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APPLICATIONS OF SOFT COMPUTIONG IN ENGINEERING PROBLEMS

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1. Introduction

Recently, great attention has been paid to soft computing technology, because of its applicability and easiness of computation in engineering problems. This chapter introduces several applications of the soft computing in various real engineering problems. First, a new optimal restoration scheduling method is described, which was developed for damaged road networks by using Genetic Algorithm (GA). The method can propose an early restoration plan for lifeline systems after earthquake disasters. Here, two issues are focused on, the first of which is such an allocation problem that which groups will restore which disaster places, and the second is such a scheduling problem what order is the best for the restoration. In order to solve the two problems simultaneously, GA is applied, because it has been proven to be very powerful in solving combinatorial problems. However, road networks after earthquake disasters have an uncertain environment, that is, the actual restoring process should be performed by considering various uncertainties simultaneously. Therefore, GA Considering Uncertainty (GACU) was developed to treat various uncertainties involved.

Next, an optimal maintenance planning of bridge structures using multi-objective genetic algorithm is described, which can provide several practical scheduling candidates that the bridge owner can select by considering the situation and constraints.

A structural health monitoring system is introduced, which can treat the changes of systems and environments. By adapting to the environment, it is not necessary to prepare any previous knowledge and examination for the underlying structures and environment. In other words, it is not necessary to use a precise modelling and analysis method before conducting the health monitoring. In the system, both Adaboost and GMDH (Group Method of Data Handling) are used for the learning and compared by paying attention to the accuracy of prediction.

In order to establish a rational maintenance program for structures, it is necessary to collect enough data about the material and structural characteristics and to evaluate the structural damage in a quantitative manner. However, it is difficult to avoid the subjectivity of inspectors when visual data are used for the evaluation of damage or deterioration. The method can evaluate the damage condition of existing structures by using the visual information given by digital photos. It is based upon such new technologies as image processing, photo-grammetry, pattern recognition, and artificial intelligence.

2. Optimal Restoration Scheduling of Damaged Road Networks Using Genetic Algorithm

The purpose of this research is to propose an early restoration for lifeline systems after earthquake disasters. Here, two issues are focused on, the first of which is such an allocation problem that which groups will restore which disaster places, and the second is such a scheduling problem what order is the best for the restoration. In order to solve the two problems simultaneously, Genetic Algorithm (GA) is applied, because it has been proven to be very powerful in solving combinatorial problems. However, road networks after earthquake disasters have an uncertain environment, that is, the actual restoring process should be performed by considering various uncertainties simultaneously. GA Considering Uncertainty (GACU) can treat various uncertainties involved, but it is difficult to obtain the schedule which has robustness. In this study, an attempt is made to develop a decision support system of the optimal restoration scheduling by using the improved GACU.

2.1 Genetic Algorithm Considering Uncertainty

Here, it is assumed that a road network is damaged, in which multiple portions are suffered from damage so that it cannot function well. The objective of this study is the realization of quick restoration of the lifeline system. It is intended to determine the optimal allocation of restoring teams and optimal scheduling of restoring process. Then, the following conditions should be taken into account [1] [2]:

1. The optimal allocation of restoring team, optimal scheduling of restoring process, and optimal selection of restoring method must be determined simultaneously.
2. A portion of the road network is suffered from several kinds of damage that have a hierarchical relation in time.

As an example of restoration, a road network is considered, which has 164 nodes as shown in Figure 1. This model corresponds to an area damaged by the 1995 Kobe earthquake. For this road network, the following restoration works are necessary to recover the function:

1. work (A): work to clear the interrupted things : 38 sites (1 - 38)
2. work (B) : work to restore the roads : 50 sites (1 - 50)

Then, the limitation and restriction of each work should be considered, for instance, work (B) should be done after work (A). Work (B) consists of the following three works; work to repair the roads, work to reinforce the roads and work to rebuild the roads. The waiting places of restoring teams for work (A) and work (B) are shown by the number A (1-8) and B (1-8), respectively.

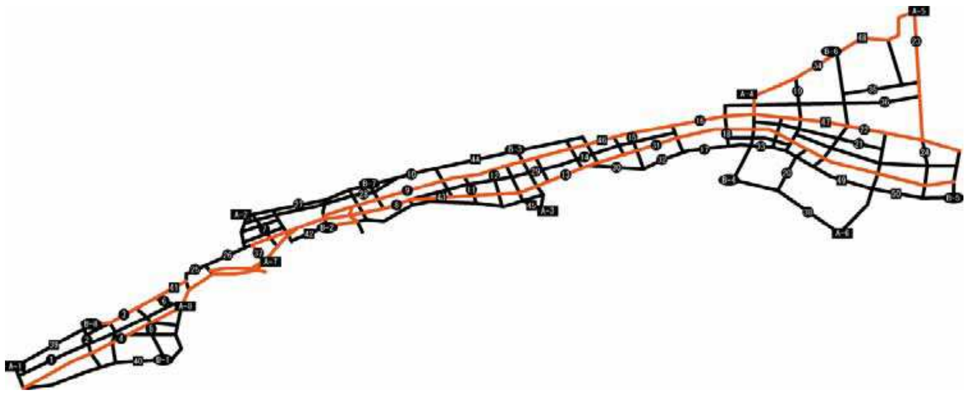

Fig. 1. Road network model

2.2 Restoration Scheduling

Weighting factors are prescribed for the links with damage, which are denoted by w_i (i=1~n_L). n_L is the total number of damaged links. Then, the restoring rate after q days, R^q, is expressed as follows:

