Knowledge-based System Acquisition for Competitiveness Predictions in Decision Making

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Abstract—The competitiveness knowledge can help making national strategies and decisions. However, the computerization of competitiveness knowledge is hard to be fulfilled. The reason includes competitiveness properties cover a broad range of criteria and their relationship is not well structured. This research proposes a knowledge-based system for competitiveness, taking advantages of the object-oriented technique to integrate preference information and mathematical measures. Furthermore, extending the derived knowledge beyond the original understanding is designed to provide the competitiveness features, utilities, and patterns.

Keywords: competitiveness, knowledge-based system, object-oriented design.

I. INTRODUCTION

A knowledge-based system of competitiveness can enhance national management, strategy and decision [1, 2, 3, 4, 5, 6]. Basically, the system has three parts, i.e. information input, evaluation process, and knowledge output [1, 3, 4, 6]. The effect of knowledge depends on evaluation under partially known and unknown situations. The evaluation for the known issues should get confession from stakeholders and make the unknown issues sensible to users. Currently, there are three potential problems for the knowledge-based systems. First is the difficulty in knowledge acquisition. Second is the knowledge evaluation. Not enough in knowledge often challenges decision making. Before clear knowledge is available, evaluation can hardly proceed. Third is that knowledge does not have a fixed shape thus making the computerization hard to design. This research aims to design a knowledge-based system for competitiveness which can discover knowledge by identifying implications and providing mathematical measures for implications, which are expressed as rigid and reliable rules. The rules and extensions are named as knowledge in this research.

With the aforementioned problems, the key challenges of constructing the knowledge-based system for competitiveness [7] are summarized as the following:

- Implications should be proposed for identifying the knowledge competitiveness. World Competitiveness Yearbook (WCY) assumes criteria comprise competitiveness [11]. However, its methodology does not provide implications to help understanding competitiveness.
- Composite knowledge of WCY should be constructed. The elements of knowledge such as implications and measures might not make enough sense to users. The composite technique can reveal knowledge when facing unclear or unknown.

To overcome the above challenges, an object-oriented technique [8, 9, 10, 11] is used to design a knowledge-based system for competitiveness, called KBC, shown in Fig. 1. The process of KBC has three stages. Stage I acquires preference information. Stage II generates implications with measures of certainty, coverage, and accuracy rates which are defined in Section 2. Stage III formulates composite knowledge from the derived objects. Technically, the competitiveness knowledge by implications and reliability are constructed with the object-oriented technique to computerize dominance-based rough set approach (DRSA). As a whole, users can see a knowledge-based system built above the logics and mathematical operations. The expected results include competitiveness features, utilities, and patterns.

This paper has two parts. The first is about the object-oriented design for DRSA. The second is about the expected results. The remainder of this paper is organized as follows: Section 2 reviews WCY, DRSA and OOD, Section 3 presents the propositions for the KBC prototype, Section 4 addresses the expected results, Section 5 presents discussions on KBC, and finally concluding remarks are presented to close the paper.

II. LITERATURE REVIEW

This section contains three parts, first is about WCY dataset, second is about DRSA, and third is about trans-
forming DRSA properties to knowledge.

A. WCY

IMD annually publishes WCY, a well-known report which ranks and analyzes how a nation’s environment can create and develop sustainable enterprises [4]. WCY is a product cooperating with fifty-four partner institutes worldwide. Its ranking considers broad perspectives by gathering the latest and most relevant data on the subject and by analyzing the policy consequence. The dataset includes 59 nations, 4 consolidated factors and 20 criteria in Table 1. All criteria are homogeneous in scales.

