An Interactive Evaluation Method of Decentralized Procurement Plan by Multi-Objective Genetic Algorithm

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Abstract: This paper addresses evaluation of a decentralized procurement plan for the support of the discussion among decision-makers with considering a catastrophic disaster. For the evaluation of the decentralized procurement plan, we have formulated the decentralized procurement planning problem as 3-objective optimization problem. However, multiple-objective genetic algorithms (MOGA) to solve the problem take several minutes and display many Pareto solutions. We propose the interactive evaluation method of the decentralized procurement plan that is an expanded interactive MOGA (iMOGA) with loss evaluation simulator and solution selection by characteristics of the decentralized procurement plan. Experimental results show that the proposed method can allow the decision-makers to find their preference solutions with 38% fewer interactions than the basic iMOGA can.

1 INTRODUCTION

Supply chain is a sequence of operations such as procurement, production, logistics and sale for supplying products from suppliers to final consumers. Retailers in the supply chain procure products from suppliers and sell products to the consumers. In supply chain, there is a problem that catastrophic disasters such as earthquakes may interrupt the procurement from suppliers. The retailers suffer losses because they can not sell the products along with the consumers' demand. In order to decrease the losses, the retailer increases the stock of the products and decentralizes procurement of the product from geographically distributed multiple suppliers (Chopra and Sodhi, 2004), (Kleindorfer and Saad, 2005). However, there are so many plans of decentralizing procurement with inventory stock that the decision-makers in the retailers can not find the appropriate plan. In this paper, we address evaluating the decentralized procurement plans for the decision making.

For evaluating the decentralized procurement plans, we formulate the decentralized procurement planning problem. Decentralizing procurements can decrease the losses because surviving suppliers from the catastrophic disasters can keep supplying products to the retailers. And the increase of the stock is also available for decreasing the losses. But, the retailers have to cost in the decentralizing procurement and the control of the increased stock. This discussion leads us to formulate the decentralizing procurement planning problem as a 3-objective optimization problem to decrease the loss, the cost for the decentralization, and the cost for the stock.

Through the formulation, the decision makers can discuss the plans based on the evaluation by solving the 3-objective optimization problem by computer. For more efficient discussion, it is possible to solve the problem by the Multiple Objective Genetic Algorithm (MOGA) that is one of the meta heuristics. However, the computational time by MOGA is not so short as the decision makers can use in their discussion because MOGA is the method for finding many Pareto solutions. The decision makers can not understand many Pareto solutions and rather hope to select about 10 representative Pareto solutions based on their preferences in short time. In this paper, we apply the interactive MOGA (iMOGA) to decentralizing procurement planning problem and propose the method to display the representative solutions with fewer interactions.

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2 DECENTRALIZED PROCUREMENT PLANNING PROBLEM

2.1 Target Supply Chain Model

First, we introduce a basic supply chain model that consists of a retailer and multiple suppliers. In order to consider that a catastrophic disaster hits the supplier, we have expanded such the basic supply chain model. Fig.1 shows the target supply chain model.

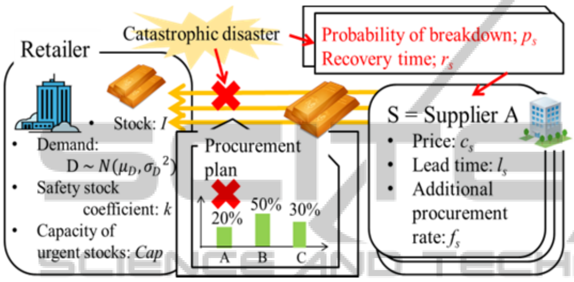

Figure 1: The target supply chain model.

Unless the catastrophic disaster happens, the retailer makes a procurement plan to replenish the stock I up to the safety stock SS. The stock I is remained products when the products for demand D is shipped from safety stock $SS; I = SS - D$. The amount of replenishment M is decided by the following:

$$M = SS - I = SS - (SS - D) = D$$

As the above formula shows, because the time for delivery to the customer from the retailer is 0, the replenishment M is equal to D. The demand D follows the Gaussian distribution. And the retailer has design the strategy of the procurement; what percent of the amount of the replenishment is assigned to each supplier. We call the rate of the assignment "order rate: o_s". In the procurement plan, the retailer orders $(o_s M)$ products to supplier s.