$$R^q = \frac{\sum_{i \in J^q} w_i \times l_i}{\sum_{i \in J^0} w_i \times l_i} \tag{1}$$

where l_i is the distance of the i–th link, J^0 is the set of damaged links, J^q is the number of restored links until q days after the disaster, and w_i is the weighting factor of the i-th link. Then, the objective function can be calculated by using the restoring day and the restoring rate.

Restoring times are calculated for each restoring work, and the minimum days necessary for each work is given as

$$d = h / t_1 \tag{2}$$

where h is the restoration time required to complete the restoration work. In this research, the restoration time is calculated by using the restoration rate for each work and the capability value. The relation between the restoration rate for each work and the capability of the teams are shown in Figure 2. The restoration rate is given as follows:

a) Small damage: In the small damage, there is no difference in capability between each team. The restoration will be completed during a fixed time. Here, 4 hours are assumed.

$$h = h_t \tag{3}$$

b) Moderate damage: In the moderate damage, there is some difference in capability between every teams, however, every teams can restore the damage.

$$h = D / A \tag{4}$$

where D is the amount of damage and A is the capability of the team, that is, the restoring amount per an hour.

c) Large damage: In the large damage, only some teams can restore, because other teams have no restoring equipment and facility necessary for the large damage.

$$h = \infty(A < A_c)$$
$$h = D / A(A \geq A_c) \tag{5}$$

The working hours per day of a restoration team is calculated by Equation 6, where t_m is the moving time to a site given by Equation 7. The shortest distance from the waiting place of the restoration team to the site is expressed as L (km), and the moving speed of the team is set to be v (km/h). h_c is the preparation time that is necessary for every works.

$$t_1 = t_0 - 2t_m - h_c \tag{6}$$

$$t_m = L / v \tag{7}$$

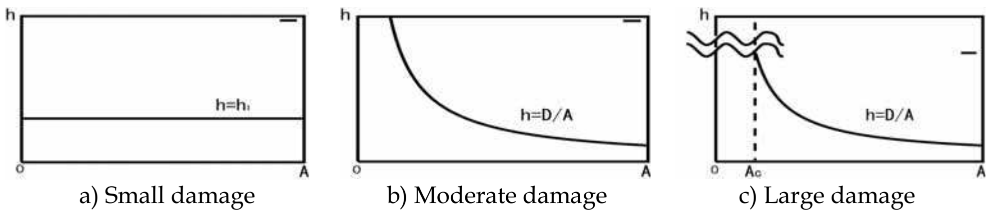

Fig. 2. Relations between restoration rate for each work and capability of teams

2.3 Influence of Uncertainty

At a devastated area after an earthquake disaster, the circumstances are changing with aftershock, fire and bad weather. The devastated area may have another damaged and the circumstances may not be constant. This is due to the uncertainty of a damage which occurs from the followings:

1. **Delay:** Delay induces the increase of restoring days of a work. The delay of the work influences the whole restoring schedule.
2. **Impossibility to restore:** Impossibility to restore is the situation that a team without sufficient restoring equipment and facility is assigned to large damage work. Such a team cannot restore the large damage work. Impossibility of work to restore causes failure of restoring schedule.

2.4 Genetic Algorithm Considering Uncertainty

In order to obtain the restoration schedule which has robustness to the uncertainty of damage, it is necessary to implement sampling many times. In GA considering uncertainty (GACU) [3], objective function is defined as the expected value of $F'(x)$ to consider the search process as the sampling.

$$F'(x) = F(x) \quad \textit{with Uncertainty} \tag{8}$$

F(x) contains a variable element, that is, uncertainty, so that *F'(x)* is changing according to the uncertainty. It is assumed that the number of sampling is age of individual. This sampling is performed by considering the evolution mechanism of inheritance, that is, gene of parents is resembled to that of children. The procedure of GACU is given as follows:

STEP 1. Generation of initial population
STEP 2. Selection of parents
STEP 3. Crossover and mutation: generation of new individuals
STEP 4. Evaluation: evaluation of new individuals and re-evaluation and adding age of alive individuals
STEP 5. Natural selection

STEP 2 to 5 are repeated until the convergence is achieved

2.5 Uncertainty of Optimal Restoration Schedule

When a restoration team arrives at the disaster site, the disaster circumstances may be different from those predicted, because devastated situations are constantly changing by the aftershock, fire disaster and bad weather, which are likely to make damage worse. Such a change of devastated area affects the scheduling process, because it takes more days than those scheduled, and furthermore it may be impossible to restore unless the restoration teams have enough ability. Therefore, in this paper, the amount of damage and the delay will be treated as uncertain factors and the restoration scheduling problem is formulated as an optimization problem with uncertainties. The influences of delay are shown in Figure 3.

