



Ontology-based supply chain decision support for steel manufacturers in China

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ABSTRACT

It is now very popular for companies to collaborate as a global supply chain (GSC) for their business benefits. Many companies are inclined to outsource manufacturing, logistics and business activities globally. The senior managers of companies are faced with more complicated and dynamic situations to make decisions than ever before. They not only have to consider the internal factors including production, inventory, and financial status, but also have to take into account the external factors such as policies, market forces, competitive behaviors, etc. To survive in today's fierce market environment, it has become increasingly important for companies to find ways to combine the multi-source decision knowledge, and utilize it to make sound decisions across the organizational boundaries.

In this paper, a rule-based ontology reasoning method is proposed to support decision makings and improve industrial practices for companies in the dynamic and heterogeneous GSC context. A shared GSC ontology is developed to describe the heterogeneous internal and external decision knowledge of the GSC companies and the dynamic market environments. It is contributed in enabling a semantic interoperable decision-making environment, along with the decision knowledge being evolved timely. In addition, semantic rules serving as decision requirements are developed to reason the shared GSC ontology to support the complicated and sound decision-makings, and also to provide suggestions on improving their industrial practices. A case study in China's iron and steel industry is introduced to justify the feasibility and effectiveness of the proposed ontology-based approaches.

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1. Introduction

In recent years, many companies in the iron and steel industry have reported drastic reduction of revenues and profits. There are many reasons for the current recession in this industry. First, the continuous increase in the prices of iron ores; secondly, the significant decrease in demand of iron and steel products from the construction and real estate industries in the midst of the global financial crisis; thirdly, there is an excess in production capabilities domestically and worldwide because many companies have not adopted prompt and sound measures to cut down production during the economic downturn. To remain competitive in the global market environment, it is of vital importance for the senior managers of steel manufacturers to make proper business decisions. In addition to the internal factors of the companies, decision makers are also required to evaluate the circumstances of the dynamic external market. For instance, how to select appropriate GSC

partners? How to learn successful experiences from competitors? How to adjust corporation business strategies?

In the era of knowledge economy, knowledge is a major determinant of competitiveness and knowledge sharing is beneficial to improve the company performance and industrial practices along the entire GSC (He, Ghobadian, & Gallear, 2013). Capabilities of generating, interpreting and deploying the multi-source knowledge are key drivers of company success, when responding to the market opportunities (Fugate, Autry, Devis-Sramek, & Germain, 2012). It is therefore very necessary to develop suitable decision support systems (DSSs) to facilitate the senior managers to compile and utilize the multi-source knowledge to answer the questions arising from the managerial and industrial practices, such as the questions mentioned above in the iron and steel industry. The rule-based reasoning system has been one of the most useful DSSs in recent years. It is based on the pre-defined rules expressing the decision purposes, which are then utilized to reason the logical relationships of the domain knowledge structure for decision support. Many researchers and practitioners have engaged in developing feasible DSSs and the rule-based reasoning systems to support decision-makings (Amailef & Lu, 2013; Chan & Ip, 2011; Chen, Huang, Bau, & Chen, 2012; Denguir-Rekik, Montmain, & Mauris,

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2009; Doumpos & Zopounidis, 2010; Fernandez, Navarro, Duarte, & Ibarra, 2013; Kozan & Liu, 2012; Milea, Frasincar, & Keymak, 2013; Zhao, Li, Wang, & Halang, 2012). A proper designed DSS or rule-based reasoning system is an interactive software-based system intended to help decision-makers in compiling useful information from raw data, documents, personal knowledge or business models, etc. to solve complicated problems and support decisions (Zhao et al., 2012). However, in GSC, companies' knowledge such as cultures, business statements, organizational structures, etc. are heterogeneous. Heterogeneity tends to cause the problem of mistakes and misunderstandings among the GSC companies. To facilitate the collaborative and dynamic decision support activities in GSC, it is essential to provide a shared domain knowledge structure to enable the GSC companies to reach mutual understanding with each other. Ontology as an explicit specification of a conceptualization (Gruber, 1993), and the agreements about the conceptual frameworks for modeling domain knowledge (Gruber, 1994), is widely applied in DSSs and rule-based reasoning systems to enable interoperable decision knowledge structures for knowledge sharing and utilization.

With respect to the current DSSs and rule-based reasoning systems for GSC's joint decision-making, three research areas are less considered: first, many existing systems excel in supporting decisions in a specific domain with single-source knowledge, but little attention has been given to considering multi-source decision knowledge, especially knowledge with heterogeneous terminologies and structures from different GSC companies, which would increase the possibilities of mistakes or misunderstandings; second, the decision background of GSC is changing all the time; variations caused by production, inventory and financial status, etc. are internal factors of changing issues, while external factors related to change are like customer demand, policy, market forces, competitive behaviors, etc.; but few researchers have considered and prepared the decision knowledge in a dynamic and evolutionary manner, which would lead to the untimely and outdated decisions to be made; third, the existing systems are aiming at providing decision support towards a current similar situation based on the historical cases; however, many old cases in the case base might have become outdated and not as practicable as before, since the precondition and the decision environment are not the same as in the past; fewer researchers have taken into account this time-varying issue. Based on the above considerations, future studies should be focused on providing a decision support method, which enables a semantic interoperable, evolutionary and time-varying decision environment for the decision support activities. The research motivation of this study is to propose a novel rule-based ontology reasoning method to support the senior managers of the heterogeneous GSC companies to make timely decisions in the ever-changing business environment.

This paper systematically presents the rule-based ontology reasoning method in threefold: first, a mutual understanding decision environment is enabled through a shared knowledge structure expressed by ontology; second, the reasoning function for decision-making purposes is achieved by pre-defining proper decision rules and discovering implicit decision knowledge from the shared ontology; at last, the proposed method is applied in two notable Chinese steel manufacturers, where one company is served as the benchmark of China's iron and steel industry, and the senior managers in another company are supposed to learn from the benchmark, and also to cope with the dynamic, complicated and fierce GSC and the gloomy market environment, in order to make sound decisions and improve its company performance. The rest of the paper is structured as follows: Section 2 reviews some ontological literatures; Section 3 briefly illustrates the ontology-based decision-support process in GSC; Section 4 introduces the construction of the shared GSC ontology, ontology evolutional

mechanisms, and rule-based ontology reasoning method; at last, Section 5 justifies the proposed ontological approaches through a case study in China's iron and steel industry and Section 6 concludes the paper and presents some future work.

2. Literature review

The rule-based ontology reasoning method for decision support in GSC involves three major ontological research efforts: ontology representation for building domain decision knowledge structures, ontology matching for mutual understanding among heterogeneous GSC companies, and ontology reasoning for implementing the decision support activities.

2.1. Ontology representation

An ontology is required to be represented to cope with the explication and conceptualization of a particular community. In reality, the development of a proper ontology has to satisfy several requirements (Devedzic, 2002; Hakimpour & Geppert, 2001): to represent the consensus knowledge of a community of people; the terms should be precisely defined and definitions of domain concepts should be highly structured; to have good stability and scalability; to be developed as a foundation for solving a variety of problems and constructing multiple applications; and also the knowledge bases should be coherent and interoperable.

A number of programming languages and standards are applicable for representing ontology, such as Ontolingua, XML (eXtensible Markup Language), RDF (Resource Description Framework), OML (Ontology Markup Language), DAML + OIL, OWL (Ontology Web Language), SWRL (Semantic Web Rule Language), etc. There are also a lot of standard ontology representation methods, such as Ontology Development 101 Method, Cyc mapping methodology, Toronto Virtual Enterprise, etc. To represent ontologies applied in particular domains, some researchers proposed specified ontology construction methods. For example, Blomqvist (2008) proposed a semi-automatic ontology construction approach based on four-phase case-based reasoning: in the retrieve phase, the input information is analyzed to extract ontology primitives and matched to the pattern base to select the appropriate design patterns; in the reuse phase, the specialized design patterns are extended and composed into a first version of ontology; in the revise phase, the ontology is evaluated and revised to improve the fit; and in the retain phase, new pattern candidates are discovered and the pattern feedback is stored. Ku, Wensley, and Kao (2008) considered seven steps for joint ventures to create enterprise ontology, i.e. knowledge acquisition, knowledge identification, ontology analysis, ontology implementation, ontology verification, knowledge reposition and knowledge sharing and development.

2.2. Ontology matching

Different companies and decision-makers intend to establish their own ontologies in defining domain knowledge. Heterogeneity will incur misunderstanding and mismatches. Semantic interoperability is the ability to resolve the semantic heterogeneous problems by sharing, aggregating or synchronizing the multi-source information in the heterogeneous environment (Vernadat, 2007).