When the catastrophic disaster hits some suppliers, the supplier can not supply their products at the rate of the probability of the breakdown p_s; $o_s = 0$ for r_s days. In order to make up the lacking products, the retailer place the orders to the surviving suppliers. Then, the supplier can supply additional products up to a ceiling of the additional procurement rate (f_s) of the order rate. Furthermore, the retailer can store the urgent stocks U up to a ceiling of the capacity Cap. When the total stock (I+U) is below the demand D, the loss L (=D-I-U) happens.

2.2 Problem Formulation

The decision-makers in the retailer make a decentralized procurement plan $\boldsymbol{P}$ that indicates both of each order rate o_s and the urgent stock U. So, the decision variables of this problem are $\boldsymbol{P}$ as shown in the following:

$$\boldsymbol{P} = \{o_1, o_2, \dots, o_n, U\}$$

The decision-makers decide the procurement plan $\boldsymbol{P}$ to decrease the loss L. But the decrease of the loss by decentralization carries cost E for orders to the suppliers that supply the high price c_s products. Here, decentralized ordering costs E is defined as the increased cost compared to the cheapest plan.

$$E = D(\sum_{s=1}^{n} c_s o_s - \min_s c_s)$$

Furthermore, the urgent stocks U also cost in being stored in the warehouse. Therefore, we formulate the decentralized procurement planning problem as the following 3-objectives optimization problem:

- Objective functions

$$f_1(\boldsymbol{P}) = \text{Loss } L \rightarrow \text{minimize}$$
$$f_2(\boldsymbol{P}) = \text{Decentralized ordering costs } E \rightarrow \text{minimize}$$
$$f_3(\boldsymbol{P}) = \text{Urgent stocks } U \rightarrow \text{minimize}$$

- Constraints

$$U \leq Cap$$
$$\sum_{s=1}^{n} o_s = 1$$

where the above described constraints are only the constraints that represent the decentralized procurement planning problem.

2.3 Research Purpose

In the multi-objective optimization problem, it is impossible to decide the optimal solution; some solutions indicate low loss and high cost, but the others indicate high loss and low cost. General approaches derive Pareto optimal solutions whose one or more objective functions' values are not worse than the other solutions, and has the decision-makers to select solutions that they prefer. The Pareto optimal solution is decided by Pareto ranking method shown in Fig. 2. Fig. 2 assumes two kinds of the objective functions (f_1, f_2) to be minimized. The most inner coordinates indicate the value of Pareto optimal solutions. The evaluation values of Pareto optimal solutions shape a Pareto curve. Generally, in order to solve such a multi-objective optimization problem, the multi-objective genetic algorithm (MOGA) has been applied (Murata and Ishibuchi, 1995), (Fonseca and Fleming, 1993). MOGA is the method to derive Pareto optimal solutions efficiently by the weighting sum of objective functions (Murata 1995) or ranking the solutions (Fonseca and Fleming, 1993). In this paper, MOGA with Pareto ranking method (Fonseca and Fleming, 1993) is applied to the problem. The basic idea of MOGA is shown in Fig. 3. MOGA is performed based on the following steps:

(1) Initialize: generate some ***P***
(2) Crossover: generate two solutions from a pair of ***P***
(3) Mutation: generate a solution from ***P***
(4) Selection: select generated ***P*** based on Pareto rank

Pareto rank indicates the rank of the solution in generated ***P***. In order to decide Pareto rank, MOGA count the number of non-dominated solutions ***x*** whose all objective functions' values are better than ***P***. Let n(***x***, ***P***) denote the number of ***x*** for ***P***. Pareto rank is decided as n(***x***, ***P***)+1. In this paper, we assume that only the solutions have Pareto rank of 1are selected.

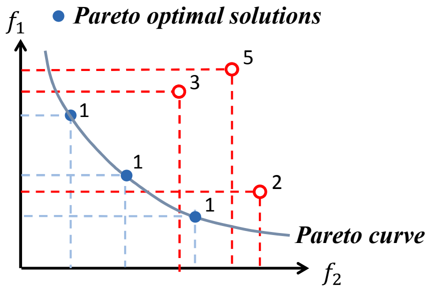

Figure 2: Pareto ranking method.

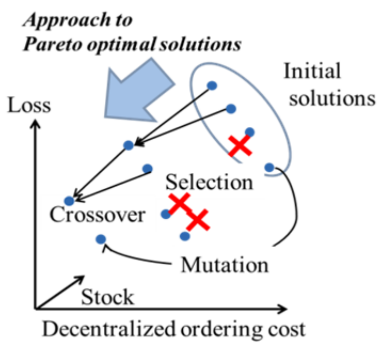

Figure 3: Basic idea of MOGA.