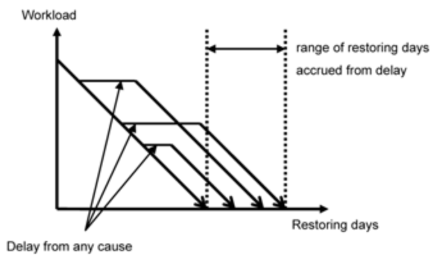

Fig. 3. The influences of delay

2.6 Application of Genetic Algorithm Considering Uncertainty

GACU is applied to obtain the optimal robust restoration schedule. Table 1 presents the parameters of GACU used here. The optimal robust schedule is presented in Figures 4 and 5. The effects of increasing the damage examined by 1000 simulations are shown in Table 2. Table 3 presents the effects of the delay examined by 1000 simulations. It is seen that teams without restoring equipment are not assigned to large damage works and medium damage works which are changeable to large damage and waiting time is properly assured to avoid the effects of delay. In addition, most of larger damage works are assigned to restoration team with high ability. The schedule is not only robust but also optimum for the early restoring. In this paper, assuming that a road network has an uncertain damage, it is intended to obtain the optimal restoring schedule considering uncertainty. From the results obtained, it is concluded that the proposed method using GACU is useful for obtaining the optimal restoring schedule with robustness to uncertainty of damage.

Population	Probability of Crossover	Probability of Mutation	Generation
500	0.6	0.005	2000

Table 1. Parameters of GACU

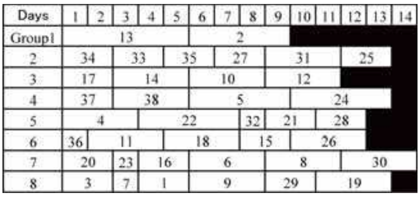

Fig. 4. The optimal robust schedule of Work (A)

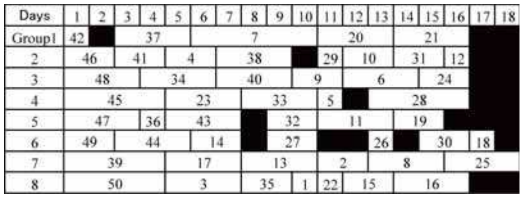

Fig. 5. The optimal robust schedule of Work (B)

Probability changed	Average of evaluation	Impossible to restore
5%	6.87	0/1000
10%	7.00	0/1000
20%	7.27	0/1000

Table 2. Effects of increasing the damage examined by 1000 simulations

Probability changed	Evaluation	SimpleGA	GACU
5%	Evaluation(Ave)	7.52	7.88
	Evaluation(Max)	8.80	7.97
	Evaluation(Min)	7.11	7.18
	Standard deviation	0.52	0.47
10%	Evaluation(Ave)	9.12	7.91
	Evaluation(Max)	17.22	8.31
	Evaluation(Min)	7.11	7.18
	Standard deviation	2.12	0.57
20%	Evaluation(Ave)	15.04	8.01
	Evaluation(Max)	17.56	8.41
	Evaluation(Min)	14.35	7.20
	Standard deviation	3.22	1.29

Table 3. Effects of the delay examined by 1000 simulation

3. Optimal Maintenance Planning of Bridge Structures Using Multi-Objective Genetic Algorithm

In order to establish a rational maintenance program, it is necessary to develop a cost-effective decision-support system that can provide us with a practical and economical plan

[4]. Although low-cost maintenance plans are desirable for bridge owner, it is necessary to consider various constraints when choosing an appropriate actual maintenance program. For example, the minimization of maintenance cost requires to prescribe the target safety level and the expected service life time. The predetermination of requirements may lose the variety of possible maintenance plans. Namely, it may be possible to find out a better solution that can largely extend the service life if the safety level can be sensitively decreased even with the same amount of maintenance cost.

3.1 Concrete Bridge Model

A group of ten concrete highway bridges are considered in this study. Maintenance management planning for ten consecutive piers and floor slabs (composite structure of steel girders and reinforced concrete (RC) slabs) is considered here [5]. Each bridge has the same structure and is composed of six main structural components: upper part of pier, lower part of pier, shoe, girder, bearing section of floor slab, and central section of floor slab.

