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AN EXPERIMENTAL EVALUATION OF A RULE-BASED APPROACH TO MANUFACTURING SUPPLIER DISCOVERY IN DISTRIBUTED ENVIRONMENTS

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ABSTRACT

Manufacturing supplier discovery in virtual environments is a computationally intensive task. Existing electronic marketplaces for manufacturing services, due to their syntactic and human-oriented approach in search, fail to build accurate connection between seller and buyers. Automation and intelligence are the two key requirements of web-based solution for efficient deployment of virtual supply chains. It was previously shown that an ontological approach, due to its semantic nature, yields more precise results compared to traditional techniques such as keyword search and vector-based methods. While the proposed ontology, known as Manufacturing Service Description Language (MSDL), can sufficiently encode structural knowledge in the manufacturing domain, it doesn't have the required level of expressivity for representing constraint knowledge. This paper introduces an extension to MSDL for formal representation of constraints and rules based on Semantic Web Rule Language (SWRL). To identify the rules and to evaluate the performance of the rule-based technique, an experimental approach is followed in this research.

Keywords: electronic marketplace; supplier discovery; semantic matching, ontology.

1 INTRODUCTION

Manufacturing outsourcing strategies have undergone profound changes over the past few decades. While cost-saving justifications were the major drivers for manufacturing companies to outsource globally in 1980s, the ability to meet quality and reliability requirements supplemented the economic considerations later in 1990s [1]. Today, due to rapid changes in customer needs and market opportunities, *responsiveness* and *flexibility* are regarded as the essential characteristics of supply chains. In this context, supply chains are increasingly becoming virtual and reconfigurable to obtain more agility and respond to market fluctuations in a more timely fashion. In deployment of virtual supply chains, rapid and efficient evaluation and selection of manufacturing partners are key requirements. Electronic marketplaces (e-marketplaces) for search and selection of manufacturing services are currently the state-of-the-practice in developing flexible supply networks for discrete part manufacturing [2, 3]. The main functions of e-marketplaces include providing buyers and seller with a virtual environment to meet and present their capabilities and needs, and streamlining various activities in different market transactions phases, namely, connection, negotiation, and execution. This research mainly deals with the *connection* phase in which market participants form partnerships to respond to a certain wok order. The growing popularity of e-marketplaces for manufacturing services can be attributed to several factors such as low cost of entrance, low cost of transaction due to elimination of market mediators, the possibility of interacting with a far larger number of potential counterparts, and equal treatment of members regardless of their size and global reach[4].

Electronic RFQ markets, referred to as RFQ *markets* henceforth, usually provide traditional means of search including keyword search, directory search, and database search on both buyer and seller data. Search criteria for querying a buyer's database typically include customer's category (process, sub-process, and product), materials, delivery location, industry, quantities (min-max), and dimensions. On the seller's side, search criteria often include process, sub-process, company name and location, and quality certification. These criteria, however, are simplistic and often provide incomplete picture of supplier's potential match with requirements, leading to identification of suppliers that are irrelevant. Also, given the syntactic nature of the keyword search, the quality of the returned results highly depends on the choice of keywords in the query or advertisement. As a result, relevant documents that use different syntax may be excluded from the search results (resulting in a false negative error) and similarly, irrelevant documents with similar syntax with the query may be deemed relevant (resulting in a false positive error) by the search engine. Because of this deficiency, the output of the search engine usually needs to be further refined by human users by reviewing the narrative description of suppliers' capabilities provided in a free-text format in order to arrive at more accurate results. However, as the size of the search space increases, human-based evaluation and screening becomes increasingly inefficient and error-prone. Therefore, it is necessary to enhance both the *intelligence* and the *automated capabilities* of search engines in RFQ markets by enabling *semantic supplier discovery*.

To address the identified gaps in the underlying information model of RFQ markets, an ontological approach is adopted in the current research. A formal ontology provides explicit representation of information semantics, thus enabling autonomous reasoning and inference by machine agents. In presence of a rich information model, more intelligent search algorithms can be employed to improve the precision of the returned results.

The proposed ontology, referred to as Manufacturing Service Description Language (MSDL) [5], is customized for representation of manufacturing needs and capabilities at different levels of abstraction including supplier-level, shop-level, and machine-level. MSDL particularly focuses on the technological aspects of manufacturing capabilities and needs such as process types, materials, tolerances, surface finish, machine tools, and technological background of supplier and customers. In MSDL, supply and demand are represented as *manufacturing services capabilities and requirements*, respectively. MSDL is coupled with a set of intelligent search algorithms that can quantify the semantic proximity of supply and demand entities based on their similarities. In the previous paper, it was shown that the proposed semantic matching method outperforms the keyword search method based on the standard metrics of information retrieval such as *precision*, *recall*, and *discounted cumulative gain* [6]. This paper introduces a rule-based extension to MSDL based on the Semantic Web Rule Language (SWRL). The objective is to enhance the expressivity of MSDL in order to support automated inference and reasoning capabilities in the search engine.

