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A fuzzy collaborative assessment approach for Knowledge Grid

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Abstract

The assessment of Knowledge Grid is important to its design, development and maintenance. The difference between Knowledge Grid and website in structure and content determines that the current website assessment approaches are not suitable for assessing the Knowledge Grid. This paper proposes a fuzzy collaborative assessment approach combining the objective and subjective assessment strategies. The objective assessment strategy integrates the criteria used in website assessment and those related to knowledge organization and management. The subjective assessment strategy assesses the quality of knowledge service through the cooperation between experts and agents. The proposed approach also provides the optimum solution for improving the performance of the Knowledge Grid based on the assessment result and constraints. We demonstrate the proposed approach through a real application.

Keywords: Assessment; Fuzzy sets; Knowledge Grid; Knowledge space; Optimization

1. Introduction

Knowledge Grid is a mechanism that shares and manages the distributed heterogeneous resources spread across the Internet in a uniform way [15]. The Knowledge Grid mainly includes two parts: (1) a resource space model RSM that uniformly organizes information, knowledge, and service resources in normal forms, and (2) an operable knowledge browser that enables users to conveniently locate, browse and manage resources by using an easy-to-use interface. The Knowledge Grid enables both the knowledge browser and agents to access and manage the well-organized knowledge resources in way of a *single semantic image* [16].

The assessment of Knowledge Grid can help developers know the weaknesses of the Knowledge Grid so as to take effective improvement actions. It can also enable users or agents to select a suitable Knowledge Grid to solve problems. However, the difference between Knowledge Grid and website in structure and content determines that the current website assessment approaches are not suitable for assessing the Knowledge Grid.

The current approaches and tools for website assessment are only suitable for testing the technical criteria such as the response time and the browser compatibility of the website. For example, the assessment approach based on the analysis of the online Web click streams [3], the approach to validate the navigational structure of a website [2], the assessment of Web search services [9], the analysis of the impact factors of the performance and scalability of a database-driven website [12], and the method for assessing documents in SGML-format [8].

The performance of Knowledge Grid concerns the objective and subjective criteria. The objective criteria

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measure the technical performance of the Knowledge Grid, while the subjective criteria reflect the preferences of the experts and users. The subjective assessment is easily influenced by the bias, while the objective assessment ignores the users' preferences [4,14]. The separate use of the two approaches could not achieve a satisfied assessment result.

An ideal assessment approach should consider the social, the cultural, the economic and the technical factors. In the proposed approach, the objective and subjective assessment criteria are established by taking into account the experiences of the Knowledge Grid developers, the software assessment standards, and the suggestions of users [10,13]. The objective assessment criteria consist of two parts: the criteria commonly used in website assessment and those related to knowledge organization and management. We use the available network testing software to obtain the former and develop a system to test the latter. The subjective assessment about the quality of knowledge service carries out through the cooperation between experts and agents [1]. The overall performance assessment of the Knowledge Grid is determined by the membership functions of the integrated assessment value [6,11]. Finally, we propose an optimum solution to improve the performance of Knowledge Grid.

2. Structure of Knowledge Grid and framework of the proposed approach

The relationship between the knowledge space and the knowledge-using mechanism of the Knowledge Grid is shown in Fig. 1. Users can access the knowledge space through the knowledge browser or agents. The knowledge space is a multi-dimensional space [15]. A three-dimensional knowledge space has been suggested as: $KS = (Location, Level, Category)$, where the *Location* dimension describes the storage location of the knowledge resources, the *Level* dimension identifies the knowledge level, and the *Category* dimension reflects the classification. The constitution of the knowledge space is shown in Fig. 2, where each point can be either a sub-space or a semantic link network consisting of semantic links and knowledge nodes. A semantic link network can be either completely connective or consists of fragments (called *semantic fragments*). The closely interrelated nodes constitute the *semantic clique*. The maximum flow/minimum cut theorem can be used to efficiently identify the semantic clique in each fragment [7].

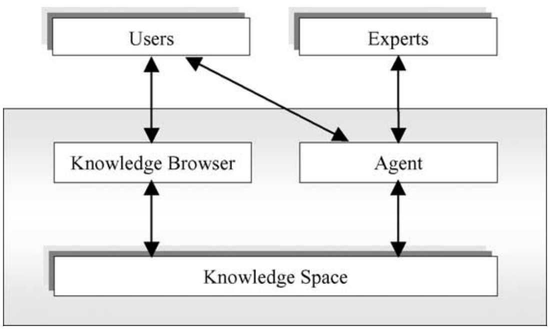

Fig. 1. Knowledge space and knowledge-using mechanism.