Regarding decision process involved by multiple knowledge providers, many researchers adopt ontology to describe their respective knowledge, and adopt the ontology matching technique to resolve the semantic heterogeneous problems (Chen & Chen, 2009; Jung, 2009; Malucelli, Palzer, & Oliveira, 2006; Udrea, Getoor, & Miller, 2007; Zhao et al., 2012). Malucelli et al. (2006) compared lexical and semantic similarities among the heterogeneous

ontologies defined in different agents. Ontology matching was conducted based on concept names, characteristics, relations, etc. Lexical similarity identification, WordNet-based semantic similarity and N-grams for description were introduced in their study. Udrea et al. (2007) proposed an integrated learning algorithm in the alignment of data and schema for ontology matching and logical reasoning. In their approach, the lexical similarity was calculated based on Winkler (1994)s approach and WordNet dictionary; the structural and extensional similarities were calculated by Jaccard distance. Chen and Chen (2009) adopted Jaccard Coefficient for ontology matching to generate similarities of name, essential information and relationship. Based on the ontology matching results, an ontology merging algorithm was employed to merge concepts and relationships of different ontologies. Jung (2009) proposed a novel method of integrating business ontologies of heterogeneous business processes based on calculating the class similarities. Accuracy and the minimum number of manual alignments were considered for performance evaluation. Zhao et al. (2012) developed ontology matching method in e-business decision support systems. Novel algorithms of syntactic analysis measuring the difference between tokens by edit distance, semantic analysis based on WordNet as semantic relation and similarity assessment of tree-structured graphs with the Tversky similarity model were proposed.

2.3. Ontology reasoning

Ontology representation and matching are essential for knowledge sharing in GSC. The ultimate purpose is not only to reach mutual understanding among the GSC companies, but most importantly to make the best use of the multi-source knowledge to support senior managers to make sound decisions. Ontology reasoning is a suitable solution to support decision-making activities. The basis of the method comprises a shared ontology and some pre-defined rules expressing the decision purposes. The new and implicit decision knowledge is retrieved through reasoning the logical relationships of the shared ontology and reusing the existing decision knowledge.

Many researchers have applied the ontology reasoning technique to support complicated decision-making activities (Chen et al., 2012; De Potter et al., 2012; Lin, Chuang, Liou, & Wu, 2009; Milea et al., 2013; Minutolo, Esposito, & Pietro, 2012). Lin et al. (2009) introduced the association rule to determine the supply chain suppliers. Four steps were proposed, i.e. identifying the critical parts, determining the supplier sets, identifying primary suppliers and identifying secondary suppliers for complementary. Minutolo et al. (2012) presented a pattern-based knowledge editing system to guide and support the creation and formalization of condition-action clinical recommendations. If-then rules were built and reasoned towards the ontological models. De Potter et al. (2012) introduced ontology to solve interoperability problems between multiple knowledge providers. They adopted the Euler reasoning engine, which is a backward chaining reasoner enhanced with Euler path detection, to support logic-based medicinal ontology reasoning. Chen et al. (2012) developed an ontology reasoning based recommendation system based on SWRL and JESS in the medical domain. The system was able to analyze the symptoms of diabetes as well as to select the most appropriate drug from related drugs, which could help doctors to integrate multi-source information to make complicated decisions. Milea et al. (2013) proposed a time-aware framework for decision support. They adopted the temporal Web Ontology Language (tOWL) to represent time-varying knowledge for historical information. The temporal reasoner was used to determine the temporal validity of the input knowledge, which avoided enforcing or checking data related to restrictions manually.

Comparing with the previous ontological methods in the decision process, many researchers established specific ontology to describe the domain decision knowledge. When multiple decision-makers engage in the same decision process, the ontology is supposed to be agreed by all of them. They have to utilize the shared terminologies and knowledge structures, even though it will bring them a lot of inconveniences to follow the quite different languages, regulations or conventions to express their decision purposes and read the decision suggestions. In addition, little attention has been given to evolve the ontologies as time goes by, which is essentially important for ontologies applied in the decision support activities.

Therefore, the most important issue emerged is the need for a dynamic rule-based ontology reasoning method, which enables different decision-makers to acquire sound and timely decision suggestions according to their own customs. In this study, separate ontologies are built for different decision-makers, and a matching mechanism is proposed to enable a mutual understanding environment. Thus, the decision-makers can express their decision purposes and read the decision suggestions by utilizing their own terminologies and knowledge structures in the rule-based ontology reasoning process. Moreover, in the ontology representation process, not only the evolutionary characteristics are considered, but also the time-varying concerns are taken into account, to facilitate a timely updated decision knowledge environment for decision-making activities.

3. Ontology-based decision support process

In today's globalized economy, companies tend to develop collaborative supply chain relationships or alliances worldwide (Fugate et al., 2012). GSC partners can get hold of the opportunities for market growth and cost saving through sharing their knowledge, skills and resources. The GSC structure is not static, it has to be reconfigurable and agile so that it can quickly adapt and respond to the dynamic market and economic conditions.

Four roles in GSC are considered in this paper, i.e. core company, competitor, supplier and customer. Fig. 1 depicts the dynamic GSC structure considered in this study: one Chinese steel manufacturer acquires iron ore from the Australian suppliers, and then sells its products to North America for automobile and military manufacturing; another Chinese steel manufacturer also acquires iron ore from Australian suppliers, but supplies its products to the construction industry in Asia and to the defence industry in North America. Depending on business and economic needs, new suppliers may join and an existing customer may choose to leave the current supply chain.

The decision environment is very dynamic and heterogeneous. A dynamic and interoperable decision environment is required to support decision-making at the senior management level in the core company. An ontology-based decision support process is proposed in this study. As shown in Fig. 2, the process of ontology-based decision support is divided into two steps, i.e. decision knowledge pre-preparation and rule-based decision support. Each step is explained as follows:

- Decision knowledge pre-preparation: to understand the heterogeneous knowledge from different GSC companies, the knowledge should be first defined and expressed explicitly in separate formal structures (i.e. ontology representation); and the terminologies with similar semantic from different ontologies should then be merged together to express the same meaning that can be understood by all GSC companies (i.e. ontology matching and ontology integration); considering the dynamic decision environment, the shared ontology is evolved

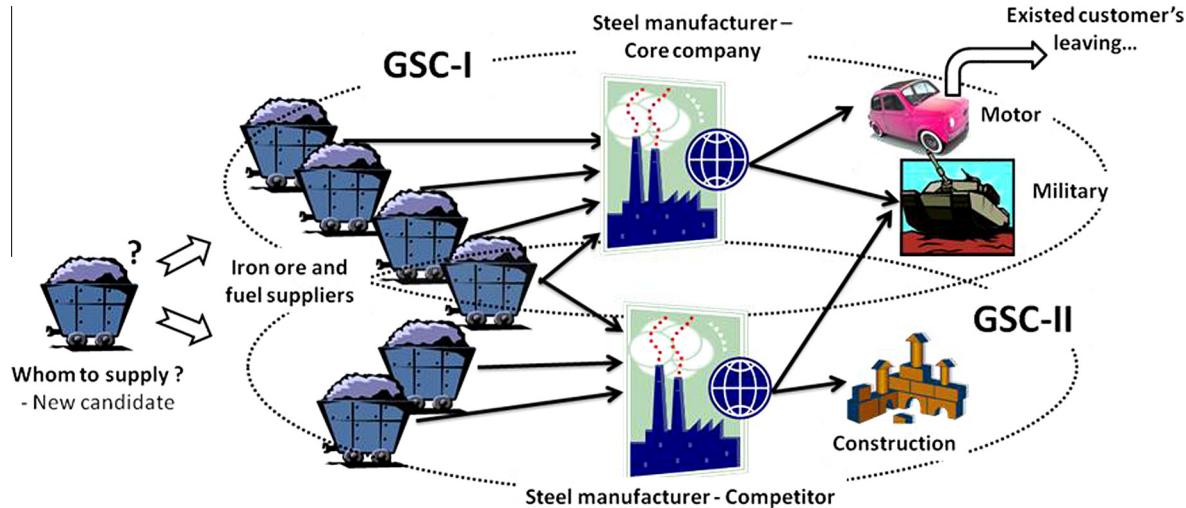


Fig. 1. The dynamic GSC structure with the steel manufacturer as the core company.

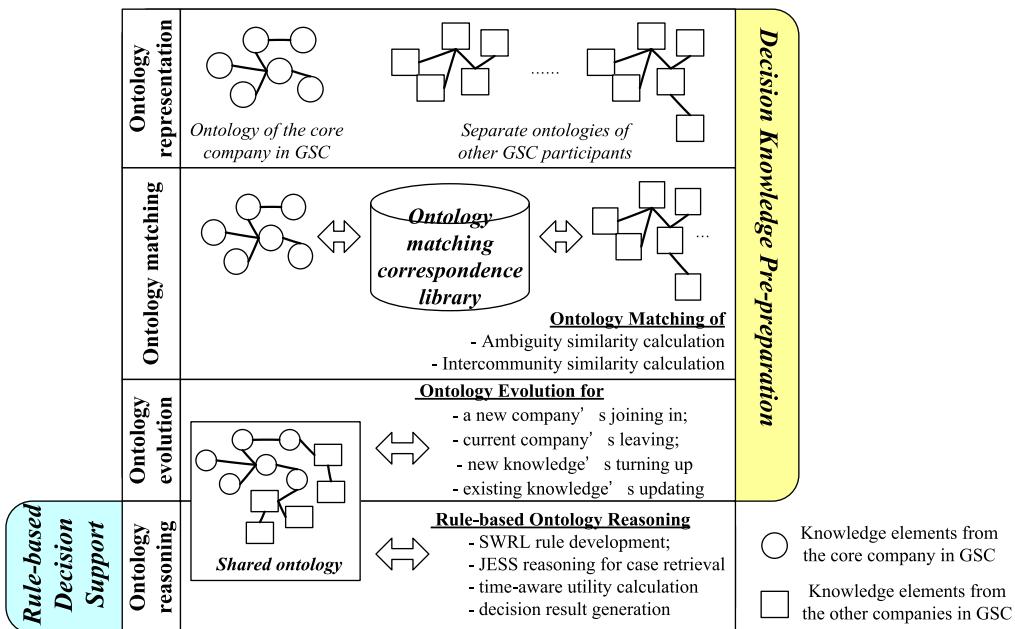


Fig. 2. Ontology-based decision support process.

accordingly to enable a dynamic environment to support decision-making (ontology evolution).

