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jart@aleph.cinstrum.unam.mx

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Ke, C. K.

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Research on Optimized Problem-solving Solutions: Selection of the Production Process

C. K. Ke

Department of Information Management
National Taichung University of Science and Technology
Taiwan, Republic of China
ckk@nutc.edu.tw

ABSTRACT

In manufacturing industries, various problems may occur during the production process. The problems are complex and involve the relevant context of working environments. A problem-solving process is often initiated to create a solution and achieve a desired status. In this process, determining how to obtain a solution from the various candidate solutions is an important issue. In such uncertain working environments, context information can provide rich clues for problem-solving decision making. This work uses a selection approach to determine an optimized problem-solving process which will assist workers in choosing reasonable solutions. A context-based utility model explores the problem context information to obtain candidate solution actual utility values; a multi-criteria decision analysis uses the actual utility values to determine the optimal selection order for candidate solutions. The selection order is presented to the worker as an adaptive knowledge recommendation. The worker chooses a reasonable problem-solving solution based on the selection order. This paper uses a high-tech company's knowledge base log as a source of analysis data. The experimental results show that the chosen approach to an optimized problem-solving solution selection is effective. The contribution of this research is a method which is easy to implement in a problem-solving decision support system.

Keywords: Problem-solving, context-based utility model, multi-criteria decision analysis, ELECTRE, adaptive knowledge recommendation.

1. Introduction

Problem-solving is an important process that enables corporations to create competitive advantages. In business enterprises, especially manufacturing, various problems may occur during the production process [1, 2, 3]. Problem can be complex and must be considered in their relevant context in the working environment. A problem-solving process is often initiated to choose a solution which will achieve the desired status. In the process, determining a reasonable solution from among candidate solutions to resolve the problem becomes an important issue. In such uncertain environments, problem features collected by a production system are usually partial or incomplete. Exploring the problem's contextual information and the relevant attributes providing adaptive knowledge support are also key points in effective problem-solving [2].

Quality of Service (QoS) is an important consideration in evaluating the desirable solution for

a specific problem. Worker feedback on an evaluation process can be represented as a utility model reflecting the satisfaction a worker observes from choosing a successful problem-solving solution [4]. The worker provides a utility model [5] before committing to a solution. In a complex problem situation, contextual information in the working environment provides rich clues for problem-solving decision making. Based on contextual information and the relevant attributes of a problem, uncovering hidden knowledge is important. Therefore, contextual information and relevant attribute analysis can quantify all of the influences of the various factors and their relationships to consolidate a utility model. The worker's context-based utility model can be applied to monitoring context information and relevant attributes in order to evaluate the problem-solving solution's QoS. The worker will obtain the expected value of the issue of interest by choosing a solution.

Based on various issues of interest, selecting a reasonable problem-solving solution from a large number of candidate solutions requires a multi-criteria decision analysis. A multi-criteria decision analysis [6] is concerned with structuring and solving decision and planning problems involving multiple criteria. The purpose is to support decision makers facing such problems. Typically, a unique optimal solution does not exist for such problems, so it is necessary to use decision maker preferences to differentiate between solutions. Therefore, a multi-criteria decision analysis is required to formulate the selection order of the various candidate solutions for a specific problem. The formulated selection order helps to optimize a worker's ability to solve a problem.

This paper explores the context of a problem and uses a selection approach for candidate solutions to assist the worker in acquiring a reasonable problem-solving solution. First, each problem-solving solution has a formalization process. A context-based utility model explores the problem's contextual information to obtain the candidate solution actual utility values. Then, a multi-criteria decision analysis uses the actual utility values to determine the optimal selection order of the candidate solutions. Finally, the results are considered as reasonable problem-solving knowledge for the worker. The selected solution from the problem-solving process is for a specific problem. This work explores a high-tech company's knowledge base log for analysis data. The system and use cases have been proposed in previous researches [2, 4]. In this paper, an experiment is conducted to demonstrate that the selection approach is effective. The main contribution of this work is demonstrating an effective solution selecting method which is easy to implement in a problem-solving decision support system.

