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Applying Evolutionary Design of Experiments to Sensitivity Analysis of Tsunami Evacuation Simulation

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Abstract—"Evolutionary Design of Experiments" (in short EDoE) was proposed to get an approximated result of system analysis with less number of numerical simulation executions of complex systems. In this paper, the goal is to apply the proposed method based on EDoE to tsunami evacuation simulation and evaluate the effectiveness of the proposed method. An agent based computer simulation is able to help us to make a suitable decision for actual social complex systems. In a case of evacuation from natural disasters, for instance, a planning of evacuation from tsunami in Kanazawa Japan is one of the most important political issues. Local government desires not only to estimate evacuation time but also to ensure mobility at the disaster. To evaluate the mobility, comparisons between various scenarios are required. Since actual road map contains a lot of roads, it is still difficult to check up all combinations of possible road injuries even if we can use super computers. In a context of design and analysis of experiments, selecting a set of road injuries is called design of experiments and such comparison is called sensitivity analysis. To find significant road injuries, a lot of computer resources have been required. In the proposed method, a better design which treats only significant factors is found via fitness function in terms of function optimization. To confirm the obtained designs are reasonable, numerical experiments are performed. Finally, we conclude that the proposed method enable to find better design with less experiment costs.

1. Introduction

It is important to estimate sensitivity of nonlinear systems. Especially in social systems, the number of input variables is usually large. Moreover, independences of input variables are usually unclear. Therefore, careful and comprehensive analyses of sensitivity is always required even if it takes a lot of computational cost to obtain system outputs. Evolutionary Design of Experiments[1] (in short EDoE) was proposed to get an approximated result of system analysis with less number of numerical simulation executions of complex systems. In this paper, the goal is to build a method which can be applied to tsunami evacuation simulation at Kanazawa, Japan.

An agent based computer simulation is able to help us to make a suitable decision for actual social complex systems. In a case of evacuation from natural disasters, for instance, a planning of evacuation from tsunami in Kanazawa Japan is one of the most important political issues. From an execution of agent based numerical simulation, we can obtain an estimated evacuation time in feasible elapsed time. On the other hand, local governments want to not only estimate evacuation time for various scenarios but also find significant factors which make evaluation time worse. To evaluate such significance of factors, a lot of comparisons between the scenarios are required. The number of scenarios get explosively larger as the number of system inputs increases. In the context of tsunami evacuation, availability of roads in target area is seemed as significant factors. Since actual area map contains a lot of roads, it is still difficult to check up all combinations of road injuries even if we can use super computers.

In a context of design and analysis of experiments, selecting a set of road injuries is called design of experiments and such comparison is called sensitivity analysis. As the number of system inputs gets larger, generally, more experiment costs are required to apply sensitivity analysis. Moreover, it is more difficult to distinguish significant and independent input variables. Since conventional design of experiments was proposed not for large scale models, a lot of computer resources have been required to find significant designs for such large scale models. It is because that design of experiments has been studied on wide field to apply it to systems in which independences of input variables are ensured.

In this paper, we show a case study of applying sensitivity analysis to tsunami evacuation. Then, we address a novel method to iteratively find a better design of experiments based on EDoE. Finally, better designs are found out and we conclude that the proposed method enable to find better design with less experiment costs.

2. Kanazawa Tsunami Evacuation Simulation

2.1. Summary

Tsunami evacuation time in which the target location is at Onomachi, Kanazawa, Ishikawa, Japan (See Fig. 1), was estimated[2]. At the area of Onomachi, Kanazawa, Ishikawa, Japan, earthquake–triggered tsunami may hit. Therefore, it is required that evacuation from tsunami will be finished in shorter time. However, there are many factors which may make evacuation time worse such as broken bridges and snow covered roads. If some bridges will be broken and if some road will be covered with deep snow, people will change their evacuation route. Fig. 2 shows eleven bridges which may be broken by earthquake and eleven roads which may be covered with deep snow. Evacuation time may be affected by conditions of bridges and roads. Such bridges and roads are treated as main factors. Since such bridges and roads are connected geographically, independences of main factors are not clear. Therefore, it is important to estimate significance of each main factor and significance of each interaction of main factors.

Condition of bridges are described as $\in [0, 1]$ and condition of roads also are described as $\in [0, 1]$. Here, 0 means that the bridge is broken or the road is covered with deep snow. Conditions of main factors are described as $[b1, b2, \ldots, b11, s1, s2, \ldots, s11]$ for eleven road adn for eleven snow road. The number of feasible combinations of conditions is 2^{22} and it took about 11,650 days on single CPU core to estimate evacuation time for whole scenarios.