Table 1. Four factors and twenty criteria of WCY 2013

<table>
<thead>
<tr>
<th>Economic Performance</th>
<th>Business Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>q₁ Domestic Economy</td>
<td>q₁₁ Productivity and Efficiency</td>
</tr>
<tr>
<td>q₂ International Trade</td>
<td>q₁₂ Labor Market</td>
</tr>
<tr>
<td>q₃ International Investment</td>
<td>q₁₃ Finance</td>
</tr>
<tr>
<td>q₄ Employment</td>
<td>q₁₄ Management Practices</td>
</tr>
<tr>
<td>q₅ Prices</td>
<td>q₁₅ Attitudes and Values</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Government Efficiency</td>
<td>Infrastructure</td>
</tr>
<tr>
<td>q₆ Public Finance</td>
<td>q₁₆ Basic Infrastructure</td>
</tr>
<tr>
<td>q₇ Fiscal Policy</td>
<td>q₁₇ Technological Infrastructure</td>
</tr>
<tr>
<td>q₈ Institutional Framework</td>
<td>q₁₈ Scientific Infrastructure</td>
</tr>
<tr>
<td>q₉ Business Legislation</td>
<td>q₁₉ Health and Environment</td>
</tr>
<tr>
<td>q₁₀ Societal Foundation</td>
<td>q₂₀ Education</td>
</tr>
</tbody>
</table>

B. DRSA

DRSA is a powerful technique of relational structure and has been successfully applied in many fields [12-16]. In classification application, it can be used to induce objects assigned to $C_I^t$ (the upward union of classes which includes objects ranked at least $i^t$) or to $C_I^u$ (the downward union of classes which includes objects ranked less than $i^t$), where $C_I$ is a cluster set containing ordered classes $C_I^t$, $t \in T$ and $T = \{1, 2, ..., n\}$. The formulations for the above statement can be expressed as $C_I = \{C_I^1, ..., C_I^t, ..., C_I^n\}$, $C_I^t = \{y \in U : y$ is ranked in the top position $\}$, $C_I^u = \{y \in U : y$ is ranked in the second position $\}$, ..., and $C_I^n = \{y \in U : y$ is ranked in the bottom position $\}$; where $U$ is a set with decision makers’ preference orders. For all $s, t \in T$ and $s \geq t$ (rank of $s \geq$ rank of $t$), every object in $C_I^s$ is preferred to be at least as good as any of object in $C_I^t$. They are constructed as:

The dominating union: $C_I^s = \bigcup C_I^t$ for $s \geq t$
The dominated union: $C_I^s = \bigcup C_I^t$ for $s < t$

Another representation of the dominating sets relies on a set of criteria, $P$. It follows the dominance principle of requiring each chosen object at least as good as a boundary object $x$ in all considered criteria. The granules of a dominating set based on $P$ can be viewed as the granular cones in the criteria value space. Vice versa the dominated sets follow the dominance principle and have granules in the opposite direction. These cones are categorized into $P$-dominating and $P$-dominated sets [26], respectively. It is said that object $y$ $P$-dominates object $x$ with respect to a criteria set $P$ (denotation $yDPx$). Given $x, y \in U$ and $P$, let dominance sets as:

$P$-dominating set: $D_P^n(x) = \{y \in U, yDPx\}$

$P$-dominated set: $D_P^n(x) = \{y \in U, xDPy\}$

where $x, y \in Cl$, $x$ plays a role for the boundary of $D_P^n(x)$ or $D_P^n(x)$, $y \geq x$ for $D_P^n(x)$, $x \geq y$ for $D_P^n(x)$, and all $q \in P$. The association between $C_I^t$ and $P$-dominating set should keep dominance consistency requiring $y \in Cl^t$ and $y \in P$-dominating.

Two approximations are defined for illustrating the dominance consistency.

$P(C_I^t) = \{x \in C_I^t, D_P^n(x) \subseteq C_I^t\}$

$\overline{P}(C_I^t) = \bigcup_{x \in C_I^t} D_P^n(x)$, $\overline{Bn}(C_I^t) = \overline{P}(C_I^t) - P(C_I^t)$

$P(C_I^u) = \{x \in C_I^u, D_P^n(x) \subseteq C_I^u\}$

$\overline{P}(C_I^u) = U - P(C_I^{t+1})$, $\overline{Bn}(C_I^u) = \overline{P}(C_I^t) - P(C_I^u)$

where $t = 1, ..., n$, $\overline{Bn}(C_I^t)$ and $\overline{Bn}(C_I^u)$ are $P$-doubtful regions. $P(C_I^t)$ is defined by requiring that the largest union of $P$-dominating sets should be included in $C_I^t$. $\overline{P}(C_I^t)$ is defined by requiring that the smallest union of $P$-dominating sets should contain all elements of $C_I^t$. These two approximations present the proper and possible assignments of objects into $C_I^t$ respectively. The objects belonging to the possible but not proper assignment are categorized as doubtful.