The remainder of this paper is organized as follows. Section 2 reviews related works on the problem-solving process, a context-based utility model, multi-criteria decision analysis, knowledge management and retrieval. Section 3 introduces a selection approach for an optimized problem-solving process by a context-based utility model and a multi-criteria decision analysis. The experiments and relevant

discussions are shown in Section 4. Finally, Section 5 presents our conclusions of this work and suggestions for future work.

2. Related works

The related literature covers the problem-solving process, the context-based utility model, multi-criteria decision analysis, knowledge management and retrieval.

2.1 Problem-solving process

In manufacturing industries, various problems may occur during the production process. [1, 2, 3]. These problems may include such issues as unstable production systems, poor production performance and low machine utilization. Problem solving is the thought process that resolves various difficulties and obstacles between the current problem and the desired solution [2]. 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 investigated are used for problem-solving and suggest the circulation of knowledge to avoid knowledge inertia [7]. In the problem-solving process, workers determine what solution needs to be used to resolve a problem [8]. Such a solution involves both human wisdom and enterprise knowledge. Workers may observe a problem, collect contextual information from the enterprise knowledge repository, explore possible causes and identify operational conditions, in deciding on an appropriate solution [2].

2.2 Context-based utility model

According to the definitions [9, 10], context is the location of the user, the identities of people and objects that are near the user, and the status of devices with which the user interacts. Context is defined [10] as any information that can characterize the situation of an entity, whether it is a user, place, service, service relevant objects, etc. "Environment" is used to replace "activity" in the context categorization [9]. These context types are used to characterize the situation of a particular

entity. Furthermore, these types of context information can provide the information (who, what, when, where and why) related to a particular entity. This work considers context as any information that can characterize the status of a problem-solving solution.

Quality of Service (QoS) is an important consideration in evaluating a problem-solving solution. Worker feedback on an evaluating process can be represented as a utility model reflecting the satisfaction a worker derives from choosing a solution [4]. The worker provides such a utility model [5] before committing to using a solution. In a complex problem, contextual information in the working environments provides rich clues for problem-solving decision making. Exploring the relevant contextual information to discover hidden knowledge is important. Contextual information analysis can quantify all of the influences of the various factors and their relationships to consolidate the utility model. Therefore, the worker's context-based utility model can be applied to monitoring information in order to evaluate the solution's QoS. The worker will get the expected value of the issue of interest by choosing a solution.

2.3 Multi-criteria decision analysis

Multi-attribute decision making (MADM) and multi-criteria decision making (MCDM) have played important roles in solving multi-dimensional and complicated problems. ELECTRE (Elimination Et Choice Translating Reality) is a family of multi-criteria decision analysis methods [6, 11]. ELECTRE methods include two main phases. The first phase constructs the outranking relationships for a comprehensive comparison of each pair of actions. The second phase elaborates on the recommendations based on the results obtained by an exploitation procedure from the first phase.

The nature of the recommendation depends on the 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

problems. ELECTRE II, ELECTRE III, ELECTRE IV and ELECTRE-SS were designed for solving ranking problems. ELECTRE TRI was designed for solving sorting problems. This research uses a modified version of the ELECTRE method [12] to determine the optimal selection order of candidate solutions. The selection order is presented to the worker as adaptive decision support knowledge.

2.4 Knowledge management and retrieval

Knowledge management is an important issue for business enterprises. A codified strategy for managing knowledge is storing explicit knowledge, especially in document form, in a structure repository [13]. However, with the growing amount of information in organization memories, enterprises face the challenge of helping users find pertinent information in knowledge management systems (KMS). Accordingly, knowledge retrieval is considered a core technique for accessing information in knowledge repositories [14]. Translating user information needs into queries is not easy. Information retrieval (IR) techniques [15] are applied to access codified organizational knowledge [16]. The mechanism combines Information filtering (IF) with a profiling method to model user information needs. It is an effective approach that proactively delivers relevant information to users. The technique has been widely utilized in the areas of information retrieval and recommender systems [17, 18, 19]. This paper explores a high-tech company's knowledge base log [2] for analysis data. Knowledge management and retrieval techniques are used to ensure that the experiment demonstrates the effectiveness of this work.

