Specifying Uncertainties in Inter-Agent Dependencies using Rough Sets and Decision Table

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Abstract- **In Multi-Agent System (MAS), tasks are disseminated and delegated to other agents with a rationale of sharing mutual expertise. The inter-agent dependency signifies a compliance that facilitates a depender agent to accomplish a goal through the Service Provider Agents (SPAs) in a distributed environment. A number of uncertainties and ambiguities are involved with inter-agent dependencies. The inter-agent goal, soft goal or task dependencies ambiguously assist in the selection of appropriate service provider agents that would complicate the design of the system. Therefore, to reduce the complexity of the final system, it is essential to specify these uncertainties at requirements engineering phase so that coordination issues among agents could be resolved in a cooperative environment. This paper employs the decision table and the fundamental concepts of rough sets viz. indiscernible relation, approximations and boundary regions to specify ambiguities in the selection of appropriate SPAs that would assist the developer in deciding future course of action to resolve the uncertainties in framing an unambiguous Software Requirements Specification (SRS).**

Keywords
Multi-Agent System (MAS), Software Requirements Specification (SRS), Degree of Dependency (DoD), Type of Dependency, Rough Sets, Equivalence Class, Indiscernible Relation, Decision Table.

1. INTRODUCTION

Agents exhibit a high degree of inter-agent cooperation to achieve designated goals. The success of Multi-Agent System (MAS) depends on how well these agents cooperate with each other. Modeling cooperation with a thrust in finding an appropriate agent for delegating a task is a challenging area of MAS as it requires thorough analysis of the dependencies that exist among agents.

An important aspect for MAS is the specification of inter-agent dependencies. A number of inter-agent dependencies viz. goal, task, soft goal and resource dependencies are involved with the goals of agents. In a goal dependency, an agent depends on service provider agents for obtaining a goal. The depender agent does not provide the specific procedures to the service provider agents [1] and service provider agents itself, have to streamline the accomplishment of the goal. Task dependency is similar to a goal dependency, except that the depender agent provides the specification of guidelines to the service provider agents to perform the goal [1]. In a resource dependency, the depender agent depends on other agents for the availability of some physical or informational entities viz. project reports, files or some artifacts etc. A soft-goal dependency is similar to a goal dependency, except that the goal to be achieved is not sharply defined [1]. Efficiently, effectively, satisfactorily, cost effectively and user friendliness etc. are the examples of soft-goals.

Out of these inter-agent dependencies goal, soft goal and task dependencies are of prime concern. A number of uncertainties and ambiguities are involved with the inter-agent dependencies. The inter-agent goal, soft goal or task dependencies ambiguously assist in the selection of service provider agents with their appropriate reputation scores in the e-market [11]. For example the goals with only goals dependency may require the service provider agents with the reputation scores at least [60%-70%) or [70%-80%). In a similar manner, the goals with both goal and soft goal dependencies may require the service provider agents with higher reputation scores i.e. [70%-80%) or [80%-100%]. But it would not be a wise decision to assign a goal with only goal dependency to a high scored service provider agent with high rates.

In a Multi-Agent System (MAS), a number of inter-agent dependencies along with a number of uncertainties would complicate the design of the system and hence it would increase the complexity of overall system. Therefore to handle the complexity of such a system, it necessitates specification of uncertainties in inter-agent dependencies that would assist developer to resolve his ambiguities for designing various agents in distributed paradigm and hence assist him in taking future course of action.

Literature reports various ways to handle the inter-agent cooperation. i*[1], Gaia [2], Tropos [3], Formal Tropos [4], NorMAS-RE [5], B-Tropos [6] have been recommended for analyzing inter-agent dependencies. These frameworks model inter-agent dependencies using various modeling diagrams, dependence networks and specification languages, but don't provide any support for identification and quantification of the dependency needs of an agent. Delegating a goal without identifying and quantifying the dependency needs of an agent may result in excessive communication overheads and affect the quality of MAS. To address this problem, this work presents

In order to specify these kind of uncertainties and ambiguities, decision table and fundamental concepts of rough sets viz. indiscernible relation, approximations and boundary, negative and positive regions are employed. To measure the degree of confidence associated with inter-agent dependencies, the concept of accuracy of approximation is employed. To resolve these uncertainties in the decision table, the concept of domain specific DoD detailed in our previous work [8], is specified.

The organization of the paper is as follows: Section 2 presents an introduction to rough sets. Section 3 presents specification of uncertainties in inter-agent dependencies. Section 4 presents experimental results and finally section 5 concludes the paper.

