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Development of decision support system for emergency management in water treatment plants

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ABSTRACT

The occurrence of natural disasters such as floods, droughts, and earthquakes may cause water supply to stop working, which may also lead to social disasters and economic damages. Therefore, it is essential to prepare an emergency response management system to prepare disasters in water treatment infrastructures. In this study, a decision support system (DSS) responding to an emergency was proposed to systematically address possible problems in water treatment plants affected by various disasters. The DSS consists of several modules in the stages for planning, disaster sensing, and response and each module was developed based on a different approach depending on its function and purpose. The paper illustrates each module in detail and discusses the application in the proposed situation.

Keywords: Disaster; Water treatment; Decision support system; Decision tree; Rule-based expert system; Monte-Carlo simulation

1. Introduction

Recently, natural disasters such as floods, droughts, and earthquakes have frequently occurred around the world [1–3]. The risk of water contamination as a result of natural disasters or human activities has been also increasing [4,5]. Disasters happen without notice, and the higher the frequency, the greater the recovery cost from disasters [6,7]. The water supply sector is one of the places that are facing a diverse set of issues related to the adverse impact of disasters [8–10]. For example, failures of water supply systems, which are caused by natural disasters or water contamination, may result in illness and loss of life as well as negative effects on economic and social conditions [8,11]. Accordingly, it is necessary for water supply systems to prepare emergency situations by natural or man-made disasters [6,9,10].

Emergency management encompasses a variety of activities, such as training and preparation, early signal detection, planning, mitigation, response, and recovery, which are usually carried out to cope with potentially catastrophic events caused by natural hazards or human behavior [12,13]. The combination of hazards, vulnerability, and inability to reduce the potential negative consequences of risk results in disaster [14]. Some disasters can result from multiple hazards, or, more often, to a complex combination of both natural and man-made causes [15]. Accordingly, structured and coordinated management is fundamental to be prepared and to minimize the consequences that an emergency may originate [16]. Different approaches to emergency management can be found in various places including the water supply sectors [15,17–20].

A decision support system (DSS) is an information system that supports technical or organizational decision-making activities [21,22]. DSSs serves the management, operations, and planning levels of an organization and help people make decisions about problems that may be rapidly changing and not easily specified in advance [23–25]. They allow systematic responses to the problems caused by various

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reasons. Therefore, DSS is one of the key techniques to manage emergencies related to disasters [10,12,22]. Investigating DSS has been a continuing concern in disaster research. One of the techniques used in DSSs is multi-criteria decision analysis (MCDA), which can evaluate a large number of decision criteria and candidate solutions with comparisons and priority determinations [26–28]. The ability of the priority calculations makes the MCDA techniques an appropriate tool to use in measuring the impact of the criteria on the decision environment [29,30]. Another technique is a decision tree, which is a decision support tool using a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility [31]. It is one way to display an algorithm that only contains conditional control statements. The Monte Carlo simulation is also a powerful decision-making tool, which is a computer-operated technique for a physical process being simulated many times [32,33]. This way, possible risks in quantitative analysis and decision-making come to light. In addition, rule-based expert systems, which use rules as the knowledge representation for knowledge coded into the system, are also used for DSS [34,35].

While a substantial amount of works has been done on the development of DSSs in other sectors, relatively few works have been devoted to establishing them for water supply sectors [10,12,15,16,21–26,29–34]. Accordingly, this study proposed a DSS as a way to respond to disasters that occur in water treatment plants. The purpose of the proposed DSS is to provide sufficient and representative knowledge for administrators related to water treatment to assist in timely and improved decisions. Individual modules have been developed in a variety of approaches to create decision systems. This paper briefly describes the following four modules:

(1) MCDA method for the selection of an emergency water supply system,

(2) a decision tree for water quality prediction with various treatment options,

(3) investment planning for preventive disaster response based on Monte-Carlo simulation, and

(4) a rule-based expert system prototype to respond to emergencies related to water contamination in water treatment plants.

2. Materials and methods

Fig. 1 shows the proposed structures of the DSS for water treatment and its stages. The DSS consists of five stages, including planning, disaster sensing, response, recovery, and interaction with people. The planning stage involved a database on past disaster cases and the disaster sensing stage aims at the early warning of disaster risks. The response stage provides information on immediate actions. The recovery and interaction stages correspond to the estimation and optimization of recovery cost and information sharing, respectively. This study focused on the development of four modules in the first three stages: a module for the selection of an emergency water supply system; a module for water quality prediction with various treatment options; a module of investment planning for preventive disaster response; a module for decision-making to respond emergency by sudden water contamination. In each case, different approaches and modeling techniques were applied depending on the objectives of the modules, which are described below.

2.1. Selection of an emergency water supply system

A multi-objective optimization model was developed for the comparison of different options for emergency water supply. The list of technologies for the emergency water supply was prepared based on the guideline by the USEPA report [36] (Table 1). Analytic hierarchy process (AHP), which utilizes pairwise comparisons in order to do the ranking [37], was applied using the following evaluation criteria: reliability, implementation, capacity, cost, and modulization. The weighting factors for the evaluation criteria were determined based on the guideline in the USEPA report. A group of experts in the field of water treatment was selected to carry out AHP. Three types of disasters, including droughts, water contamination, and earthquake, were considered. Then, the Visual PROMETHEE (Preference Ranking Organization METHod for the Enrichment of Evaluations) software was used to analyze the results [38–41]. The summary of the process for the development of this module is illustrated in Fig. 3a.