2.2. Sensitivity Analysis

It is generally hard to obtain 2^{22} simulation results. But 2^{22} simulation results can be obtained and we can apply sensitivity analysis to the simulation results. There are several method to get a result of sensitivity analysis. Here, the following linear model is employed as sensitivity analysis model.

$$Y = XA + E \tag{1}$$

Where, $Y = [y^{(1)}, y^{(2)}, \ldots, y^{(m)}]^T$ are evacuation time, X=$[[1, x_1^{(1)}, x_2^{(1)}, \ldots, x_n^{(1)}]^T, \ldots, [1, x_1^{(m)}, x_2^{(m)}, \ldots, x_n^{(m)}]^T]^T$ are factors defined by states, A is a vector of coefficients

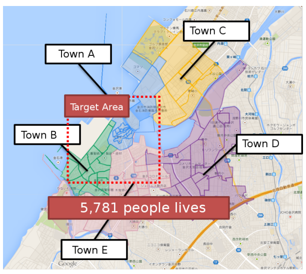

Figure 1: NIGECHIZU SIMULATOR has been developed by AIST and the target area of tsunami evacuation simulation was at Onomachi, Kanazawa, Ishikawa, Japan[2].

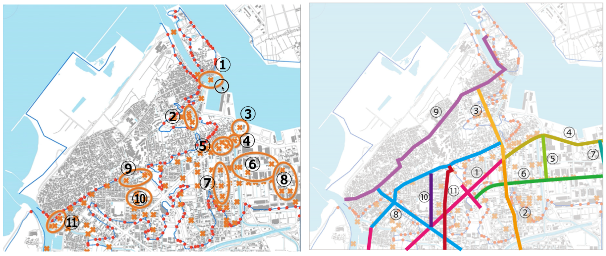

Figure 2: Locations of eleven bridges with potential to be broken and eleven roads with potential to be covered with deep snow are shown[2]

$n \times 1$, $E = [e^{(1)}, e^{(2)}, \ldots, e^{(m)}]^T$ are residuals $e^{(i)} \sim N(0, \sigma^2)$. Larger values of elements in A mean that the corresponding factors more affects simulation results. Therefore, finding better design which includes such significant factors with less number of evaluating scenarios is strongly required. Table 1 shows A as the result of sensitivity analysis.

Table 1: Factors and their values of A which is obtained by applying regression analysis to whole simulation results are described.

Factor	A	Factor	A
s7b6	186.9	s7s5	-23.2
s1	180.7	s4b8	-25.1
s4b6	169.1	s7b8	-25.3
b4b6	141.5	s1s5	-31.1
b5b6	141.2	s4s7	-36.2
b5b3	106.0	s4b7	-38.9
b4b3	105.7	b5	-50.3
s7b4	68.1	b4	-50.6
s7b5	67.9	s1b3	-76.7
s4b4	45.4	s4	-170.9
s4b5	45.1	s1b6	-178.8
s4b3	29.1	b3	-240.8
b8	25.2	s7	-246.4
s7b7	13.7	s1b4	-259.6
s4s5	5.4	s1b5	-259.9
s5	5.0	b5b4	-339.9
b7	1.5	s1s7	-358.6
s1b8	1.4	b6	-439.8
s1b7	-8.5	s1s4	-491.1
		Intercept	4421.5

3. Evolutionary Design of Experiment (EDoE)

A goal of EDoE is to obtain appropriate designs for sensitivity analysis. Here, a design is described as a set of state patterns like $*0000000*0000000000000$. A state pattern includes several states and each state is described one among "0" or "*". Only when state is equal to "*", the associated state can be both "0" and "1". For example, with a state pattern $*0000000*0000000000000$ which includes two "*"s, sensitivity analysis is applied to four tsunami evacuation scenarios with 000000000000000000000, 100000000000000000000, 000000001000000000000 and 100000001000000000000. Therefore, in sensitivity analysis, both of main factors associated with the positions of two "*"s and interactions of such main factors can be considered.

The best design is defined as the design which has state patterns with less number of "*"s and accuracy of analysis results is better. State patterns which have less number of "*"s require less number of simulation executions. On the other hand, since accuracy of analysis results is obtained only after applying sensitivity analysis, it is difficult to find better state patterns without background knowledges. It is because the appropriate pattern is depend on system models. Therefore, we find better designs by trial and error with state patterns evaluated by certain fitness functions. Moreover, methods to generate new designs based on the fitness function are required. The following sections, we discuss the requirements about fitness functions and methods to generate state patterns.

3.1. Fitness Function

Each state pattern must be evaluated without referring the results of other sensitivity analysis. Here, we have an assumption that a better state pattern makes variance of Y, (in short $V(Y)$) larger. We believe that obtaining larger values of elements of A is expected when $V(Y)$ gets larger. On the other hand, simulation execution costs get higher as the number of "*" included in state patterns gets larger. From the above, we consider a better state pattern makes $V(Y)$ larger and includes less number of "*".

Though the number of significant main factors is depend on system models, best design should have every significant main factors. However, without background knowledges the appropriate number of "*"s is unclear. Therefore, designs with several number of "*"s should be found. To make clear the relationships between value of $V(Y)$ and the number of "*"s, numerical experiments are curried out.