As described in Fig. 3, the framework of the proposed approach consists of the following steps: (1) generate the objective and subjective assessment criteria; (2) objectively assess the Knowledge Grid; (3) subjectively assess the Knowledge Grid; (4) integrate the objective and subjective assessment result according to the assessment value and the progressive weight distribution function; (5) overall performance assessment; and (6) propose the optimum improvement solution.

3. Approach

3.1. Generate the assessment criteria

The process of generating the objective and subjective assessment criteria is shown in Fig. 4. The Knowledge Grid developers propose the initial criterion set, and experts are invited to vote for the criteria online. The initial criteria will be filtered according to the weighted average preferences and a predefined threshold. The new criterion set consists of the reserved criteria and those suggested by the experts. Advice and suggestions of the experts make the assessment criteria more complete and reasonable. After generating the new assessment criterion set, the experts are invited to revote and rank the criteria in a descending order. As a result, the criteria with high ranks construct the final assessment criterion set.

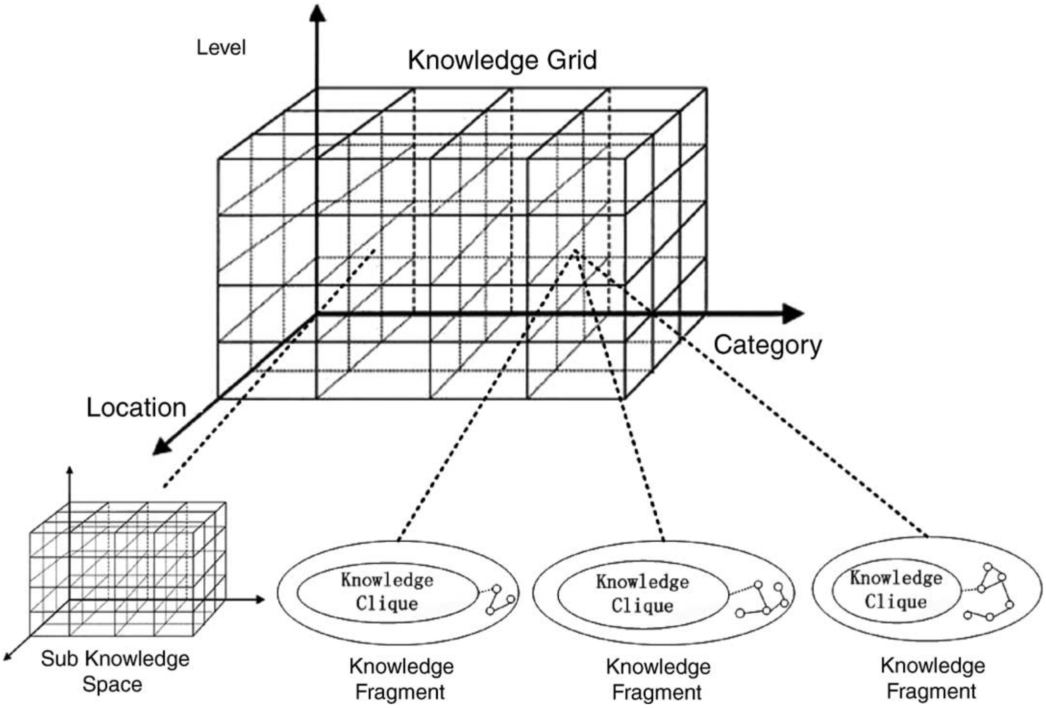

Fig. 2. The constitution of the knowledge space.

3.2. Objectively assess the Knowledge Grid

The objective Knowledge Grid assessment criteria concern the knowledge organization, knowledge management, and technical aspects. The objective criteria related to knowledge organization include: the *knowledge coverage degree*, *ratio of redundant semantic links*, and *ratio of inconsistent semantic links*. The

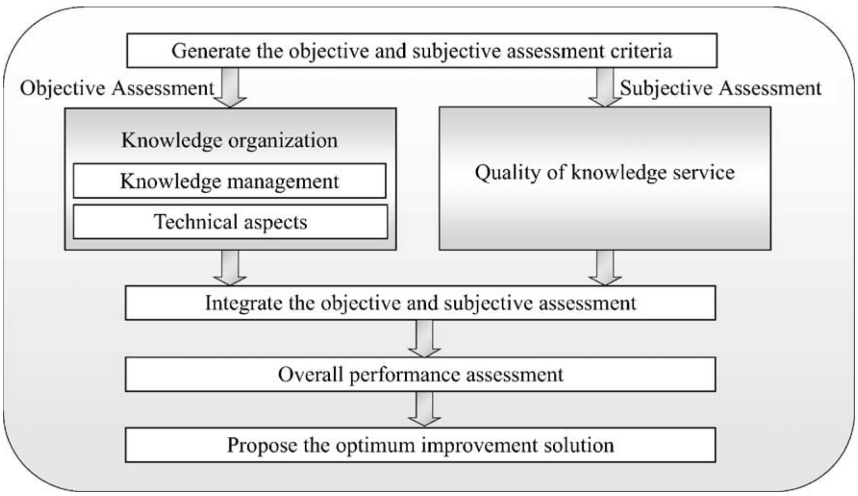

Fig. 3. The framework of the fuzzy collaborative assessment approach for Knowledge Grid.