The remainder of this paper is organized as follows. In Section 2 , related works in service representation are discussed. Section 3 provides a brief introduction to the ontology and its corresponding search algorithms. In Section 4 , the knowledge-based aspects of supplier search will be discussed and a rule-based approach will be introduced for inferring new capabilities based on the stated ones. Section 5 deals with experimental evaluation of the proposed semantic search approach. The last section provides concluding thoughts.

2 RELATED WORK

In the context of Web Services, the most prominent standard for service representation is Web Service Description Language (WSDL) that allows service providers to describe their services using a standard XML schema. The standard and predefined structure of WSDL enables application developers to interact with Web Services without previous knowledge of their contents. Researchers have employed WSDL for service representation in distributed manufacturing. For example, Shi et al. Shi[7] adopted WSDL for resource description in manufacturing grids. However, due to its rigid structure, WSDL provides little formal semantic, thus inhibiting possibilities for automated service discovery and execution. To enable service modeling at a semantic level, several representations were proposed including Web Service Modeling Ontology[8], Semantic Web Services Framework [9], WSDL-S [10], and OWL-S [11]. For instance, by representing Web Services in a computer-interpretable manner, OWL-S enables automatic service discovery, invocation, composition and interoperation. To describe a service, OWL-S uses the notions of Service Profile (i.e., what the service does), Service Model (i.e., how the service works) and Service Grounding (i.e., how to use the service). Service abstraction in OWL-S, due to its generic nature, is applicable to manufacturing service as well. However, since OWL-S is designed at the outset for modeling Web Services, it doesn't have the necessary building blocks for describing manufacturing services in a detailed fashion.

Kulvatunyour *et al*. [12] proposed an extension to OWL-S to make it applicable to description of manufacturing services. To this end, the Service Category property in OWL-S service profile was supplemented by *manufacturing operation* as a new service category. The manufacturing operation category, in this model, is further augmented by defining several sub-classes of manufacturing operation (e.g., Material Removal operation) together with their associated processes (e.g., Hole Making) and attributes. In this way, manufacturing service capability knowledge can be represented in *service profile* and shared among the members of the virtual supply chain. However, the proposed model is limited to representation of structural knowledge and does not include constraint knowledge. Cai *et al.* [13] proposed a model for representation of manufacturing services which utilizes OWL for formalization of structural knowledge and Semantic Web Rule Language (SWRL) [14] for formalization of constraints between various components of structural knowledge. Although the proposed model provides the required level of expressivity, the core concepts of the ontology are not adequately formalized through necessary and sufficient conditions. Other proposed ontologies in supply chain service modeling are mainly focused on capability representation at an operational level [15, 16]. However, they fail in providing the required means for representation of manufacturing capabilities from a *technological* point of view. In supplier discovery, operational capabilities should be taken into account only after technological competencies of suppliers are verified. A study of online marketplaces in aerospace industry showed that a lack of consideration of technological capabilities of suppliers is one reason why some suppliers are unwilling to participate in such marketplaces [17]. This paper presents an extension to MSDL in order to further enhance its expressivity through representing complex rules and constraints.

3 THE PROPOSED FRAMEWORK

The proposed framework for supplier discovery has two core components: the MSDL ontology for formal representation of manufacturing services and a set of search and inference algorithms. This section provides a short description of these components.

3.1. Manufacturing Service Description Language

MSDL uses OWL-DL[1], a sub-language of OWL [18] as the ontology language. OWL is recommended by World Wide Web Consortium (W3C) as the ontology language of the Semantic Web. OWL uses XML as the syntax language, hence it has enough portability, flexibility, and extensibility for web-scale applications. OWL-DL uses Description Logic (DL) that provides formal syntax and semantics for developing information and knowledge models with a domain of interest in terms of concepts, relationships between concepts, and the logical restrictions that concepts must satisfy. Since MSDL's semantics are mainly in the form of concept definitions and their interrelations, the expressivity offered through DL is sufficient for knowledge representation in this work. Due to its mathematically rigorous formalism, DL supports automated reasoning services such as concept subsumption, concept equivalence, and concept consistency. The scope of MSDL, in the initial development is limited to conventional machining services such as turning, drilling, and milling. MSDL provides the required means for semantic annotation of manufacturing services in order to enable semantically enhanced search capabilities in RFQ markets.