2. BRIEF INTRODUCTION TO ROUGH SETS

The concept of rough set was originally proposed by Pawlak [25]. Its methodology is concerned with the classification and analysis of imprecise, uncertain or incomplete information and knowledge. It has been successfully applied in many real-life problems in fault diagnosis, medical diagnosis, defect detection of automotive glass, remote sensing land use/cover classification [25] etc. The starting point of rough set theory is an information system. The information system contains data about objects of interest characterized in terms of some attributes. If condition and decision attributes are distinguished in the information system, then such a system is called a decision table. The few of the definitions significantly concerned with the theory of rough sets and Decision Table are provided below.

Definition i: The **information system** or **Information Table** is referred to an ordered 4-tuple IS=$\{U, Q, V, f\}$, where U is the sets of objects, Q is the set of features (attributes), $V = \cup_{q \in Q} v_q$ is the set of all possible values of features, while $f : U \times Q \rightarrow V$ is called the information function s.t. $v_q^x = \underset{x}{f}(q)$, where $v_q^x \in V$.

Definition ii: The **Decision Table** is an extended form of the information system designated as DT=$\{U, C, D, V, f\}$ s.t. $C \cup D= Q$, where C is set of conditional attributes and D is set of decisional attributes and Q is total attributes incorporating conditional as well as decisional and set V and f have its standard meanings as defined in information set.

Definition iii (Equivalence Class): Let $E \subseteq U \times U$, be an equivalence relation on U. The equivalence relation divides the universe into a family of pair-wise disjoint subsets. An equivalence relation E can be represented by a mapping from U to 2^U, where 2^U is the power set of U. For an object $x \in U$, the equivalence class containing x is given by:

$$[x]_E = \{y \in U | \, xEy\} \qquad (1)$$

Definition iv (Equivalence classes defined on the Information system of real numbers):

Let U be the set of real numbers in the interval [0,10) i.e. U=[0,10). Let each element $x \in U$ be defined by two features making up the set of features $\{q_1, q_2\}$, where q_1 is the integral part of the number x and q_2 is the decimal part of x. Then x can be represented as a set of integral and fractional parts i.e . $x = \{q_1, q_2\}$ s.t. $x = q_1 + q_2$.

The information functions may be defined as follows:

$$f_x^{q_1} = \text{Int}(x) \qquad (2)$$

$$f_x^{q_2} = x - \text{Int}(x) \qquad (3)$$

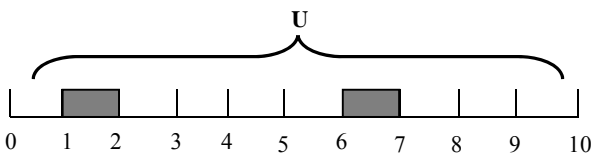Where Int (x) means the integral part of the argument x.

Figure 1. Example of equivalence class of [1]$_E$ and [6]$_E$

Figure 1 illustrates two equivalence classes $[1]_E$ and $[6]_E$ of real numbers having 1 and 6 as its integral values respectively.

Definition v (Indiscernible relation): Objects characterized by the same information are indiscernible (similar) in view of the available information about them. A binary relation over set $B \subseteq U$ denoted as $\tilde{B}$ is called an B-indiscernible relation and is defined by

$$x \, \tilde{B} \, y \text{ if and only if } a(x) = a(y) \text{ for every } a \in B \qquad (4)$$

Where a (x) denotes the value of attribute a for object x. $\tilde{B}$ is also an equivalence relation. If $(x, y) \in \tilde{B}$ we will say that x and y are B-indiscernible and binary relation would be called B-indiscernible relation.

The equivalence relation is a relation that maps the x element of an equivalence class to y element and indiscernible relation is an equivalence relation that forms the relation on one or more equivalence classes. The equivalence classes of the B-indiscernible relation are denoted by $[X]_{\tilde{B}}$

Definition vi (Rough set): The sets that cannot be sharply defined using the set of attributes Q. In other words, every set defined by the lower and upper approximations is called as rough set [25].

Definition vi.(a) (Lower Approximation): Lower approximation set of a set X, with regard to universe U and Q as set of attributes, is the set of all objects , which can certainly be classified as elements of set X, employing the set of attributes Q. If $\tilde{B}$ is an indiscernible relation over X, then lower approximation denoted as $\underline{\tilde{B}}X$ can be defined as:

$$\underline{\tilde{B}}X = \{x \in U : [X]_{\tilde{B}} \subseteq X\} \qquad (5)$$

That means the equivalence class of any object against set of attributes Q, belonging to universe U is entirely contained in the set X.