2.2. Water quality prediction with various treatment options

To determine appropriate combinations of water treatment processes, it is necessary to predict the water quality by them. A methodology based on a decision tree was proposed to address this issue in this study. Experimental results in a bench-scale system were used, which were reported in our previous work. The unit processes considered here were a sand filter, microfiltration, granular activated carbon (GA), and nanofiltration (NF). The water quality parameters including total dissolved solids, total organic carbon, UV absorbance at 254 nm (UV254), and suspended solids were predicted. The number of total data points was 96. The details of the experimental conditions are described in the previous study [42]. Using the experimental data, the decision tree was obtained by WEKA, which is a workbench for machine learning to aid in the application of machine learning techniques to a variety of real-world problems, in particular, those arising from agricultural and horticultural domains [43]. The following conditions were used for the generation of the decision tree: The number of predictor variables was 2 and the type of tree was single. The maximum slitting levels were 10 and the splitting algorithm was the least square method. The minimum size node to split was 10 and the maximum categories for continuous predictors were 200. The summary of the process for the development of this module is illustrated in Fig. 3b.

2.3. Investment planning for preventive disaster response

Although proactive planning to reduce the impact of disasters is essential, it is difficult to determine how much investment should be done to minimize the economic damages. Since there are inherent uncertainties, it is not easy to make a plan for proactive investment. In this study, Monte Carlo simulation was carried out to consider

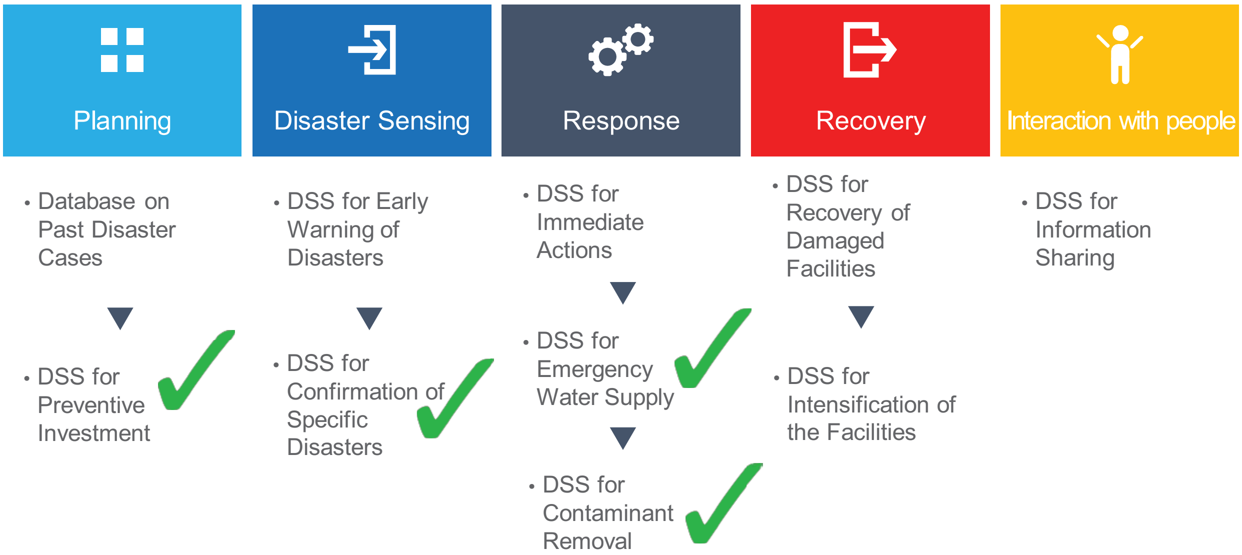

Fig. 1. Proposed structures for the DSS for the water treatment plant and its modules.