- Rule-based decision support: to utilize the shared existing knowledge for decision-making purposes, the decision-makers should pre-define some rules as their decision requirements in a machine-readable manner (i.e. SWRL rule development); and then introduce knowledge reasoning engine (JESS in this study) to retrieve the desired knowledge; at last, the time-varying considerations should be taken into account for finalizing the ultimate decisions.

4. Methodology

In this section, the rule-based ontology reasoning method for decision support in China's iron and steel industry is proposed. It relies on constructing a shared and evolutionary ontology, and formalizing the condition-action decision rules. The ultimate aim is

to facilitate the senior managers of the core company in one GSC to learn the successful experiences from its competitors, and adjust its own operating strategies to improve the company performances and industrial practices as well.

4.1. Separate ontology representation

Ontology is defined as a structure $O = (C, R, A, T, I)$. Class (C) represents the basic concepts or categories of the domain knowledge; Relation (R) represents the relationships between the classes, regarded as Object Property; Attribute (A) represents the different characteristics of the classes, regarded as Data Type Property; Data set (T) represents the data type values of the attributes; Instance identifier (I) represents the content and context of the respective classes.

To demonstrate the rule-based ontology reasoning method in this study, two selective separate ontologies are briefly constructed i.e. the ontology of the core company (represented as

core-ontology, shown in Fig. 3) and the ontology of a competitor company (represented as competitor-ontology, shown in Fig. 4). To facilitate the dynamic decision support activities and to incorporate the time-varying considerations in the historical cases, an instance of the competitor-ontology that incorporates time information is shown in Fig. 5.

As shown in Fig. 3, five main classes are considered in the core-ontology:

- Company: it describes the information of the core company, including operating strategies, financial status and the products it produces;
- Product: it describes the information of the products that the core company produces, including the primary market where the products sold, product name, product category, and real-time product price;
- Primary market: it describes the primary market that the core company sells its products to, or the locations of its customers. The market policies are described, such as the stimulus policy, deflationary policy, etc.;
- Policy: it describes the real-time policies such as deflation or stimulus, etc.;
- Financial status: it describes the real-time financial status of the core company, such as the share price and credit grade, etc.

The instances of the core-ontology describe knowledge like: A Steel Company sells carbon steel, special steel and stainless steel, etc. to North American and Asia markets. For the products it produces, carbon steel is a new type product, while special and stainless steel are traditional products. Its pricing strategy is adjusted semiannually. The share prices during 2009 till 2012 are 0.1, 0.336, –0.369 and –0.438, respectively. Similarly, the yearly credit

grade and policies in different market are defined in the corresponding instances as well.

As shown in Fig. 4, eleven main classes are considered in the competitor-ontology:

- Corporation: it describes the information of the competitor company, including manufacturing and financial performances, yearly business strategies, raw materials and products, etc.;
- Financial status: it describes the financial status of the competitor company, including yearly credit rating, total profit and earning per share;
- Supplier: it describes the supplier information of the competitor company, including locations, and the main products sold to the competitor company in different years;
- Customer: it describes the customer information of the competitor company, including locations, and business industries that customers belong to in different years;
- Product: it describes the product information of the competitor company, including product name, price, product type, inventory and its customer;
- Product type: it describes the yearly product type information, such as newly developed product or traditional product, etc.;
- Price: it describes the yearly quoted price information;
- Price strategy: it describes the yearly pricing type, such as increasing price, decreasing price or keeping price unchanged, etc.;
- Inventory: it describes the yearly inventory level information, such as high inventory level, medium inventory level and low inventory level;
- Location: it describes the geographical locations, such as Asia, Europe, America, etc. The area policies are described in this class, such as deflation policy and stimulus policy;

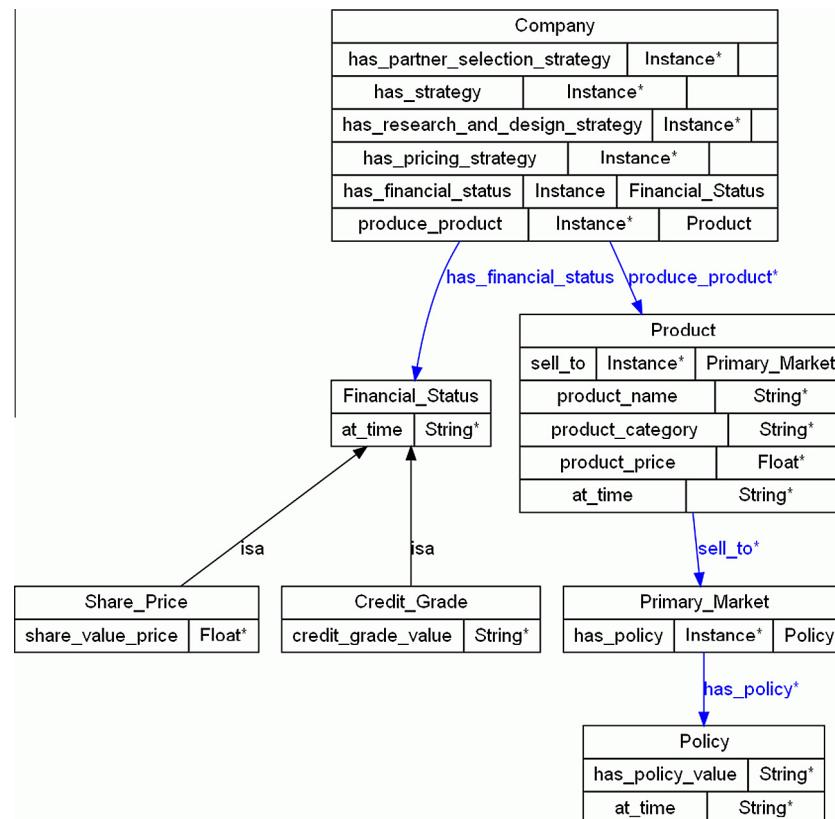


Fig. 3. Core-ontology structure with classes, relations and attributes.