Because MOGA is the method for deriving many different Pareto optimal solutions, there are following problems in the use of MOGA for the support of the decision-makers' discussion.

- The decision-maker has their preferences of the solutions, e.g. the loss is more important than the cost for the stock. But they can not select the preference solution from many Pareto optimal solutions.
- MOGA takes several minutes to solve the decentralized procurement planning problem.

The decision-makers have to wait the response from MOGA in their discussion.

So, our research purpose is to allow the decision-makers to find preference solution in a minute.

3 INTERACTIVE EVALUATION METHOD OF DECENTRALIZED PROCUREMENT PLAN

3.1 Outline of the proposed Method

Because many Pareto optimal solutions are hard for decision-makers to select and are derived in several times, we introduce the interactive MOGA (iMOGA) that stops the crossover and the mutation in a short time and displays about 10 representative solutions to the decision-makers (Ishibashi, 2011), (Hiroyasu, 2008), (Takagi, 2001). Fig. 4 shows the outline of the interactive evaluation method by iMOGA.

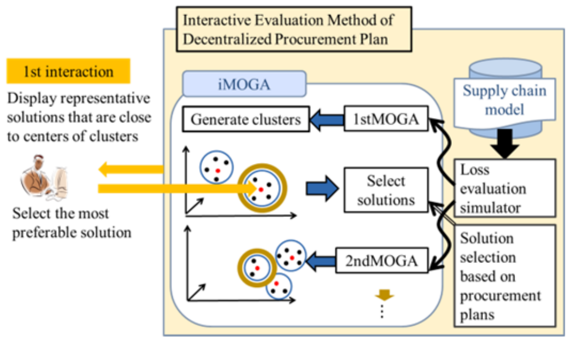

Figure 4: Outline of the interactive evaluation method by iMOGA.

iMOGA executes MOGA with fewer crossovers and mutations several times in order to display the solutions in a short time. The proposed method uses the general crossovers and mutations method: blend crossover (Takahashi and Kita, 2001) and mutation to exchange randomly selected two o_s each other. Because the decision-makers can watch only about

10 solutions, iMOGA makes about 10 clusters of the solutions by MOGA. In this method, we apply k-means method as a typical clustering algorithm (Hearst, 2006). And, the decision-makers select the preferable solution from the displayed representative solutions that are closest to the center of each cluster. Basic iMOGA uses the solutions in the cluster that the decision-maker selects for the next GA. By repeating MOGA and the decision-makers' selection, the preference solution appears in iMOGA.

Furthermore, in order to display the preference solutions through fewer times of the interaction, the proposed method has the following two functions:

- Loss evaluation simulator

Because the breakdown happens at random and the demand changes with following the Gaussian distributions, it is impossible to evaluate loss L uniquely. The loss evaluation simulator can evaluate the distribution of the loss L by Monte Calro Method.

- Solution selection based on decentralized procurement plan

iMOGA uses the solutions in the cluster that the decision-makers select. However, if the preference solution is not in the cluster, it becomes difficult to search the preference solution by the crossover and the mutation.

3.2 Loss Evaluation Simulator

The outline of the loss evaluation simulator is shown in Fig. 5. As shown in Fig. 5, the probability of the distribution is not Gaussian distribution. A survey in Japan reports that the catastrophic earthquake happens below 1%. So, it is not appropriate to evaluate the loss as the expectation of the probability distribution of the loss because there is potential for underestimating the loss (Azaron et al., 2008), (Wu et al., 2010).

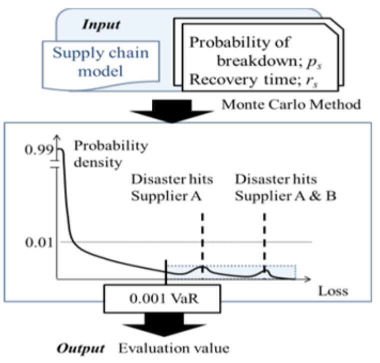

Figure 5: Outline of loss evaluation simulator.

In order to evaluate such the catastrophic disaster that causes great loss but rarely happens, we introduce the index of Value at Risk (VaR) (Johnathan, 2010). By integrating the probability density from the largest loss in the distribution to the smaller, the loss when the value of integral is a certain rate (0.001 in Fig.5) is VaR of the rate (0.001 VaR in Fig.5).