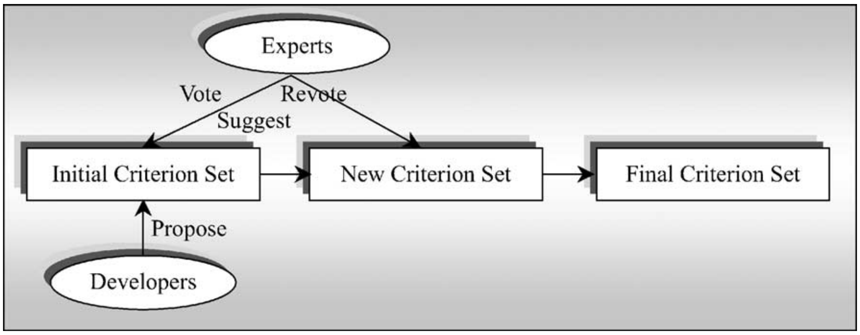

Fig. 4. Two-stage online voting to generate the assessment criteria.

knowledge coverage degree of the Knowledge Grid reflects the connectivity of the stored knowledge. It can be computed as follows:

$$K_{\mathrm{C}} = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{m}\sum_{j=1}^{p}\frac{N_{\mathrm{C}j}}{N_{\mathrm{F}j}}, \tag{1}$$

where $(1/m)\sum_{j=1}^{p} N_{\mathrm{C}j}/N_{\mathrm{F}j}$ reflects the *average knowledge coverage degree* of network i and satisfies $N_{\mathrm{C}j}/N_{\mathrm{F}j} \geq \alpha$, $\alpha \in [0, 1]$ the knowledge density threshold, $N_{\mathrm{C}j}$ the number of knowledge nodes in clique j of network i, $N_{\mathrm{F}j}$ the number of knowledge nodes in fragment j of network i, $p \in Z^{+}$, and $p \leq m$ (the number of fragments in network i), and n the number of semantic link networks in the Knowledge Grid.

The *redundant semantic link* means such a link that the deletion of which does not affect the semantics of the semantic network. The ratio of the redundant link number to the total link number is taken as one of the objective criteria. The *inconsistent semantic link* means that two or more semantic links contradict each other. The big ratio of the inconsistent link number to the total links will form negative impact on the performance of the Knowledge Grid.

The criteria related to the knowledge management are assessed as follows: the *consistency* reflects the content correctness of the Knowledge Grid and can be computed by the ratio of the number of consistent knowledge nodes to the total number. The *conciseness* is assessed according to the ratio of the number of non-redundant knowledge nodes to the total number. The *active nodes* are the nodes that are activated in a certain frequency and used by the users or agents. The bigger the ratio of the number of active nodes to the total number, the better the performance of the Knowledge Grid is. The *up-to-date degree* is the ratio of the newly updated knowledge nodes to the total knowledge nodes. The *knowledge category coverage degree* reflects the ratio of categories (i.e., disciplines) in the Knowledge Grid to the available knowledge categories (the digital library classification can be used as the category standard). The *knowledge level coverage degree* reflects the ratio of levels in the Knowledge Grid to the standard knowledge level classification (four knowledge levels are suggested in [15]). The *satisfaction of users' interests* reflects the average accordance of actual knowledge nodes distribution to the distribution of users' interests, which can be computed as follows:

$$K_{\mathrm{S}} = \frac{1}{n}\sum_{i=1}^{n}(1 - |\alpha_{d_i} - \beta_{d_i}|), \tag{2}$$

where $|\alpha_{d_i} - \beta_{d_i}|$ is the absolute value of the differences between α_{d_i} (the ratio of users who are interested in category d_i to the total users) and β_{d_i} (the ratio of the number of knowledge nodes about category d_i to the total number of knowledge nodes), and n the total number of the categories.

The technical assessment criteria include: (1) the *response time*, i.e., the duration from inputting a query to obtaining the answer; and, (2) the *across platform understandability*, i.e., whether the representation and using of knowledge is platform irrelevant or not.

3.3. Subjectively assess the Knowledge Grid

We use $V_{1\times n} = (p_{ij})^{\mathrm{T}}(j = 1, \ldots, n)$ to denote the preference vector of expert i for the n subjective criteria. The weighted average and variance of the preferences are considered when computing the subjective assessment value.