There are four levels of formalization when annotating service descriptions represented in natural language with semantic markups. In the first level of formalization, core concepts of the domain of interest are represented through formal classes with known properties. For example, buyers and sellers of manufacturing services are represented by *Customer* and *Supplier* classes respectively. Both *Customer* and *Supplier* are sub-classes of the *Actor* class, an imported class from the OWL-S[2] ontology. The *Actor* class contains the generic attributes required for introducing market participant including name, physical address, phone, fax, and web URL. In the second level of formalization, *relationships* between the defined concepts are introduced to further annotate the concepts. For example, the *Supplier* class is connected to the *Industry* and *Product* classes through *hasIndustryFocus* and *hasProductFocus* properties respectively to describe the background and expertise of suppliers. In MSDL, supply and demand are represented by *SupplierProfile* and *RFQ* classes, respectively. As can be seen in Figure 1, *SupplierProfile* has two major components, namely, the *Supplier* and the *ManufacturingServices* that the supplier provides. Manufacturing Services are further described through their associated processes, materials, resources, and supporting services.

Figure 2 shows the concept diagram for RFQ. As shown in this figure, each RFQ has exactly one *Customer*. Also, an RFQ can have multiple *Services*. Each RFQ has a *Part* class connected to it through the *hasPart* property. The *Part* class is used for defining the attributes of the part contained in the query.

Introduction of *is-a* relationships in the second level of formalization results in formation of explicit taxonomies. Taxonomy can be regarded as a light-weight ontology that contains a collection of parent-child relationships that satisfy

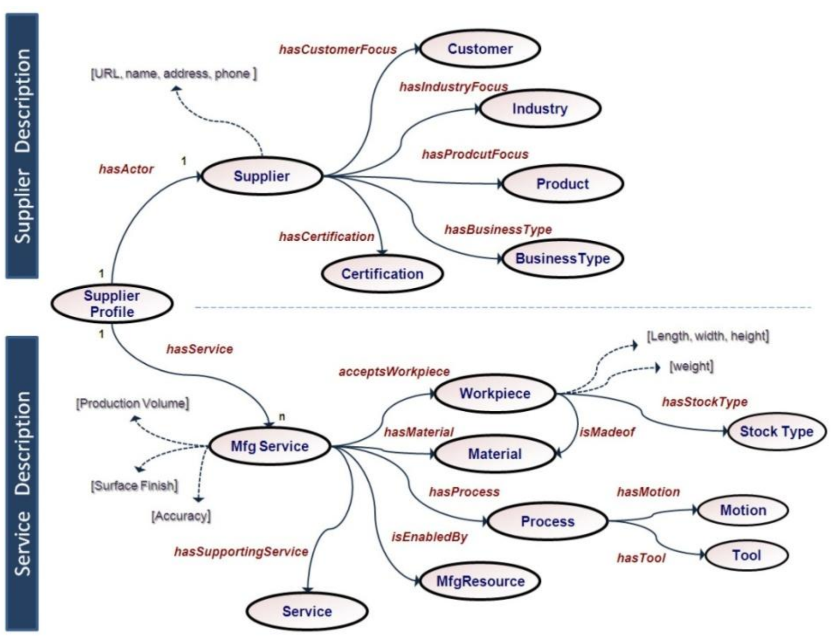

Figure 1: Concept diagram for Supplier Profile class

[1] http://www.w3.org/TR/owl-guide/

[2] http://www.ai.sri.com/daml/services/owl-s/1.0/

non-overlapping and exhausting conditions. For example, North American Industry Classification System[3] (NAICS) and United Nations Central Product Classification[4] (UN CPC) are

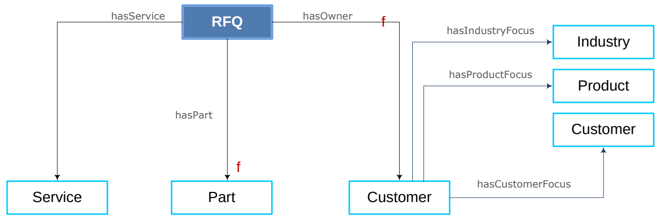

Figure 2: Concept Diagram for RFQ in MSDL

the taxonomies incorporated in MSDL for representing the semantics of *Industry* and *Product* classes respectively.

In the third level of formalization, concepts are further annotated by different types of restrictions, such as *quantifier*, *cardinality*, and *hasValue* restrictions, to from *defined* concepts. For example, concepts such as *Process* and *Material* are formally defined through necessary and sufficient conditions. Figure 3 provides the formal definition of the *End Milling* process based on the major feed and cutting motions involved in this process. Since concepts such as *Motion*, *Tool*, *Machining*, and *Axis* have their own formal definitions; software agents can understand and interpret the *meaning* of the end milling process as opposed to merely relying on its name as a string of characters. In a similar fashion, all machining processes are uniquely defined in MSDL based on the type of motions they provide. Materials are also defined axiomatically in MSDL through their mechanical, chemical, and physical properties. For example, aluminum and stainless steel are defined in the ontology as shown in Figure 4. DL reasoners, such as Racer[5] or Pellet[6] can be used to classify a flat set of *defined* classes and arrive at an inferred taxonomy. In other words, an axiomatic approach for encoding semantics can address the classification needs as well. Using the first three levels of formalization, *structural knowledge* can be represented formally in OWL. However, OWL cannot adequately formalize the rules and constraints imposed between multiple properties. To enhance the expressivity of OWL and enable users to formulate IF-TEHN rules in terms of OWL concepts, Semantic Web Rule Language (SWRL) was introduced as an extension to OWL. This paper describes how MSDL is extended by SWRL rules to allow advanced inference and reasoning during supplier discovery process.