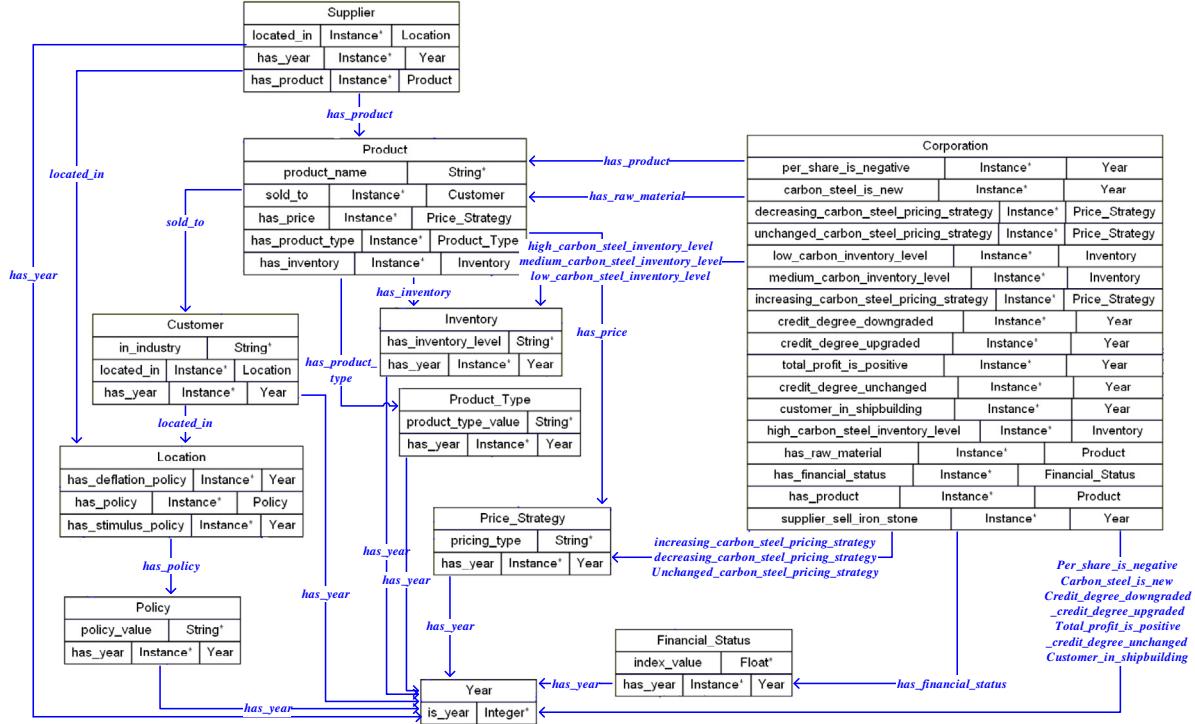


Fig. 4. Competitor-ontology structure with classes, relations and attributes.

```
<?xml version="1.0"?>
...
<rdf:RDF xmlns="http://www.owl-ontologies.com/Ontology1364089323.owl#">
<Corporation rdf:ID="B_Steel_Company">
  <has_primary_business rdf:datatype="#xsd:string">Iron and Steel</has_primary_business>
  <located_in rdf:resource="#Asia"/>
  <has_product rdf:resource="#wide_and_thick_plate"/>
  <has_product rdf:resource="#carbon_steel"/>
  ...
  <has_supplier rdf:resource="#Supplier_1"/>
  <has_supplier rdf:resource="#Supplier_2"/>
  <has_customer rdf:resource="#Customer_shipbuilding"/>
  <has_customer rdf:resource="#Customer_auto_industry"/>
</Corporation>
<Product rdf:ID="carbon_steel">
  <has_inventory_level rdf:datatype="#xsd:string">low</has_inventory_level>
  <has_type rdf:datatype="#xsd:string">new</has_type>
  <has_price rdf:resource="#carbon_steel_2012"/>
  <has_price rdf:resource="#carbon_steel_2008"/>
  <has_price rdf:resource="#carbon_steel_2010"/>
  <has_price rdf:resource="#carbon_steel_2011"/>
  <has_price rdf:resource="#carbon_steel_2009"/>
  <sold_to rdf:resource="#Customer_shipbuilding"/>
  <sold_to rdf:resource="#Customer_auto_industry"/>
</Product>
<Price rdf:ID="carbon_steel_2008"/>
...
</rdf:RDF>
```

- The primary business of B Steel Company is in Iron and Steel industry;
- It is located in Asia;
- It produces products as wide and thick plate, carbon steel, etc.

- The company has two suppliers;
- It has two customers in shipbuilding industry and auto industry.

The inventory level of carbon steel is low;
Carbon steel is a new type of product;

The prices of carbon steel from year 2008 till year 2012 are provided here;

The carbon steel is mainly sold to a shipbuilding customer and an auto industry customer;

Fig. 5. An instance of the competitor-ontology incorporating the time-aware information.

- Year: it describes the operating time in terms of years.

The instances of the competitor-ontology are given in Fig. 5. It represents that a company named *B Steel Company* has primary

business scope in iron and steel industry; its main products include wide and thick plate, carbon steel, etc.; besides, the time-varying information is provided in the instance as well. The prices of carbon steel from Year 2008 till Year 2012 are stored in the ontology.

Similarly, other time-varying information is given, such as yearly earning per share, total profit and credit-rating, etc. The time-varying information can facilitate the senior managers to make sound decisions, on the basis of the companies' historical performances.

Different GSC companies always adopt different terminologies and knowledge structures to build different ontologies. The approach and concept of the ontologies of other GSC companies are similar and not presented here to avoid repetition.

4.2. The shared GSC ontology model

As exemplified by the core-ontology and the competitor-ontology in Section 4.1, different GSC companies' knowledge is structured in different ontologies in this study. To reach semantic interoperability between them, their properties are matched mutually. The accumulated similarities are utilized to reach mutual understanding of the heterogeneous classes, and also to facilitate the integration of the two ontologies into a shared GSC ontology.

Reference sources such as dictionaries have to be used to obtain the meanings of terms in various contexts and to calculate the semantic similarity between different terms. In this study, wordnet is adopted as the dictionary, and the hypernyms and hyponyms relations are introduced to express the meaning of the terms (Miller, Beckwith, Fellbaum, Gross, & Miller, 1990; <http://wordnet.princeton.edu>). Hypernyms and hyponyms are different abstraction levels, just like generic terms vs. the more specific ones. The ontology matching algorithm is presented as follows

First, assuming that CN_{ci} and PN_{cj} represent the i -th class name and the j -th property name of the core ontology, respectively; and CN_{pi} and PN_{pj} represent the i -th class name and the j -th property name of the competitor ontology, respectively.

Then, the similarities between respective ontologies are determined as follows:

- With WordNet, get all the senses and their hypernyms of PN_{cj} and PN_{pj} , i.e. PN_{cj}^* and PN_{pj}^* ;
- The lengths of all paths between PN_{cj}^* and PN_{pj}^* are calculated according to Leacock, Chodorow, and Miller (1998)'s semantic similarity theory. The length of the path indicates the ambiguity between two properties, and it follows the rule that: the shorter the path is, the more similar two properties are. Suppose L is the length of the shortest path between PN_{cj}^* and PN_{pj}^* , then $sim_{ambiguity}(PN_{cj}, PN_{pj})$ can be calculated by Eq. (1), and α is a smoothing parameter valued between [0, 1].

$$sim_{ambiguity}(PN_{cj}, PN_{pj}) = e^{-\alpha L} \quad (1)$$

- According to Wu and Palmer (1994)'s semantic similarity theory, the depths of all properties in set of PN_{cj}^* and PN_{pj}^* are calculated. The depth indicates the intercommunity between two properties, i.e. the extent of the shared characteristics. Suppose H is the biggest depth between PN_{cj}^* and PN_{pj}^* , $sim_{intercommunity}(PN_{cj}, PN_{pj})$ can be then calculated by Eq. (2), and β is a smoothing parameter valued between [0, 1].

$$sim_{intercommunity}(PN_{cj}, PN_{pj}) = \frac{e^{\beta H} - e^{-\beta H}}{e^{\beta H} + e^{-\beta H}} \quad (2)$$

- To synthesize both ambiguity and intercommunity between two properties, the final property similarity can be calculated by Eq. (3), and $w_1 + w_2 = 1$.

$$sim(PN_{cj}, PN_{pj}) = w_1 sim_{ambiguity}(PN_{cj}, PN_{pj}) + w_2 sim_{intercommunity}(PN_{cj}, PN_{pj}) \quad (3)$$

The length of the path and the depth between two properties in the above process are explained in Fig. 6.

As shown in Fig. 6, two properties are expressed by their senses achieved from WordNet. If $sense_1^i = sense_2^j$, the path is " $sense_1^1, sense_1^2, \dots, sense_1^i, sense_2^{i-1}, \dots, sense_2^1$ ", and the length of the path is $i+j-2$. If $sense_1^m = sense_2^n$, $sense_1^{m-1} = sense_2^{n-1}, \dots, sense_1^i = sense_2^j$, the depth is $sense_1^1, \dots, sense_1^i$ or $sense_2^1, \dots, sense_2^n$, and the depth is $m-i+1$ or $n-j+1$. Here, $sense_i^i$ denotes the i -th sense of Property₁.

After calculating the similarities between the two ontologies, they are integrated into a shared knowledge structure on the basis of the similarity calculation results. The process is described as below:

- Calculate the similarities between $\{PN_{cj}\}$ from class CN_{ci} and $\{PN_{pj}\}$ from class CN_{pi} ; and generate similarity sets as $\{sim(PN_{cj}, PN_{pj})\}$
- Determine the correspondent PNs, which are of the biggest similarities in the similarity set:

$$\text{If } \forall PN_{pl}, \quad sim(PN_{cj}, PN_{pj}) \geq sim(PN_{cj}, PN_{pl}) \quad (4)$$

Then, PN_{cj} and PN_{pj} are regarded as the correspondent PNs.

- Calculate CN similarities by Eq. (5), which indicates that the similarity of two CNs, i.e. CN_{ci} and CN_{pi} , is the average of all the correspondent PNs' similarities between two CNs:

$$sim(CN_{ci}, CN_{pi}) = \frac{\sum_{(num(PN_{cj}), num(PN_{pj}))} Sim(PN_{cj}, PN_{pl}) / min}{min(num(PN_{cj}), num(PN_{pj}))} \quad (5)$$

- Determine the correspondent CNs, which are of the biggest similarity in similarity set:

$$\text{If } \forall CN_{pl}, \quad sim(CN_{ci}, CN_{pi}) \geq sim(CN_{ci}, CN_{pl}) \quad (6)$$

Then, CN_{ci} and CN_{pi} are regarded as the correspondent CNs.

- Create corresponding semantic relations between correspondent PNs and correspondent CNs, respectively, such as "sameAs", "sibling", etc., defined as equivalent relations between correspondent ontology elements.
- Add C_{pi} in the shared ontology structure.

In this way, the core-ontology and the competitor-ontology are integrated together to represent the shared terminologies, and to facilitate the core company to understand the knowledge of the competitor company. In the cases involving more companies in GSC, the separate ontologies of different companies are integrated

If the i -th sense of Property₁(*) is equal to the j -th sense of Property₂(*), the length of path between two properties is $i+j-2$, the path is $sense_1^1, sense_1^2, \dots, sense_1^i, sense_2^{i-1}, \dots, sense_2^1$

$Property_1(*) = (sense_1^1, sense_1^2, \dots, sense_1^i, \dots, sense_1^m)$

$Property_2(*) = (sense_2^1, sense_2^2, \dots, sense_2^j, \dots, sense_2^n)$

If the i -th - m -th senses of Property(*) is equal to the j -th - n -th senses of Property₂(*) one by one, the depth between two properties is $m-i+1$ (or $n-j+1$), the path is $sense_1^1, \dots, sense_1^m$ or $sense_2^1, \dots, sense_2^n$

Fig. 6. Interpretations of expressions in the process of similarity calculation.

in the same way to provide a shared and interoperable decision knowledge structure to support decision activities.