Let $P = (P_{1j}, \dots, P_{mj})^{\mathrm{T}}$ be the subjective assessment vector of m experts for criterion j, $W = (W_1, \dots, W_m)^{\mathrm{T}}$ be the weight vector. The overall subjective assessment for criterion j can be computed by

$$\mu_j = \alpha \times \bar{X}_j - \beta \times S_n^2 = \alpha \times \sum_{i=1}^{m} P_{ij} \times W_i - \beta \times \frac{1}{m-1} \sum_{i=1}^{m} (P_{ij} - \bar{X}_j)^2, \quad (3)$$

where $\bar{X}_j = \sum_{i=1}^{m} P_{ij} \times W_i$ is the weighted average, $S_n^2 = (1/(m-1)) \sum_{i=1}^{m} (P_{ij} - \bar{X}_j)^2$ the variance, and $\alpha \in [0, 1]$, $\beta \in [0, 1]$ (i.e., the weights of the two) satisfy $\alpha + \beta = 1$.

3.4. Integrate the objective and subjective assessment

Let $C = \{c_1, c_2, \dots, c_n\}$ be the final assessment criterion set, the objective and subjective assessment value construct a K-measurable function $h(c_i)$, and the progressive weight distribution function $HW(c_i) = \sum_{k=1}^{i} w_k$ is 0-fuzzy metric. By using fuzzy integral approach, the overall assessment of the Knowledge Grid can be computed by

$$\mu = \bigvee_{i=1}^{n} [h(c_i) \wedge HW(c_i)], \quad (4)$$

where "$\wedge$" means by minimum operation, and "$\vee$" means by maximum operation.

3.5. Overall performance assessment for the Knowledge Grid

According to the experts' suggestions, four fuzzy grades: E (*Excellent*), G (*Good*), F (*Fair*), P (*Poor*), and the corresponding membership functions are established and shown in Fig. 5. The membership functions of the integrated assessment value indicate the overall performance of the Knowledge Grid:

$$\mu_{\mathrm{E}}(u) = \begin{cases} 0, & 0 \le u \le 0.8, \\ \dfrac{u - 0.8}{0.1}, & 0.8 < u \le 0.9, \\ 1, & 0.9 < u \le 1, \end{cases} \quad (5)$$

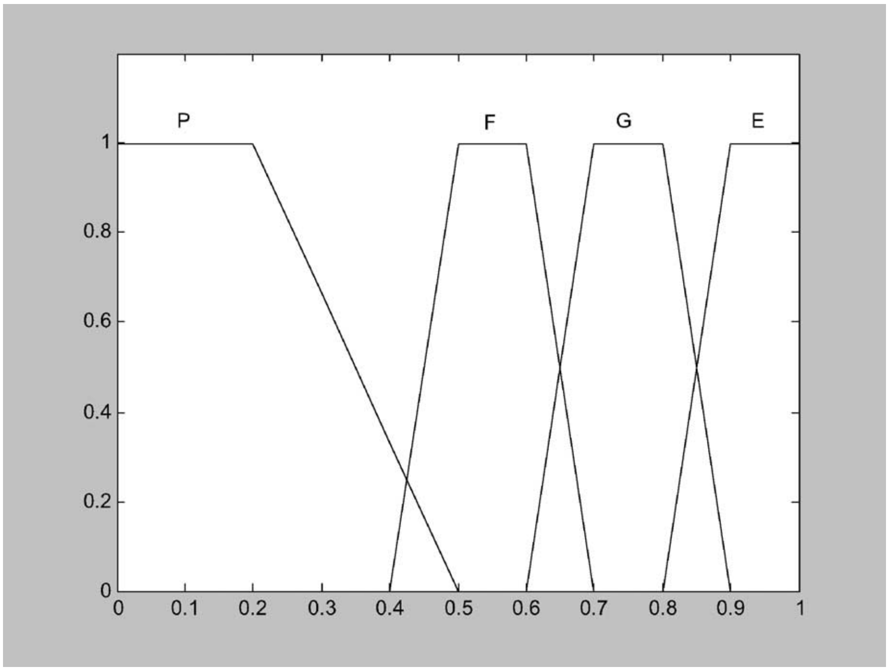

Fig. 5. Fuzzy membership functions.