3.2. Similarity measurement

The search space of an RFQ market is populated by the profiles of the suppliers that provide various types of manufacturing service together with the RFQs that encode demand entities. The goal is to quantify the similarities of each profile in the search space with a particular service request formulated as an RFQ. The similarity of a supplier profile (SP) to a given query (Q) is calculated as weighted average of the similarities of the actor (i.e., the supplier who provides the service) and the service portion of the query, as shown by the following equation:

$$Sim(Q, SP) = W_{actor}\, Sim_{actor} + W_{service}\, Sim_{service}$$

The algorithm used for similarity measurement utilized the taxonomy-based and feature-based techniques. For example,

```
EndMilling ≡ Machining
and hasMotion some (Motion
        and hasAxis only cAxis
        and hasMovingAgent only Tool
        and hasMotionType value "cutting")
and hasMotion some (Motion
        and hasAxis only (xAxis or yAxis)
        and hasMovingAgent only Part
        and hasMotionType value "feed")
and hasTool some (Tool
        and hasCuttingEdge only(CuttingEdge
        and isContinuous value false))
```

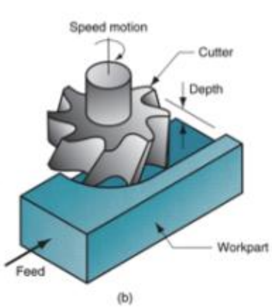

Figure 3: Formal definition of end milling process (picture courtesy of John Wiley & Sons Inc.)

[3] http://www.census.gov/eos/www/naics/
[4] http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=16

[5] http://www.sts.tu-harburg.de/~r.f.moeller/racer/
[6] http://clarkparsia.com/pellet/

since MSDL contains explicit classifications of industries and products, the similarity scores for instances of *Industry* and *Product* classes are determined through a *taxonomy-based approach* as shown by the following equation [19]:

$$Sim(C_A,C_B)=\frac{2\log(IC_{sa})}{\log(IC_A)+\log(IC_B)}$$

where IC_A and IC_B are the information content (IC) of the two nodes (A and B) being compared and IC_{sa} is the information content of their shared ancestor, or common parent, in the taxonomy tree. In this equation, the numerator represents the amount of information required for describing the commonalities of concepts A and B, while the denominator measures the total amount of information required for describing each concept individually.

A *feature-based method* can be employed for measuring the similarities of instances of defined classes such as *Process* or *Material* classes through a comparison of each item's conditions:

$$Sim(A,B)=\frac{n_{A\cap B}}{n_{A\cap B}+\mu n_{A-B}+\nu n_{B-A}}$$

Where $\eta_{A\cap B}$ is the number of conditions common to both the query and the search space classes, η_{A-B} is the number of conditions in the query that are not in the search space, and η_{B-A} is the number of conditions in the search space that are not in the query class. The variables μ and ν are weighting factors to allow for stressing the importance of the query or the search space.

The interested reader is referred to [20] for a detailed discussion on the search algorithm. The algorithm is implemented in JAVA and it interacts with MSDL descriptions through OWL-API. The implemented search algorithm, due to its semantic nature, is more intelligent than mere keyword-based, or vector-based, technique. Therefore, as verified experimentally in a previous research [21] , the proposed search approach is capable of building semantically sound connections between supply and demand. However, it can be argued that the implemented algorithm has not capitalized sufficiently on the reasoning and inference services enabled by knowledge representation formalism of MSDL. In fact, the implemented algorithms only rely on the limited subset of hierarchical taxonomic knowledge representation and feature-based concept representation but they don't use additional domain knowledge in form of rules of good practice and heuristic rules, which may be captured in the form of production rules. To improve the intelligence of the search algorithm, it is necessary to enhance its knowledge-based features. The next section deals with rule capturing and encoding in MSDL.

4 RULE-BASED CAPABILITY EVALUATION

Human experts utilize two types of information when analyzing

Aluminum	Stainless Steel
○ Non-Ferrous	○ Ferrous
○ hasCorrosionResistance some **High**	○ hasCorrosionResistance some **High**
○ hasDuctility some **High**	○ hasDuctility some **High**
○ hasElectricalConductivity some **Medium**	○ hasSpecificCuttingPower has **34.125**
○ hasEnergyContent some **High**	○ hasStiffness some **High**
○ hasOxidationRate some **Low**	○ hasStrength some **High**
○ hasRecyclability some **High**	○ hasToughness some **High**
○ hasSolderabilty some **High**	○ hasWearResistance some **High**
○ hasSpecificCuttingPower has **15.015**	○ hasWeldability some **High**
○ hasWeldability some **High**	