Environmental conditions can significantly affect the degree of deterioration of the structures and may vary from location to location according to geographical characteristics such as wind direction, amount of splash, etc. To take the environmental conditions into account, the deterioration type and year from completion of each bridge are summarized in Table 4.

Bridge number	Years from completion	Deterioration type
B01	2	neutralization of concrete
B02	2	neutralization of concrete
B03	0	chloride attack (slight)
B04	0	chloride attack (medium)
B05	0	chloride attack (severe)
B06	0	chloride attack (medium)
B07	0	chloride attack (severe)
B08	1	chloride attack (medium)
B09	1	chloride attack (slight)
B10	1	chloride attack (slight)

Table 4. Years from completion and type of deterioration caused by environmental conditions

3.2 Maintenance Strategies and Life-Cycle Cost

In order to prevent deterioration in structural performance, several options such as repair, restoring, and reconstruction are considered. Since the effects may differ even under the same conditions, average results are adopted here. Maintenance methods applicable to RC slab may vary according to the environmental conditions and are determined considering several assumptions [6].

Life-Cycle Cost (LCC) is defined as the total maintenance cost for the entire bridge group during its life. This is obtained by the summation of the annual maintenance costs through the service life of all the bridges. The future costs are discounted to their present values. However, the discount rate is assumed to be zero in this study. Other costs, such as indirect construction costs, general costs, and administrative costs, etc., are calculated in accordance with Cost Estimation Standards for Civil Construction [7]. The direct construction costs consist of material and labor costs and the cost of scaffold. For calculating the construction costs, the following assumptions are taken into account:

1. The cost of scaffold can be reduced by sharing. For example, scaffold can be shared for repairing the bearing and the bearing section of RC slab, consequently reducing the scaffolding cost.
2. Indirect construction costs, such as general administrative costs, can be saved by implementing several repairs in the same year. The ratio of indirect to maintenance costs decreases as the direct costs increase. The value of LCC is reduced when multiple components are repaired simultaneously.

3.3 Multi-Objective Genetic Algorithm (MOGA)

Genetic Algorithm (GA) is an evolutionary computing technique, in which candidates of solutions are mapped into GA space by encoding. The following steps are employed to obtain the optimal solutions [8]: a) initialization, b) crossover, c) mutation, d) natural selection, and e) reproduction. Individuals, which are solution candidates, are initially generated at random. Then, steps b, c, d, and e are repeatedly implemented until the termination condition is fulfilled. Each individual has a fitness value to the environment. The environment corresponds to the problem space and the fitness value corresponds to the evaluation value of objective function. Each individual has two aspects: Gene Type (GTYPE) expressing the chromosome or DNA and Phenomenon Type (PTYPE) expressing the solution. GA operations are applied to GTYPE and generate new children from parents (individuals) by effective searches in the problem space, and extend the search space by mutation to enhance the possibility of individuals other than the neighbour of the solution. GA operations that generate useful children from their parents are performed by crossover operation of chromosome or genes (GTYPE) without using special knowledge and intelligence. This characteristic is considered as one of the reasons of the successful applications of GA.

3.4 Application of MOGA to Maintenance Planning

It is desirable to determine an appropriate life-cycle maintenance plan by comparing several solutions for various conditions [6]. A new decision support system is developed here from the viewpoint of multi-objective optimization, in order to provide various solutions needed for the decision-making.

In this study, LCC, safety level and service life are used as objective functions. LCC is minimized, safety level is maximized, and service life is maximized. There are trade-off relations among the three objective functions. For example, LCC increases when service life is extended, and safety level and service life decrease due to the reduction of LCC. Then, multi-objective optimization can provide a set of Pareto solutions that cannot improve an objective function without making other objective functions worse.

Then, objective functions are defined as follows:

Objective function 1 : $C_{total}=\Sigma LCC_i \rightarrow min$ (9)

where LCC_i = LCC for bridge i

Objective function 2 : $Y_{total} = \Sigma\ Y_i \rightarrow max$ (10)

Constraints : $Y_i > Y_{required}$

where Y_i = Service life of bridge i , $Y_{required}$ = Required service life

Objective function 3 : $P_{total} = \Sigma\ P_i \rightarrow max$ (11)

Constraints : $P_i > P_{target}$

where P_{target} = Target safety level

The above objective functions have trade-off relations to each other. Namely, the maximization of safety level or maximization of service life cannot be realized without increasing LCC. On the other hand, the minimization of LCC can be possible only if the service life and/or the safety level decreases.

