

## *Research Article*

# **A Selection Approach for Optimized Problem-Solving Process by Grey Relational Utility Model and Multicriteria Decision Analysis**

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Received 21 January 2012; Accepted 17 April 2012

Academic Editor: Jung-Fa Tsai

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In business enterprises, especially the manufacturing industry, various problem situations may occur during the production process. A situation denotes an evaluation point to determine the status of a production process. A problem may occur if there is a discrepancy between the actual situation and the desired one. Thus, a problem-solving process is often initiated to achieve the desired situation. In the process, how to determine an action need to be taken to resolve the situation becomes an important issue. Therefore, this work uses a selection approach for optimized problem-solving process to assist workers in taking a reasonable action. A grey relational utility model and a multicriteria decision analysis are used to determine the optimal selection order of candidate actions. The selection order is presented to the worker as an adaptive recommended solution. The worker chooses a reasonable problem-solving action based on the selection order. This work uses a high-tech company's knowledge base log as the analysis data. Experimental results demonstrate that the proposed selection approach is effective.

## **1. Introduction**

Problem solving is an important process that enables corporations to create competitive advantages. In manufacturing industries, various problem situations may occur during the production process [1, 2]. A situation denotes an evaluation point to determine the status of a production process. A problem may occur if there is a discrepancy between the actual situation and the desired one [3]. Thus, a problem-solving process is often initiated to achieve the desired situation. In the process, workers determine what action needs to be taken to resolve the situation. For a given problem, a situation may occur with various features

according to the context at that time. Due to the uncertain characteristics of situations, several causes and possible actions may exist for a specific situation. Workers may observe a problem situation, collect relevant information from the enterprise knowledge repository, explore possible causes, and identify operational conditions in order to decide appropriate action [3, 4].

Quality of Service (QoS) is an important consideration in evaluating a problem-solving solution. Worker feedback of an evaluating process can be represented as a utility model reflecting the satisfaction a worker observes from taking an action. The worker provides such a utility model [5] before committing to take an action. Grey relational analysis [6, 7] can quantify all influences of various factors and their relation to consolidate the utility model. Therefore, the worker's grey relational utility model can be applied to the monitoring information in order to evaluate the action's QoS. The worker will get the expected value of the issue of interest from taking an action. Based on various issues of interest, how to select the reasonable action from a large number of candidate actions requires a multicriteria decision analysis. A multicriteria decision analysis [8] is concerned with structuring and solving decision and planning problems involving multiple criteria. The purpose is to support decision makers facing such problems. Typically, there does not exist a unique optimal action for such problems, and it is necessary to use decision maker's preferences to differentiate between actions. Therefore, a multicriteria decision analysis is required to discover the selection order of the various actions for a specific situation. The discovered selection order helps worker to solve the situation.

This work uses a selection approach to candidate actions to assist the worker in acquiring a reasonable problem-solving action. Action formalization, a grey relational utility model, and a multicriteria decision analysis are used to obtain an optimal selection order for candidate actions. Then, the selected action for a specific situation is taken through a problem-solving process. The result is considered a reasonable problem-solving solution for the worker. This work explores a high-tech company's knowledge base log as the analysis data. The prototype system and use cases are proposed in the previous research [4]. In this work, we have an experiment to demonstrate that the proposed approach is effective. The contribution of this research is in demonstrating a method which is easy to implement in a problem solving knowledge recommendation system for selecting a reasonable solution.

The remainder of this paper is organized as follows. Section 2 reviews related works on problem solving, grey relational analysis, multicriteria decision analysis, knowledge management, and retrieval. Section 3 introduces a selection approach for optimized problem-solving process by a grey relational utility model and a multicriteria decision analysis. Section 4 describes an experimental data of a high-tech company's knowledge base. An experiment of the knowledge base log and discussions are showed in Section 5. Finally, Section 6 presents our conclusions.

## **2. Related Works**

The related literature covers problem solving, grey relational analysis and utility model, multicriteria decision analysis, knowledge management, and retrieval.