4.3. The evolution of the shared ontology

In many ontology-based DSSs and rule-based ontology reasoning systems, ontology designers seldom take into account the knowledge evolutionary issues. However, the decision environment is very dynamic in reality. In this section, four GSC evolution scenarios are discussed in view of decision knowledge updating, as shown in Fig. 7. The ontology evolution operations are offline activities, but the evolved shared ontology is applied in online decision support activities. Each scenario for GSC decision knowledge updating is interpreted as below:

Scenario 1 (New company joining in GSC): With the development of GSC and its market environment, the core company would like to invite new companies to join in the alliance and seek for more benefits such as demanding low quoted price from new iron ore suppliers, exploring more customers to sell its new type carbon steel, etc. New companies are required to publish company-specific knowledge, e.g. capabilities of supplying, types of resources, and availabilities to the core company for knowledge sharing and decision purposes. The decision knowledge of the new company is represented in a separate ontology, i.e. Ontology (New); then, the semantic similarities between ontology (New) and the shared ontology are calculated; at last, ontology (New) is integrated into the shared ontology according to the ontology matching results.

Scenario 2 (Current GSC partner leaving GSC): A current GSC company may leave the alliance due to the reasons coming from the inside of the company or the outside of the market environment. For example, when a very big order is placed by one steel manufacturer, due to the limitations of its capabilities and availabilities, the iron ore supplier may choose to leave the current alliance and join in other collaborations. The capabilities of the leaving company should be carefully checked, in case of leading to unnecessary bad consequences such as transaction breaks off. If it is the exclusive company with an exclusive capability that is still needed, or it has uncompleted current tasks, etc., the core company should

generate a new task to call for new companies to join in the GSC to replace the functionalities of the leaving company.

Scenario 3 (A new task is required): When the core company initiates a new task such as product catalogue expansions, calling for new services, etc., a new instance is generated in the task related classes. Detailed specification of the task is described in the dataset of the new instance. After that, the capabilities of the current GSC partners are checked. If someone is able to fulfill the new tasks, the tasks will be assigned to the qualified GSC partner; if no one is qualified, a task of calling for new company will be initialized.

Scenario 4 (A current task is finished): After a current task is finished, the participating GSC partners may leave the current alliance. The capabilities of the current GSC companies related to the completed tasks are carefully checked. If no more capabilities of the related companies are required, they may be released from the alliance. They will remain in the current alliance if they have other capabilities relevant to some uncompleted tasks.

With regard to the dynamic changes of the GSC structure and the market environment, the knowledge evolution situations are not limited to the above mentioned four scenarios. These scenarios are selected to illustrate how the domain decision knowledge can be evolved in the shared GSC ontology. It is necessary to note that, under the consideration of ontology evolution, the decision-makers can utilize the most updated decision knowledge to support decision activities, and it can improve the decision quality to some extent. An outgoing GSC partner may join the alliance or cooperate with the core company again. Therefore, ontology elements such as classes, relations, attributes, etc. related to the leaving company are remained in the shared GSC ontology. In the same way, ontology elements related to the completed task are remained as well, in case that a similar or same task is required in the future.

4.4. Rule-based ontology reasoning

To support prompt and sound decision-makings on the basis of the shared ontology established in the preceding sections, the rule-based ontology reasoning method is proposed in this section. Semantic Web Rule Language (SWRL), which combines the Web

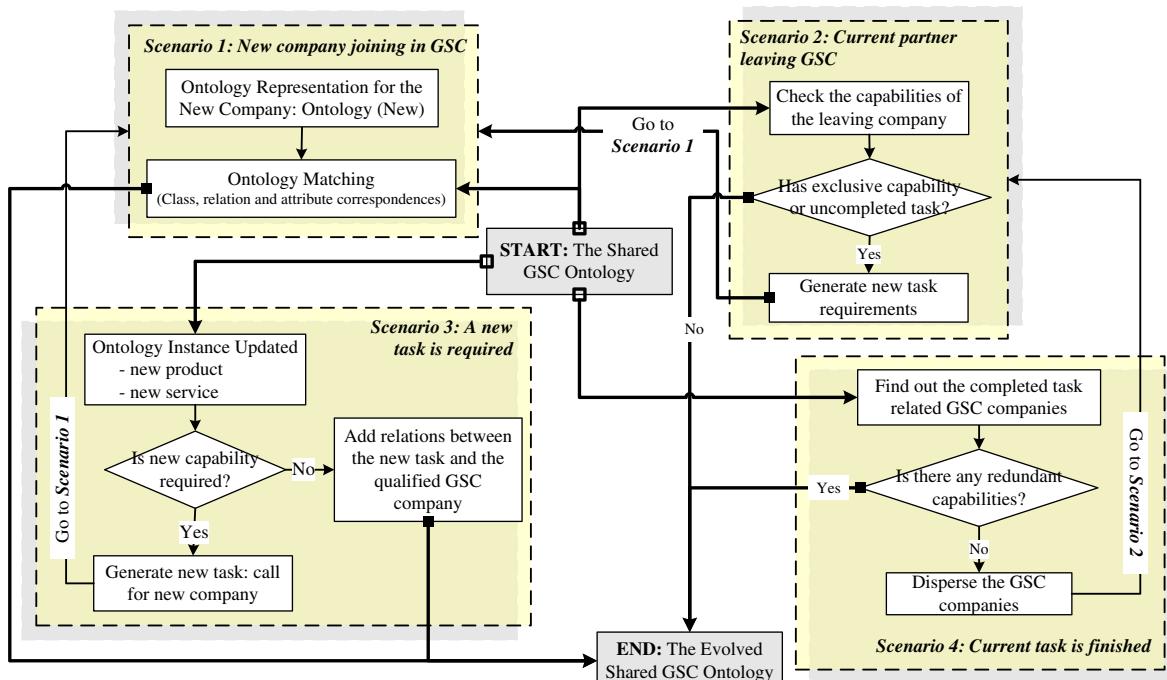


Fig. 7. Evolutionary scenarios for GSC development.

Ontology Language (OWL) and the Rule Markup Language (RuleML), is adopted to identify the implicit semantic relationships among the knowledge explicitly defined in the shared ontology. A SWRL reasoning rule is in the form of an antecedent and consequent (Horrocks et al., 2004) as shown in Eq. (7).

$$\text{Antecedent} \rightarrow \text{consequent} \quad (7)$$

The antecedent expresses the decision-maker's decision requirements, and the consequent expresses the decision suggestions of the rule-based reasoning results. To better comprehend the SWRL rules, two common atoms in SWRL syntax used in this study are introduced as follows:

- $C(?x)$: If x is an instance of the class C , or the value of its data type property, then $C(?x)$ holds;
- $P(?x, ?y)$: If x is related to y by property P , then $P(?x, ?y)$ holds;

In SWRL syntax, a rule can be defined in a form that both the antecedent and consequent are conjunctive atoms $a_1 \wedge a_2 \wedge \dots \wedge a_n$ and $b_1 \wedge b_2 \wedge \dots \wedge b_n$, respectively; Then the rule can be expressed as shown in Eq. (8):

$$a_1 \wedge a_2 \wedge \dots \wedge a_i \dots \wedge a_n \rightarrow b_1 \wedge b_2 \wedge \dots \wedge b_j \dots \wedge b_n; \quad (8)$$

Here, atoms a_i and b_j can be either $C(?x)$ or $P(?x, ?y)$. Some built-ins in the SWRL syntax are briefly introduced as follows:

- swrlb:equal : It is satisfied if the first argument and the second argument are the same;
- swrlb:lessThan : It is satisfied if two arguments are both in the same type, and the first argument is less than the second argument according to a type-specific ordering; it has some similar built-ins as $\text{swrlb:lessThanOrEqual}$, swrlb:greaterThan , and $\text{swrlb:greaterThanOrEqual}$;
- $\text{swrlb:stringEqualIgnoreCase}$: It is satisfied if the first argument is the same as the second argument, and their upper or lower case is ignored.

In this study, two SWRL rule templates are introduced, i.e. property-oriented and built-in-oriented, which are introduced in Eqs. (9)–(12):

- The property-oriented rule template moves property values from one individual to another to infer the implicit relationships between two individuals, as shown in Eq. (9). It means: according to the facts of classes x and y have a relationship P_1 , and classes y and z have a relationship P_2 , it can be deduced that classes of z and x have a relationship P_3 :

$$C(?x) \wedge P_1(?x, ?y) \wedge C(?y) \wedge P_2(?y, ?z) \rightarrow P_3(?z, ?x) \quad (9)$$

- The built-in-oriented rule template incorporates built-ins to infer the implicit relationships between individuals on the basis of the various types of instance values.