3.5 Numerical Example

In the implementation of MOGA, the GA parameters considered are as follows: number of individuals = 2000, crossover rate = 0.60, mutation rate = 0.05 and number of generations = 5000. Figures 6 to 9 present the results obtained by MOGA. Each figure shows the comparison of the results of the 1st generation (iteration number) and the 5000th generation. In Figure 6, the solutions at the 1st generation spread over the design space. This means that the initial solutions can be generated uniformly. After the 5000th generation, the solutions tend to converge to a surface, which finally forms the Pareto set as the envelope of all solutions. The number of solutions at the 5000th generation is much larger than that at the 1st generation. This indicates that MOGA could obtain various optimal solutions with different LCC values, safety levels, and service lives. From Figure 6, it is seen that MOGA can find out good solutions, all of which evolve for all the objective functions, and the final solutions are sparse and have discontinuity. In other words, the surfaces associated with the trade-off relations are not smooth. This implies that an appropriate long term maintenance plan cannot be created by the repetition of the short term plans.

In Figure 7, the vertical axis represents safety level, whereas the horizontal axis represents LCC. Although at the 1st generation, the solutions may have a rather linear relation between safety level and LCC, the relation shows non-linearity through the convergence process. This implies that the safety level may be significantly increased if the LCC can be slightly increased, when the service life is fixed. Figure 8 presents the relation between LCC and service life. Since LCC and service life have a rather perfect positive linear correlation, it can be said that the service life can be extended if LCC can be increased. On the other hand, there is no distinct relation between safety level and service life, as shown in Figure 9. It should be noted that the safety level may not be raised even if the service life is shorten, under a constant LCC. Namely, the relation between safety level and service life is so unclear that the extension of service life should be done with careful examination.

Finally, it is confirmed that the proposed method using MOGA can provide many near-optimal maintenance plans with various reasonable LCC values, safety levels and service lives.

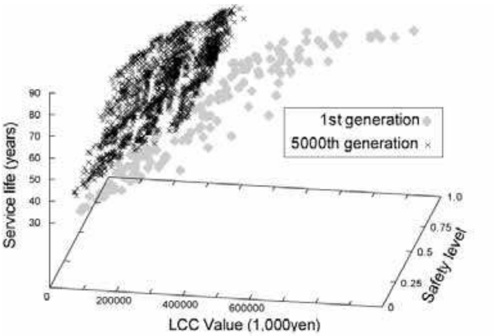

Fig. 6. Pareto solutions obtained by MOGA

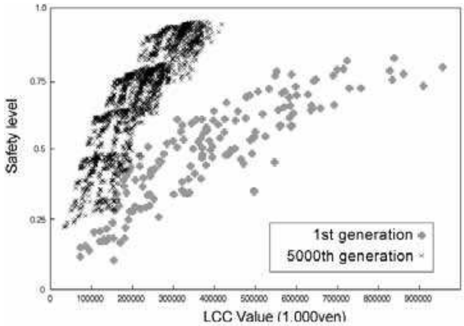

Fig. 7. Relation between LCC and safety level

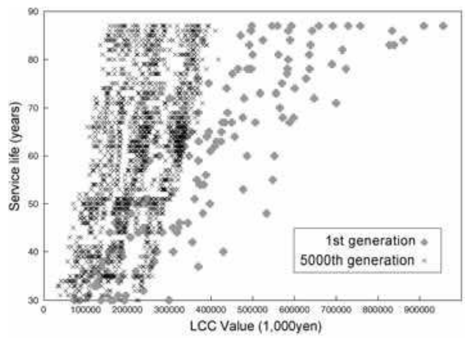

Fig. 8. Relation between LCC and service life

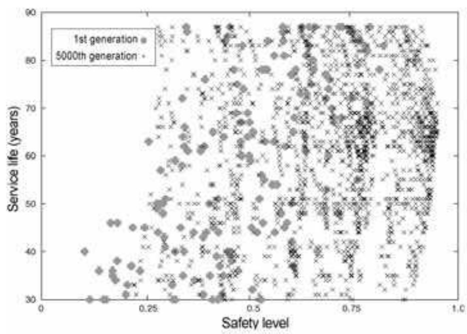

Fig. 9. Relation between safety level and service life

4. Health Monitoring System Using Learning System

Recently, many researches have been made on health monitoring of existing structures such as buildings, bridge and other civil structures. Many structures are becoming superannuated and deteriorated. Furthermore, in Japan, natural disasters like typhoon and earthquake have occurred frequently so that the damage assessment of existing structures is very important. In order to evaluate the damage state of structures health monitoring technology is quite promising to provide useful information. In the health monitoring, there are still some problems in modelling, analysis and experimental examination for practical use.

An attempt was made to develop a structural health monitoring system that can adapt to the structural systems and environments, by introducing the learning ability. By introducing the learning ability, it is not necessary to prepare any previous knowledge and examination for the underlying structures and environment. In other words, it is not necessary to use the precise modelling and analysis method before conducting the health monitoring.