### **2.1. Problem-Solving Process**

In business enterprises, especially the manufacturing industry, various problem situations may occur during the production process [1, 2], for example, poor production performance,

system overload, and low machine utilization. A situation denotes an evaluation point to determine the status (i.e., desirable or undesirable) of a production process. A problem may occur if there is a discrepancy between the actual situation and the desired one [3]. For example, when the current production output is below the desired level, the production line may have some problems. Thus, a problem solving process is often initiated to achieve the desired situation. Problem solving is the thought process that resolves various difficulties and obstacles spread in the gap between the current problem and its desired solution [4].

Various approaches have been proposed to support problem solving. Allen et al. enforced a problem-solving process based on the knowledge gained from solving previous similar problems [9]. Chang et al. implemented a self-improvement helpdesk service system [1], and Park et al. developed a decision support system for problem solving in a complex production process [2]. More recently, Yang et al. proposed integrating the case-based reasoning (CBR) approach with ART-Kohonen neural networks (ART-KNNs) to enhance fault diagnosis in electric motors [10]. Moreover, Guardati introduced RBCShell as a tool for constructing knowledge-based systems, whereby previously solved problems are stored in the case memory to support problem solving in new cases [11].

In a complex production process, problem solving is usually knowledge intensive. Past experience or knowledge, routine problem-solving procedures, and previous decisions can be used to enhance problem solving. The types of knowledge are investigated to use for problem solving and suggest the circulation of knowledge to avoid knowledge inertia [12]. In the problem-solving process, workers take several problem-solving steps to determine what action needs to be taken to resolve the situation [3]. Such action involves both human wisdom and enterprise knowledge. Workers may observe a problem situation, collect relevant information from the enterprise knowledge repository, explore possible causes, and identify operational conditions in order to decide appropriate action [4].

## ***2.2. Grey Relational Analysis and Utility Model***

The grey relational analysis (GRA) is an important method in the grey system theory [7]. The GRA has been widely used in a number of areas, such as manufacturing [13], transportation [14], and the building trade [6]. In the grey system theory, the GRA is essentially believed to have captured the similarity measurements or relations in a system. Generally, the procedure of grey relation analysis includes grey relation generation and grey relational grade calculation steps. The grey relation generation step removes anomalies associated with different measurement units and scales by the normalization of raw data. The grey relational grade calculation step uses the grey relational coefficient to describe the trend relationship between an objective series and a reference series at a given point in a system [15].

Quality of Service (QoS) is an important consideration in evaluating a problem-solving action. Worker feedback of an evaluating process can be represented as a utility model reflecting the satisfaction a worker observes from taking an action. The worker provides such a utility model [5] before committing to take an action. GRA can quantify all influences of various factors and their relation to consolidate the utility model. Therefore, the worker's grey relational utility model can be applied to the monitoring information in order to evaluate the action's QoS. The worker will get the expected value of the issue of interest from taking an action.

### **2.3. Multicriteria Decision Analysis Method, ELECTRE**

Multicriteria decision-making (MCDM) approach has played an important role in solving multidimensional and complicated problems. ELECTRE (Elimination Et Choice Translating Reality) is a family of multicriteria decision analysis methods [8, 16]. ELECTRE methods are developed in two main phases. In the first phase, the outranking relations are constructed for a comprehensive comparison of each pair of actions. In the second phase, the recommendations are elaborated from the results obtained by an exploitation procedure from the first phase. The nature of the recommendation depends on the following problems: choosing, ranking, or sorting. The evolutions of ELECTRE methods include ELECTRE I, ELECTRE IV, ELECTRE IS, ELECTRE II, ELECTRE III, ELECTRE IV, ELECTRE-SS, and ELECTRE TRI. Each method is characterized by its construction and exploitation procedure. ELECTRE I, ELECTRE IV, and ELECTRE IS were designed to solve choice problem. ELECTRE II, ELECTRE III, ELECTRE IV, and ELECTRE-SS were designed for solving ranking problems. ELECTRE TRI was designed for solving sorting problems. This work uses a modified version of the ELECTRE method [17] to discover an optimal selection order of candidate actions. The selection order is presented to the worker as a recommended solution.