$$\mu_G(u) = \begin{cases} 0, & 0 \leq u \leq 0.6, \\ \dfrac{u-0.6}{0.1}, & 0.6 < u \leq 0.7, \\ 1, & 0.7 < u \leq 0.8, \\ \dfrac{0.9-u}{0.1}, & 0.8 < u \leq 0.9, \\ 0, & 0.9 < u \leq 1, \end{cases} \tag{6}$$

$$\mu_F(u) = \begin{cases} 0, & 0 \leq u \leq 0.4, \\ \dfrac{u-0.4}{0.1}, & 0.4 < u \leq 0.5, \\ 1, & 0.5 < u \leq 0.6, \\ \dfrac{0.7-u}{0.1}, & 0.6 < u \leq 0.7, \\ 0, & 0.7 < u \leq 1, \end{cases} \tag{7}$$

$$\mu_P(u) = \begin{cases} 1, & 0 \leq u \leq 0.2, \\ \dfrac{0.5-u}{0.3}, & 0.2 < u \leq 0.5, \\ 0, & 0.5 < u \leq 1. \end{cases} \tag{8}$$

3.6. *Propose the optimum improvement solution*

Let T be the total investment, δ_i $(i = 1, \dots, n)$ and T_i be the extent and cost of criterion c_i to achieve the best performance, w_i be the weight, and x_i be the actual investment for c_i. The linear programming model for the optimum improvement solution is as follows:

$$\text{Object function :} \quad \text{Max}\, z = \sum_{i=1}^{n} \frac{\delta_i \times w_i}{T_i} \times x_i, \tag{9}$$

Constraint conditions:

$$x_1 + x_2 + \cdots + x_n \leq T, \quad x_1 \leq T_1, \dots, x_n \leq T_n,$$
$$x_1, x_2, \dots, x_n \geq 0. \tag{10}$$

The optimum solution $X = (x_1, \dots, x_n)^T$ is one of the feasible solutions, which makes the best performance of the Knowledge Grid. Fig. 6 further illustrates the parameters in formula (9), where T_i and T_j are the total cost needed for criterion c_i and c_j to achieve the best performance, and the dark rectangles represent the actual improvement under the actual investment x_i and x_j.

4. Application

This section demonstrates the proposed approach step by step through assessing our developed Knowledge Grid prototype.

4.1. *Generate the assessment criteria*

Fig. 7 shows the process and user's operation interfaces for generating the final criteria. The two-round of voting generates the final objective criteria:

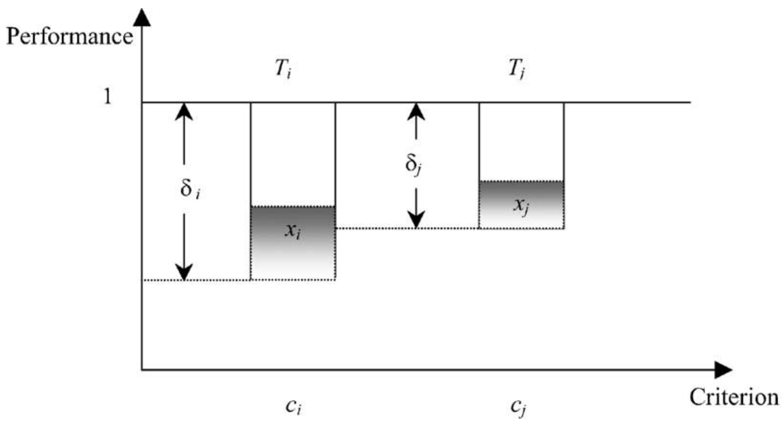

Fig. 6. Graphical representation of the parameters in formula (9).