3. The approach for optimized problem-solving solution selection

In this section, a selection approach using a modified version of the ELECTRE method [12, 20, 21] for candidate problem-solving solutions is described in terms of a context-based utility model and multi-criteria decision analysis. The approach includes the use of problem-solving solution formalization, the context-based utility model for candidate solutions, and the selection order discovery of candidate problem-solving solutions.

3.1 Problem-solving solution formalization

Problem-solving solution formalization is the initial and essential task of the selection approach. This paper refers to a utility-based reputation model [5] to formalize problem-solving solution QoS items in order to reinforce the context-based utility model.

Let $X = \{x_1, x_2, \dots, x_n\}$ denote the set of solutions, and $x \in X$. Let SP denote the set of solutions providers, $b \in SP$ and function $S : SP \rightarrow P(X)$ denote the solutions provided by a solution provider, where P represents the power set operator. Let SW denote the set of workers in the system, and $w \in SW$. Each solution has associated issues of interest, denoted by set I , which workers are interested in monitoring, and $i \in I$. Function IS represents the set of issues of interest for a solution: $IS : X \rightarrow P(I)$. Function $O^w : X \times SP \times I \rightarrow R$ denotes the expectations of worker w for the solutions he undertakes where R denotes the real numbers. Notation $v_{s,i}^{w,b}$ represents the expectations of worker w on issue i concerning the solution s supplied by provider b .

In a problem-solving environment, a potential issue of interest could be the quality of the solution. A worker can develop a context-based utility model which reflects the satisfaction he perceives from choosing a problem-solving solution.

3.2 Context-based utility model for candidate solutions

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

The problem's text description and relevant attributes are assumed to be context information. The contextual information of a specific interest issue i of a problem is used as a QoS item to build a reference case S_j . S_j is set as a desired problem solution with expected utility values for specific interest issues. The candidate solution text description and relevant attributes form a comparative case S_k , $k = \{1, 2, \dots, m\}$. Let T_j be the set of identifying terms extracted from the description of a problem reference case S_j . An

identifying term vector \vec{S}_j is created to represent S_j . The weight of the term t_i in \vec{S}_j is defined by Eq. 1.

$$w(t_i, S_j) = \begin{cases} 1 & \text{if } t_i \in T_j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Let $\text{sim}^T(S_k, S_j)$ denote the similarity value of the two cases, S_k and S_j , based on their context descriptions. The similarity value is derived by computing the cosine value of the identifying term vectors of S_k and S_j . The similarity value $\text{sim}^A(S_k(\text{attrb}_x), S_j(\text{attrb}_x))$ of the two cases, S_k and S_j , are defined in Eq. 2, derived according to their values of attribute x ; $\text{value}(S_k(\text{attrb}_x))$ denotes the transformed value of attribute x of S_k , which is calculated by the discretization process.

$$\begin{aligned} \text{sim}^A(S_k(\text{attrb}_x), S_j(\text{attrb}_x)) \\ = \begin{cases} 1 & \text{if } \text{value}(S_k(\text{attrb}_x)) \text{ equals } \text{value}(S_j(\text{attrb}_x)) \\ 0 & \text{otherwise} \end{cases} \end{aligned} \quad (2)$$

The similarity function [2] used to compute the similarity measured between cases S_k and S_j is defined in Eq. 3. The similarity function is modified by considering the combination of the similarities of text descriptions and attribute values.

$$\delta = w_T \text{sim}^T(S_k, S_j) \quad (3)$$

$$+ \sum_{x=1}^m w_x \text{sim}^A(S_k(\text{attrb}_x), S_j(\text{attrb}_x))$$

where $\text{sim}^T(S_k, S_j)$ is the similarity value derived from the identifying term vectors of S_k and S_j ; $\text{sim}^A(S_k(\text{attrb}_x), S_j(\text{attrb}_x))$ is the similarity value obtained from the values of attribute x ; w_T is the weight factor for the text description, and w_x is the weight given to attribute x . Note that the summation of w_T and all w_x is equal to 1. If $\text{value}\delta$ is closer to 1, it means that S_k and S_j have high correlation. If $\text{value}\delta$ is closer to 0, it means that S_k and S_j have low correlation.