Definition vi.(b) (Upper Approximation): Upper approximation set of a set X, with regard to universe U and Q as set of attributes, is the set of all objects , which can be possibly classified as elements of set X, using the set of attributes Q. If $\tilde{B}$ is an indiscernible relation over X, then upper approximation denoted as $\overline{\tilde{B}}X$ can be defined as:

$$\overline{\tilde{B}}X = \{x \in X : [X]_{\tilde{B}} \cap X \neq \emptyset, \text{where } X \subseteq U\} \qquad (6)$$

The above definition of upper approximation says that the object $x \in X$, is an element of the upper approximation, if the whole equivalence class, to which it belongs, has a non-empty intersection with the set X. In other words, if at least one element of a given equivalence class belongs to the set X, then each element of this equivalence class belongs to the upper approximation of the set X.

Definition vii ($\tilde{B}$-positive region): The $\tilde{B}$-positive region of the set X is defined as:

$$\text{Pos}_{\tilde{B}}(X) = \underline{\tilde{B}}X \qquad (7)$$

That means the positive region of the set X is equal to its lower approximation.

Definition viii ($\tilde{B}$-boundary region): $\tilde{B}$-boundary region of the set X is defined as:

$$\text{Bn}_{\tilde{B}}(X) = \overline{\tilde{B}}X \setminus \underline{\tilde{B}}X \qquad (8)$$

The difference of upper and lower approximation is called the boundary region. That means the boundary region of X consists of all elements that cannot be classified uniquely to a specific set.

Definition ix ($\tilde{B}$-negative region): $\tilde{B}$-negative region of the set X is defined as:

$$\text{Neg}_{\tilde{B}}(X) = U \setminus \overline{\tilde{B}}X \qquad (9)$$

The negative region of the set X is the set of the objects $x \in U$ that certainly do not belong to the set X.

Definition xi ($\tilde{B}$-accuracy of approximation): The $\tilde{B}$-accuracy of approximation of the set X can be defined as:

$$\text{Accur}_{\tilde{B}}(X) = \overline{\underline{\tilde{B}X}} \div \overline{\overline{\tilde{B}X}} \qquad (10)$$

The symbol $\overline{X}$ denotes the cardinality of the set X. The accuracy approximation of the set X is represented as the ratio of the cardinality of lower approximation and upper approximation and always, $0 \leq \text{Accur}_{\tilde{B}}(X) \leq 1$. If $\text{Accur}_{\tilde{B}}(X) = 1$, then X is a definable set regarding its attributes, that is, X is crisp set that can be sharply defined with 100% degree of confidence regarding its attributes. If $\text{Accur}_{\tilde{B}}(X) < 1$, then X is a rough set concerning its attributes.

3. SPECIFICATION OF UNCERTAINTIES IN INTER-AGENT DEPENDENCIES

The inter-agent dependency depicts a compliance that facilitates a depender agent to accomplish a goal through the dependee agent in a distributed environment [1], [2]. To carry out cooperative activities, tasks are disseminated and delegated to other agents with a rationale of sharing mutual expertise and potential. In such a distributed environment where a goal may be assigned to one or more service

provider agents, the developer is required to know the Type of Dependency (ToD) viz. goal, task, soft goal and resource dependencies involved with goal as well as the Degree of Dependency (DoD) so that he should be able to select the service provider agents with suitable scores.

The ToD reflects the users' perception to get his work done while DoD represents the actual scenario of criticality associated with the goal and is computed on the basis of domain knowledge of the goal. For a scenario the user may want the procurement of raw material and packaging items efficiently and effectively leading to the high soft goal dependencies associated with these two procurement goals. Now it is a big concern for the developer- whether to assign both the goals with high soft goals dependencies to the service provider agents with high scores and henceforth the high rates or go for the service provider agents with fewer score. Such kind of uncertainties and ambiguities are involved with the inter-agent dependencies. In order to specify these kind of uncertainties and ambiguities, decision table and fundamental concepts of rough sets viz. indiscernible relation, approximations and boundary, negative and positive regions are employed. To measure the degree of confidence associated with inter-agent dependencies, the concept of accuracy of approximation is employed.

To facilitate the decision making in the selection of service provider agents with suitable scores, domain specific DoD is also employed that quantifies the actual dependency needs associated with a goal and resolves the ambiguities involved with the selection of suitable service provider agents. A brief overview of ToD and DoD is provided below.