Eq. (10) means: the fact of class x has a data type property P_1 with the value “ a ”, and if “ a ” is the same as a certain string or other types of contents depicted in the double quotation marks, it can then be deduced that classes y and x have a relation P_2 :

$$\begin{aligned} & C(?x) \wedge P_1(?x, ?a) \wedge \text{swrlb : equal}(?a, \text{a string or others}) \\ & \wedge C(?y) \rightarrow P_2(?y, ?x) \end{aligned} \quad (10)$$

Eq. (11) means: the fact of class x has an integer or float, etc. type property P_1 with value “ a ”; if “ a ” is less than certain value, it is deduced that classes y and x have a relation P_2 . The swrlb:lessThan can be replaced by $\text{swrlb:lessThanOrEqual}$, swrlb:greaterThan , and $\text{swrlb:greaterThanOrEqual}$, with corresponding meanings:

$$\begin{aligned} & C(?x) \wedge P_1(?x, ?a) \wedge \text{swrlb : lessThan}(?a, \text{numeric}) \\ & \wedge C(?y) \rightarrow P_2(?y, ?x) \end{aligned} \quad (11)$$

Eq. (12) means: the fact of class x has a string type property P_1 with content “ a ”; if “ a ” is equal to a string specified in the double quotation marks, it is deduced that classes y and x have a relation P_2 :

$$\begin{aligned} & C(?x) \wedge P_1(?x, ?a) \wedge \text{swrlb : stringEqualIgnoreCase}(?a, \text{a string}) \\ & \wedge C(?y) \rightarrow P_2(?y, ?x) \end{aligned} \quad (12)$$

The actual SWRL rules applied in this study can be a single or the combination of the above rule templates, where all the ontology elements are adopted to comprise the SWRL rules. These rules are utilized to infer the knowledge structure of the shared GSC ontology in order to achieve implicit relationships between the core company and other GSC companies.

5. Case study

5.1. Case background

A Steel Company and *B Steel Company* are well-known steel manufacturers in mainland China. The earnings per share for both companies during Year 2009 and Year 2012 are compared in Table 1. Their financial data in Year 2011 and Year 2012 is compared in Table 2.

Both companies are located in mainland China under the same domestic policies and regulations, and in the same international market. Established in 1916 and as the earliest steel production base in mainland China, *A Steel Company* has a glorious history and once named as the cradle of the new China's steel industry. However, it is being involved in a huge operating crisis right now. From the earnings per share shown in Table 1, *B Steel Company* has performed steady in recent years but *A Steel Company*'s performance is getting worse and worse. It is not hard to find from the financial data that the performances of the two companies are quite different. As shown in Table 2, in Year 2012, *B Steel Company* achieved a negative fluctuation range of operating profits compared with the same period in Year 2011, but all of its operating profit, total profit, net profit and earnings per share were positive. In contrast, *A steel company* suffered a big deficit last year. This phenomenon was reported and analyzed to some extent by the media, including the Wall Street Journal (Chinese Edition, <http://cn.wsj.com/gb/>) and Caixin.com (<http://www.caixin.com/>), etc. *A Steel Company* declared in its financial statement that the company was heavily influenced by the continuing gloomy steel market, especially the steel price declined further more in the latter part of Year 2012. However, under close observation, it is easy to detect some deeper reasons inside the company. Among steel manufacturers in mainland China, *A Steel Company* suffered the worst loss. There are three main reasons. First, it has the problem of heavy overcapacity, and has to bring along the huge inventory holding cost. Secondly, it has an outdated raw material pricing scheme that the raw material purchasing contract is signed semiannually regardless of the price's trend is going higher or lower. Normally, the ironstone purchasing is based on spot pricing or quarterly pricing; but when the ironstone's price declines, *A Steel Company* has to

Table 1

Earnings per share of *A Steel Company* and *B Steel Company* during Year 2009 and Year 2012.

Earnings per share (RMB/share)	Financial Year	<i>A Steel Company</i>	<i>B Steel Company</i>
2012.6		-0.438	0.59
2011.12		-0.369	0.42
2010.12		0.336	0.73
2009.12		0.1	0.33

The data is collected from <http://www.10jqka.com.cn/>.

Table 2

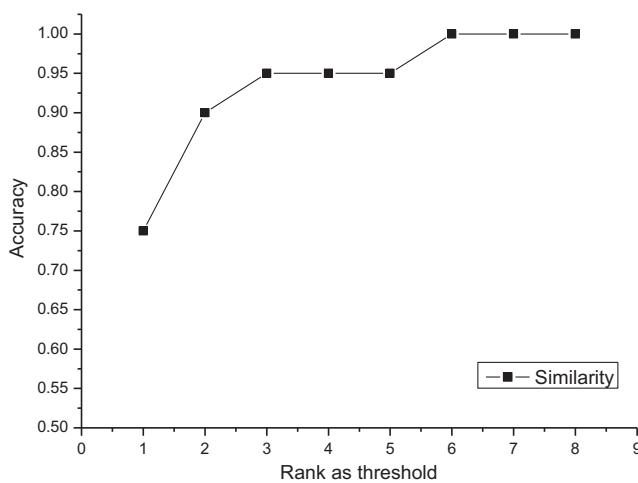
Financial status of A Steel Company and B Steel Company in Year 2011 and Year 2012.

Item	A Steel Company Current period in 2012	Same period in 2011	Fluctuation range (%)	B Steel Company Current period in 2012	Same period in 2011	Fluctuation range (%)
Operating profit (million RMB)	−452,900	−2100	−21466.67	3612	8839	−59.13
Total profit (million RMB)	−449,500	6800	−6710.29	13,132	9260	42.81
Net profit (million RMB)	−3170	239	−1426.36	10,305	7362	39.98
Earnings per share (RMB/share)	−0.438	−0.369	−18.70	0.59	0.42	39.98

The data is collected from <http://www.10jqka.com.cn/>.**Table 3**

Property and class correspondence library.

	Correspondence	Similarity	Rank
Property correspondences	Has year	0.6779	1
	Has product	1	1
	Per share is negative	0.5345	1
	Carbon steel is new	0.3990	3
	Credit degree downgraded	0.6038	1
	Credit degree upgraded	0.6287	1
	Credit degree unchanged	0.6137	1
	Has policy	1	1
	Has financial status	1	1
	Product name	1	1
	Sell to	1	1
	Has price	0.6852	2
	Has product type	0.6251	2
	Pricing type	0.5949	6
	Policy value	0.7041	1
	Product type value	0.6494	2
	Is year	0.6779	1
	Corporation	0.6681	1
Class correspondences	Product	0.8276	1
	Financial status	0.6779	1

**Fig. 8.** Matching accuracy with rank threshold changing.

bear with the high contracted price for at least several months. The third reason is that the company has not paid enough attention to adjust the industrial structure into more segment markets, which causes the loss of potential customers to some extent. Comparatively, B Steel Company is the second most profitable steel manufacturer in the world. It has removed the less profitable operating departments such as stainless steel and special steel departments,

to emphasize on new products such as carbon steel's operating and researching; it keeps improving the current manufacturing processes to lower the carbon emission and seeking for new breakthroughs of the current techniques; it also develops collaborations with its downstream industries to achieve energy-saving and emission-reduction within the entire supply chain.

The objective of this study is to provide a rule-based ontology reasoning method to facilitate companies to make prompt and sound decisions in the dynamic and heterogeneous market environment. In this case study, it is assumed that the proposed method is to serve the senior managers of A Steel Company to improve the company performance and the industrial practice. B Steel Company as a benchmark is selected to support decision-making activities for the senior managers of A Steel Company.

5.2. Ontology matching and the shared ontology integration

In order to facilitate the senior managers of A Steel Company to make decisions on the basis of utilizing B Steel Company's decision history and past performances, semantic interoperability should be reached as first between their decision knowledge. The separate ontologies for A Steel Company and B Steel Company were roughly constructed as core-ontology and competitor-ontology, respectively, in Section 4.1. The pair-wise similarities of properties and classes from both ontologies are calculated according to the ontology matching algorithm proposed in Section 4.2. The property and class correspondence library with their similarity and rank of similarity is displayed in Table 3.