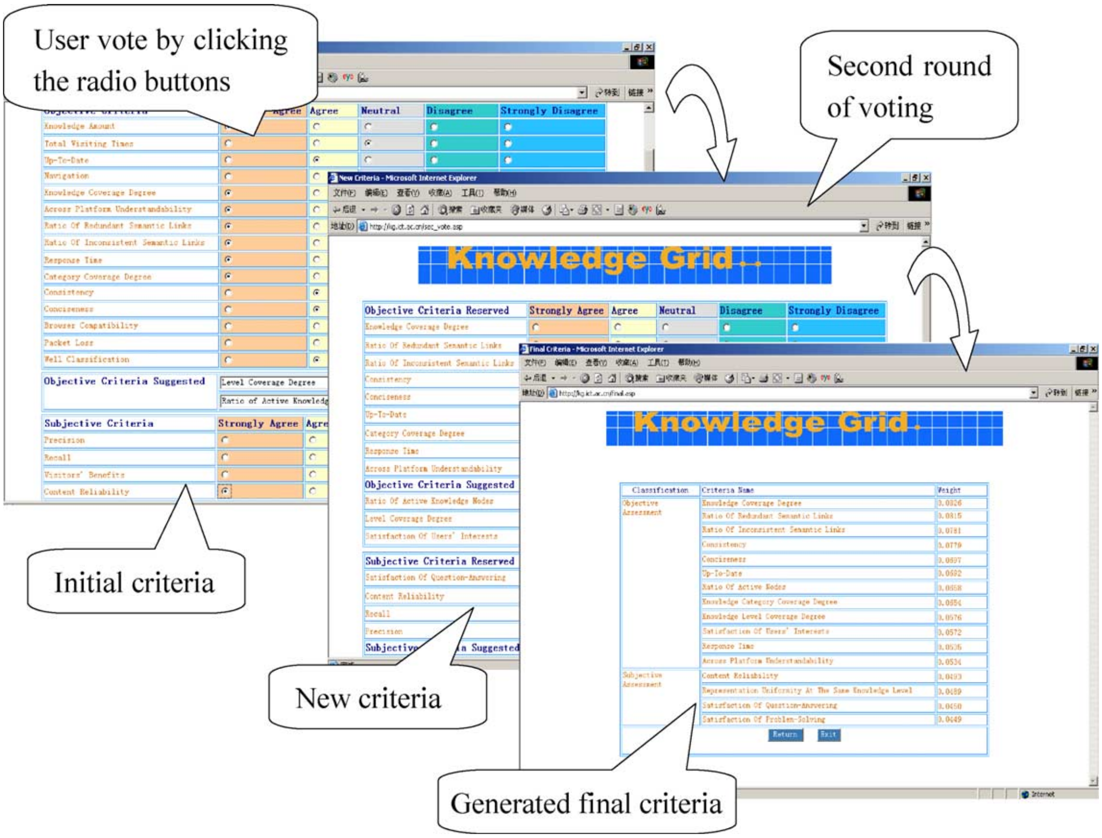

Fig. 7. Process and user's operation interfaces for generating the final criteria.

$$C = \{knowledge\ coverage\ degree,\ ratio\ of\ redundant\ semantic\ links,\ ratio\ of\ inconsistent\ semantic\ links,\ consistency,\ conciseness,\ up\text{-}to\text{-}date,\ ratio\ of\ active\ nodes,\ knowledge\ category\ coverage\ degree,\ knowledge\ level\ coverage\ degree,\ satisfaction\ of\ users'\ interests,\ response\ time,\ across\ platform\ understandability\}.$$

The subjective criteria are described in Table 1. The normalized weight vector for the objective and subjective criteria is

$$W = (0.0826, 0.0815, 0.0781, 0.0779, 0.0697, 0.0692, 0.0658, 0.0654, 0.0576, 0.0572, 0.0535, 0.0534, 0.0493, 0.0489, 0.0450, 0.0449)^{\mathrm{T}}.$$

Table 1
Description of the final subjective assessment criteria

Criteria	Description
Content reliability	The extent to which the knowledge source is reliable
Representation uniformity at the same knowledge level	The extent to which the knowledge representation styles unify at the same knowledge level
Satisfaction of question-answering	The extent to which experts are satisfied with the returned answers to the proposed questions
Satisfaction of problem-solving	The extent to which experts are satisfied with the returned solutions to solve the problems

Table 2
Objective assessment results for the Knowledge Grid

Classification	Criteria	Testing result		Grade	Assessment value
Knowledge organization	Knowledge coverage degree	0.7		Good	0.7
	Ratio of redundant semantic links	0		Excellent	1
	Ratio of inconsistent semantic links	0		Excellent	1
Knowledge management	Consistency	0.826		Good	0.826
	Conciseness	0.757		Good	0.757
	Up-to-date	0.842		Good	0.842
	Ratio of active nodes	0.602		Fair	0.602
	Knowledge category coverage degree	0.325		Poor	0.325
	Knowledge level coverage degree	1		Excellent	1
	Satisfaction of users' interests	0.753		Good	0.753
Technical aspects	Response time	Modem 14.4 K	62.81 s	Poor	0.2
		Modem 28.8 K	32.41 s		
		Modem 56 K	17.47 s		
		ISDN 128 K	8.84 s		
		T1 1.44 M	2.61 s		
	Across platform understandability	XML-based, text-based, not RDF-based		Fair	0.5

4.2. Assess the performance of the Knowledge Grid

The testing result of the objective assessment is shown in Table 2. To perform the subjective assessment, we randomly select 50 samples from the expert assessment repository satisfying: (1) each assessment has an equal probability to be chosen as a sample; and (2) the value of each selected sample is independent. According to formula (3), the subjective assessment vector is computed and denoted as $A = (0.537, 0.623, 0.654, 0.579)^{\mathrm{T}}$.