3.1. Type of Dependency (ToD):

Inter-agent communication is one of the main concerns of Agent-Oriented requirements engineering that is delineated as managing inter-agent dependencies and interaction among various agents performing collaborative activities. A number of inter-agent dependencies are involved with the goals of agents. The classification of Type of Dependency (ToD) i.e. viz. goal, task, soft goal and resource dependencies from user requirements is detailed in our previous work [8, 10]. In a goal dependency, an agent depends on service provider agents for obtaining a goal. The depender agent does not provide the specific procedures to the service provider agents [8] and service provider agents itself, have to streamline the accomplishment of the goal. Task dependency is similar to a goal dependency, except that the depender agent provides the specification of guidelines to the service provider agents to perform the goal [8]. In a resource dependency, the depender agent depends on other agents for the availability of some physical or informational entities viz. project reports, files or some artifacts etc. A soft-goal dependency is similar to a goal dependency, except that the goal to be achieved is not sharply defined [8]. Efficiently, effectively, satisfactorily, cost effectively and user friendliness etc. are the examples of soft-goals.

3.2. Degree of Dependency (DoD):

Degree of Dependency (DoD) is defined as a parameter to quantify an agent's dependency needs for delegating a goal in a distributed environment. For designating a goal to other agents, an agent requires to exercise its own dependency requirements which may originate from domain knowledge. The prediction and customization of DoD is accomplished using Analytical Inference Model (AIM) proposed in our previous work [5].

The AIM for evaluating DoD is considered in three steps. In step I, domain knowledge of a goal that may be vague and fuzzy, is inferred by domain experts from the real data set obtained from historical records of business environment. The inferred domain knowledge is employed to obtain rule base. In step II, The Mamdani Fuzzy Inference System is applied on fuzzy domain knowledge and rule base to quantify dependency requirements devised in the form of DoD [3]. The data set incorporating various values of domain characteristics and DoD is decomposed in two parts- training data and test data. In step III, Analytical Neuro Fuzzy System combining the potential benefits of Artificial Neural Network (ANN) and Fuzzy Logic (FL) is employed that makes use of training algorithm viz. back propagation or hybrid to learn from training data and results in Sugeno based Analytical Inference Model. This model further is validated using test data. The resultant model is employed to predict DoD and tailor various domain characteristics as per desired level of DoD within constrained resources. The details of evaluation of DoD is provided in our previous work [8, 10].

To specify the inter-Agent dependencies, decision table is employed. The layout of the decision table is given in the table 1. The specification of inter-agent dependencies using decision table would incorporate ToD and DoD as the conditional attributes, while various service provider agents with various scores as the decisional attributes. Various values of numerous cells would reflect the decision rules associated with the goals of various agents. The uncertainties and ambiguities evolved out of the decision table are specified using the fundamental concepts of rough sets viz. indiscernible relation, approximations and boundary, negative, positive regions and accuracy of approximation.

Table 1 The layout of Decision Table

Conditional Attributes	Decisional Attributes
Decision Rules	

The specification of inter-agent dependencies and the uncertainties in relation thereto is illustrated in the case study.

3.3. Rationale

The detailed specification of uncertainties associated with inter-agent dependencies assist the developer to decide the future course of action to resolve the uncertainties in framing an unambiguous SRS.

4. EXPERIMENTAL RESULTS

To illustrate the application of the proposed methodology, a case study of materials e-procurement MAS is provided. Materials e-procurement MAS is composed of a number of agents including purchase head, raw materials, assets, spares and packaging items agents etc. having the capabilities of procuring various materials in an open and distributed environment [13]. The purchase head agent was held responsible for all procurement activities. To ease its burden a number of service provider agents viz. raw materials, packaging agents etc. exhibiting a number of roles, were introduced and allocated various goals and tasks. The SteelVendrDevelop and SteelPurchase raw material agents were held responsible for developing vendors and procuring steel items respectively. Similarly other agents were allocated remaining procurement services.

4.1. Specifying Uncertainties in Inter-Agent Dependencies

In order to specify inter-dependencies involved with the selection of service provider agents, a knowledge rule base was formulated. A decision table of 50 goals as illustrated in figure 2(a) was utilized for the experiment. In order to comprehend the user perception in inter-agent dependencies, ToDs for the goals viz. task, goal and soft goal were identified using the method detailed in our work [2]. The service provider agents were categorically decomposed in various classes having their Rep_Scores as [60%-70%), [70%-80%) or [80%-100%]. The agents with Rep_Scores less than 60% were ignored. The knowledge rule base incorporated inter-agent dependencies as its antecedent part and agents with various Rep_Scores as its consequent part as illustrated in table 2.