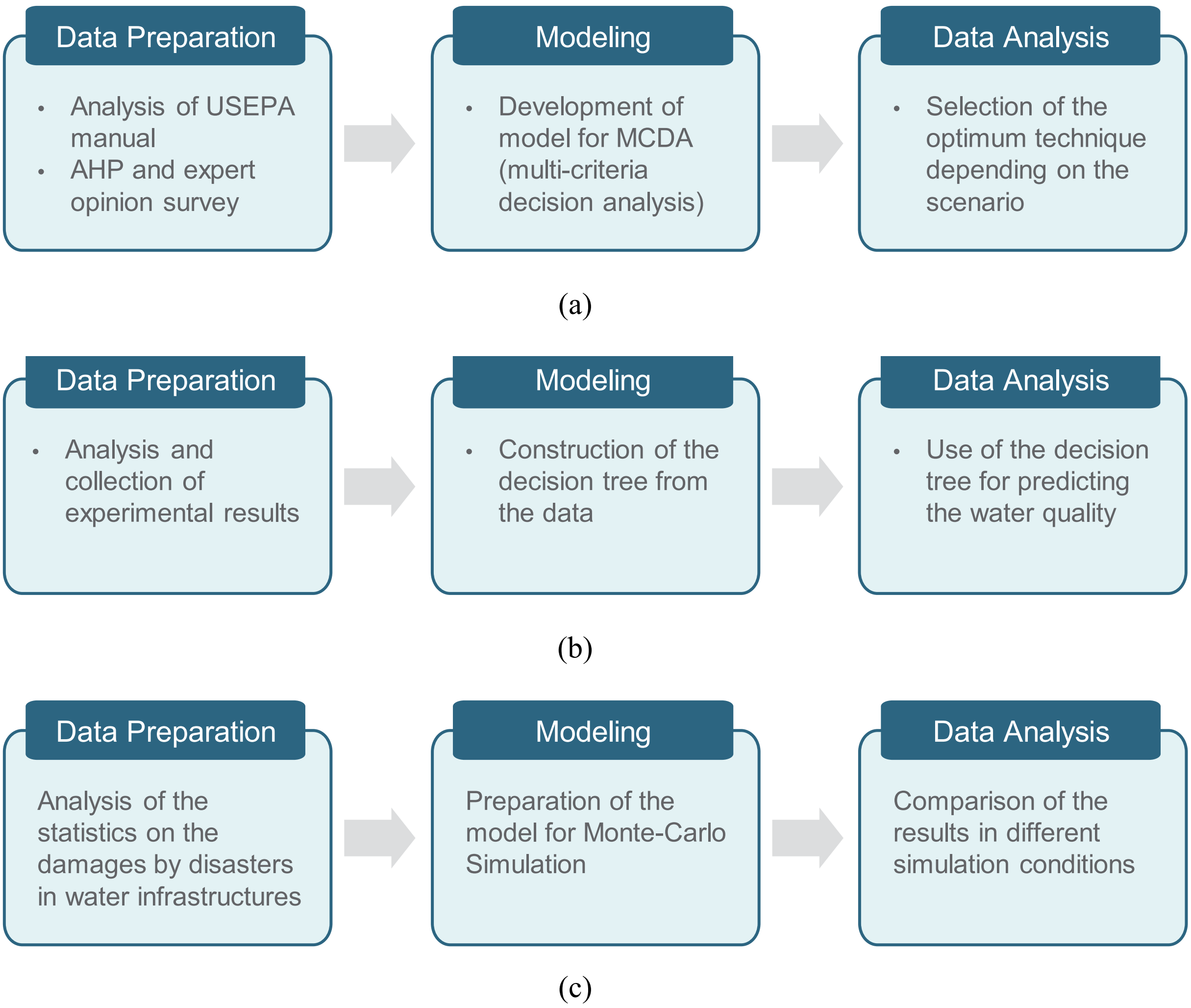

Fig. 2. Summary of the process for the development of modules for (a) the selection of an emergency water supply system, (b) water quality prediction with various treatment options, and (c) module of investment planning for preventive disaster response.

	Evaluations		Reliability	Implementation	Capacity	Cost	Transportati...	Mobilization ...
☑	Bottled water		9.00	9.00	4.00	4.00	6.00	8.00
☑	Reverse osmosis		10.00	8.00	10.00	6.00	8.00	7.00
☑	Filtration		8.00	9.00	10.00	8.00	8.00	8.00
☑	Point-of-Use Tre...		9.00	9.00	8.00	6.00	8.00	8.00
☑	Bottle in-house		8.00	10.00	4.00	6.00	9.00	9.00
☑	Multi-source wat...		8.00	4.00	10.00	5.00	5.00	6.00
☑	Rainwater harve...		5.00	9.00	4.00	10.00	8.00	6.00
☑	Transport in tank...		9.00	9.00	5.00	4.00	8.00	8.00

Fig. 3. Summary of the relative importance of in the evaluation criteria for emergency water supply options (the maximum is 10.0).

these uncertainties. Using the statistical data in the Korean Disaster annual report, the annual expenses to recover damages by disasters were obtained. Then, they were used to obtain a probability distribution, which was applied to the Monte Carlo simulation, which was carried out. The simulation periods were 10, 20, and 100 y, respectively. The summary of the process for the development of this module is illustrated in Fig. 3c.

2.4. Decision-making to respond to an emergency by sudden water contamination

Rule-based systems use rules as the knowledge representation for knowledge coded into the system. The tool used for the rule-based system in this study was Exsys Corvid [44], which a problem-solving and decision-making system based on knowledge of logical rules. The "If – Then" rules simply imitate the critical thinking technique used by domain experts when solving material selection problems. Based on the contents of the manual used in the water treatment plants in Korea, the rules were developed and implemented as the expert system in the Corvid program.

3. Results and discussions

The four modules are described in this section as examples of the modules in the decision supporting system for emergency management in the water treatment plant.

3.1. Selection of an emergency water supply system

Decision support for the selection of emergency water supply technologies was developed using an MCDA technique. First, the emergency water supply options, the evaluation criteria, and the disaster scenarios were selected. Then, AHP was carried out to analyze the water supply options. Fig. 3 shows a summary of the results from the AHP test. Each option was found to have pros and cons. For example, the reliability of the bottled water is high (9.0) but the scores for the capacity and cost criteria are low (4.0). On the other hand, rainwater harvesting has low reliability and capacity but shows a high score for the cost criterion, implying that the water cost is low. The other options also show advantages and disadvantages.

Using these results, it is possible to compare different water supply options under different disaster scenarios. For instance, the ranking and rainbow chart of different water supply options are illustrated for the response to earthquakes in Fig. 4. The higher value of the ranking indicates that the corresponding options are more appropriate. As depicted in Fig. 4a, reverse osmosis (0.2857), and point of use treatment (0.2429) were found to be better in this case. On the other hand, multi-source water supply (–0.4143) and rainwater harvesting (–0.3857) was not desired. This is because the reliability and capacity are important in the case of droughts. Since both reverse osmosis and point of use treatment have high scores for the two criteria, they were recommended by the analysis. Fig. 4b shows the rainbow chart for the water supply options. It was found that reverse osmosis has advantages due to its high reliability, capacity, cost-effectiveness, and transportation/distribution and disadvantages due to mobilization time and implementation. Multi-source water supply was analyzed to have an advantage due to capacity but disadvantages due to the other criteria.

In addition to the drought, other disasters such as water contamination and earthquake were considered in the MCDA analysis. The results are shown in Fig. 5. Depending on the type of disasters, the ranking of the water supply options change. For example, bottle-in-house shows a high ranking for the drought problem but exhibits lower rankings for the water contamination and earthquakes. This suggests that the emergency water supply options should be selected by considering various aspects and the MCDA method proposed in this study has the potential for the support to systematic decision-making.