It is necessary to decide the distribution of the loss for deciding VaR. Therefore, the proposed method uses Monte Carlo method that samples form the distribution of the demand and the probability of the breakdown and decide the loss (Johnathan, 2010). In order to evaluate the loss for the recovery time r_s days, the proposed method uses the time-series simulation with a set of sampled values shown in Fig. 6.

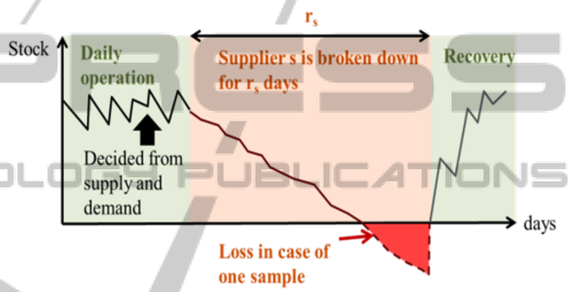

Figure 6: Time-series loss simulation.

After sampling by Monte Carlo method, the time-series simulator evaluates the loss by using the sample set of the demand. As shown in Fig. 6, there no losses before the breakdown. When the breakdown happens, the supply from the supplier that is broken down is 0. Then the retailer places orders to the other suppliers additionally. But, if the demand is larger than the supply, the stock is decreased day by day. Finally, the stock is exhausted and the demand is regarded as the loss until the supplier is recovered.

3.3 Solution Selection based on decentralized Procurement Plans

In order to search the preference solution that is not in the cluster selected by the decision-makers, the proposed method selects not only the solutions in the selected cluster but also a part of the other solutions. From the other solutions, it is necessary to select the solutions that tend to generate the preference solutions by crossover. In the decentralized procurement planning problem, there are the relations between the plan and the preference. Fig. 7 shows the relation and our approach to decide which

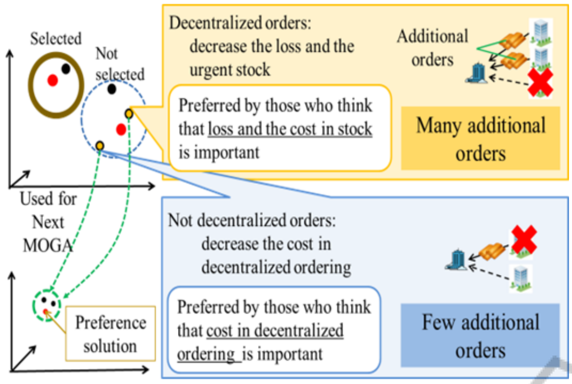

Figure 7: Approach to select solutions.

solutions to be used in addition to the solutions in the selected cluster.

As described in section 3.2, the retailer places orders to surviving suppliers when the catastrophic disaster prevents some suppliers to supply products. As Fig. 7 shows, when the retailer plans the decentralized ordering to many suppliers, the loss and the urgent stock can be decreased by additional orders. This plan is preferred by those who think that the loss and the cost for stock are important. On the other hand, when the retailer does not decentralize the orders, the loss and the urgent stock can not be decreased, but the cost for decentralized ordering is decreased. This plan is preferred by those who think that cost for decentralized ordering is important. Therefore, the proposed method selects the solutions that indicate either decentralized ordering or not-decentralized ordering, and generate preference solutions by crossover of the solutions.

In order to select such plans, the amount of the additional orders is an effective index. The amount of the additional orders is large in the decentralized procurement plan. Here, the process of selecting solution based on the amount of the additional orders is shown in Fig. 8. The amounts of the additional orders are calculated in the loss evaluation simulator and follow the Gaussian distribution. By using the amounts of the additional orders, the proposed method selects the solutions that have large amount or small amount of the additional orders by the following:

(1) The proposed method calculates the frequency distribution of average additional orders based on the solutions by the loss evaluation simulator.
(2) From the distribution, the proposed method selects the solutions whose average additional orders in the top or bottom N%.

The selected solutions are used for next MOGA together with the solutions in the cluster that the

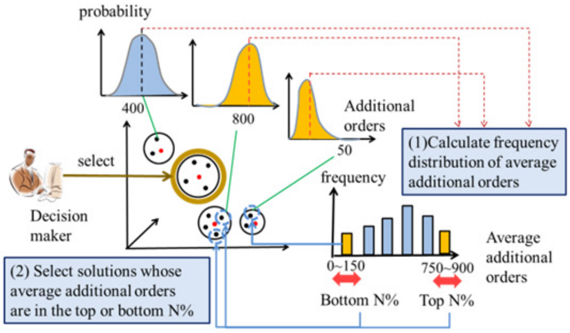

Figure 8: Process of selecting solution based on the amount of the additional orders.

decision-makers select.