4.1 AdaBoost

Boosting method uses such two learning algorithm with high precision (Strong learning algorithms) and learning algorithm with low precision (Weak learning algorithm). AdaBoost is one of the Boosting methods. AdaBoost is used for pattern recognition problems frequently.
The AdaBoost creates several learning hypotheses by using given weak learning algorithms at a round cycle. At the round cycle, re-sampling of learning data are performed by using the given probability distribution. At the next round, probability is updated to choose data that make errors at the round. By repeating this process, it is possible to obtain plural hypothesis that have different characteristics. The strong algorithm gives unification by combining each weak learning algorithm with weights. Figure 10 shows the concept of AdaBoost.

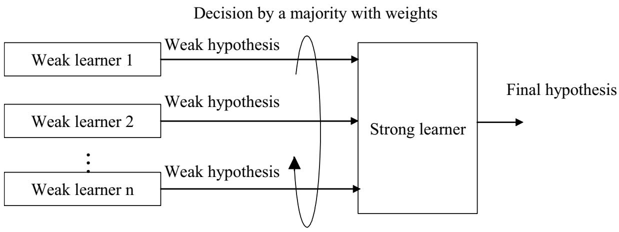

Fig. 10. Conception of AdaBoost

AdaBoost executes the recognition by combining plural weak learning algorithms like Figure 10, where no restriction exists on each weak learning algorithm. For even equal number of input and output data, it allows to use all different algorithms. By using a soft computing method like neural network for the weak learning algorithm, it is possible to obtain the same advantage.
The AdaBoost can obtain the high quality and versatile hypothesis by few teaching data. It also has such merits that algorithm is easy and the number of parameters adjusted is few.

4.1.1 Procedure of Adaboost

Adaboost can apply to the pattern recognition problem with multiple classifications. In this case, the 2-value with -1 and 1 is treated. Adaboost is repeated t (t=1, 2, 3, …, T) times. Procedure of Adaboost is shown below.

Step 1: Obtain the learning data
Give the teaching data (x_1, y_1), ..., (x_n, y_n).
Step 2: Initialize the probability distribution
Initialize the probability distribution using the next equation. In this equation, $D_t(i)$ is the probability distribution of teaching data i at round t.

$$D_t(i) = 1 / m \tag{12}$$

Step 3: Steps 4 to 6 as a round and repeat T times

Step 4: Obtain weak hypothesis h_t

By learning setting times of weak learning algorithm, obtain weak hypothesis. The learning data is chosen by probability based $D_t(i)$. Then, precision of weak hypothesis is calculated by the next equation using probability of error using D_t.

$$\varepsilon_t = P_{ri-Di}[h_t(x_i) \neq y_i] = \sum_{i:h_t(x_i)\neq y_i} D_t(i) \tag{13}$$

Step 5: Decide the importance of weak hypothesis

Decide the importance of weak hypothesis used the majority decision with the weight by the next equation.

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right) \tag{14}$$

Step 6: Update probability distribution

Update probability distribution of teaching data by the recognition result when using weak hypothesis h_t. Probability of teaching data producing the error recognition by h_t is increased, and learning is concentrated to the difficult teaching data. Equation to update of the probability distribution is as follows:

$$\begin{aligned} D_{t+1}(i) &= \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-at}\,(h_t(x_i) = y_i) \\ e^{at}\,(h_t(x_i) \neq y_i) \end{cases} \\ &= \frac{D_t(i) e^{-\alpha_t y_i h_t(x_i)}}{Z_t} \end{aligned} \tag{15}$$

In this equation, Z_t is the factor to normalize the probability distribution.

Step 7: Obtain final hypothesis

Final hypothesis H_t is obtained by the majority decision with weighs of weak hypotheses. The equation to obtain the H_t is .

$$H(x) = \mathrm{sgn}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right) \tag{16}$$

4.2 Vibration Analysis

In this section, vibration analysis is done by numerical simulation. At the numerical simulation, deterioration of objective structure and the vibration characteristics of structural change are assumed. Vibration at intact situation and deteriorated situation are compared using a multiple freedom structure. Through the numerical simulation, it is concluded that the method can find the deterioration of structure by analyzing vibration response.

4.2.1 Vibration

Vibration of structure can be defined by the next equation.

$$M \cdot u''(t) + C \cdot u'(t) + K \cdot u(t) = 0 \tag{17}$$

In the equation, u(t) is the displacement of structure at time t, M is mass, C is damping ratio and K is stiffness. Equation 17 has no external force, and therefore it is called free vibration. However, usually external force exists.

$$M \cdot u''(t) + C \cdot u'(t) + K \cdot u(t) = p(t) \tag{18}$$

where p(t) is external force.