Figure 4: Formal definition of aluminum and stainless steel

the technological capabilities of manufacturing suppliers: 1) supplier-specific capability description and 2) manufacturing domain knowledge. Supplier-specific capability is provided by the supplier profile and typically includes type of machineries and equipment the supplier possess, services offered, and types of parts the supplier can accommodate with respect to overall dimensions, material, tolerances, and surface finish. The manufacturing domain knowledge refers to the general manufacturing knowledge of the experts that help them reason about capabilities of the supplier beyond what is explicitly presented in the profiles. Therefore, to improve the performance of the proposed system with respect to the level of match with experts' judgments, it is necessary to enhance the its knowledge-based aspects. In fact, the quality of the search results directly depends on the richness of the ontology in terms of the level of details incorporated in the axiomatic definition of the concepts as well as the number and the diversity of rules encoded in the ontology. Ideally, the supplier discovery process should be supported by an inference engine that systematically employs inference steps similar to that of a human expert and continually expand its knowledge-base through learning form experience and instructions. To this end, we attempt to develop a sound understanding of the human experts' reasoning process in supplier selection and to formally encode the process to the possible extent.

4.1. <u>Rule Capturing:</u>

Human's reasoning and cognition mechanism has been the subject of research in the Artificial Intelligence (AI) community for several decades now. *Expert systems* developed in AI domain are intended to replicate the way a human expert analyzes a particular situation by using different reasoning techniques such as rule-based, case-based, fuzzy logic, neural networks, and Bayesian networks. Rule-based techniques, due to their structured nature, are the most common techniques adopted in expert systems. In general, it is very difficult to understand and model human's thought process in its entirety merely through a set of rules. However, there are some basic rule-based reasoning patterns that can be tracked in human's reasoning process such as *inductive*, *deductive*, *abductive*, and *analogical* reasoning. Most expert systems contain some sort of inductive or deductive reasoning capability. Deductive reasoning argues from the general to a specific instance. For example, let's assume that we know as a fact *that all machining processes are subtractive*. Then if process P is a machining process, we can *logically* conclude that P is a subtractive process. A deductive argument claims that if its premises are true, its conclusion must be true.

Inductive reasoning, in contrast, draws generalized conclusions from a finite collection of specific observations. For example, suppose that based on the past experience, we observed that all suppliers who serve aerospace industry have precision machining capability. Then, by induction, we can say all suppliers who work for aerospace industry can do precision machining. An inductive argument claims that if its premises are true, its conclusion is probably true. Inductive reasoning is particularly useful in constructing new rules that can be used later for deductive reasoning. Abduction, on the other hand, allows a precondition to be abducted from a consequence. For example, if a supplier doesn't quote on a certain RFQ, by abduction we can say that this particular supplier probably doesn't have the technological capabilities to meet the requirements. In other words, abductive reasoning provides the most likely, or the best, explanation for a consequence. In the context of supplier discovery process, capability inferences can

Inference Type I:
In this type of inference (deductive), the expert infers a new capability (, i.e., the *k* th capability of type *i*) based on an existing capability ( ) of the same type ( ). The inferred capability is not explicitly stated in the supplier's profile.

Example:
Premise 1: Supplier A can machine Hastealloy (which is a super alloy)
Premise 2: Inconel is also a supper alloy with similar properties to Hastealloy
Conclusion: Supplier A can machine Inconel as well.

Inference Type II:
In this type of inference (deductive), the expert infers a new capability ( ) based on a different type of capability ( ) that is explicitly stated in the supplier's profile.

Example:
Premise 1: Supplier A serves aerospace industry.
Premise 2: Suppliers who work with the aerospace industry typically have precision capabilities.
Conclusion: It is highly likely that Supplier A has precision machining capabilities.

Inference Type III:
In this type of inference (deductive), the human expert infers a necessary capability ( ) based on an existing requirement ( ) stated in the RFQ.

Example:
Premise 1: RFQ1 requires prototyping capabilities.
Premise 2: For prototyping, manual machining is the preferred method of fabrication.
Conclusion: Suppliers without manual machining capabilities are less likely to quote on RFQ1.

Figure 5: Three types of inferences in capability reasoning

Table 1: Examples for different types of rules

Type I rules	Type II rules	Type 3 rules
IF a supplier has fabrication services, THEN it is very likely the supplier can provide welding service.	IF a supplier has finishing AND plating capabilities, THEN the supplier can meet MIL standards for surface finish	IF an RFQ requires prototyping THEN the qualified suppler must have manual machining capabilities.
IF a supplier has tool design services, THEN the supplier can also provide fixture design service.	IF a supplier has screw machine capabilities, THEN the supplier can machine small, tight tolerance parts.	IF an RFQ requires MIL standards, THEN the qualified supplier must have plating or finishing capabilities.
IF a supplier provides face milling services, THEN the supplier can also provide end milling services.	IF a supplier can cut sheet metals with thickness larger than 1 inch, THEN the supplier must have water jet cutting capabilities.	IF an RFQ requires reverse engineering, THEN the qualified supplier must have CAD capabilities.

be divided into three main categories, as shown in Figure 5. Type I and II inferences deal with inferring new capabilities based on the existing ones whereas, Type III inferences is about inferring necessary capabilities based on the stated requirements.