### **2.4. Knowledge Management and Retrieval**

A repository of structured, explicit knowledge, especially in document form, is a codified strategy for managing knowledge [18, 19]. However, with the growing amount of information in organization memories, knowledge management systems (KMSs) face the challenge of helping users find pertinent information. Accordingly, knowledge retrieval is considered a core component in accessing information in knowledge repositories [20, 21]. Translating users' information needs into queries is not easy. Most systems use information retrieval (IR) techniques [22] to access organizational codified knowledge [23]. The use of information filtering (IF) with a profiling method to model users' information needs is an effective approach that proactively delivers relevant information to users. The technique has been widely used in the areas of information retrieval and recommender systems [24–26]. The profiling approach has also been adopted by some KMSs to enhance knowledge retrieval [27–29], whereby information is delivered to task-based business environments to support proactive delivery of task-relevant knowledge [20, 27, 30].

This work explores a high-tech company's knowledge base log [4] as the analysis data. Knowledge management and retrieval techniques are used to enforce an experiment to demonstrate that the proposed selection approach is effective.

## **3. The Selection Approach for Optimized Problem-Solving Process**

This section describes a selection approach to candidate actions in terms of grey relational utility model and multicriteria decision analysis, including problem-solving action formalization, grey relational utility model for candidate actions, and selection order discovery by a modified version of the ELECTRE method [17].

### **3.1. Problem-Solving Action Formalization**

Problem-solving action formalization is an essential and initial task in our proposed selection approach. This work refers to the use of a utility-based reputation model [5] to formalize an action's QoS items in order to enforce the utility model.

Let  $A = \{a_1, a_2, \dots, a_n\}$  denote the set of actions, and let  $a \in A$ . Let  $AP$  denote the set of actions providers, let  $b \in AP$ , and let function  $S : AP \rightarrow P(A)$  denote the actions provided by an action provider, where  $P$  represents the power set operator. Let  $SW$  denote the set of worker of the system, and let  $w \in SW$ . Each action has associated issues of interest, denoted by set  $I$ , whose workers are interested in monitoring, and  $i \in I$ . Function  $IS$  represents the set of issues of interest for an action:  $IS : A \rightarrow P(I)$ . Function  $O^w : A \times AP \times I \rightarrow R$  denotes the expectation of the worker  $w$  for the actions he takes, where  $R$  denotes the real numbers. Notation  $v_{a,i}^{w,b}$  represents the expectation of worker  $w$  on issue  $i$  of action  $a$  supplied by provider  $b$ .

In a problem-solving environment, a potential issue of interest could be the QoS. Based on the expectations, a worker can develop a utility model which reflects the satisfaction he perceives from taking an action.

### 3.2. Grey Relational Utility Model for Candidate Actions

After the expectation formalization process of a problem-solving action's specific interest issue, a grey relational utility model is developed to represent worker satisfaction with action acquisition.

Let  $U_{a,i}^{w,b}(v)$  denote the utility that worker  $w$  gets by obtaining the actual value  $v \in R$  on issue  $i$  from action  $a$  of provider  $b$ . Each expected value  $v$  of specific interest issue  $i$  of an action used as a QoS item to build a comparative vector  $a_i = (U_{a_i,i_1}^{w,b}(v_1), U_{a_i,i_2}^{w,b}(v_2), \dots, U_{a_i,i_n}^{w,b}(v_n))$ ,  $i = \{1, 2, \dots, m\}$ . This work sets the  $a_0$  as a desired action with expected utility values of specific interest issues. It forms a reference vector  $a_0 = (U_{a_0,i_1}^{w,b}(v_1), U_{a_0,i_2}^{w,b}(v_2), \dots, U_{a_0,i_n}^{w,b}(v_n))$ . Utilities are normalized and scaled to  $[0, 1]$  by grey relation consideration [31, 32], as shown in (3.1) and (3.2). Larger-the-better means that the larger target value is better, and smaller-the-better means that the smaller target value is better. Therefore,  $U_{a,i}^{*w,b} R \rightarrow [0, 1]$ .