Various rules were framed in accordance with the type of dependency. The agents with high Rep_Scores [60%-70%) or [70%-

80%) were involved for the goals with goal dependency, while the goals with only task dependency were unlikely to be assigned to high scored agents having high service charges and therefore were delegated to the agents with Rep_Scores [60%-70%). The goals having both the dependencies viz. goal and soft goal or task and soft goal were delegated to the agents with highest Rep_Scores i.e. [70%-80%) or [80%-100%].

Table 2 Selection of service provider agents characterized by ToD

SNo.	Knowledge Rule Base			
	ToD			Service provider agents with Rep_Scores
	Goal dependency	Task dependency	Soft goal dependency	
1	Y	N	Y	[70%-80%)
2	Y	N	Y	[80%-100%]
3	Y	N	N	[60%-70%)
4	Y	N	N	[70%-80%)
5	N	Y	Y	[70%-80%)
6	N	Y	N	[60%-70%)

An attempt was made to automate the specification of inter-agent dependencies and the uncertainties in relation thereto using the ROSETTO-a rough set tool kit [12]. The decision table was decomposed into training and test data of size 25 goals each using the binary splitter as illustrated in figure 2(c). The Split factor signifies the split ratio of decision table. The Random Number Generator (RNG) speed signifies the speed of RNG for the random slit of goals. The training data was used for generating a reduced set of rules to induce a classifier and the test data was used for analyzing classification of goals.

(a)

(b)

(c)

(d)

Figure 2 (a) Decision table (b) equivalent XML code (c) binary splitter (d) training and test data

4.2. Rule Analysis

To induce a reduced set of attributes and henceforth minimized rules, Johnson's Algorithm [12] was applied on training data. The 6 rules of table 2 were reduced to 4 rules and 3 attributes were reduced to 2 attributes as illustrated in figure 3.
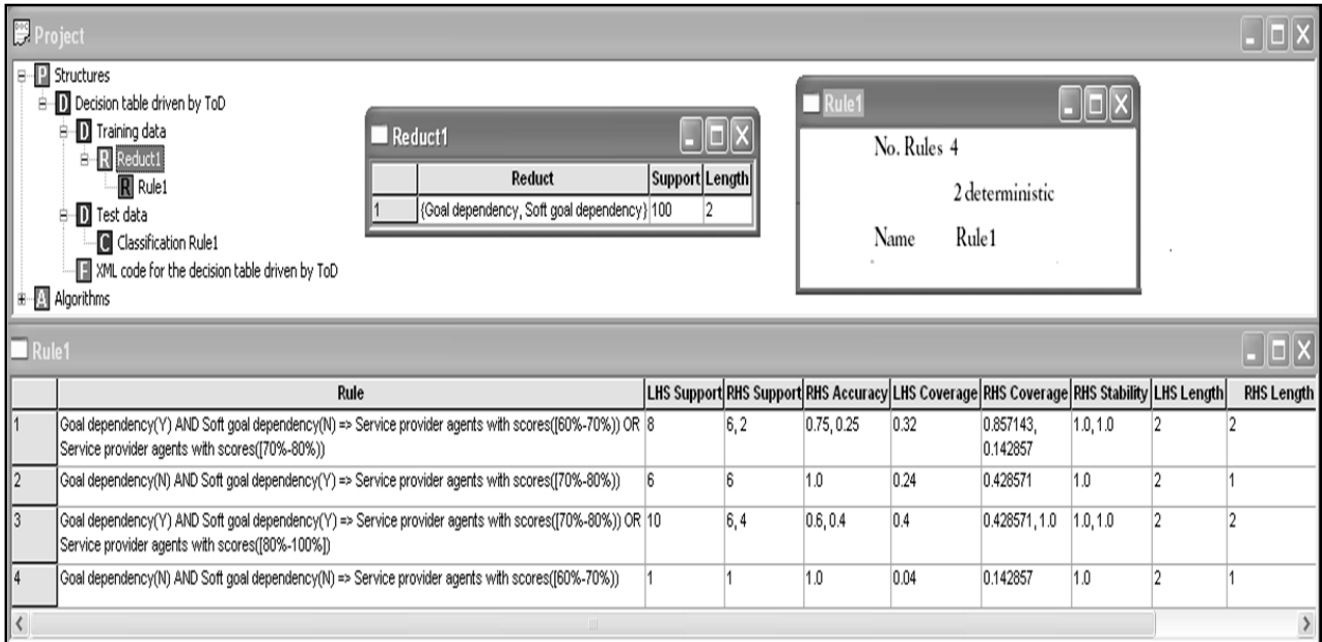