The aforementioned inferences can have different levels of complexity when it comes to implementation in an ontological reasoner such as the MSDL search engine. For example, in presence of an asserted *material* taxonomy, Type I inference is only the matter of traversing the taxonomy and finding the siblings of the queried material. However, in absence of an explicit classification, the first step in Type I inference is to classify the concepts in order to construct an inferred classification. The main prerequisite for automated classification is formal definition of the concepts to be classified through necessary and sufficient conditions. One promising area for applying Type I inference is formation of part families based on their formal definitions represented through necessary and sufficient conditions. Table 1 provides some examples for some of the rules that can be applied for capability inference.

4.2. Rule Encoding:

SWRL is an extension of OWL that provides the ability to define complex rules and perform more advanced reasoning about concepts in an ontology. SWRL rules are used by automated reasoners such as Pellet[7] and Hermit[8] to interpret the rules. In the proposed supplier discovery methodology, SWRL rules can be used in three different ways as described below:

Narrowing down the search space:

SWRL rules can be used for narrowing down the search space to a set of highly relevant suppliers before performing the quantitative ranking process. For example, the following SWRL rule limits the search space to a specific sub-set of suppliers based on their industry focus and material processing capabilities.

SupplierProfile(?r) ^ has Actor(?r, ?a)
^ hasIndustryFocus(?a, ?i) ^ HandtoolManufacturing(?i)
^ hasService(?r, ?s) ^ hasMaterial(?s, ?m) ^ Titanium(?m)
→ SearchSpace(?r)

The rule above states that the *SearchSpace* is composed of SupplierProfiles that has an *Actor* with an industry focus of *hand tool manufacturing* and the profile advertises a service that is capable of working with *titanium materials*. It involves examining SupplierProfile from the perspective of both the *hasActor* property and the *hasService* property in the same rule as well as combining properties and classes in the same statement.

Performing inferences involving numeric values:

OWL reasoners cannot perform manipulations and inferences involving numbers and arithmetic. For example, in MSDL, a service can have an accuracy in the form of a decimal number. With OWL alone, it is not possible to specify a class of “precision services” that has an accuracy in the form of a decimal number that is less than 0.001 because OWL is unable to perform that numerical check. Instead, if a “precision services” class was needed, SWRL can be used to implement the rule and a reasoner can determine which individuals in the ontology belong to the class. Specifically, the SWRL rule can be stated as:

Service(?s) ^ has Accuracy(?s, ?a) ^ swrlb:LessThan(?a, 0.001)
→ PrecisionService(?s)

SWRL includes a number of built-in libraries which when used in rule syntaxes are prefaced with “swrlb”. These built-in libraries allow for comparisons, as shown above, mathematical

[7] http://*clarkparsia.com/pellet/*
[8] http://*hermit-reasoner.com/*

operations, list operations, string manipulation, and date and time operations. This allows SWRL rules to provide the needed functionality to perform a variety of interpretations and extended reasoning processes.

Capability inference:

As discussed earlier, inferring new capabilities based on the explicitly stated ones is a key feature in semantic supplier discovery that can be enabled by incorporation of SWRL rules. Table 2 provides some examples for the rules that can be applied to extract inferred capabilities. With these rules implemented, the intelligence of the search engine can be improved as it can extract inferred capabilities, or lack of capabilities, form the explicitly stated ones.

5 EXPERIMENTAL EVALUATION

To determine the effectiveness and accuracy of the proposed supplier discovery technique, it was evaluated experimentally and its results were compared to the discovery results obtained from human experts. The experts selected in this experiment had manufacturing engineering background and

Table 2: SWRL rules together with their interpretations.