Let $\delta \times v = \xi$; $U_{s,i}^{w,b}(\xi)$ denote the utility that worker w gets by obtaining the actual value $\xi \in R$

on issue i from solution s of provider b . Utilities are normalized and scaled to $[0, 1]$ by Eqs.4 and 5. Based on various issues of interest, selecting the best solution from a large number of solutions requires a multi-criteria decision analysis.

$$U_{s,i}^{*w,b}(\xi) = \frac{U_{s,i}^{w,b}(v) - \min_i U_{s,i}^{w,b}(v)}{\max_i U_{s,i}^{w,b}(v) - \min_i U_{s,i}^{w,b}(v)}. \quad (4)$$

$$U_{s,i}^{*w,b}(\xi) = \frac{\max_i U_{s,i}^{w,b}(v) - U_{s,i}^{w,b}(v)}{\max_i U_{s,i}^{w,b}(v) - \min_i U_{s,i}^{w,b}(v)}. \quad (5)$$

3.3 Determining a selection order of solutions through the modified ELECTRE method

For the second task, this paper uses a modified version of the ELECTRE method to determine the selection order for candidate solutions. If there are m candidate solutions which involve n QoS items, the matrix of expected values can be shown as in Eq. 6. The modified version of the ELECTRE method [12, 20, 21] is used to determine the optimal selection order of a solution. The decision matrix Q is a normalization matrix from the solution normalization process described in Sections 3.1 and 3.2.

$$Q = [Q_{ij}]_{m \times n} = \begin{bmatrix} U_{1,1}^{w,b}(\xi_{1,1}^{w,b}) & \cdots & U_{1,n}^{w,b}(\xi_{1,n}^{w,b}) \\ \vdots & \ddots & \vdots \\ U_{m,1}^{w,b}(\xi_{m,1}^{w,b}) & \cdots & U_{m,n}^{w,b}(\xi_{m,n}^{w,b}) \end{bmatrix}. \quad (6)$$

To calculate the weighted normalization decision matrix, a weight for each QoS item must be set to form a weighted matrix (W). The multiplication of a normalization matrix Q by a weighted matrix W gets the weighted normalization decision matrix V ($V = QW$), as shown in Eq. 7.

$$V = [v_{ij}]_{m \times n} = [Q_{ij}]_{m \times n} \cdot [W_{ij}]_{n \times n}. \quad (7)$$

Compare arbitrarily 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} ($C_{ij} = \{k | v_{ik} \geq v_{jk}\}$) or the discordance set D_{ij} ($D_{ij} = \{k | v_{ik} < v_{jk}\}$). The sum of each component's weight forms a concordance matrix C , as shown in Eq. 8.

$$C = [c_{ij}]_{m \times m}, c_{ij} = \frac{\sum_{k \in C_{ij}} w_k}{\sum_{k=1}^n w_k}. \quad (8)$$

A discordance matrix can be presented as $D = [d_{ij}]$, as shown in Eq. 9.

$$D = [d_{ij}]_{m \times m}, d_{ij} = \frac{\max_{k \in D_{ij}} \{v_{ik} - v_{jk}\}}{\max_{k \in S} \{v_{ik} - v_{jk}\}}. \quad (9)$$

The reverse complementary value is used to modify D to get the modified discordance matrix D' ($D' = 1 - D$). 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 modified discordance matrix to calculate the production and get the modified total matrix A ($A = C \circ D'$, Hadamard product of C and D'). We get the maximum value a_j of each column from the modified total matrix. The purpose is to determine the modified superiority matrix. To make of 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 Eq. 10.

$$E' = [e'_{ij}], \begin{cases} e'_{ij} = 1, & a_{ij} \geq \bar{a} \\ e'_{ij} = 0, & a_{ij} < \bar{a} \end{cases}. \quad (10)$$

Finally, the matrix E' indicates that solution i is better than solution j . We can eliminate solution j and show it as: $A_i \rightarrow A_j$.