4.2.2 Wind force

In this research, wind is used for the external force. Wind force is calculated by wind velocity as follows:

$$F = \frac{1}{2} C\rho A V^2 \sin^2 \alpha \tag{19}$$

where C is wind coefficient, ρ is air density, A is effective area and α is effect angle. Those values used in this research are shown in Table 5.

air density	0.125 ($kgf \cdot sec^2/m^4$)
Coefficient	2
effect angle	90 (°)
effect area	200 (m^2)

Table. 5 Parameters

4.2.3 Method of vibration analysis

Runge-Kutta method is used to solve the differential equations for the numerical simulation. The following simultaneous equations are solved.

$$\begin{cases} P = u'(t) \\ P' = -(C \cdot P + K \cdot u(t) + P(t)) / M \end{cases} \tag{20}$$

4.2.4 Model of structure

A three-degree-of-freedom structure is employed for the object model. Therefore, Equation 18 is extended to a matrix form.

$$[M] \cdot \{u''(t)\} + [C] \cdot \{u'(t)\} + [K] \cdot \{u(t)\} = \{p(t)\} \tag{21}$$

In this equation, [M], [C] and [K] are the matrices of mass, damping and stiffness. The matrices of three-degree-freedom structure used in this research are shown as follows:

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} \tag{22}$$

$$C = \begin{bmatrix} c_1 + c_2 & -c_2 & 0 \\ -c_2 & c_2 + c_3 & -c_3 \\ 0 & -c_3 & c_3 \end{bmatrix} \tag{23}$$

$$K = \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ -k_2 & k_2 + k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \tag{24}$$

where m_i, k_i and c_i are mass, damping factor and stiffness of each story.

4.2.5 Pilot study

In this section, numeric simulation is done using sine curve for the external force. In the numerical simulation, the intact situation and deteriorated situation at each story are compared. The deterioration is assumed to reduce 10% of stiffness at every 10000 steps. Figure 11 to Figure 13 show the difference of displacement for the intact situation and the situation that deterioration occur at each story. Figure 12 shows the difference of displacement for the intact situation and the situation that deterioration occurs at the first story.

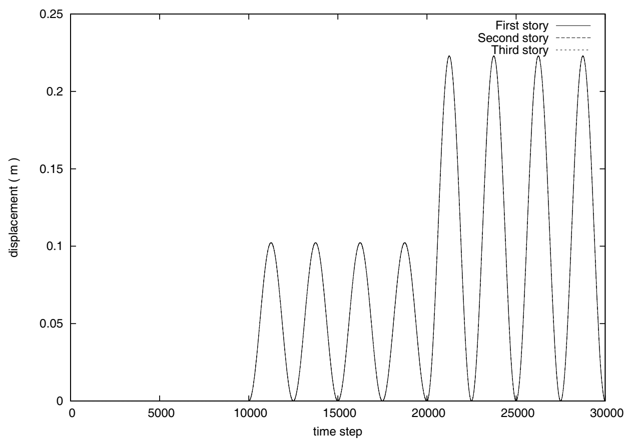

Fig. 11. Difference of displacement (Case of degradation accrual first story)

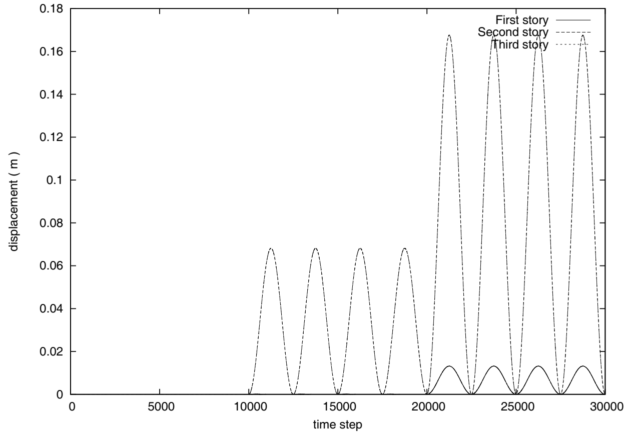

Fig. 12. Difference of displacement (Case of degradation accrual second story)

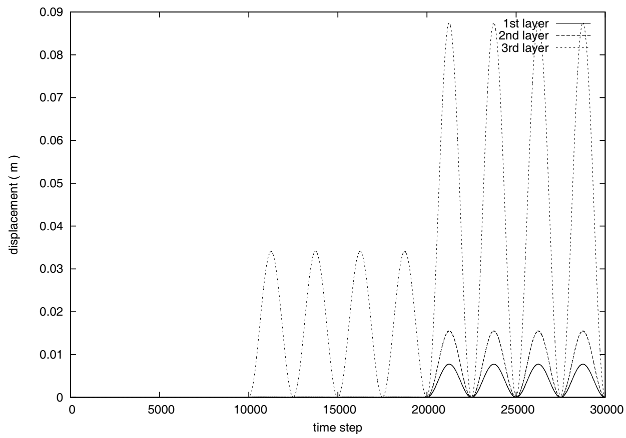

Fig. 13. Difference of displacement (Case of degradation accrual third story)

From Figure 11 to Figure 13, the behavior of structure changes by position, even the same size deterioration. Whereas the differences of response of each story is the same when the first story has deterioration, the difference of response of the first story is smaller than other stories and second story's one and third story's one are the same, when the second story has deterioration. Also, the difference of response of the third story is bigger than other stories and the first story and those of the second story is the same, when the second story has deterioration. Then, it is confirmed that it is possible to identify the difference of intact structure and the structure with damage at the i-th story. Herewith, it is possible to identify the position of deterioration by comparing the difference of response.