The assessment vector incorporating the objective and subjective criteria can be denoted as $H = (0.7, 1, 1, 0.826, 0.757, 0.842, 0.602, 0.325, 1, 0.753, 0.2, 0.5, 0.537, 0.623, 0.654, 0.579)^{\mathrm{T}}$. The weight and the progressive weight distribution function of the criteria are constructed in Table 3. According to formula (4), the final assessment value can be computed as:

Table 3
The weight and progressive weight distribution function

Criteria (c_i)	Weight (w_i)	Progressive weight distribution function HW (w_i)
Knowledge coverage degree	0.0826	0.0826
Ratio of redundant semantic links	0.0815	0.1641
Ratio of inconsistent semantic links	0.0781	0.2422
Consistency	0.0779	0.3201
Conciseness	0.0697	0.3898
Up-to-date	0.0692	0.459
Ratio of active nodes	0.0658	0.5248
Knowledge category coverage degree	0.0654	0.5902
Knowledge level coverage degree	0.0576	0.6478
Satisfaction of users' interests	0.0572	0.705
Response time	0.0535	0.7585
Across platform understandability	0.0534	0.8119
Content reliability	0.0493	0.8612
Representation uniformity at the same knowledge level	0.0489	0.9101
Satisfaction of question-answering	0.0450	0.9551
Satisfaction of problem-solving	0.0449	1

Table 4
Related data in the optimum linear programming model

Criteria (c_i)	Item	Weight w_i	Assessment value a_i	Extent to improve δ_i	Cost needed T_i ($)	Optimum investment x_i ($)	Weighted performance improvement $\delta_i \times w_i \times x_i/T_i$
Objective assessment	Knowledge coverage degree	0.0826	0.7	0.3	5000	3495	0.0173
	Ratio of redundant semantic links	0.0815	1	0	1000	0	0
	Ratio of inconsistent semantic links	0.0781	1	0	1000	0	0
	Consistency	0.0779	0.826	0.174	3000	2180.3	0.0099
	Conciseness	0.0697	0.757	0.243	4000	1585	0.0067
	Up-to-date	0.0692	0.842	0.158	5000	0	0
	Ratio of active nodes	0.0658	0.602	0.398	3000	3000	0.0262
	Knowledge category coverage degree	0.0654	0.325	0.675	8000	5217.2	0.0288
	Knowledge level coverage degree	0.0576	1	0	1000	0	0
	Satisfaction of users' interests	0.0572	0.753	0.247	6000	0	0
	Response time	0.0535	0.2	0.8	7500	4522.5	0.0258
	Across platform understandability	0.0534	0.5	0.5	9000	0	0
Subjective assessment	Content reliability	0.0493	0.537	0.463	7000	0	0
	Representation uniformity at the same level	0.0489	0.623	0.377	8000	0	0
	Satisfaction of question-answering	0.0450	0.654	0.346	6000	0	0
	Satisfaction of problem-solving	0.0449	0.579	0.421	10000	0	0

$\mu = (0.0826 \wedge 0.7) \vee (0.1641 \wedge 1) \vee (0.2422 \wedge 1) \vee (0.3201 \wedge 0.826) \vee (0.3898 \wedge 0.757) \vee (0.459 \wedge 0.842) \vee (0.5248 \wedge 0.602) \vee (0.5902 \wedge 0.325) \vee (0.6478 \wedge 1) \vee (0.705 \wedge 0.753) \vee (0.7585 \wedge 0.2) \vee (0.8119 \wedge 0.5) \vee (0.8612 \wedge 0.537) \vee (0.9101 \wedge 0.623) \vee (0.9551 \wedge 0.654) \vee (1 \wedge 0.579) = 0.705.$

4.3. Overall assessment and the optimum investment solution

Based on the membership functions (5), (6), (7) and (8), the membership degree of the integrated assessment value is computed as $\mu_{\mathrm{E}}(0.705) = 0$, $\mu_{\mathrm{G}}(0.705) = 1$, $\mu_{\mathrm{F}}(0.705) = 0$, $\mu_{\mathrm{P}}(0.705) = 0$. So the performance of the Knowledge Grid most probably belongs to "*Good*" category. The linear programming model of the optimum investment solution is as follows:

$$\text{Object function:} \quad \mathrm{Max}\, z = \sum_{i=1}^{16} \frac{\delta_i \times w_i}{T_i} \times x_i, \tag{11}$$

Constraint conditions:

$$\begin{aligned} &x_1 + x_2 + \cdots + x_{16} \le 20\,000, \\ &x_1 \le 5000, \ldots, x_{16} \le 10\,000, \\ &x_1, x_2, \ldots, x_{16} \ge 0. \end{aligned} \tag{12}$$

The optimum solution $X = (x_1, \ldots, x_{16})^{\mathrm{T}}$ suggests the optimum performance improvement. The extent of criterion c_i to be improved is denoted as $\delta_i = 1 - a_i$ (the assessment value of c_i, $i = 1, \ldots, n$). The weighted performance improvement of c_i is computed by $\delta_i \times w_i \times x_i/T_i$. The total investment $20,000 can obtain 11.47% optimal performance improvement. The data used in the optimum linear programming model is shown in Table 4.