4 EVALUATION EXPERIMENT

4.1 Target of Experiment

The target retailer deals with electronic device that the retailer procures from 3 suppliers A, B and C (Mitsukuni et al., 1997). The demand to the retailer follows Gaussian distribution of $N(1500, 250000)$. The safety stock coefficient is 1.96 and the retailer stores the safety stock SS:

$$SS = 1500 \times Lead\ time + 1.96 \times \sqrt{Lead\ time \times 250000} = 7960$$

The parameter setting of the suppliers is shown in Table 1.

Table 1: Parameter setting of the suppliers.

	Supplier		
	A	B	C
Price [yen]	1,000	1,010	1,020
Lead time [day]	4		
Probability of breakdown	0.83%	0.126%	0.06%
Recovery time [day]	30		
Additional procurement rate	20%		

In this experiment, we use the agent to express the decision-makers' preferences and evaluate the proposed method by simulating the decision-makers' selection. The agent selects the representative solution in the interaction based on the following utility function (Shixin et al., 2006):

$$Utility\ Function = \sum_{i=1}^{3} \omega_i f_i(\boldsymbol{P})$$

$$\sum_{i=1}^{3} \omega_i = 1$$

By changing the weight ω_i randomly 250 times, we have the 250 kinds of agents to find their preference solution. The agent gives up the search when the interaction is over 10 times. In order to compare the proposed method, we applied the following methods too:

- Brute force search method
  Brute force search method searches Pareto optimal solutions by evaluating all the solutions. The preference solution is displayed but many Pareto optimal solutions are also displayed. And the computation time is so long that the decision-makers can not use for the discussion.
- MOGA
  As described in the section 2.3, MOGA is the method to search efficiently Pareto optimal solutions. As well as the brute force search method, MOGA displays many Pareto optimal solutions.
- iMOGA
  As described in the section 3.1, iMOGA repeats short MOGA. iMOGA does not select the solution based on the amount of the additional orders.

First, MOGA, iMOGA and the proposed method generate the solutions through changing the order rates by 10% or the urgent stock by *Cap* / *Lead time* for the initialization of the solutions. And, MOGA, iMOGA and the proposed method performs the blend crossover; a new solution is generated from 2 solutions by selecting a supplier randomly and set new order rate on the selected one as a uniform random number based on the order rates of 2 solutions. MOGA and iMOGA performs mutations to exchange order rates among supplier A, B and C. The mutation rate is 1%. The proposed method does not perform the mutation because the proposed method selects solutions, described in section 3.3, to diversify the solutions. In iMOGA and the proposed method, 6 generations are generated in MOGA and 10 representative solutions by k-means clustering are displayed for one interaction.

The computer used in this experiment has the specification of Intel® Xeon® 2.1GHz 32 cores [1]and 128 GB Memory. The evaluation criteria are the following:

- Response time

Response time indicates how long the decision-makers can wait the output from each method after they execute the methods. The decision-maker can wait about 10 or 20 seconds. Decision-making takes several minutes, but the decision-makers have to check as many solutions as possible. So the decision-makers can wait only 10 or 20 seconds to get the output.

- The number of the interactions
  iMOGA and the proposed method have the decision-makers to select the solutions interactively. The better method can decrease the number of the interactions by displaying the preference solutions early.
- Rate of successful search
  Because the decision-makers give up the search in 10 interactions, the rate of successful search indicates the rate of the preference solutions to be displayed within 10 interactions.

[1] Intel and Xeon are trademarks or registered trademarks of Intel Corporation.

4.2 Experimental Result

The response time, the number of interactions and the rate of the successful search are shown in Fig. 9, Fig. 10, and Fig. 11, respectively.

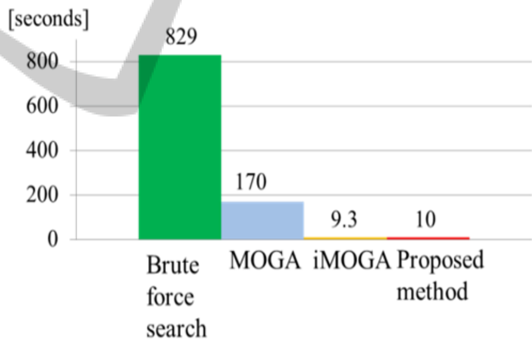

Figure 9: Response time.