3.2. Water quality prediction with various treatment options

Another module for decision supporting based on an accurate prediction of treated water quality by various treatment systems was also developed based on the decision tree technique. This is important for disaster management because the suitability of the treatment should be immediately and intuitively determined under emergency situations. Based on the removal efficiency, the effectiveness of the treatment technique was expressers either as "Yes" or

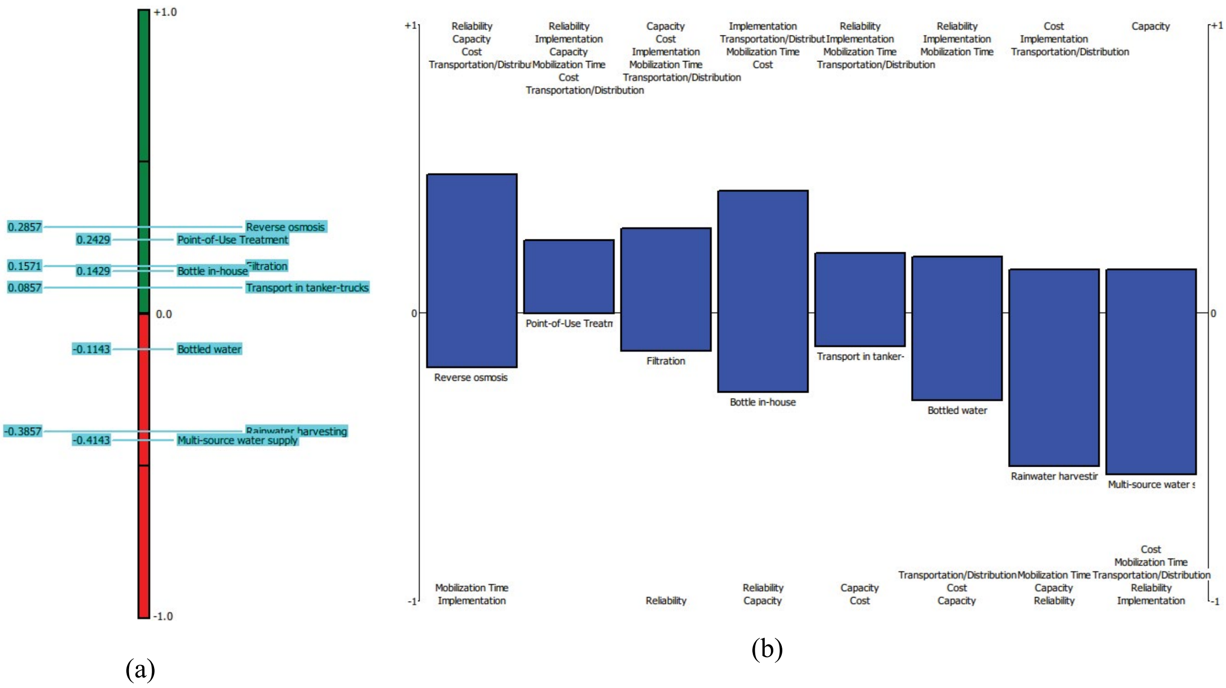

Fig. 4. Comparison of emergency water supply options in the case of drought (a) PROMETHEE ranking and (b) rainbow chart.

"No". The results are shown in Fig. 6. First, the tree was split depending on the types of treatments. The first group includes GAC and NF and the second group includes MF and sand filter. In each group, the effectiveness of the treatment was classified. With the changes in the feed and product water qualities, the treatment process may or may not effective. The quantitative guidelines were also obtained. Accordingly, this model tree has the potential to be used for the evaluation of water treatment unit processes depending on the situation.

3.3. Investment planning for preventive disaster response

A Monte Carlo simulation-based decision-making technique was attempted for analyzing the effectiveness of investments to preemptively respond to disasters. To begin, disaster recovery costs for water infrastructures from 1996 to 2016 were obtained from the Korean disaster annual report. As shown in Table 1 , they have shown large variations throughout this period. Then, a set of probability distributions were compared to fit the data. Among them, a Weibull distribution was found to show the best fitting as illustrated in Fig. 7.

Using this probability distribution, a series of the Monte Carlo simulations were carried out to estimate the economic damages by disasters. Fig. 8 shows the results of the Monte Carlo simulations over a period of 10, 20, and 100 y. When the simulation period was 10 y, the maximum cost was estimated to 1,400 billion won per year (Fig. 8a). It was similar or less with the simulation period of 20 y (Fig. 8b). However, it increased to 2,300 billion won per year with the simulation period of 100 y (Fig. 8c). This suggests that higher investment is required to prepare disasters with a longer period of time. Again, this technique was expected to be useful to roughly calculate the investment for proactive actions to future disasters.

3.4. Decision-making to respond to an emergency by sudden water contamination

The final module describes in this paper is a rule-based expert system for decision-making to respond to an emergency by sudden water contamination. First, the rule for this decision was established based on the Manual of Response to the Drinking Water Crisis Response Manual prepared by the Ministry of Environment [45]. According to this manual, there are three major types of disasters which are water quality abnormality/pollution, destruction of drinking water facilities, and drinking water systems shut down. Among various types of water contamination, the cases of benzene, ethylbenzene, toluene, xylene (BETX) were considered as an example.

Fig. 9 shows the flowchart of the countermeasures and procedures when BETX occurs in the water source. The Ministry of Environment generally detects odors when the concentrations of benzene, toluene, ethylbenzene, and xylene are more than 10, 50, 100, and 100 mg/L, respectively. If this is an emergency situation, GAC or air stripping should be applied. Otherwise, the long-term measure will be done. However, the procedures in the manual are rather complex and difficult to be implemented in the field.