Larger-the-better is as follows:

$$U_{a,i}^{*w,b}(v) = \frac{U_{a,i}^{w,b}(v) - \min_i U_{a,i}^{w,b}(v)}{\max_i U_{a,i}^{w,b}(v) - \min_i U_{a,i}^{w,b}(v)}. \quad (3.1)$$

Smaller-the-better is as follows:

$$U_{a,i}^{*w,b}(v) = \frac{\max_i U_{a,i}^{w,b}(v) - U_{a,i}^{w,b}(v)}{\max_i U_{a,i}^{w,b}(v) - \min_i U_{a,i}^{w,b}(v)}. \quad (3.2)$$

Then the grey relation equation [25, 32, 33] is used to calculate the grey relational grade between reference vector and comparative vectors, partial equation as shown in (3.3). The  $U_{a_0,i}^{w,b}(v)$  is a partial utility of reference vector, and  $U_{a_k,i}^{w,b}(v)$  is a partial utility of comparative vector. If the grey relational grade value  $\Gamma_{0k}$  is closer to 1, it means that  $U_{a_0,i}^{w,b}(v)$  and  $U_{a_k,i}^{w,b}(v)$

have high correlation. If the grey relational grade value  $\Gamma_{0k}$  is closer to 0, it means that  $U_{a_0,i}^{w,b}(v)$  and  $U_{a_k,i}^{w,b}(v)$  have low correlation:

$$\Gamma_{0k} = \Gamma(U_{a_0,i}^{w,b}(v), U_{a_k,i}^{w,b}(v)) = \frac{\bar{\Delta}_{\max} - \bar{\Delta}_{0k}}{\bar{\Delta}_{\max} - \bar{\Delta}_{\min}}, \quad \text{where } \bar{\Delta}_{0k} = \left( \sum_{k=1}^n [\Delta_{0k}(v)]^\rho \right)^{1/\rho}, \quad (3.3)$$

where  $\rho = \{1, 2, \dots, m\}$ .  $\bar{\Delta}_{\max}$  is the largest value of  $\bar{\Delta}_{0k}$  and  $\bar{\Delta}_{\min}$  is the smallest value of  $\bar{\Delta}_{0k}$ . Based on the grey relational grade value  $\Gamma$ , a threshold value is used to filter out the low correlation actions, and the remainders are considered as candidate actions for solving a specific problem situation.

In Sections 3.1 and 3.2, the worker will get the expected value of the issue of interest from taking an action. Based on various issues of interest, how to select the reasonable action from a large number of candidate actions requires a multicriteria decision analysis.

### 3.3. Discover a Selection Order of Actions by a Modified ELECTRE Method

For the second task, this work uses a modified version of the ELECTRE method to discover the selection order for candidate actions. If there are  $m$  candidate actions which involve  $n$  QoS items, the matrix  $Q$  of expected values can be shown as (3.4). We use 8 steps to discover the optimal selection order of action using a modified version of the ELECTRE method [17]:

$$Q = [Q_{ij}]_{m \times n} = \begin{bmatrix} v_{1,1}^{c,b} & \cdots & v_{1,n}^{c,b} \\ \vdots & \ddots & \vdots \\ v_{m,1}^{c,b} & \cdots & v_{m,n}^{c,b} \end{bmatrix}. \quad (3.4)$$

*Step 1.* To calculate the weighted normalization decision matrix, a weight for each QoS item must be set to form a weighted matrix ( $W$ ), as shown in:

$$W = \begin{bmatrix} W_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & W_n \end{bmatrix}_{n \times n}. \quad (3.5)$$