IF a supplier has screw machine capabilities, THEN the supplier can machine small, tight tolerance parts. [SWRL Rule:] Supplier(?supp) ^ hasService(?supp, ?svc) ^ hasProcess(?svc, ?proc) ^ ScrewMachineProcess(?proc) → PrecisionSuppliers(?s) [Translation:] Every supplier that has a service that has a process of "ScrewMachineProcess" is a "PrecisionSuppliers". When performing the similarity calculation, "bonus" points will be assigned to a supplier for precision machining if the service “hasAccuracy” property of < 0.001 or the supplier is a member of the "PrecisionSuppliers" class.
IF a supplier can cut sheet metals with thickness larger than 1 inch, THEN the supplier must have water jet cutting capabilities. [SWRL Rule:] Supplier(?supp) ^ hasService(?supp, ?svc) ^hasProcess(?svc, ?proc) ^ LocalizedDeformation(?proc) ^ acceptsWorkpiece(?svc, ?wp) ^ hasShape(?wp, ?shape) ^ Plane(?shape) ^ hasWidth(?wp, ?width) ^ swrlb:greaterThanOrEqual(?width, 1.0) →WaterJetCuttingSupplier(?supp) [Translation:] Every supplier that has a service of “LocalizedDeformation” that accepts a workpiece that has shape of “plane” and has thickness greater than or equal to “1.0” is a “WaterJetCuttingSupplier”. When the list of processes a supplier offers is compiled prior to the matchmaking process, if a supplier is a member of the “WaterJetCuttingSupplier” class, then the “WaterJetCutting” process will be added to its list of available processes.
IF an RFQ requires prototyping, THEN the qualified suppler must have manual machining capabilities. [SWRL Rule:] Suppler(?supp) ^ hasService(?supp, ?svc) ^ hasProcess(?svc, ?proc) ^ hasTool(?proc, ?tool) ^ isComputerControlled(?tool, ?comp) ^ swrlb:equal(?comp, “false”) → ManualMachiningSupplier(?supp) [Translation:] Every supplier that has a service that has a process that has a tool with the “isComputerControlled” property of false is a member of the “ManualMachiningSupplier” class. When performing a query which requires prototyping, the SWRL rule above is run. The suppliers that are placed into the “ManualMachiningSupplier” class will be the only suppliers considered in the matchmaking process.
IF an RFQ requires MIL standards for plating or finishing, THEN the qualified supplier must have abrasive cleaning capabilities. [SWRL Rule:] Supplier(?supp) ^ hasService(?supp, ?svc) ^ hasProcess(?svc, ?proc) ^ AbrasiveCleaning(?proc) →AbrasiveCleaningSupplier(?supp) [Translation:] Every supplier that has a service that has a process of “AbrasiveCleaning” is a member of the “AbrasiveCleaningSupplier” class. When performing a query which required MIL standards for plating or finishing, the SWRL rule above is run. The suppliers that are placed into the “AbrasiveCleaningSupplier” class will be the only suppliers considered in the matchmaking process.
IF an RFQ requires reverse engineering, THEN the qualified supplier must have CAD capabilities. [SWRL Rule:] Supplier(?supp) ^ hasService(?supp, ?svc) ^ CADService(?svc) → CADSuppliers(?supp) [Translation:] Every supplier who has the service “CADService” is a “CADSupplier”. When processing a query which specifies an RFQ with reverse engineering, the SWRL Rule above is run. The suppliers who are a member of the “CADSuppliers” class are those suppliers who will be used in the matchmaking process.

Required processes	Machining, Turning, Grinding, Heat Treating
Material	Alloy Steel
Stock	Rod
Dimensions	3.277 inch x 0.25 diameter
Tolerances	+ 0.001 -0.000
Special Fixture	None
Surface finish	Plated per MIL-STD-171
Secondary operations	Heat treating per AISI 8640 or 8740
Quantities to be quoted	10
Annual Usage	N/A

Industries serving	Machinery manufacturing (Firearms, high precision small parts)
Product focus	Gun manufacturing
Certifications	N/A

Figure 6: Query for Firing Pin

were actively involved in providing various supply chain services, including capability matching, to small-to-medium sized manufacturing companies. The base collection in this experiment was composed of 18 suppliers provided by the domain experts. All selected suppliers had a website where they advertised their manufacturing capabilities and services. Each supplier's website was examined to determine what services they offered and what areas of expertise they advertised. This information was manually converted into MSDL representation to create a profile, represented by *SupplierProfile* class in MSDL, for each supplier. The focus was primarily put on services, processes, machine tools, as well as industry and product focuses of the suppliers when extracting information from the websites. The text from the suppliers' websites used to create the profiles in the ontology was included in a document given to the domain experts to be used for capability matching.

Figure 6 shows the RFQ used in this experimentation. This RFQ describes the manufacturing requirements for producing ten pieces of a firing pin requiring machining, grinding and heat treating services. In their previous project, the domain experts sent the RFQ to the 18 suppliers used in this experiment. Of those 18 suppliers, seven submitted bids for the firing pin. Neither the domain experts nor the MSDL search engine used that prior knowledge in this experiment.