The relationships between the QoS items of the candidate solutions as well as the optimal selection

order for all candidate solutions are obtained. The candidate solution is the solution provided by the solution provider. The worker can follow the selection order to get a reasonable problem-solving solution.

4. Experiments and result discussions

This section presents the experimental knowledge base log, experiments, experimental results and relevant discussions of the wafer manufacturing problem case used.

4.1 Experimental knowledge base log

We used a high-tech company's knowledge base log as a source of analysis data [2, 20]. For specific problems, 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 target problems. Information Retrieval (IR) and text mining techniques are used to extract the key terms of relevant documents for a specific problem. The extracted key terms form a problem profile, which is used to model the information needs of the workers. We assume 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. Different workers may find different solutions for the same problem according to their skills and experience. The problem-solving log records historical problem solving instances.

4.2 Experiments

The experiments on the wafer manufacturing problem in a high-tech company [2, 20] are shown in this section. A wafer manufacturing process in the semiconductor foundry is comprised of 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 (de-ionized; ultra-pure) water to remove debris left over from the mounting wax and/or polishing agent. A stable water supply system is used to deliver ultra-pure water for wafer cleaning and is vital in semiconductor manufacturing. The company's

knowledge base log was used as a source of analysis data. This paper used knowledge retrieval techniques to analyze the data and 1,077 relevant data records were obtained from the wafer cleaning step in the wafer manufacturing process. The retrieved data records involve 72 problems from 7 inter-databases, 23 workers, and 238 solutions. In this research, seven domain experts assisted in carrying out the experiments and the evaluation of the results.

4.2.1 Problem-solving solution formalization and context-based utility model

When a worker suffers from a specific problem, various suppliers provide problem-solving solutions. We use problem-solving solution formalization and a context-based utility model to pre-compute a worker's expected list of supplied solution QoS items and facilitate a multi-criteria decision analysis to discover an optimal selection order for candidate solutions.

First, the problem-solving solution formalization process identifies the worker, solution, and solution providers. Then, the worker can decide the indicators (Quality of Service items) of the current problem. We used abnormal problems in wafer cleaning as a simple use case. The worker sets Performance, Error Rate and Duration Time as the QoS items for an abnormal problem. Then the relevant values of the QoS items and solutions are recorded in a table, as shown in Table 1. Solutions A, B and C are used as the candidate solutions to demonstrate the experiments using the proposed method. For example, solution A sets the QoS item, abnormal problem, where the Performance degree is High, Error Rate is Middle, and Duration Time is evaluated as Slow.

	Performance	Error Rate	Duration Time
Solution A	High	Middle	Long
Solution B	Middle	Low	Normal
Solution C	Low	High	Short

Table 1. Property of QoS item and solution for an abnormal problem.

After the problem-solving action formalization process, a context-based utility model is developed to represent worker satisfaction with the solution acquisition. Each QoS item is normalized and scaled to [0, 1]. Then, Table 1 is transformed into Table 2.

	Performance	Error Rate	Duration Time
Solution A	0.40	0.35	0.22
Solution B	0.35	0.38	0.35
Solution C	0.25	0.27	0.43

Table 2. Transformed property of QoS item and solution for an abnormal problem.

4.2.2 The selection order discovery of candidate problem-solving solutions

This work uses a modified version of the ELECTRE method [12, 20, 21] to discover the optimal selection order of candidate solutions for solving a specific problem. The decision matrix Q of expected values can be shown as follows:

$$Q = \begin{bmatrix} 0.40 & 0.35 & 0.22 \\ 0.35 & 0.38 & 0.35 \\ 0.25 & 0.27 & 0.43 \end{bmatrix}.$$

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

$$W = \begin{bmatrix} 0.25 & 0 & 0 \\ 0 & 0.4 & 0 \\ 0 & 0 & 0.35 \end{bmatrix}.$$