The multiplication of a normalization matrix  $Q$  by a weighted matrix  $W$  gets the weighted normalization decision matrix ( $V = QW$ ), as shown in:

$$V = [v_{ij}]_{m \times n}. \quad (3.6)$$

*Step 2.* Compare arbitrary different row  $i$  and row  $j$  in the weighted normalization decision matrix  $V$  to make sure of the concordance and discordance set. If value  $v$  of row  $i$  is higher

than value  $v$  of row  $j$ , the component  $k$  can be classified as the concordance set  $C_{ij}$  or the discordance set  $D_{ij}$ . The concordance set  $C_{ij}$  or the discordance set  $D_{ij}$  is shown as:

$$C_{ij} = \{k \mid v_{ik} \geq v_{jk}\}, \quad D_{ij} = \{k \mid v_{ik} < v_{jk}\}. \quad (3.7)$$

*Step 3.* The sum of each component's weight forms a concordance matrix  $C$ , as shown in:

$$C = [c_{ij}]_{m \times m'} \quad c_{ij} = \frac{\sum_{k \in C_{ij}} w_k}{\sum_{k \in 1}^n w_k}. \quad (3.8)$$

*Step 4.* We use a formula to get the discordance matrix.  $S$  is the set including all QoS items,  $S = \{1, 2, \dots, n\}$ , as shown in:

$$d_{ij} = \frac{\max_{k \in D_{ij}} \{|v_{ik} - v_{jk}|\}}{\max_{k \in S} \{|v_{ik} - v_{jk}|\}}. \quad (3.9)$$

Therefore, a discordance matrix can be presented as  $D = [d_{ij}]_{m \times m}$ .

*Step 5.* The reverse complementary value is used to modify  $D$  to get the modified discordance matrix  $D'$ . The calculation of  $D'$  is shown as:

$$D' = [d'_{ij}]_{m \times m'} \quad d'_{ij} = 1 - d_{ij}. \quad (3.10)$$

*Step 6.* To show the large component value of the candidate solution, when the expected value is larger, we combine each component  $c_{ij}$  of the concordance set with the discordance matrix to calculate the production and get the modified total matrix  $A$  (*Hadamard product of  $c_{ij}$  and  $d'_{ij}$* ), as shown in:

$$A = [a_{ij}]_{m \times m'} \quad a_{ij} = c_{ij} \circ d'_{ij}. \quad (3.11)$$

*Step 7.* Get the maximum value  $a_j$  of each column from modified total matrix. The purpose is to determine the modified superiority matrix, as shown in:

$$a_j = \max\{a_{ij} \mid i = 1, 2, \dots, m\}, \quad j = 1, 2, \dots, m. \quad (3.12)$$

To make sure to get a reasonable solution, we have to rank  $a_j$  from small to large:  $a_1, a_2, \dots, a_m$ . The threshold  $\bar{a}$  is set behind the smallest value  $a'_1$  and the next smallest value  $a'_2$ . If the value  $a_{ij}$  is smaller than threshold  $\bar{a}$ , it is replaced as 0 or 1. Then we get the modified total superiority matrix, as shown in:

$$E' = [e'_{ij}]', \quad e'_{ij} = \begin{cases} 1, & a_{ij} \geq \bar{a}, \\ 0, & a_{ij} < \bar{a}. \end{cases} \quad (3.13)$$