3.1.1. Numerical Experiments for Defining Fitness Function

Here, simplified simulation model is employed to make sure that $V(Y)$ is available to find better designs. The formulation of the simplified model is shown in equation (2) and its model parameters are shown in table 2.

$$y = a_0 + \sum_{i=1}^{8} a_i x_i + \sum_{i=1}^{8} \sum_{j=i+1}^{8} b_{ij} x_i x_j \qquad (2)$$

where, $a_0, a_1, \ldots, a_8$ are constant, x_i is a model parameter and y is model output. x_i is input which can be equal to either 0 or 1. Values of $a_0, a_1, \ldots, a_8$ are set as the following Talbe 2.

Table 2: Values of coefficient in system model 1 are shown.

a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
0	1500	1000	500	0	0	0	0	0

	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8
b_2	-1200	–	–	–	–	–	–	–
b_3	0	0	–	–	–	–	–	–
b_4	0	0	0	–	–	–	–	–
b_5	0	0	0	1000	–	–	–	–
b_6	0	0	0	0	0	–	–	–
b_7	0	0	0	0	0	0	–	–
b_8	0	0	0	0	0	0	0	–

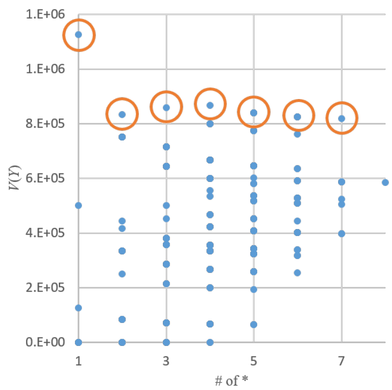

Figure 3: Relationships between designs and variances are shown.

Relationships between state patterns and variances are shown in Fig. 3. From the viewpoint of obtaining better sensitivity analysis results, better state patterns which make variance of Y larger are marked with a circle. Such better state patterns exist in several number of "*"s. In considering the simplified model, however, the best design includes four "*"s and its variance is largest among designs which include four "*"s. Therefore, we should take a strategy to find better designs which makes $V(Y)$ larger with evaluating state patterns which include less and several number of "*"s. It is because that comparison between the value of variances has less meaning in Fig. 3.

3.2. Generate New State Pattern

There is no best way to find the best design without background knowledges for the system model. But we show an strategy to find better designs. Here, a stochastic search algorithm to find better state patterns based on the strategy is proposed. Then, the algorithm is evaluated with the simplified model.

3.2.1. A Stochastic Search Algorithm

In order to find better state patterns which make their variance larger, methods like Genetic Algorithm's crossover and mutation are applied in generating new state

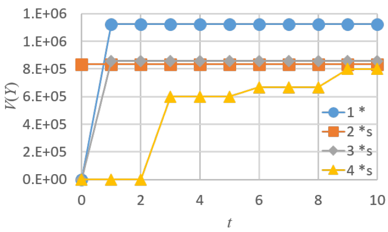

Figure 4: Variances of best designs for each number of "*"s are shown.

patterns. Pseudo-code of proposed algorithm is described as follows.

1. generate initial state patterns which have just 2 "*"s ($t = 0$)

2. evaluate variance of Y for each state pattern

3. generate new state pattern which must include $NA(t)$ or less number of "*"s and must not same as previously generated state patterns

4. if terminated condition is satisfied then exit, else return 2

3.2.2. Numerical Experiments for Evaluating Proposed Algorithm

A new state pattern is generated via the following processes. In crossover process, a pair of state patterns is selected by using rank 2 tournament selection among survived state patterns and each state in a new state pattern is ether state of selected one or another stochastically. In mutation process, for each state of the new state pattern, the value is replaced with "*" with certain mutation rate. Since crossover and mutation processes may increase number of "*"s, "*" in the new state pattern is randomly replaced with 0 until the number of "*"s is less or equal to $NA(t)$. Here, $NA(t)$ is a function that returns an integer value and the returned value increase as t gets large. When maximum value of t is 10, $NA(t \leq 2) = 3$ and $NA(t \leq 10) = 4$ are defined. New state patterns are generated until the number of unique state patterns is same as the number of initial state patterns. Variances of generated designs are evaluated and designs which makes $V(Y)$ less are died until the number of existing designs is more than the number of initial designs.

Fig. 4 shows the result of applying proposed methods. Best state patterns which include three or less number of "*"s were found in early generation. On the other hand, the best state pattern which includes four "*"s was found in 9th generation. Since the best state pattern was found, this search process as a design is good.

4. Discussion

For a simplified model, proposed algorithm could find a better design without treating whole feasible designs. In order to apply evolutionary design of experiment, fitness function and methods to generate state patterns are required. Definition of fitness function and definition of the methods may affect the search process as design. Moreover, the best state pattern was found in later generation. Therefore, effectiveness of algorithm to find better designs in early generation is significant.

5. Conclusion

Evolutionary Design of Experiments is a novel method to find appropriate designs without evaluating whole feasible input values. A simplified model was built in order to evaluate the proposed algorithm. For a simplified model, it seems that proposed algorithm could find a better design with less number of model evaluations.

The proposed algorithm can be applied to make a design for Kanazawa tsunami evacuation problem. Applied algorithm and evaluate obtained designs will be shown in presentation.

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