3the operators and managers has been designed and developed. Fig. 10 shows a logic block created with the Exsys Corvid program. The logic block is used to recognize disasters that occur in water treatment. This logic

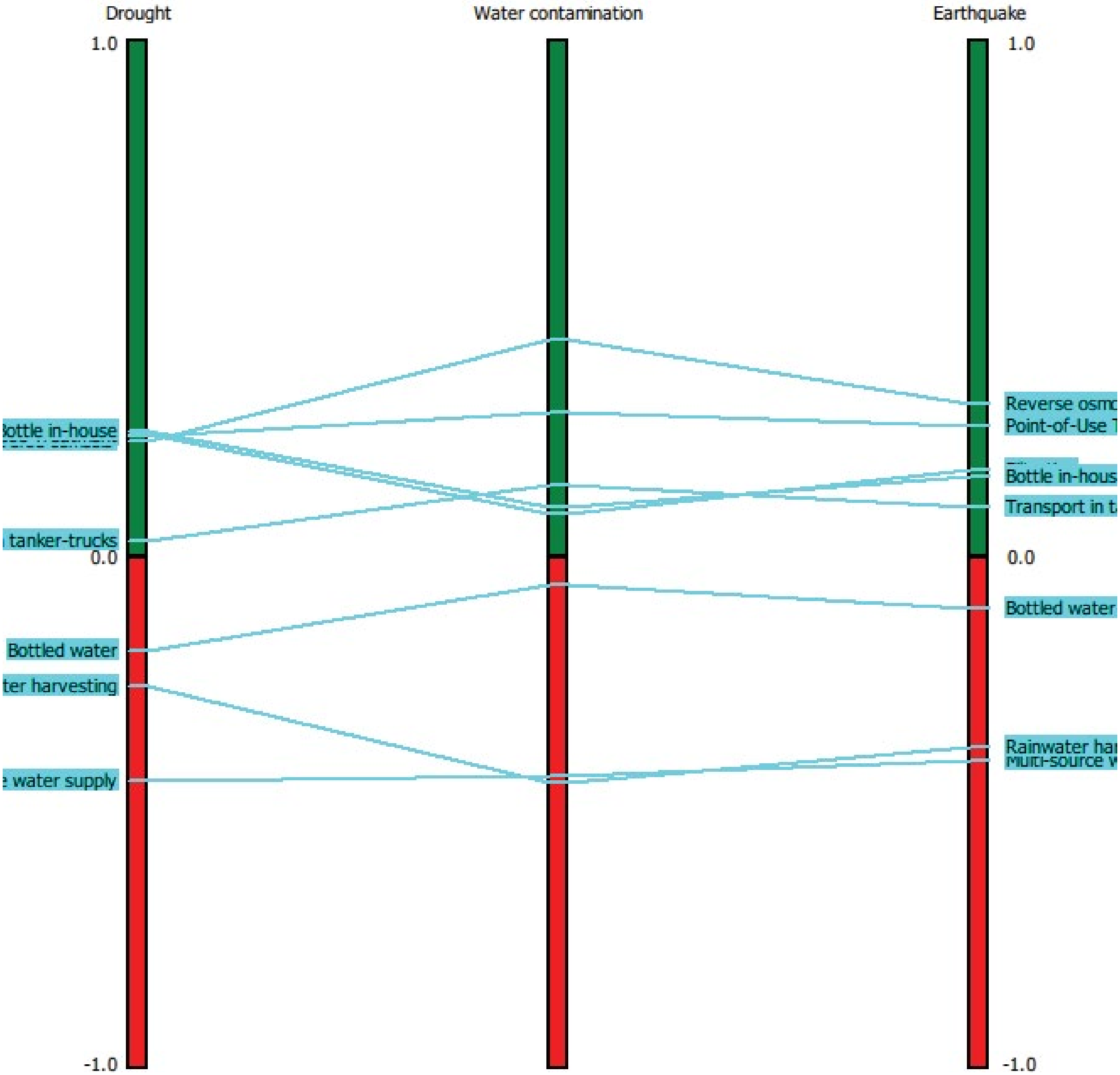

Fig. 5. Comparison of PROMETHEE ranking for emergency water supply options under different disaster scenarios.

Table 1
List of emergency water supply

Category	Group	Water supply option
Treatment	Centralized or satellite	Reverse osmosis
		Filtration
		Multi-source water treatment
	Point-of-use	Point-of-use treatment
		Rainwater harvesting
Storage	Warehouse	Bottled water
	In-system	Bottle-in-house