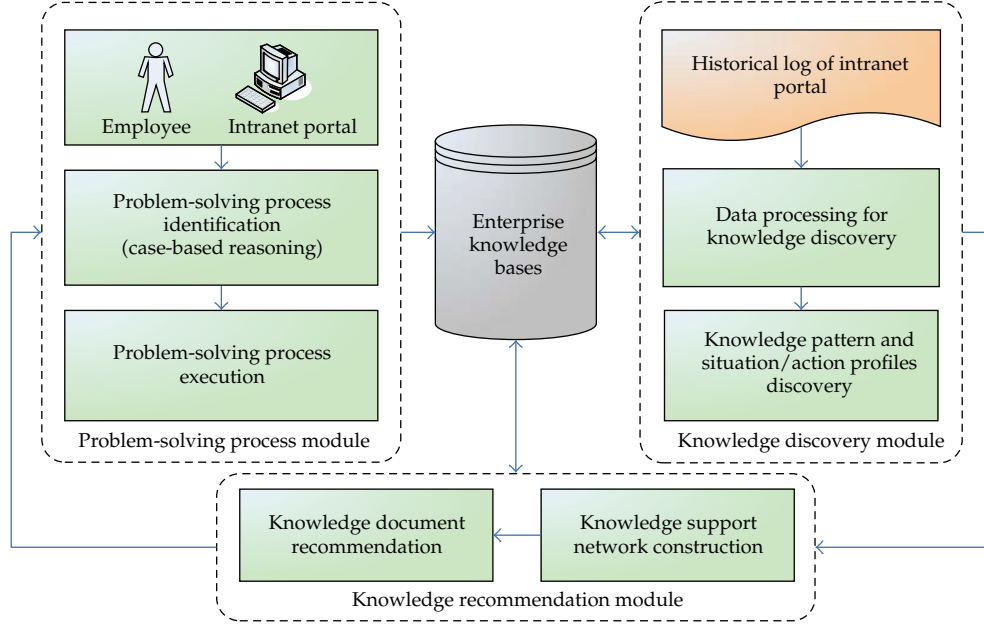


Figure 1: Knowledge support framework for problem solving [4].

Step 8. Finally, we get  $e'_{ij} = 1$  from the matrix  $E'$ . It indicates that solution  $i$  is better than solution  $j$ . We can eliminate solution  $j$  and show it as  $A_i \rightarrow A_j$ .

From Steps 1 to 8, we get the relationship among the QoS items of the candidate actions and get the optimal selection order for all candidate actions. The candidate action is the action provided by an action provider. The worker can follow the selection order to take a reasonable action.

#### 4. Experimental Knowledge Base Log

In this section, we fetch a high-tech company's knowledge base log as the analysis data. In the previous research [4], the proposed knowledge support framework for problem-solving is as shown in Figure 1. The proposed framework records the problem-solving steps, including the situations and actions as well as the corresponding knowledge documents accessed in the historical log. The knowledge discovery module employs mining technology to extract hidden knowledge from the historical problem solving log. The extracted knowledge, including situation/action profiles, decision making, and dependency knowledge, is used to provide knowledge support. The knowledge base comprises historical logs, discovered knowledge patterns, situation/action profiles, and enterprise knowledge documents. This component acts as an information hub to provide knowledge support for problem solving.

For specific situations or actions, relevant information (documents) accessed by workers is recorded in the problem-solving log. Historical codified knowledge (textual documents) can also provide valuable knowledge for solving the target problem. Information retrieval (IR) and text mining techniques are used to extract the key terms of relevant documents for a specific situation or action. The extracted key terms form the situation/action profile, which is used to model the information needs of the workers. This work assumes that



a generic problem-solving process is specified by experts to solve a problem or a set of similar problems encountered on a production line. When the production line encounters a problem, a problem-solving process is initiated. The situations that occurred in a problem may vary due to the uncertainty of the constantly changing business environment. Moreover, different workers may take different actions to solve a problem according to their skills and experience. The problem-solving log records historical problem solving instances.

## 5. The Experiments and Results Discussion

This section presents the experiment, results, and relevant discussion of the wafer manufacturing problem use case.

### 5.1. Experiments

This paper uses the wafer manufacturing problem [4] as a useful example to illustrate the experiment. A wafer manufacturing process in a semiconductor foundry is used to illustrate the proposed approach. The process comprises the following steps: crystal growing, wafer cutting, edge rounding, lapping, etching, polishing, cleaning, final inspection, packaging, and shipping. The wafer cleaning step mainly uses DI (deionized, ultrapure) water to remove debris left over from the mounting wax and/or polishing agent. A stable water supply system to deliver ultrapure water for wafer cleaning is therefore vital in semiconductor manufacturing. The knowledge retrieval technique is used to explore the knowledge base log which includes 1,077 relevant data records of wafer cleaning step in a wafer manufacturing process. The discovered data records involve with 72 situations from 7 interdatabases, 23 workers, and 238 actions. The 5 domain experts assist this experiment to carry out and evaluate.