The multiplication of a normalization matrix Q and a weighted matrix W produces the weighted normalization decision matrix V ($V = Q \cdot W$) shown as follows:

$$V = Q \cdot W = \begin{bmatrix} 0.40 & 0.35 & 0.22 \\ 0.35 & 0.38 & 0.35 \\ 0.25 & 0.27 & 0.43 \end{bmatrix} \cdot \begin{bmatrix} 0.25 & 0 & 0 \\ 0 & 0.4 & 0 \\ 0 & 0 & 0.35 \end{bmatrix}.$$

$$= \begin{bmatrix} 0.1 & 0.14 & 0.077 \\ 0.0875 & 0.152 & 0.1225 \\ 0.0675 & 0.108 & 0.1505 \end{bmatrix}.$$

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

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

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

$$C_{13} = \frac{\sum_{k \in C_{13}} w_k}{\sum_{k=1}^3 w_k} = \frac{W_1 + W_2}{W_1 + W_2 + W_3} = 0.65,$$

$$C = \begin{bmatrix} - & 0.25 & 0.65 \\ 0.75 & - & 0.65 \\ 0.35 & 0.35 & - \end{bmatrix}.$$

A discordance matrix can be presented as D .

$$\begin{aligned} D_{13} &= \frac{\max_{k \in D_{13}} \{v_{1k} - v_{3k}\}}{\max_{k \in S} \{v_{1k} - v_{3k}\}} \\ &= \frac{\max\{0.0735\}}{\max\{0.0325, 0.032, 0.0735\}} = 1 \end{aligned}$$

$$D = \begin{bmatrix} - & 1 & 1 \\ 0.44 & - & 0.64 \\ 0.74 & 1 & - \end{bmatrix}.$$

A modified discordance matrix can be presented as D' .

$$D' = 1 - D = \begin{bmatrix} - & 0 & 0 \\ 0.56 & - & 0.36 \\ 0.26 & 0 & - \end{bmatrix}.$$

A modified total matrix can be presented as A .

$$A = C \circ D' = \begin{bmatrix} - & 0 & 0 \\ 0.42 & - & 0.234 \\ 0.091 & 0 & - \end{bmatrix}.$$

A modified total superiority matrix is shown as E .

$$E' = \begin{bmatrix} - & 0 & 0 \\ 1 & - & 1 \\ 1 & 0 & - \end{bmatrix}$$

Finally, we get the optimal selection order for all candidate solutions. The experiment results show

that solution B is better than solution A ($e'_{21} = 1$, $A_2 \rightarrow A_1$); solution B is better than solution C ($e'_{23} = 1$, $A_2 \rightarrow A_3$), and solution C is better than solution A ($e'_{31} = 1$, $A_3 \rightarrow A_1$). The worker can follow the optimal selection order to get a reasonable solution.

4.3 Experiment results

An adapted system framework of context-based knowledge support has been proposed in [2, 20], as shown in Figure 1.

The proposed framework [2] uses rule inference to infer possible situation features based on context information. Association rule mining and case-based reasoning are employed to identify similar situations. Moreover, the framework employs information retrieval techniques to extract context-based situation profiles of model worker information needs when handling problem situations in certain contexts. Knowledge support can thus be facilitated by providing workers with situation-relevant information based on the profiles.