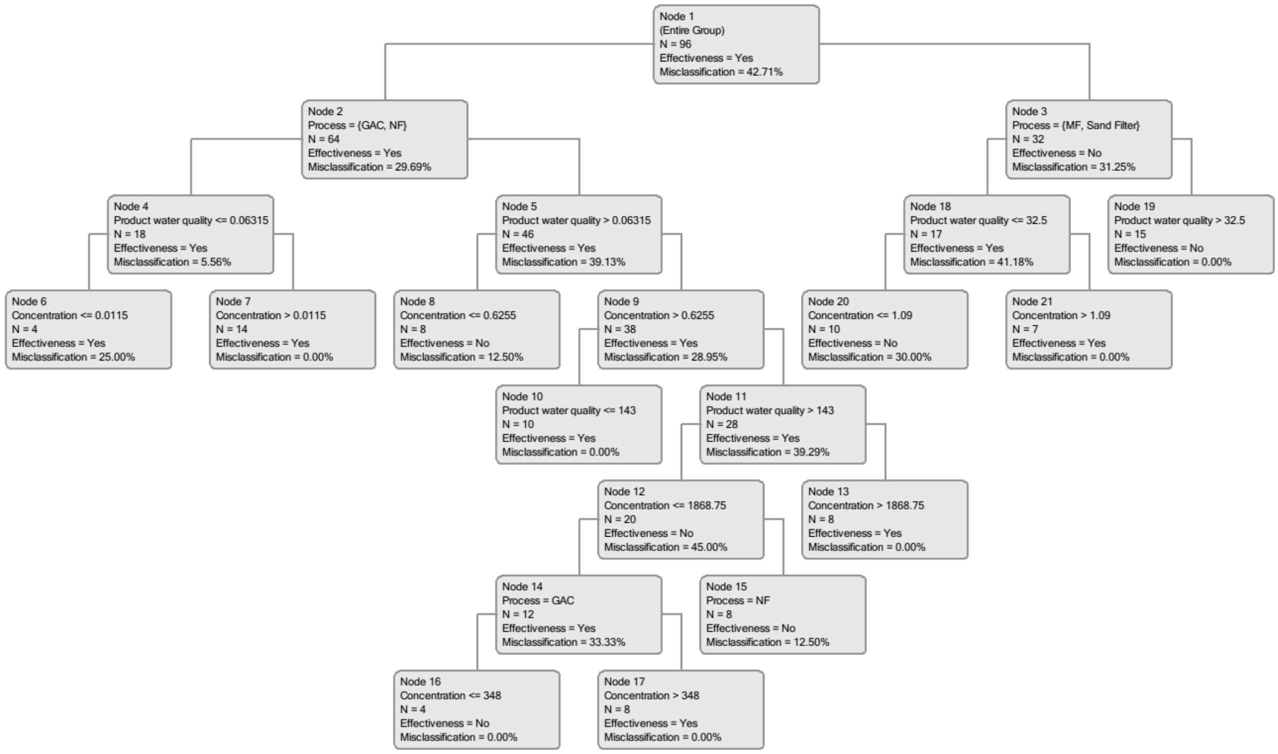

Fig. 6. Decision tree to compare the influent and treated water quality to analyze the efficiency of each unit process for specific contaminants.

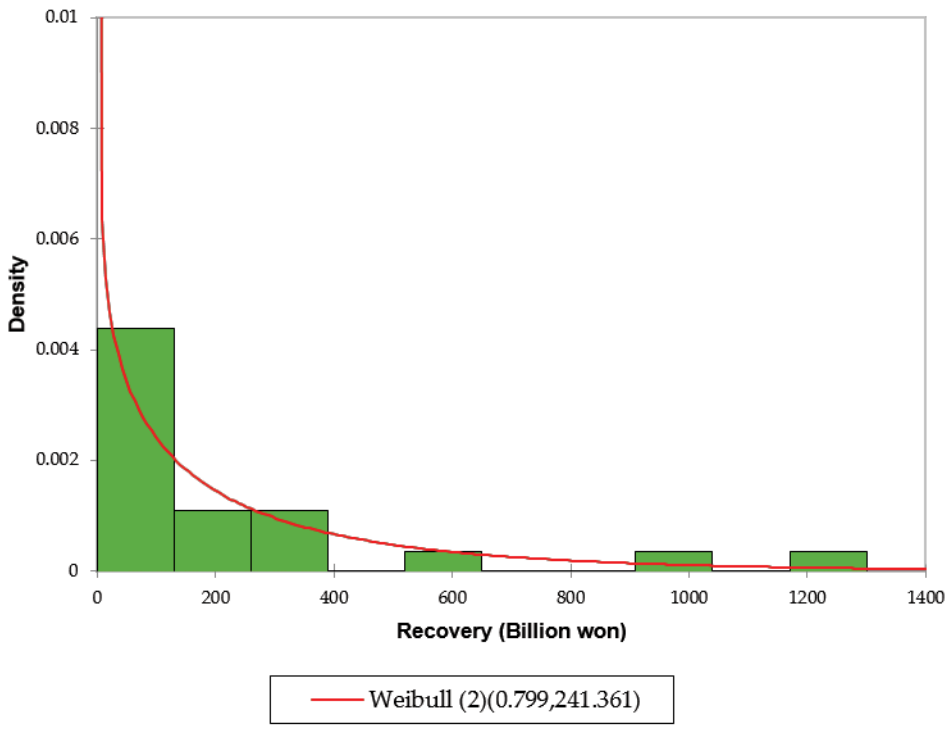

Fig. 7. Weibull distribution according to disaster recovery costs.