#### 5.1.1. Problem-Solving Action Formalization and Grey Relational Utility Model

When the worker suffers from a specific problem situation, there are various suppliers providing the problem-solving actions. The problem-solving action formalization and a grey relational utility model are used to precompute the worker's expected list of supplied action QoS items and facilitate a multicriteria decision analysis to discover an optimal selection order of candidate actions.

First, the problem-solving action formalization process identifies the worker, action, and action providers. Then, the worker can decide the indicators (quality of service items, QoS items) of current problem situation. We use abnormal situation of wafer cleaning as a simple example. The worker sets performance, quality, and duration time as the QoS items for abnormal situation. Then the relevant values of QoS items and actions are recorded in a table, as shown in Table 1. For example, action A sets the QoS item, abnormal situation, where the performance degree is high, quality degree is middle, and duration time is evaluated as slow.

After the problem-solving action formalization process, a grey relational utility model is developed to represent worker satisfaction with the action acquisition. The action C is filtered out because of its low grey relational grade, and the reminder actions A, B, D are considered as the candidate actions for solving a specific problem situation. Each QoS item is normalized and scaled to [0, 1]. Then, Table 1 is transformed into Table 2.

**Table 1:** Property of QoS item and action for abnormal situation.

	Performance	Quality	Duration time
Action A	High	Middle	Slow
Action B	Low	High	Normal
Action C	Low	Low	Slow
Action D	Middle	Low	Quick

**Table 2:** Transformed property of QoS item and action for abnormal situation.

	Performance	Quality	Duration time
Action A	0.34	0.32	0.22
Action B	0.31	0.35	0.25
Action D	0.32	0.28	0.30

### 5.1.2. The Selection Order Discovery of Candidate Actions

A modified version of the ELECTRE method [17] is used to determine the optimal selection order of candidate actions to solve a specific problem situation. The decision matrix  $Q$  of expected values can be shown as follows:

$$Q = \begin{bmatrix} 0.34 & 0.32 & 0.22 \\ 0.31 & 0.35 & 0.25 \\ 0.32 & 0.28 & 0.30 \end{bmatrix}. \quad (5.1)$$

The weighted matrix ( $W$ ) for each QoS item is shown as follows:

$$W = \begin{bmatrix} 0.4 & 0 & 0 \\ 0 & 0.35 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}. \quad (5.2)$$

The multiplication of a normalization matrix  $Q$  and a weighted matrix  $W$  which gets the weighted normalization decision matrix  $V$  ( $V = QW$ ) is shown as follows:

$$V = \begin{bmatrix} 0.136 & 0.112 & 0.055 \\ 0.124 & 0.1225 & 0.0625 \\ 0.128 & 0.098 & 0.075 \end{bmatrix}. \quad (5.3)$$

The concordance set  $C_{ij}$  or the discordance set  $D_{ij}$  is shown as follows:

$$\begin{aligned} C_{12} &= \{1\}, & D_{12} &= \{2,3\}, & C_{13} &= \{1,2\}, & D_{13} &= \{3\}, \\ C_{21} &= \{2,3\}, & D_{21} &= \{1\}, & C_{23} &= \{2\}, & D_{23} &= \{1,3\}, \\ C_{31} &= \{3\}, & D_{31} &= \{1,2\}, & C_{32} &= \{1,3\}, & D_{32} &= \{2\}. \end{aligned} \quad (5.4)$$

The sum of each component's weight forms a concordance matrix  $C$ :

$$C_{13} = \frac{\sum_{k \in C_{13}} w_k}{\sum_{k=1}^3 w_k} = \frac{W_1 + W_2}{W_1 + W_2 + W_3} = 0.75,$$

$$C = \begin{bmatrix} - & 0.4 & 0.75 \\ 0.6 & - & 0.35 \\ 0.25 & 0.65 & - \end{bmatrix}. \quad (5.5)$$