The proper assignments can be expressed with the coverage rate defined by Pawlak [17, 18] and Greco et al. [12, 13, 14, 15]. There are two typical coverage rates (CR) for the upward unions $C_I^t$ and the downward union $C_I^u$, which are formulated as follows:

$CR(C_I^t) = \frac{|P(C_I^t)|}{|C_I^t|}$, $CR(C_I^u) = \frac{|P(C_I^u)|}{|C_I^u|}$

The symbol $CR$ is used to express “the probability of DMUs in the P-lower approximation relatively belonging to the corresponding union of decision classes.” Alternatively, the accuracy rate presents the ratio of the proper assignment to the possible assignment. Two typical accuracy rates ($\alpha$) are listed as:
\[ \alpha(Ct^t_\phi) = \frac{|P(Ct^t_\phi)|}{|P(Ct^t_\phi)|} = \frac{|P(Ct^t_\phi)|}{|U - |P(Ct^t_\phi)|} \]

\[ \alpha(Ct^t_\phi) = \frac{|P(Ct^t_\phi)|}{|P(Ct^t_\phi)|} = \frac{|P(Ct^t_\phi)|}{|U - |P(Ct^t_\phi)|} \]

The symbol \( \alpha \) is used to present "a ratio of the cardinalities of \( t \)-lower approximation to those of \( t \)-upper approximation, i.e., the degree of the properly classified approximation relative to the possibly classified approximation." The relative importance of criteria in mathematics is reviewed next. A certainty rate for providing confidence is formulated as:

\[ \text{Cer}(\phi, \psi) = \frac{\text{Card} \, || \, \phi \cap \psi ||}{\text{Card} \, || \, \phi ||} \quad \text{for} \quad \phi \rightarrow \psi \]

where \( \phi \) and \( \psi \) are sets for condition and conclusion. \( \text{Card} \, || \, \cdot \, || \) means the number of elements in a set. The ratio represents the confidence degree of conclusion mapped from the condition elements, \( \text{Card} \, || \, \phi \, || \). A high confidence means most of the condition objects map to the conclusion set.

Saaty (2001) proposed that pair-wise comparisons and inductions can be formulated as ratios, and then transformed into the priority of criteria, or the criteria weights [19]. He also mentioned that the ratios represent how much more or less a criterion is as compared to another, and that its application can determine how close the criteria are. Also, he emphasized that ratio operations are independent from irrelevant alternatives. Thus the ratio scales derived from different (criteria) scales can be implemented mathematically to generate a characteristic ratio with invariance. Based on these theories, a multiplication of two or three ratios can be used to express measures for classification. The technique of OOD related to build DRSA is reviewed next.

C. OOD

The technique of OOD related to KBC includes encapsulation, inheritance, interface, polymorphism, and composition. The inheritance can distribute object properties in hierarchical structure. The generalized properties are located in the topper level and the more detailed are in the lower. The encapsulation plays the core for integrating the data and methods together when the properties are covered in the same tree structure. The interface provides links between classes which might cross over different structure trees. The polymorphism provides information types to an object such as itself or parents' forms. This is a programming skill to generalize the operations which makes programs easier to implement. The composite class comprises different objects’ properties such that the derived knowledge can be extended or expanded.