Figure 3 Statistics of reduced knowledge rule base

The attribute "task dependency" was removed without any loss of information and remaining two attributes labeled as {Goal dependency, Soft goal dependency} were capable of characterizing the goal dependencies with 100% support. Out of 4 rules, 2 rules were found to be deterministic that facilitated goals to uniquely belong to a specific category of service provider agents and remaining 2 rules were found to be non deterministic that contributed in inducing the uncertainties and ambiguities in inter-agent dependencies. The following statistics viz. support, coverage, accuracy and length were observed for measuring the performance of rules.

- **LHS support:** LHS support refers to the number of goals in training data matching IF-part. The value of LHS support as 8 for rule 1 signifies 8 goals matching its IF-part.
- **RHS support:** RHS support refers to the number of goals in training data matching both IF and THEN-part. The value of RHS support with multiple components signifies the uncertainties associated with the rule. The RHS support 6 and 2 for rule1, signifies that total 8 goals have their IF part equivalent to rule1. Six goals have their THEN part equivalent to "Service provider agents with Rep_Scores [60%-70%) and two goals to "Service provider agents with Rep_Scores [70%-80%).
- **RHS Accuracy:** RHS support divided by LHS support results in the RHS accuracy. In case of two or more decisions the accuracy is distributed to two or more components with the same ratio as in the components of RHS support. For rule1, the RHS support is 3:1, with this rationale the same ratio is maintained in RHS accuracy.
- **LHS Coverage:** LHS coverage is a metric to observe the proportion of the goals in training data having the same IF part as in the rule. LHS coverage is computed by dividing LHS support by total number of goals in training data.
- **RHS Coverage:** RHS coverage is a metric to observe the proportion of the goals in training data having the same decision as in the corresponding rule.

$$\text{RHS Coverage} = \frac{\text{RHS Support}}{\text{no.of goals in training data with identical decision}} \quad (11)$$

For rule1, the RHS coverage is =6/7=0.857143, where 7 refers to the number of goals having its decision part as "Service provider agents with Rep_Scores [60%-70%)".

- **LHS Length:** Number of attributes in IF-part of the rule.
- **RHS Length:** Number of decisions in THEN-part of the rule.

4.3. Interpretation and Observations

The reduced knowledge rule base was employed on test data to remove unnecessary attribute "task dependency" without loss of any information. Thus obtained test data as illustrated in figure 4, was treated as the universal set in analyzing various uncertainties. In order to specify and analyze the ambiguities and uncertainties, the concepts of lower, upper approximations, negative, boundary regions and accuracy of approximations were applied on rough sets of test data. The sets of goals belonging to various service provider agents were marked with the letters $X_{[60\%-70\%)}$, $X_{[70\%-\%80)}$ and $X_{[80\%-100\%]}$ and represented as:

$$X_{[60\%-70\%)} = \{x_6, x_{11}, x_{22}, x_{23}, x_{28}, x_{41}, x_{42}, x_{46}, x_{49}\} \quad (12)$$
$$X_{[70\%-80\%)} = \{x_1, x_4, x_7, x_{12}, x_{15}, x_{19}, x_{21}, x_{31}, x_{33}, x_{34}, x_{43}, x_{50}\} \quad (13)$$
$$X_{[80\%-100\%]} = \{x_2, x_{13}, x_{17}, x_{24}\} \quad (14)$$

The lower and upper approximations were designated as $\underline{A}X$ and $\overline{A}X$. The goals of $X_{[60\%-70\%)}$ belong to the equivalence classes $[x_6]_{\tilde{A}}$ and $[x_{11}]_{\tilde{A}}$, but only the equivalence class $[x_6]_{\tilde{A}}$ having the goals $\{x_6, x_{22}, x_{42}, x_{46}, x_{49}\}$ with no goal and soft goal dependencies, is entirely contained in $X_{[60\%-70\%)}$ and hence fabricates the lower approximation $\underline{A}X_{[60\%-70\%)}$. The rough set theory illustration on $X_{[70\%-80\%)}$ is detailed in figure 4(b).