A discordance matrix can be presented as  $D$ :

$$D_{13} = \frac{\max_{k \in D_{13}} \{|v_{1k} - v_{3k}|\}}{\max_{k \in S} \{|v_{1k} - v_{3k}|\}} = \frac{\max\{0.02\}}{\max\{0.008, 0.014, 0.02\}} = 1,$$

$$D = \begin{bmatrix} - & 0.875 & 1 \\ 1 & - & 0.51 \\ 0.7 & 1 & - \end{bmatrix}. \quad (5.6)$$

A modified discordance matrix can be presented as  $D'$ :

$$D' = \begin{bmatrix} - & 0.125 & 0 \\ 0 & - & 0.49 \\ 0.3 & 0 & - \end{bmatrix}. \quad (5.7)$$

A modified total matrix can be presented as  $A$ :

$$A = \begin{bmatrix} - & 0.05 & 0 \\ 0 & - & 0.1715 \\ 0.075 & 0 & - \end{bmatrix}. \quad (5.8)$$

A modified total superiority matrix is shown as  $E'$ :

$$E' = \begin{bmatrix} - & 1 & 0 \\ 0 & - & 1 \\ 1 & 0 & - \end{bmatrix}. \quad (5.9)$$

Finally, the optimal selection order is determined for all candidate actions. The experiment results show that action  $B$  is better than action  $D$  and action  $D$  is better than action  $A$ . The worker can follow the selection order to get a reasonable action.

**Table 3:** The experimental results of abnormal situation of wafer cleaning step.

Method	Candidate actions	Item	
		Precision	Recall
The method in [4]	32	62.8% (86/137)	75.4% (86/114)
This paper's method	26	68.3% (86/126)	83.5% (86/103)

## 5.2. Experimental Results and Relevant Discussions

This work used an actual abnormal situation of wafer cleaning step in a wafer manufacturing process use case of a high-tech company to demonstrate that the proposed approach is effective. Supplying an adaptive problem-solving solution to a worker will help the business enterprise improve the service and quality. In the experiment of an actual abnormal situation of wafer cleaning step in a wafer manufacturing process use case, the experimental results are shown in Table 3.

In knowledge base log of the wafer cleaning step, a method proposed in [4] and this paper's method are enforced to the experiments. The method proposed in [4] means that worker follows the experiential rules from the knowledge discovery process to take a problem-solving action. The experimental result shows that precision is 62.8% and recall is 75.4%. This paper's method uses a grey relational utility model to filter out low correlation actions. The candidate actions for an abnormal situation decrease from 32 to 26 actions. The experimental result shows that precision is 68.3% and recall 83.5%. The selection method used in this work seems to be more effective than the method proposed in [4].

In the experiment process and result analysis, this research found that weight value in multicriteria decision analysis tasks and worker feedbacks are the critical factors that influenced the experimental results. For example, the weight and normalization values are indistinguishable. These situations prevent the system from identifying the best solution for recommendation. This study checks and adjusts the weight and normalization values to enhance the distinguishing ability. The worker feedback influences how to decide the QoS items. The QoS item is the critical factor for the grey relational utility model and the multicriteria decision analysis processing.

## 6. Conclusion

In business enterprises, especially the manufacturing industry, various problem situations may occur during the production process. In a problem-solving process, how to determine an action needed to be taken to resolve the situation becomes an important issue. This work proposes a selection approach for optimized problem-solving process to assist workers in taking a reasonable action. A grey relational utility model and a multicriteria decision analysis are used to determine the optimal selection order of candidate actions. The selection order is presented to the worker as an adaptive recommended solution. The worker fetches a reasonable problem-solving action based on the selection order. The contribution of this research is in demonstrating a method which is easy to implement in a problem-solving knowledge recommendation system for selecting a reasonable solution.

A high-tech company's knowledge base log is used for an experiment. In the experiment process and result analysis, this research found that weight value in a multicriteria decision analysis task and worker feedback influenced the experimental results. Future work should pay more attention to designing a worker feedback mechanism for

QoS item identification. The worker feedback would help the proposed selection approach by intelligent tuning and learning to improve the service quality incrementally. The recommended technique is to consider combining with more intelligent methods to enhance the effect.

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