The pseudo code about a class encapsulating data and methods is presented as italic statements.

```
Public class A_class {
    Data declaration;
    Constructor \{a template for object initiation\};
    Method declaration and implementation;
    }
    The pseudo code about a subclass inheriting from A_class is presented as:
    Public class B_class extends A_class {
        Sub_data declaration;
        Super(inheritance from parents);
        Sub_method declaration and implementation ();
    }
    The pseudo code about interface integrating methods from different classes is presented as:
    Public interface C_interface {
        C.1 methods ();
        C.2 methods ();
    }
    This interface design gives methods declaration, which is implemented in different classes.
    The pseudo code for polymorphism provides an object more than one information type such that forms of itself and parents can appear in the running time of programs.
    The pseudo code for composition is presented as:
    Public class D_composite {
        Public String B_class();
        Public float E_class();
    }
```

III. OBJECT-ORIENTED COMPETIVENESS

This section has two parts. First is about knowledge implications, presented in Proposition 1 to 5 [20, 21]. Second is the knowledge computerization, presented in Proposition 6.

**Proposition 1**: Information system of DRSA

\[ \text{DRSA} = (U, \{Q_j \times f \times V, Ct^t_\phi \}) \] 

where \( U \) is a set contains \( n \) objects, \( Q \) is a set of \( m \) criteria, \( f : U \times Q \rightarrow V \), \( V_Q = (V_q1, V_q2, \ldots, V_qm) \), is a function mapping from objects and criteria to values, \( Ct^t_\phi \) is a dominating union having nations at least not less than \( t \), and \( t \) is a rank place like \( 10^b \). This proposition transforms sets into an information system by defining by object \( IS \_\text{DRSA} \).

**Proposition 2**: Preference orders

\[ r_{xj} \geq r_{yj} \iff f(x, q_j) \geq f(y, q_j), \quad \forall x, y \in U \] 

where \( f \) is a function that maps a criterion to a preference value for a nation. For instance, \( r_{xj} \) and \( r_{yj} \) are preference values of nation \( x \) and \( y \) with respect to \( q_j \).

**Proposition 3**: A dominating rule

\[ q^t_{j'} \rightarrow Ct^t_\phi \] 

where \( q^t_{j'} \) is a set of nations within the top \( t \) positions with respect to \( q_j \). This rule associates a domi-
Proposition 4: Accurate coverage rate \( g_j' \) of an induction rule
\[ g_j' = g'(q_{j,t}^{\geq}) \rightarrow Cl_{t}^{\geq} \]
where \( g_j' \) is the conditional fuzzy density for \( q_{j,t}^{\geq} \rightarrow Cl_{t}^{\geq} \) which is a unique value to present the degree that \( q_j \) supports nations to compete the top \( t \) positions. Technically, it is an accurate coverage rate, \( 0 \leq g_j' \leq 1 \). Its derivation is described in [16]. Fig. 2 presents the concept of Proposition 4. \( P(q_{j,t}^{\geq} \rightarrow Cl_{t}^{\geq}) \) is the lower approximation containing the boundary object \( x \) and objects at least as good as \( x \) in all considered criteria. The considered criteria belong to \( P \). \( \bar{P}(q_{j,t}^{\geq} \rightarrow Cl_{t}^{\geq}) \) is the upper approximation containing the boundary object \( \bar{x} \) and objects at least as good as \( \bar{x} \) in all considered criteria. \( q_{j,t}^{\geq} \) is an approximation, \( q_{j,t}^{\geq} = \bigcup_{s \geq t} q_{j,s} \), containing nations ranked in at least \( t^{th} \) with respect to criterion \( q_j \). The boundary objects \( x \) and \( \bar{x} \) are presented as slash lines for \( Cl_{t}^{\geq} \). To find out the positions for \( x \) and \( \bar{x} \), the optimization technique could backwardly search the optimal CFD then solve the positions for them. The mathematical model is presented in Model I.