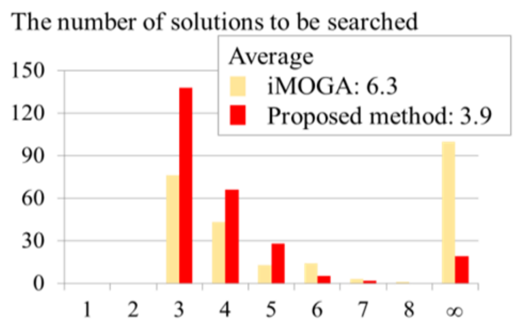

Figure 10: The number of the interactions.

Fig. 9 shows that brute force method and MOGA takes over a few minutes, which is not available for the decision-makers discussion. On the other hand,

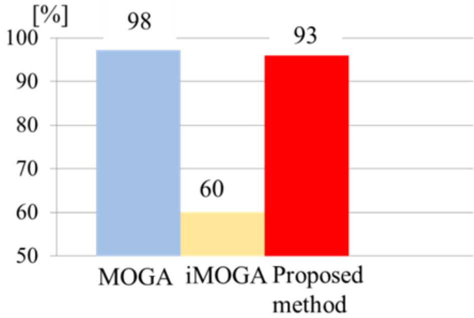

Figure 11: The rate of the successful search.

iMOGA can be executed in 9.3 seconds, and the proposed method can be executed in 10 seconds. Response time of proposed method is a little bit longer than that of iMOGA because of selecting the solution based on the amount of the additional orders. But the increase of the computational time is trivial for the decision-makers.

Fig. 10 shows the result of the interaction by 250 kinds of the agent. The proposed method can search the preference solutions for the half of the agents with 3 interactions. The more preference solutions are searched up to 7 interactions. Finally, the proposed method can not search 7% of the preference solutions within 10 times of the interactions. iMOGA can search the preference solutions for 30% of the agents with 3 interactions and also search more solutions up to 7 interactions. iMOGA can not search 40% of the preference solutions within 10 times of the interactions. As shown in Fig. 10, the average of the interactions by the proposed method is 3.9 and one by iMOGA is 6.3. So, the proposed method can succeed in decreasing the number of the interactions by 38% compared to iMOGA.

Focusing the rate of the successful searches shown in Fig. 11, MOGA can search the preference solutions for 98% of the agents within 10 interactions. The proposed method can search the preference solutions for 93% of the agents within 10 interactions. This indicates that the proposed method is as available as MOGA from the viewpoint of the accuracy of displaying the preference solutions. Because iMOGA selects solutions for next MOGA only from a selected cluster, iMOGA often fails to search the preference solutions within 10 interactions.

From the experimental result, it is confirmed that it is possible to search more preference solutions by the proposed method with fewer interactions compared to iMOGA. And the representative solutions are displayed within 10 seconds, which is short enough to support the discussion.

5 CONCLUSIONS

In this paper, we proposed an interactive evaluation method of decentralized procurement plan by Multi-objective genetic algorithm (MOGA). Although MOGA has been applied to the multi-objective optimization problem, the decision-maker can not understand many Pareto optimal solutions by MOGA. And, MOGA takes several minutes to solve the multi-objective optimization problem. Our proposed method displays the representative solutions to the decision-makers and has them to select one. By repeating this interaction, the decision-maker can search their preference solutions in a short time. In order to evaluate the loss that is caused probabilistic catastrophic disaster, we developed the loss evaluation simulator. This simulator can evaluate the loss by simulating the stock with Monte Carlo method. Furthermore, in order to decrease the interaction, the proposed method selects not only the solutions that are in the selected cluster but also the solutions that tend to generate the preference solutions based on the amount of the additional orders. Through the application of the proposed method to the supply chain model, we confirmed that the proposed method decreased the 38% of the interactions of selecting solutions compared to iMOGA.

Our future work is to expand the versatility of the proposed method to apply other supply chain model. It will be necessary to analyse the sensitivity of the parameters, especially the number of suppliers and additional procurement rates. For practical use of this method, we will implement the graphical user interface to display the representative solutions to support selecting solutions by the decision-maker.

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