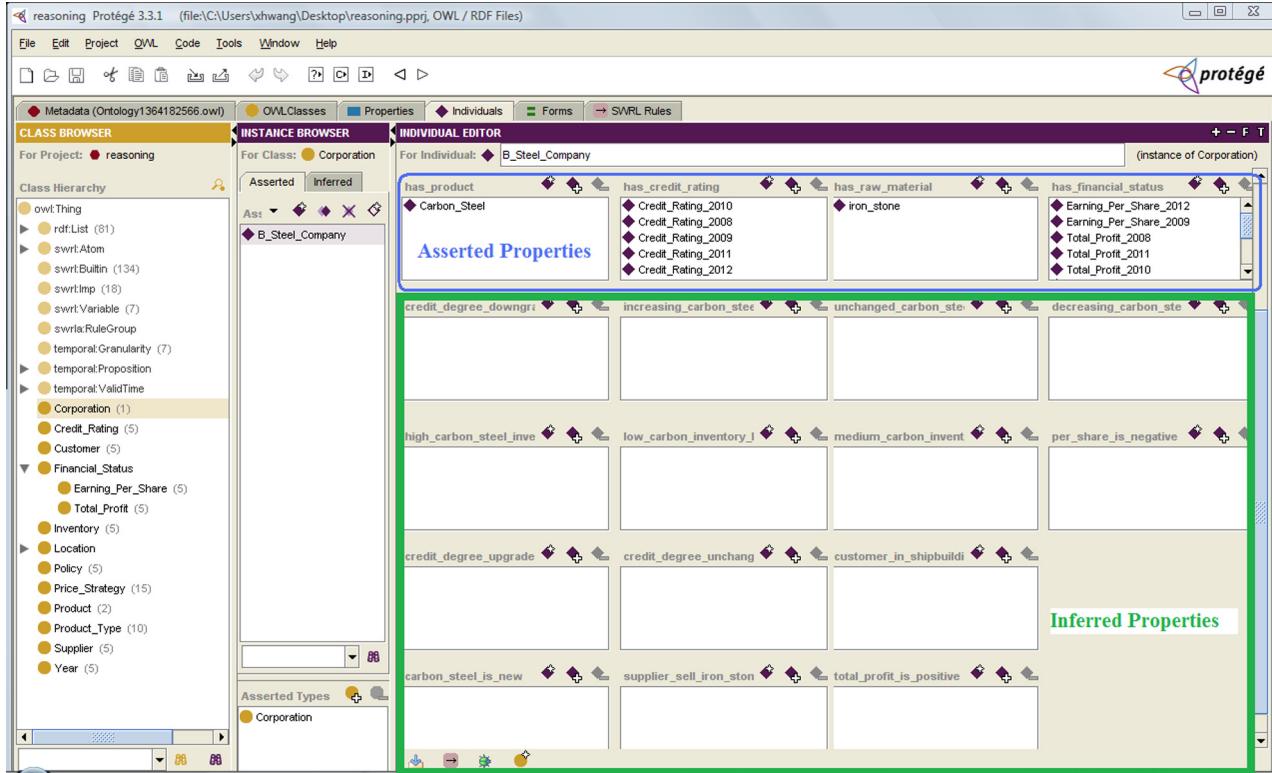


Fig. 9. Asserted and inferred properties of Class:Corporation.

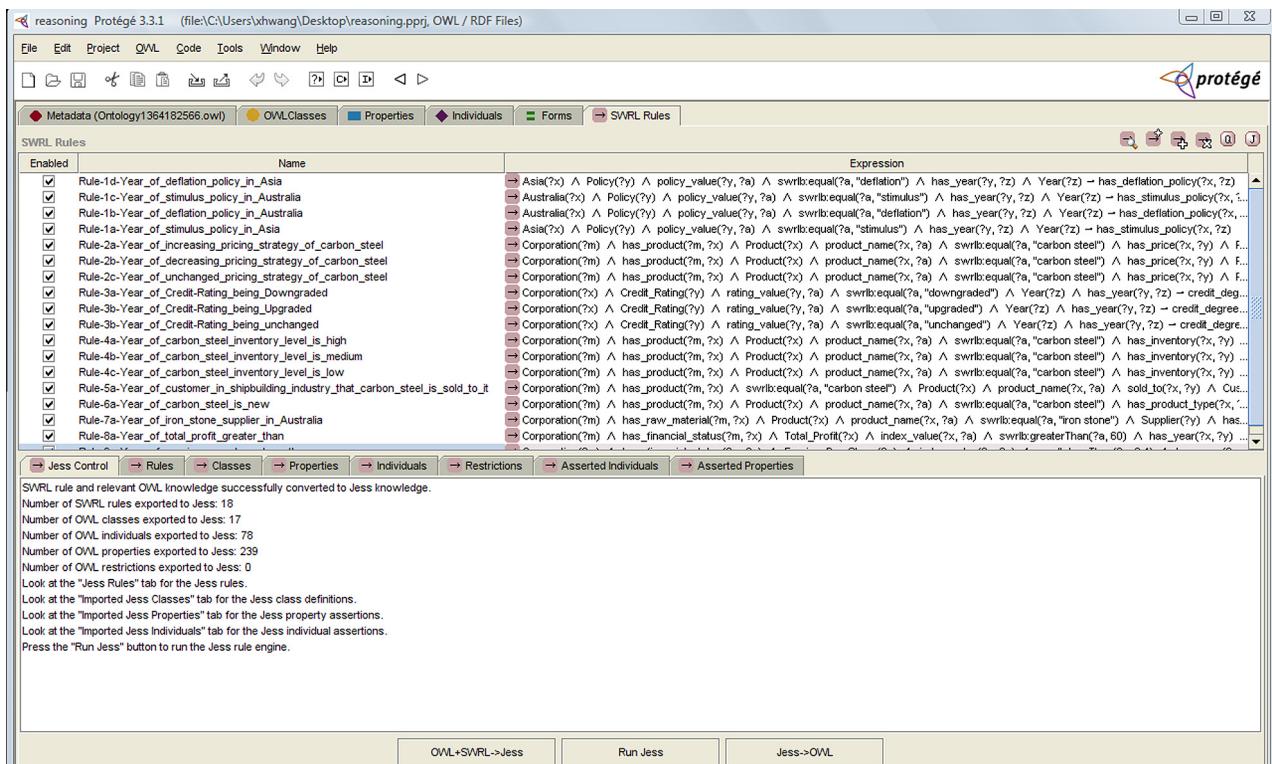


Fig. 10. Interface of SWRL rule-based JESS reasoning engine.

To determine the correct correspondences, proper threshold should be determined. Fig. 8 shows the accuracy in this case study

with different thresholds under the proposed ontology matching algorithm.

Fig. 11. Detailed reasoning processes of classes, properties and individuals.

The result shown in Fig. 8 indicates that the accuracy of the ontology matching algorithm is 0.75 in this experiment. That is, 75% pair-wise correspondences could be detected by the algorithm. If the threshold is set to be Rank 2 or above, more pair-wise correspondences could be detected. However, it will increase the output of the candidate matching pairs, which will require more amount of work from the ontology designers.

It is necessary to note that the ontology matching process is an offline activity that requires intervention and judgment of the ontology designers. As indicated in Table 3, some properties and classes of both ontologies are not listed in the correspondence library, since they do not have direct correspondent pairs in the opponent's ontology. For example, Class:Inventory and Property:has_inventory_level are decision knowledge provided by *B Steel Company*, which *A Steel Company* did not have this knowledge in its ontology. In this case, the unmatched properties and classes will be integrated into the shared ontology in their previous manners. For the matched pairs, properties like same_as and sibling will be created between the correspondent properties and classes, respectively, to connect similar terminologies between two ontologies.

According to the above processes, the shared ontology is integrated. The decision knowledge defined in the shared ontology will keep on changing according to the evolution of the decision environment and the collaborative structure of companies in GSC.

Then, the shared ontology will be timely evolved according to the ontology evolution mechanisms proposed in Section 4.3 by the ontology designers.

5.3. Rule-based ontology reasoning

With regard to China's iron and steel industry considered in this study, the implicit knowledge to be reasoned by *A Steel Company* for decision-making purposes is the operating and business strategies of *B Steel Company* in different time periods and the dynamic market environment. Three types of strategies are taken into account, i.e. pricing strategy, R&D strategy and partner selection strategy. The rule-based ontology reasoning method was implemented in Java, and Protégé was employed to parse the OWL files and the SWRL rules. JESS is used to be embedded in the protégé platform to execute rule inference. The shared GSC ontology integrated in Section 5.2 is utilized as the basic knowledge structure in the rule-based ontology reasoning process.

Fig. 9 shows the asserted properties and inferred properties of Class:Corporation of the shared GSC ontology. The asserted properties are given by the ontology designers, while the inferred properties are to store the reasoning results according to the pre-defined SWRL rules. Fig. 10 shows the interface of SWRL rule based JESS reasoning engine. The pre-defined rules are shown on the top of

Table 4

SWRL rules and the reasoning results.