Lower approximation
$$\underline{A}X_{[60\%-70\%)} = \{x_6, x_{22}, x_{42}, x_{46}, x_{49}\} \quad (15)$$
$$\underline{A}X_{[70\%-80\%)} = \{x_{21}\} \quad (16)$$
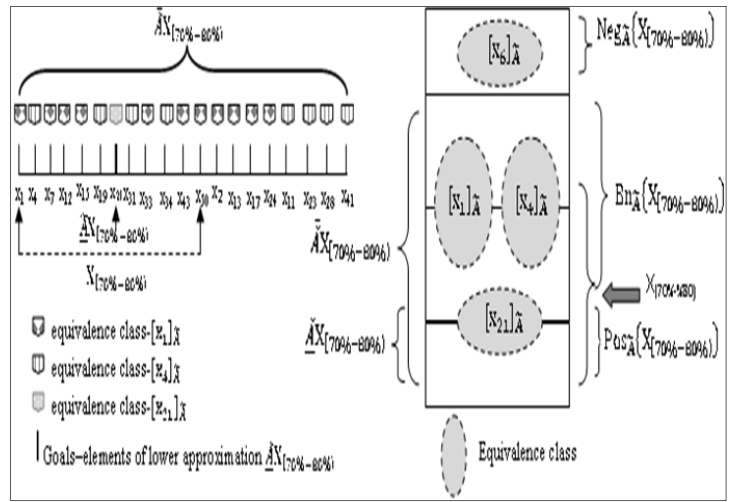$$\underline{A}X_{[80\%-100\%]} = \emptyset \quad (17)$$

Figure 4. (a) Test data as the universal set (b) fundamental concepts of rough set applied on $X_{[70\%-80\%)}$

The sets $X_{[60\%-70\%)}$, $X_{[70\%-\%80)}$ and $X_{[80\%-100\%]}$ were analyzed in terms of upper approximation, accuracy of approximation etc. in the following manner.

Upper approximation

$\overline{A}X_{[60\%-70\%)} = [x_6]_{\tilde{A}} \cup [x_{11}]_{\tilde{A}}$
$= \{x_6, x_{22}, x_{42}, x_{46}, x_{49}, x_{11}, x_{23}, x_{28}, x_{41}, x_4, x_{19}, x_{31}, x_{34}\}$
$\overline{A}X_{[70\%-80\%)} = [x_{21}]_{\tilde{A}} \cup [x_1]_{\tilde{A}} \cup [x_4]_{\tilde{A}} = \{x_{21}\}$
$\cup \{x_1, x_2, x_7, x_{12}, x_{13}, x_{15}, x_{17}, x_{24}, x_{33}, x_{43}, x_{50}\} \cup$
$\{x_4, x_{11}, x_{19}, x_{23}, x_{28}, x_{31}, x_{34}, x_{41}\}$
$\overline{A}X_{[80\%-100\%]} = [x_2]_{\tilde{A}} = \{x_1, x_2, x_7, x_{12}, x_{13}, x_{15}, x_{17}, x_{24}, x_{33}, x_{43}, x_{50}\}$

Boundary region

$Bn_{\tilde{A}}(X_{[60\%-70\%)}) = \overline{A}X_{[60\%-70\%)} \setminus \underline{\tilde{A}}X_{[60\%-70\%)}$
$Bn_{\tilde{A}}(X_{[60\%-70\%)}) = [x_{11}]_{\tilde{A}} = \{x_{11}, x_{23}, x_{28}, x_{41}, x_4, x_{19}, x_{31}, x_{34}\}$
$Bn_{\tilde{A}}(X_{[70\%-80\%)}) = [x_1]_{\tilde{A}} \cup [x_4]_{\tilde{A}}$
$\qquad = \{x_1, x_2, x_7, x_{12}, x_{13}, x_{15}, x_{17}, x_{24}, x_{33}, x_{43}, x_{50}\}$
$\qquad \cup \{x_4, x_{11}, x_{19}, x_{23}, x_{28}, x_{31}, x_{34}, x_{41}\}$
$Bn_{\tilde{A}}(X_{[80\%-100\%]}) = [x_2]_{\tilde{A}}$
$\qquad = \{x_1, x_2, x_7, x_{12}, x_{13}, x_{15}, x_{17}, x_{24}, x_{33}, x_{43}, x_{50}\}$

Negative region

$Neg_{\tilde{B}}(X_{[60\%-70\%)}) = \cup \setminus \overline{\tilde{A}}X_{[60\%-70\%)}$
$Neg_{\tilde{B}}(X_{[60\%-70\%)})$
$= \{x_1, x_2, x_7, x_{12}, x_{13}, x_{15}, x_{17}, x_{21}, x_{24}, x_{33}, x_{43}, x_{49}\}$
$Neg_{\tilde{A}}(X_{[70\%-80\%)}) = \{x_6, x_{22}, x_{42}, x_{46}, x_{49}\}$
$Neg_{\tilde{A}}(X_{[80\%-100\%]}) =$
$\{x_4, x_6, x_{11}, x_{19}, x_{21}, x_{22}, x_{23}, x_{28}, x_{31}, x_{34}, x_{41}, x_{42}, x_{46}, x_{49}\}$