Model I: Solving \( g_j' \)
\[
\begin{align*}
\text{Max} & \quad g_j' = CR(Cl_{t}^{\geq}) \times \alpha(Cl_{t}^{\geq}) \\
\text{s.t.} & \quad P(Cl_{t}^{\geq}) = D_{s}(x), \quad \bar{P}(Cl_{t}^{\geq}) = D_{s}(\bar{x}), \quad P = \{q_j\} \\
& \quad CR(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|Cl_{t}^{\geq}|}, \quad \alpha(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|P(Cl_{t}^{\geq})|} \\
& \quad \text{Certainty}(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|P_{z}|}, \quad P = \{q_j\}
\end{align*}
\]

Proposition 5: Reliability rate \( g_j^{**} \) of an induction rule
To provide a quality classification with high confidence, a unique ratio based on the three measures with respect to a criterion \( q_j \), defined as \( g_j = g'(q_{j,t}^{\geq} \rightarrow Cl_{t}^{\geq}) \) called reliability rate. \( 0 \leq g_j^{**} \leq 1 \) is implemented in Model II for a dominating union.

Model II: Solving \( g_j^{**} \)
\[
\begin{align*}
\text{Max} & \quad g_j^{**} = CR(Cl_{t}^{\geq}) \times CR(Cl_{t}^{\geq}) \times \alpha(Cl_{t}^{\geq}) \\
\text{s.t.} & \quad P(Cl_{t}^{\geq}) = D_{s}(x), \quad \bar{P}(Cl_{t}^{\geq}) = D_{s}(\bar{x}), \quad P = \{q_j\} \\
& \quad CR(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|Cl_{t}^{\geq}|}, \quad \alpha(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|P(Cl_{t}^{\geq})|} \\
& \quad \text{Certainty}(Cl_{t}^{\geq}) = \frac{|P(Cl_{t}^{\geq})|}{|P_{z}|}, \quad P = \{q_j\}
\end{align*}
\]

Proposition 6: Object-oriented design
The proposition has three parts. First is about Classes; second is Interface; third is composition defined by Java. Classes are organized in the hierarchical structure with inheritance properties. Interface provides references for implementation of integrating preference implications and mathematical measures. Composition extends knowledge beyond the original scope. Followings are the pseudo code and description about the design.

The class encapsulation is designed in italic statements:

```java
public class IS_DRSA {
    private variables;
    methods of DRSA properties ();
}
```

The information system, \( \text{DSRA} = (U, Q, f, V, Cl_{t}^{\geq}) \), can be transformed into an object class named as \( \text{IS\_DSRA} \) where the data area declaration contains private variables such as a matrix with \( n \) objects, \( m \) criteria, \( n \times m \) preferences, and \( n \times 1 \) decision values. The methods of \( \text{IS\_DSRA} \) contains data editing.

Next two subclasses are used as the basic components of knowledge.

```java
Public class Implications extends IS_DRSA implements Evaluation {
    /* Rules class give implications for DSRA */
    Public String Rules () {return q_{j,t}^{\geq} \rightarrow Cl_{t}^{\geq};}
}
```

```java
Public class Measures extends IS_DRSA implements Evaluation {
    /* Measures including DSRA or beyond DSRA are implemented here */
    Public float measures() {return CR, AR, Cer, g_j', g_j^{**};}
}
```

Next pseudo code is an integration design for implications and measures functioning as basic components of knowledge.

Public interface Evaluation {
    /* Integrating implications and measures by satisfying users requirements, only declaration is presented without

```java
```
implementation body */

Public float coverage rate (return CR);
Public float accuracy rate (return AR);
Public float accuracy rate (return Certainty);
Public float certainty rate (return ACR);
Public float coverage-accuracy-certainty rate ();
Public String Implications();
}

Users can filter implications by setting requirements on measures. Therefore, the corresponding implication to the measures can present explanations significantly to stakeholders.

The final class extends knowledge components to recognizable and sensible knowledge beyond implications.

Public class knowledge {
/* A composite class with knowledge blocks */
Public class knowledgeComponent(){};
Public class features extends knowledgeComponent(){}
Public class utilities extends knowledgeComponent(){}
Public class patterns extends knowledgeComponent(){}
}

All the above design is illustrated by a conceptual diagram in Fig. 3.

Fig 3. The OOD of competitiveness knowledge

IV. THE EXPECTED RESULTS

The resulted measures are lists in Table 2 which can be encapsulated with implications into the feature objects.