SWRL Rule	Result
Rule-1a <i>Find out the year that Asia's economic policy is stimulus</i> Asia(?x) ∧ Policy(?y) ∧ policy_value(?y, ?a) ∧ swrlb:equal(?a, "stimulus") ∧ has_year(?y, ?z) ∧ Year(?z) → has_stimulus_policy(?x, ?z)	Year 2010 Year 2011 Year 2012
Rule-2a <i>Find out the year that carbon steel's price of B Steel Company is increased</i> Corporation(?m) ∧ has_product(?m, ?x) ∧ Product(?x) ∧ product_name(?x, ?a) ∧ swrlb:equal(?a, "carbon steel") ∧ has_price(?x, ?y) ∧ Price_Strategy(?y) ∧ pricing_type(?y, ?b) ∧ swrlb:equal(?b, "increasing") ∧ has_year(?y, ?z) ∧ Year(?z) → increasing_carbon_steel_pricing_strategy(?m, ?z)	Year 2008 Year 2009 Year 2010 Year 2011
Rule-3a <i>Find out the year that the credit-rating of B Steel Company is downgraded</i> Corporation(?x) ∧ Credit_Rating(?y) ∧ rating_value(?y, ?a) ∧ swrlb:equal(?a, "downgraded") ∧ Year(?z) ∧ has_year(?y, ?z) → credit_degree_downgraded(?x, ?z)	Year 2008
Rule-4a <i>Find out the year that carbon steel's inventory of B Steel Company is high</i> Corporation(?m) ∧ has_product(?m, ?x) ∧ Product(?x) ∧ product_name(?x, ?a) ∧ swrlb:equal(?a, "carbon steel") ∧ has_inventory(?x, ?y) ∧ Inventory(?y) ∧ has_inventory_level(?y, ?b) ∧ swrlb:equal(?b, "high") ∧ has_year(?y, ?z) ∧ Year(?z) → high_carbon_steel_inventory_level(?m, ?z)	Year 2008 Year 2009 Year 2011
Rule-5a <i>Find out the year that carbon steel of B Steel Company is sold to a shipbuilding factory</i> Corporation(?m) ∧ has_product(?m, ?x) ∧ Product(?x) ∧ product_name(?x, ?a) ∧ sold_to(?x, ?y) ∧ Customer(?y) ∧ in_industry(?y, ?b) ∧ swrlb:equal(?b, "shipbuilding") ∧ located_in(?y, ?z) ∧ Asia(?z) ∧ has_year(?y, ?n) ∧ Year(?n) → customer_in_shipbuilding(?m, ?n)	Year 2008 Year 2009
Rule-6a <i>Find out the year that B Steel Company developed new types of carbon steel</i> Corporation(?m) ∧ has_product(?m, ?x) ∧ Product(?x) ∧ product_name(?x, ?a) ∧ swrlb:equal(?a, "carbon steel") ∧ has_product_type(?x, ?y) ∧ Product_Type(?y) ∧ product_type_value(?y, ?b) ∧ swrlb:equal(?b, "new") ∧ has_year(?y, ?z) ∧ Year(?z) → carbon_steel_is_new(?m, ?z)	Year 2010
Rule-7a <i>Find out the year that B Steel Company purchased iron stone from Australia</i> Corporation(?m) ∧ has_raw_material(?m, ?x) ∧ Product(?x) ∧ product_name(?x, ?a) ∧ swrlb:equal(?a, "iron stone") ∧ Supplier(?y) ∧ has_product(?y, ?x) ∧ located_in(?y, ?z) ∧ Australia(?z) ∧ has_year(?y, ?n) ∧ Year(?n) → supplier_sell_iron_stone(?m, ?n)	Year 2010 Year 2011 Year 2012
Rule-8a <i>Find out the year that total profit of B Steel Company is more than 6 billion RMB</i> Corporation(?m) ∧ has_financial_status(?m, ?x) ∧ Total_Profit(?x) ∧ index_value(?x, ?a) ∧ swrlb:greaterThan(?a, 60) ∧ has_year(?x, ?y) ∧ Year(?y) → total_profit_is_positive(?m, ?y)	Year 2010 Year 2011 Year 2012
Rule-9a <i>Find out the year that earning per share of B Steel Company is less than 0.4 RMB</i> Corporation(?m) ∧ has_financial_status(?m, ?x) ∧ Earning_Per_Share(?x) ∧ index_value(?x, ?a) ∧ swrlb:lessThan(?a, 0.4) ∧ has_year(?x, ?y) ∧ Year(?y) → per_share_is_negative(?m, ?y)	Year 2008 Year 2009

the figure, while the reasoning results are shown below. Fig. 11 shows the detailed reasoning processes of classes, properties and individuals.

The decision-makers can select a few or all of the rules to reason the shared GSC ontology. In this experiment, 18 SWRL rules, 17 owl classes, 78 owl individuals, 239 owl properties are exported to JESS. To further explain the rule-based ontology reasoning method, and justify its feasibility and effectiveness to support decision-making activities, 9 SWRL rules for *A Steel Company* are selected and interpreted in Table 4, with their reasoning results attached. After that, the decision support analysis for *A Steel Company* is discussed.

As shown in Table 4, single rule or combined rules can be utilized to support the senior managers of *A Steel Company* to make decisions. For example,

- On the basis of Rule-3a, Rule-4a and Rule-9a, it is deduced that in years when the financial status is not as good as before, the carbon steel's inventory level is relatively high; furthermore, the high inventory level would increase the inventory holding cost for the company, which will aggravate the financial status in that year. In this case, the senior managers of *A Steel Company* would seek all kinds of ways to reduce the inventory level of their products to obtain a relative good financial performance in bad years, such as reducing the price, rearranging the producing schedule, etc.; in addition, it also implies that *A Steel Company* has to coordinate with its supply chain partners to improve the planning and scheduling activities and to avoid excess production capacities.

- On the basis of Rule-4a, Rule-6a and Rule-8a, it is deduced that developing new types of products would bring positive effect on company's financial status, and also increase the product's sales in that year. In this case, the senior managers of *A Steel Company* would try to establish new policies on product development, in order to occupy more market share and profits before its competitors start the similar strategies.

- On the basis of Rule-5a and Rule-6a, it is deduced that *B Steel Company* sold its old type carbon steel to a shipbuilding factory; after it began to produce new type carbon steel, the shipbuilding factory was no longer its customer. In this case, the senior managers of *A Steel Company* would consider to sell its traditional carbon steel products to shipbuilding factories as they might still use old type carbon steel as raw materials. Moreover, it also implies that *A Steel Company* has to respond promptly to changes in the global market.

The above results indicate that, based on the existing and multi-source decision knowledge, the rule-based ontology reasoning method is able to facilitate the senior managers of *A Steel Company* to retrieve useful implicit decision knowledge such as developing pricing strategy, product development strategy and partner selection strategy, etc. Other managerial inferences and suggestions can be deduced in the same way through different rules, which are not presented here. It is then concluded that the proposed method can support sound decision-makings according to the similar, historical and suitable experiences of their collaborators or competitors; and the company performance and industrial practices will be improved accordingly as well.

6. Conclusions and future work

In the highly dynamic global market, the global supply chain has to be highly responsive and resilient. Partners in the GSC have to share information and knowledge, and to coordinate and collaborate with each other, to meet the specific goals of the supply chain. It is necessary to make use of effective and efficient decision support techniques to assist companies in the planning and implementation of the GSC strategies and functions. In this paper, a rule-based ontology reasoning method is proposed for decision support in GSC. A case study involving two well-known Chinese steel manufacturers in China's iron and steel industry is introduced.

This paper contributes in supporting decision-making activities and tries to improve the company performances and global industrial practices as well. First, ontology is adopted to represent the multi-source and heterogeneous decision knowledge from the GSC participants. Ontology matching and integration methods are proposed to enable a semantic interoperable decision environment among the distributed GSC participants. Second, the organizational structure of GSC and the decision environment are very dynamic, thus the ontology evolution method is proposed to cater for different evolutionary purposes in GSC. At last, in the proposed rule-based ontology reasoning method, not only the implicit decision knowledge is retrieved according to the explicitly defined knowledge, but also the ontology structures and rules are defined in the time-varying manner. In doing so, the decision-makers can understand and utilize the updated multi-source knowledge incorporating the time factors to make more appropriate and prompt decisions.

This paper justified the effectiveness and efficiency of the proposed rule-based ontology reasoning method to support decision-makings in two notable Chinese Iron and Steel companies. The operating strategies of the benchmark company were learnt by other companies, which aimed at improving their industrial performances themselves and across their GSCs. Besides, the proposed method could be applied in many other managerial fields to support complicated decision-makings. For example, to find out the most suitable staff inspiration strategy to improve the company productivity, to find out the most suitable enterprise's culture for international companies that would like to expand their business in other counties, and also to find out the most suitable investment channels in different economic conditions, etc.

The results presented in this paper provides basis for future research in several areas. Three of such areas are identified:

- Enhancing the ontology matching algorithm,
- Extending the scope of time-varying factors and the SWRL rules in the shared GSC ontology, and
- Knowledge elicitation and extraction for real-life industrial applications.

With regard to the integrated shared ontology, the performance of the ontology matching algorithm should be improved. In this paper, the algorithm was developed on the basis of ambiguity and intercommunity between two separate terms. The WordNet dictionary is adopted, and hypernyms relation was introduced to express the senses of the terms. However, WordNet involves many kinds of relations, such as synonyms, coordinate terms, hyponyms (... is a kind of...), holonyms (... is part of...), etc. With different relations adopted, the semantic similarity between two properties would be slightly different. Therefore, more ontology matching algorithms should be studied, evaluated and compared in future studies, and the most suitable algorithm should be determined to suit different application domains accordingly.

Regarding the time-varying factors defined in the shared GSC ontology and the SWRL rules in this paper, the year-factor was taken into account. To provide more managerial guidance in practice, more descriptions of time-varying factors should be considered, such as day, month, quarter, etc. Regarding the decision knowledge defined in SWRL rules, strategies for product development, partner selection and product pricing are considered in this study. In the future, to cater for diverse decision-making purposes in the context of GSCs, more reasoning rules should be developed to explore more implicit decision knowledge, such as how staff inspiration strategy, the construction of enterprise culture, development of different investment channels, etc. influence on the industrial performances of different GSCs.

There are two major challenges in applying the proposed method in real-life applications. On one hand, it is required to develop an automatic decision support system on the basis of the rule-based ontology reasoning method, which can enable real-life decision making activities. Under the considerations of the characteristics of ontology and the requirement of timely and distributed decision support, the multi-agent based system is a good choice. On the other hand, the quality of the collected knowledge determines the quality of the sound decisions to be made. It is therefore necessary and important to ensure the collection of reliable and accurate multi-source GSC decision knowledge, and to construct the explicit, extensible, and evolutionary domain ontology that caters for the practical decision environment.

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