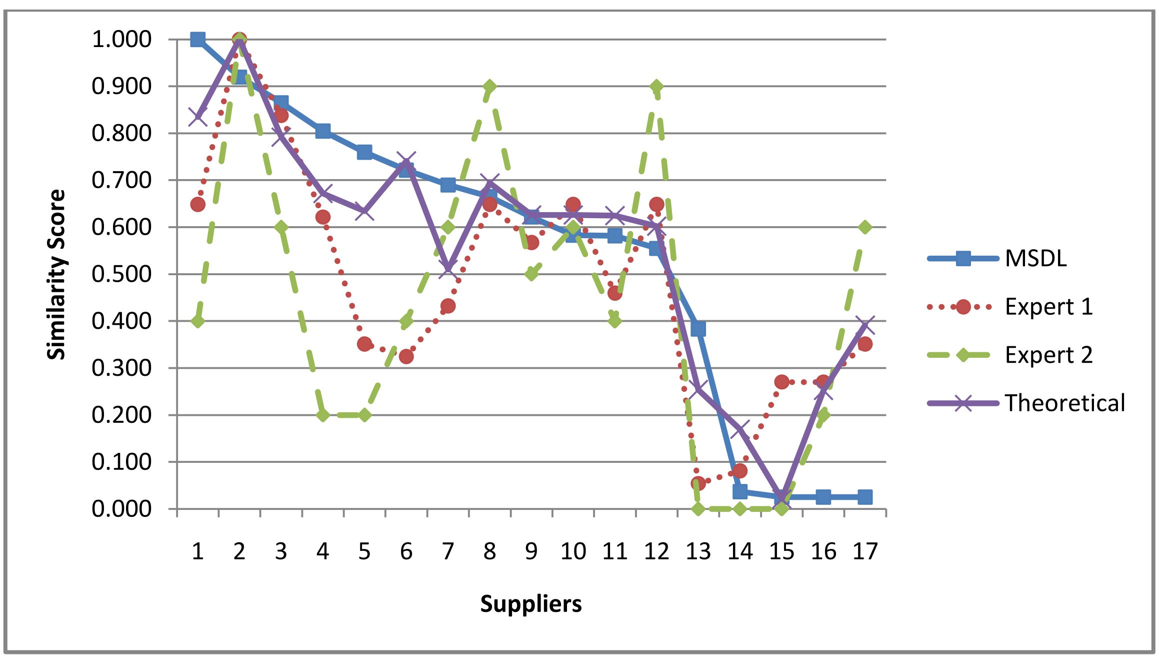

Figure 7: Supplier Ranking Comparison for the firing pin

The domain experts performed a manual matching process of the RFQ to the supplier profiles with information based on the suppliers' websites. The supplier profiles were anonymized to remove the supplier's names in order to avoid the domain experts using their previous knowledge about particular suppliers. For each supplier, the domain experts compared the supplier's profile to the query. Each expert gave weightings to different aspect of the query such as material, size, tolerances, required processes, and industry based on the perceived level of importance. Each expert returned a ranked list of suppliers based upon their reasoning process and the scores they ultimately assigned to each supplier. The MSDL search engine was also run in parallel using the given query to return its own ranked list of suppliers.

Figure 7 shows the obtained results for the firing pin RFQ. MSDL search engine was run once before activating SWRL rules and once after rule activation. As can be seen in this figure, after activation of SWRL rules, the search results demonstrate a better correlation with the experts' judgments.

6 CONCLUSIONS

This research is motivated by the need for the solutions that support accurate and rapid evaluation of manufacturing partners in virtual environments. Existing RFQ markets, due to their syntactic approach in search, fail to meet the requirements of next generation web-based markets for manufacturing services. Automation and intelligence are the two key requirements of web-based solution for efficient deployment of virtual supply chains. To this end, there is a need for standard representation of supply and demand in a formal and machine interpretable fashion together with the necessary computational algorithms that enable semantic matching between suppliers and customers. This paper provided an experimental evaluation of an ontological approach for supplier search. The ontology, referred to as Manufacturing Service Description Language, provides the required means for description of manufacturing services at a semantic level. With the aid of two types of matching algorithms, namely, taxonomy-based and feature-based, the search engine is capable of quantifying the similarities between the provided services and requested ones. In a previous research it was shown that the performance of the proposed semantic search techniques moderately exceeds that of traditional techniques such as keyword search method. In order to further improve the results, MSDL was extended by SWRL rules. The implemented SWRL rules enable the search engine to infer new manufacturing capabilities beyond the explicitly stated ones in the profiles of the suppliers, thus enhancing the performance of the search engine due to provision of a wider array of information. Also, through a rule based approach, it is possible to narrow down the search space to sub-set of relevant suppliers before performing the ranking process. The experimental evaluation revealed that with implementation rule-based approach, the results will demonstrate a better correlation with human expert's judgment.

The next step in this direction is verification of the results based on a larger sample. One of the identified challenges in the rule-based approach is selection of appropriate rule sets for different circumstances. This experimentation revealed that the defined rules are not global in nature and, consequently, cannot be applied to any and all supplier discovery scenarios. Therefore, judicial rule clustering based of different search cases defines another research task for the future. The authors acknowledge that development of a comprehensive and standard manufacturing ontology, to be used in electronic markets, calls for collective participation of academia, industry, and standard agencies. This research is mainly an attempt to demonstrate the potentials of semantic techniques for supplier search in web-based environments.

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