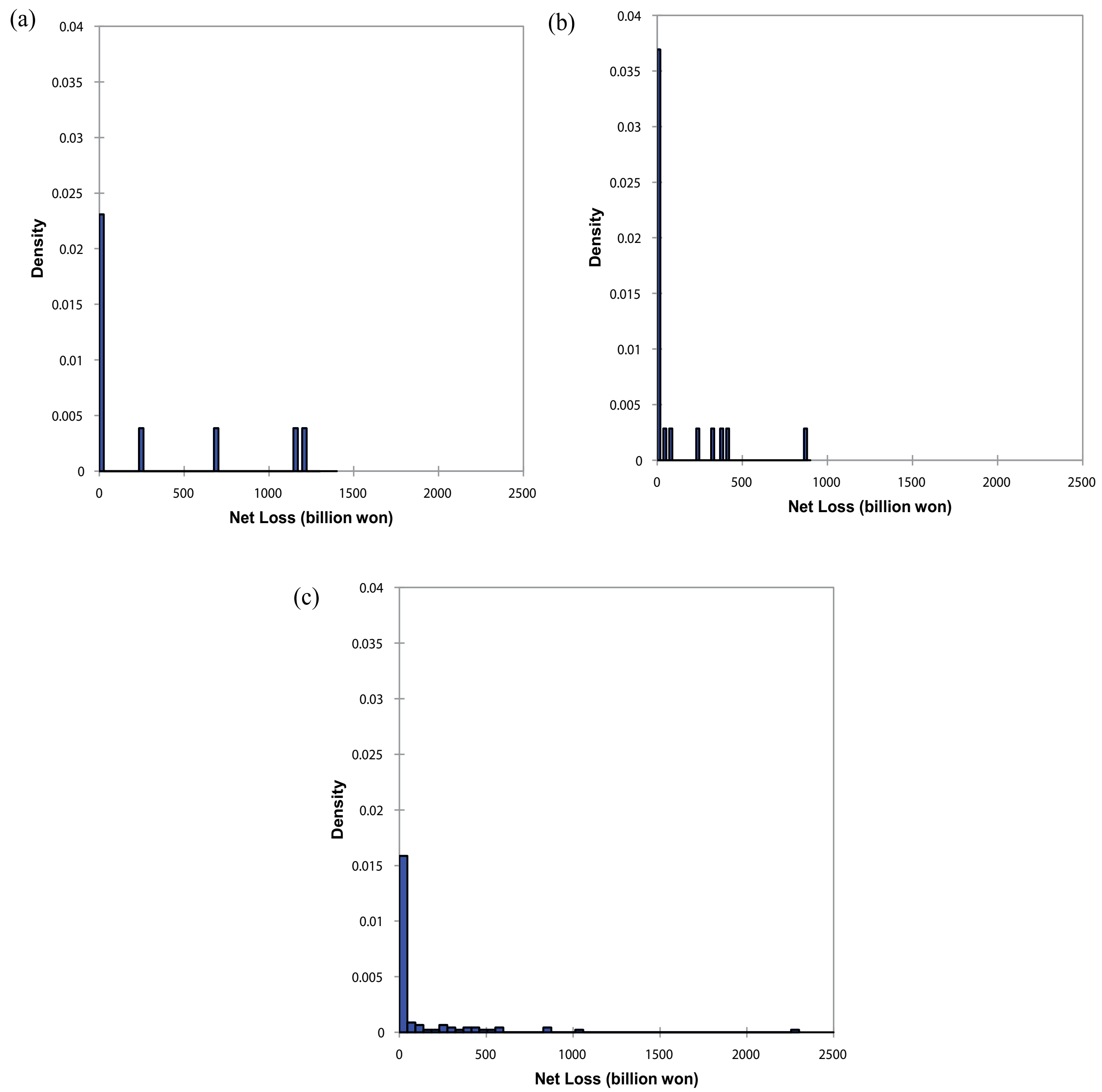

Fig. 8. Results of Monte Carlo simulations over a period of (a) 10, (b) 20, and (c) 100 y.

Table 2
Disaster recovery costs for water infrastructures from 1996 to 2016 based on Korean disaster annual report

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Recovery (billion won)	61	15	351	321	212	97	1,228	976	11	154	599
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	–
Recovery (billion won)	110	8	112	120	349	222	100	85	1	126	–

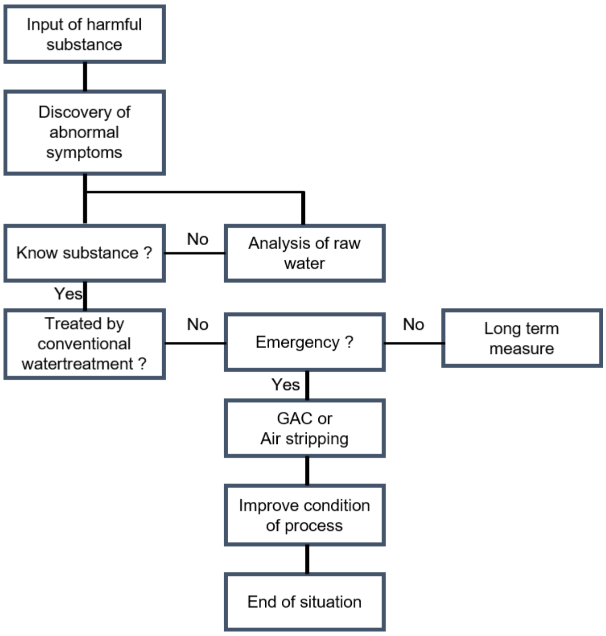

Fig. 9. Flowchart of response when water pollutant flows into the water treatment plan by the Ministry of Environment Regulation.

block is implemented to recognize the situation and, as a result, gives an answer to solve the problem. Then, Entering a command in the command block will result in the logic of the logic block. Fig. 11 shows the command block in this paper. A user interfaces display results that assist the experts to choose which type of counterplan to disaster. Accordingly, the proposed expert system may be an alternative to the manual used in water treatment plants for more accurate and convenient decision-making.

4. Conclusions

In this work, a DSS responding to an emergency was suggested as a systematic approach to solving problems in water treatment plants affected by various disasters. The DSS consists of several modules in the stages for planning, disaster sensing, and response, and the four modules were presented as parts of this DSS. The following conclusions were withdrawn:

- Decision support for the selection of emergency water supply technologies was developed using an MCDA technique. Through this technique, proper emergency water supply options could be selected by considering various aspects under various disaster scenarios. For example, reverse osmosis and point of use treatment

(a)

(b)