The contrasts between the assessment and the improvement on each criterion under the optimum solution are shown in Fig. 8, where the white portions of the bars represent the assessment, and the black portions of the bars represent the actual improvement on each criterion.

The performance improvement depends on the assessment result, the optimum improvement solution, and the actual investment. Fig. 9 compares the

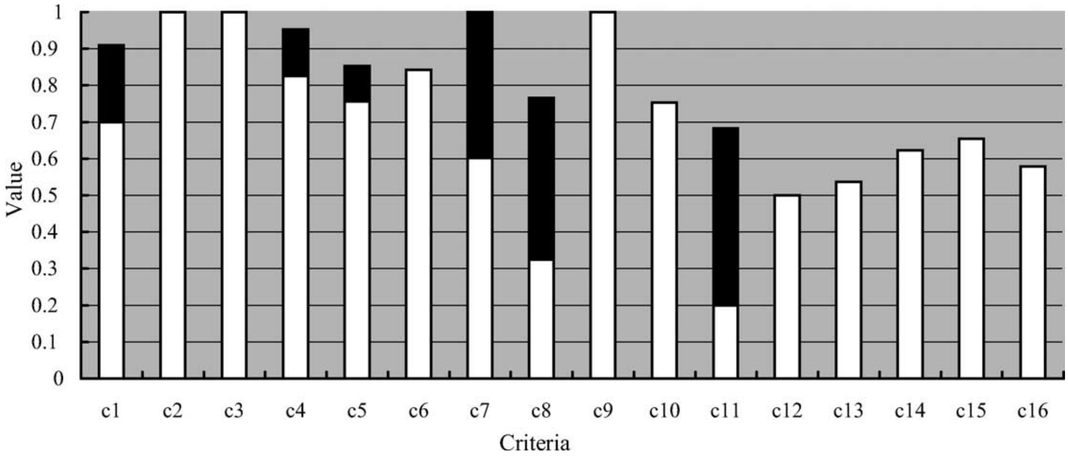

Fig. 8. Comparison between the assessment result and the improvement on each criterion.

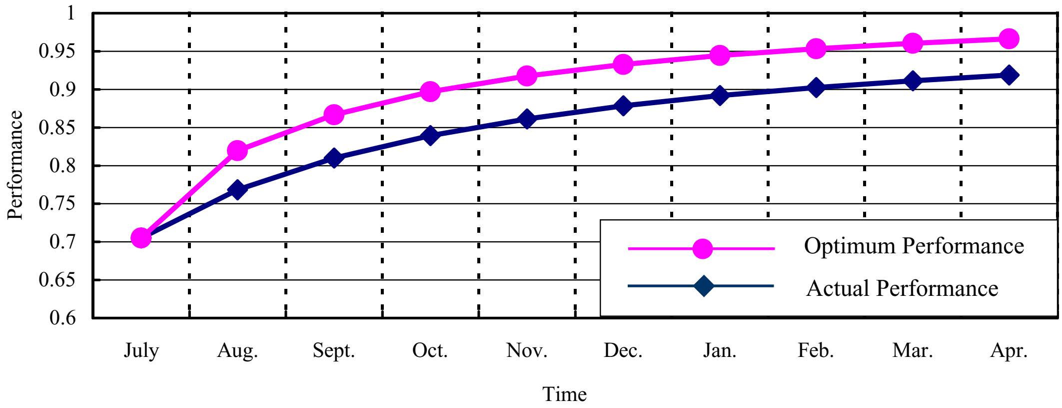

Fig. 9. Comparison between the performance under optimum solutions and the performance under actual investment solutions.

performance under the optimum solutions and the performance under actual investment. The curve above shows different performance under the optimum solutions at different time, while the curve below indicates the actual performance under the actual investment solutions at different time.

5. Conclusions

Human and the artificial support environment are two inseparable parts of an entire interconnection environment. Subjective assessment reflects human's satisfactory degree on the service provided by the artificial support environment. The combination of the subjective and objective assessment strategies can better reflect the performance of the artificial environment. This paper analyses the characteristics and structure of Knowledge Grid and proposes the approach for collaboratively assessing the performance of Knowledge Grid by combining the objective and subjective assessment strategies. The approach makes use of the fuzzy and operation approaches to realize collaborative assessment and plan the improvement. Applications show that the approach can help the developers to improve the system performance according to the assessment result and the financial constraints. The approach can also assist the users and agents to select a suitable Knowledge Grid to obtain knowledge services satisfying their requirements. Ongoing work is to make use of the dynamic assessment approach and the genetic algorithm to estimate dynamic performance [5,17].

Acknowledgements

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