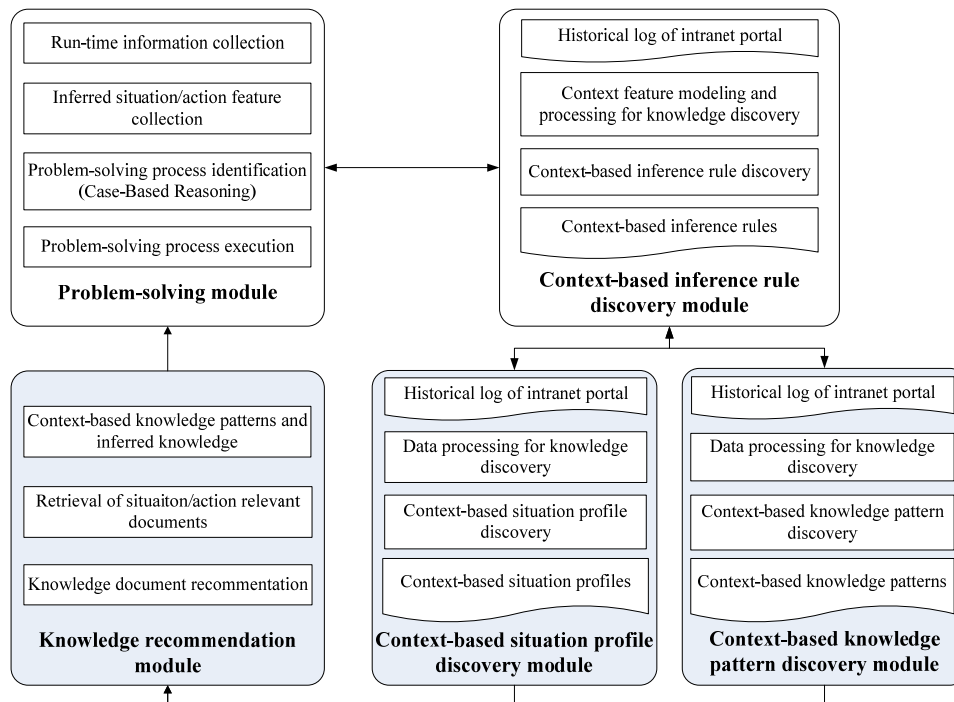


Figure 1. Adapted system framework of context-based knowledge support [2].

This work used an actual abnormal problem in a wafer cleaning task in the wafer manufacturing process 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 service and quality. The experiment results from an actual abnormal problem in a wafer cleaning task in a wafer manufacturing process use case are shown in Table 3. The selection method and items used in this paper are geared towards the experiment. The experiment results from this paper's method show that Precision is 67.15% (92/137) and Recall 80.7% (92/114). The experiment results of the method proposed in [2] show that Precision is 64.96% (89/137) and Recall is 78.07% (89/114). The selection method used in this work seems to be more effective than the method proposed in [2].

Method \ Item	Precision	Recall
The method in [2]	64.96% (89/137)	78.07% (89/114)
This paper's method	67.15% (92/137)	80.7% (92/114)

Table 3. The experimental results of abnormal problem of wafer cleaning task.

4.4 Discussions

In the experiment process and results analysis, it was found that problem solution actual utility values from the context-based utility model and the weight value in multi-criteria decision analysis tasks are the critical factors influencing experiment results. For example, the normalization utility values and weight values are indistinguishable. This prevents the method from identifying the reasonable solution for the problem-solving knowledge recommendations. This study checks and adjusts the normalization utility values and

weight values to enhance the distinguishing ability. Worker feedback influences how the QoS criterion is decided. The QoS criterion is the critical factor for the context-based utility model and the multi-criteria decision analysis processing.

5. Conclusion

In a problem-solving process, determining a reasonable solution from the various candidate solutions to resolve a problem is an important issue. In such uncertain environments, context information provides rich clues for problem-solving decision making. Therefore, this research used a selection approach for the optimized problem-solving process to assist workers in choosing reasonable solutions. A context-based utility model explored the problem's contextual information to obtain the candidate solution actual utility values. Then, a multi-criteria decision analysis employed the actual utility values to determine the optimal selection order of candidate solutions. The selection order is presented to the worker as an adaptive knowledge recommendation. The worker arrives at a reasonable problem-solving solution based on the selection knowledge. The contribution of this work is in demonstrating a method which is easy to implement in a problem-solving decision support system for selecting a reasonable solution.

A high-tech company's knowledge base log was used for the experiment. In the experiment's process and result analysis, it was found that the problem solution actual utility values from the context-based utility model and the weight values in a multi-criteria decision analysis task influenced the experimental results. Future work should pay more attention to designing a worker feedback mechanism for QoS criteria identification. Worker feedback would help the selection approach by intelligent tuning and learning and improve the service quality incrementally. The recommended technique is to consider combining this with more intelligent methods, for example, collaborative filtering techniques, to enhance the problem solving knowledge effect.

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