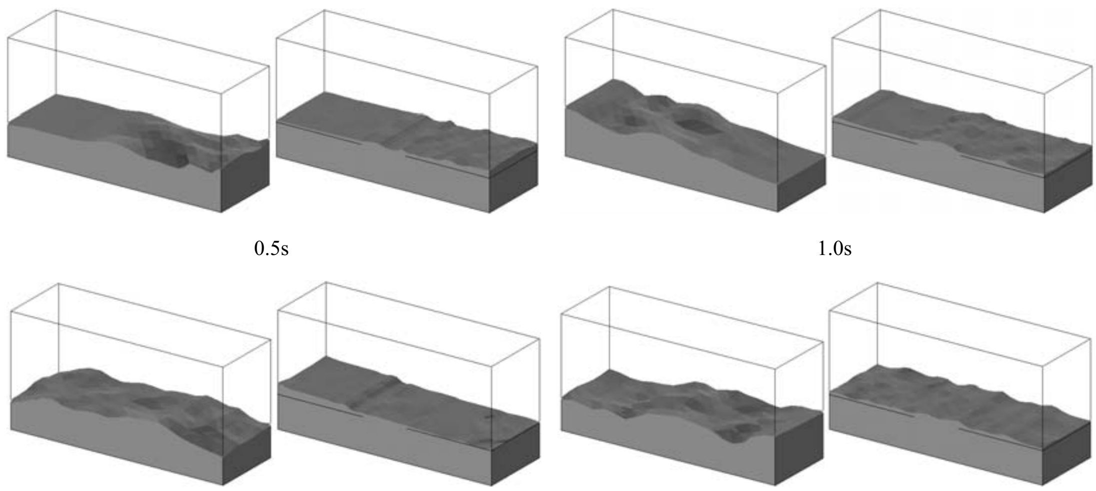


Fig. 14. Water height history of water in the rectangular tank without/with optimized baffle.



0.5s 1.0s

1.5s 2.0s

(a) Without baffle (b) With optimized baffle

Fig. 15. Water flow in a rectangular tank without/with optimized baffle.

comparison with those of the experimental result [16]. Fig. 13 shows the optimal baffle installation location for reduction of the sloshing of a rectangular tank by evolutionary optimization method and experiment. In the experimental results, the optimized baffle location is 45 mm (h_b/h_w=0.9), which gives a very similar result to that of the evolutionary optimization method. So, the suggested evolutionary optimization has validity for the reduction of sloshing.

Fig. 14 shows the water height variation history with/without optimized baffle. The water height variation is determined by the ALE analysis at the wall of the rectangular tank. In this figure, the water height "1.0" means no oscillation of water and therefore no sloshing. As the optimized baffle is installed, the water height variation becomes much smaller. Fig. 15 is the water flow in the rectangular tank without/with optimized baffle, respectively. After optimized baffle installation, high reduction of the sloshing occurs.

5. Conclusions

In this study, the optimization of baffle installation height and baffle width to reduce sloshing of a rectangular storage tank under translational motion is conducted by using a newly proposed evolutionary optimization method. The conclusions of this study are as follows:

1) Proposed optimization technique for reduction of

the sloshing uses the GA and ANN. So, the results of the sloshing analysis using ALE numerical method are directly used in the optimization algorithm. This method allows more flexibility to apply to a complicated optimization problem.

2) Sloshing reduction of 76 % could be achieved for a rectangular tank under translational excitation by the suggested optimization technique.

3) For more exact optimization, investigation of the structure of ANN, criterion of generation of the ANN-learning data and evaluation for the performance of ANN-learning is more required, which is left for the future work.

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