4.3 Proposed System

Structure of the proposed system is shown in Figure 14.

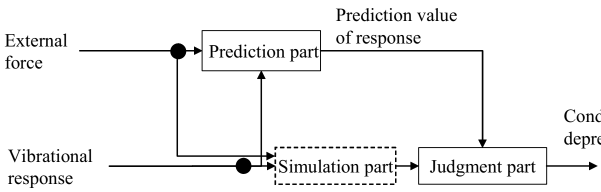

Fig. 14. Structure of proposed system

The proposed system is composed of a prediction part that learns the vibration response and predicts the next response, judgment part that detects the deterioration by analyzing the vibration response, and simulation part that analyze a vibration. Inputs to the proposed system are external force and vibration response, that is, displacement and velocity of structures. Outputs from the proposed system are the probability of deterioration and the position of deterioration.
In this research, GMDH is used for the prediction part, so that versatile rules are obtained and calculation time can be reduced. At the judgment part, fuzzy reasoning is used to detect the deterioration by comparing the prediction value and the observed value. Input data for fuzzy reasoning are prediction errors and prediction error rates. Fuzzy rule using in this research is shown in Table 6.

Input value		Output value
Error	Error ratio	Possibility of degradation
Zero	Zero	Zero
	Small	Zero
	Medium	Zero
	Big	Small
Small	Zero	Small
	Small	Small
	Medium	Medium
	Big	Medium
Medium	Zero	Medium
	Small	Medium
	Medium	Medium
	Big	Big
Big	Zero	Medium
	Small	Medium
	Medium	Medium
	Big	Big

Table 6. Fuzzy rules

By using fuzzy reasoning, calculation time can be shorten. Position of deterioration is identified by comparing prediction errors of each story. In this research, comparing the difference of prediction error of story, the story with the biggest difference is defined as the deterioration position.

4.4 Observations

In this section, numerical examination is done using sine curve and actual wind velocity. The proposed system learned those vibration responses in advance. Figure 15 shows the difference of prediction value and observed value when external force is sine curve.

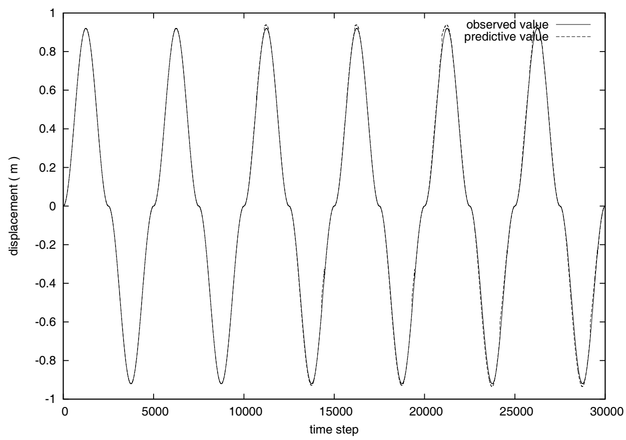

Fig. 15. Comparison of observed value and predictive value without deterioration

From Figure 15, it can be confirmed that the proposed system can identify the vibratinal characteristic by learning and predicting the vibration response. Figure 16 shows the transition of error of prediction value when the second story has deterioration.

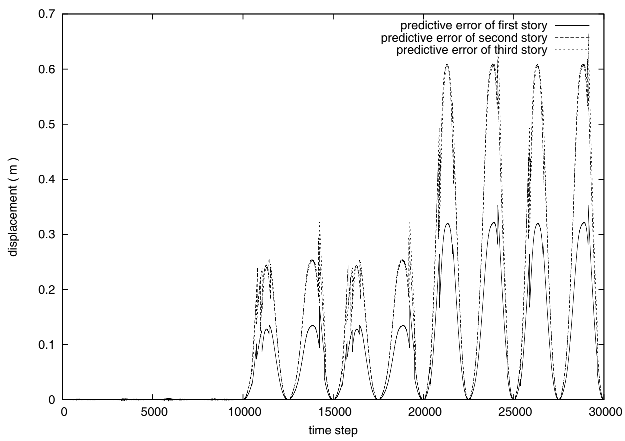

Fig. 16. Prediction error of displacement

From Figure 16, the proposed system predicts the change of stiffness and which story is deteriorated by every 10000 steps. When structural characteristic changes, the prediction error is increased. When the first story or the third story has deterioration, similar result is obtained. Figure 17 shows the output of the proposed system.