A pattern object embedded with factors and correlation coefficient is presented in Table 4.

The utility object comprises a nation name and the corresponding performance value summed from all criteria, shown in Table 3.

Table 3. Competitiveness utilities of KBC

<table>
<thead>
<tr>
<th>Nations</th>
<th>( U(x) = \sum_{i=1}^{n} w_i \cdot r_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>64.20</td>
</tr>
<tr>
<td>Canada</td>
<td>67.76</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>69.07</td>
</tr>
<tr>
<td>Malaysia</td>
<td>56.57</td>
</tr>
<tr>
<td>Norway</td>
<td>62.22</td>
</tr>
<tr>
<td>Singapore</td>
<td>53.90</td>
</tr>
<tr>
<td>Sweden</td>
<td>57.28</td>
</tr>
<tr>
<td>Switzerland</td>
<td>69.27</td>
</tr>
<tr>
<td>Taiwan</td>
<td>69.35</td>
</tr>
<tr>
<td>USA</td>
<td>64.72</td>
</tr>
<tr>
<td>Australia</td>
<td>64.20</td>
</tr>
</tbody>
</table>

A pattern object embedded with factors and correlation coefficient is presented in Table 4.

Table 4. Competitiveness correlations of KBC

<table>
<thead>
<tr>
<th></th>
<th>E</th>
<th>G</th>
<th>B</th>
<th>I</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>0.63</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.73</td>
<td>0.85</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>0.53</td>
<td>0.46</td>
<td>0.55</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 2. Competitiveness features of KBC

<table>
<thead>
<tr>
<th>Implications</th>
<th>ACR</th>
<th>AR</th>
<th>CR</th>
<th>( g' )</th>
<th>( g'' )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( q_{i,10} \rightarrow C_i^{10} )</td>
<td>0.26</td>
<td>0.60</td>
<td>0.26</td>
<td>0.16</td>
<td>0.04</td>
</tr>
<tr>
<td>( q_{i,10} \rightarrow C_i^{10} )</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>( q_{i,10} \rightarrow C_i^{10} )</td>
<td>0.46</td>
<td>0.60</td>
<td>0.46</td>
<td>0.28</td>
<td>0.13</td>
</tr>
<tr>
<td>( q_{i,10} \rightarrow C_i^{10} )</td>
<td>0.18</td>
<td>1.00</td>
<td>0.18</td>
<td>0.18</td>
<td>0.03</td>
</tr>
<tr>
<td>( q_{i,10} \rightarrow C_i^{10} )</td>
<td>0.32</td>
<td>0.80</td>
<td>0.32</td>
<td>0.26</td>
<td>0.08</td>
</tr>
</tbody>
</table>
V. DISCUSSIONS

Mathematical measures can provide rigid and objective figures. The derived implications thus can become sensible due to the measures. KBC generates the features, utilities, and patterns derived from the knowledge components and give a broad understanding about competitiveness. The advantages of KBC have two points. First, the knowledge can be computerized systematically and generated mathematically. Second, the generated knowledge can be extended beyond the original scope. As known, the mathematical operation generally can identify the significance and enhance the quality for implications. Technically, the object-oriented design encapsulates preference information and methodological measures into useful knowledge.

KBC is designed to provide computerization knowledge systematically and automatically. Based on the derived knowledge, strategies and decisions can be enhanced especially facing the unknown challenges.

The computerized information can be displayed to help stakeholders understand easily. The future work includes implementation of KBC empowered with displaying capabilities.

VI. CONCLUDING REMARKS

This research proposes a knowledge-based system for competitiveness preferences. By integrating logical implications and mathematical measures, the competitiveness features, utilities, and patterns are generated systematically and automatically. The proposed methodology transforms DRSU into a knowledge-based system through the object-oriented technique. There are some merits in this OOD. First, the preference implications and mathematical measures can be computerized systematically to generate knowledge automatically. Second, the generated knowledge can be extended beyond the original understanding thus giving more understanding about competitiveness.

REFERENCES