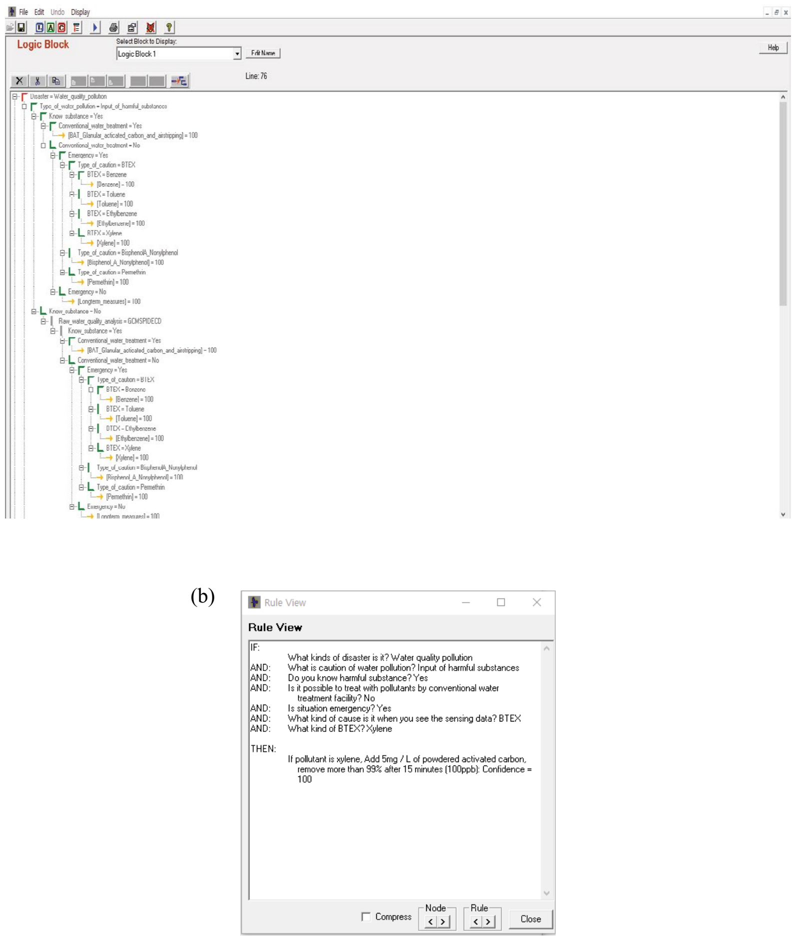

Fig. 10. Logic block and rule view of rule-based decision-making system in case of water pollution.

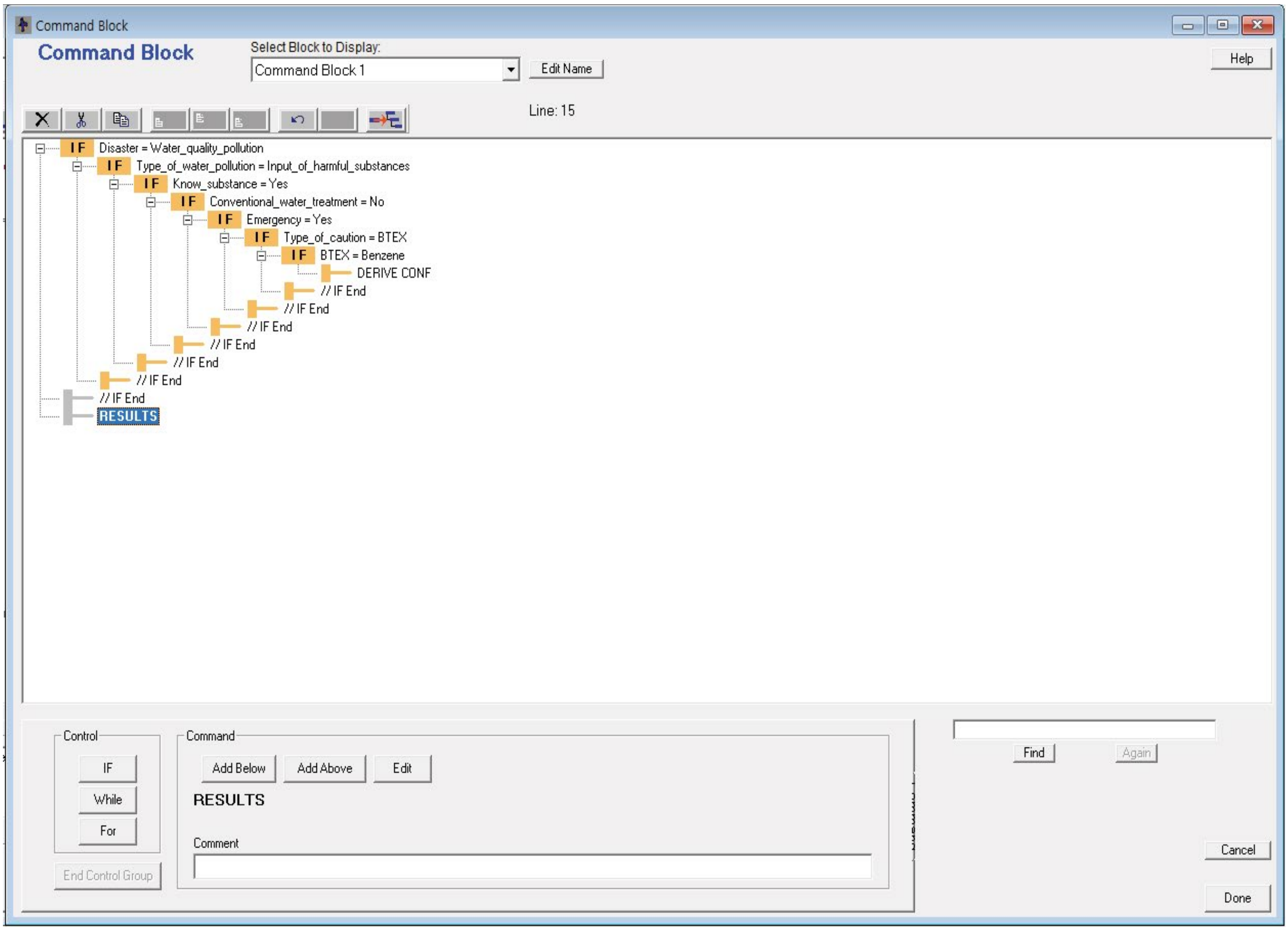

Fig. 11. Command block of rule-based decision-making system in case of water pollution.

were found to be appropriate to supply water in the case of earthquakes.

- A technique for the prediction of treated water quality by various treatment systems was developed based on the decision tree technique. Based on this, the effectiveness of the treatment technologies could be determined with the scenarios of different feed and product water qualities.
- A Monte Carlo simulation-based decision-making technique was developed for analyzing the effectiveness of investments to preemptively respond to disasters. A Weibull distribution was found to show the best fitting for the costs of disaster recovery between 1996 and 2016 in Korea. As a result of the simulation, it appears that higher investment is required to prepare disasters with a longer period of time.
- A rule-based expert system for decision-making responds to emergencies due to sudden water contamination by BETX. The procedures in the Manual of Response to the Drinking Water Crisis Response Manual prepared by the Ministry of Environment were converted to the rules in the expert system. This approach has the potential to provide a more accurate and convenient way of decision-making under an emergency situation.

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