Accuracy of approximation

$$Accur_{\tilde{B}}(X_{[60\%-70\%)}) = \overline{\overline{\underline{B}X_{[60\%-70\%)}}} \div \overline{\overline{\overline{B}X_{[60\%-70\%)}}}$$

$$Accur_{\tilde{B}}(X_{[60\%-70\%)}) = \frac{5}{13} = 38.5\%$$

$$Accur_{\tilde{B}}(X_{[70\%-80\%)}) = \frac{1}{20} = 5\%$$

$$Accur_{\tilde{B}}(X_{[80\%-100\%]}) = \frac{0}{11} = 0\%$$

In the context of fundamental concepts of rough sets applied on the set of goals, the following observations were carried out.

Observations:

➢ The goals having no goal and soft goal dependencies certainly belong to the set $X_{[60\%-70\%)}$.
➢ The goals having soft goal and no goal dependencies certainly belong to the set $X_{[70\%-\%80)}$.
➢ The goals having no soft goal dependencies possibly belong to the set $X_{[60\%-70\%)}$.
➢ The goals with goal and soft goal dependencies or only goal dependency and no soft goal dependencies or with soft goal and no goal dependencies possibly belong to the set $X_{[70\%-\%80)}$.
➢ The goals with both goal and soft goal dependencies possibly belong to the set $X_{[80\%-100\%]}$.
➢ The goals belonging to the boundary regions $Bn_{\tilde{A}}(X_{[60\%-70\%)})$, $Bn_{\tilde{A}}(X_{[70\%-80\%)})$ and $Bn_{\tilde{A}}(X_{[80\%-100\%]})$ cannot be classified uniquely to any of the sets $X_{[60\%-70\%)}$, $X_{[70\%-\%80)}$ or $X_{[80\%-100\%]}$.
➢ The goals with both goal and soft goal dependency or task and soft goal dependency certainly do not belong to the set $X_{[60\%-70\%)}$.
➢ The goals with no goal and soft goal dependencies certainly do not belong to the set $X_{[70\%-\%80)}$.
➢ The goals with only goal dependencies or with soft goal and no goal dependencies or no goal as well as soft goal dependencies certainly do not belong to the set $X_{[80\%-100\%]}$.
➢ The accuracy of approximation signifies the degree of confidence of belongingness of goals to the sets $X_{[60\%-70\%)}$ and $X_{[70\%-\%80)}$ as 38.5% and 5% respectively, while empty set $X_{[80\%-100\%]}$ is purely a rough set with 100% uncertainty in selecting service provider agents with Rep_Scores [80%-100%].

4.4. Framing Unambiguous Knowledge Rule Base

In order to resolve the uncertainties associated with ToD, concept of domain specific DoD was specified in the decision table. The evaluation of DoD driven by the domain knowledge is detailed in our previous work [8, 10]. A team of 15 developers and 20 domain experts was comprised in order to frame an unambiguous rule base. The goals with non deterministic rules having both goal and soft goal dependencies as "Y" were converted to the deterministic rules by involving DoD as [0.5,0.7] and [0.7,1] that facilitated the selection of agents with Rep_Scores [70%-80%) and [80%-100%)] respectively. The value of DoD<0.3 was ignored as the depender agent was advised not to delegate the goals with less DoD. Similarly the ambiguities with the remaining rules were resolved as illustrated in table 3.

Table3 Unambiguous reduced knowledge rule base using ToD and DoD

	ToD	Decision Rules					
Conditions	Goal dependency	Y	Y	Y	Y	N	N
	Soft Goal dependency	Y	Y	N	N	Y	N
	DoD						
	0.3<=DoD<0.5	-	-		Y	-	Y
	0.5<=DoD<0.7	Y	-	Y	-	Y	-
	0.7<=DoD<=1	-	Y	-	-	-	-
	Agents with Rep_Scores						
Actions	[60%-70%)				X		X
	[70%-80%)	X		X		X	
	[80%-100%]		X				

The training data was revised in order to incorporate ToD and DoD as per unambiguous rule base and the Johnson's Algorithm [13] was further applied to reduce unnecessary attributes as well as rules without loss of any information. The resultant rule base after second reduction is illustrated in figure 5.
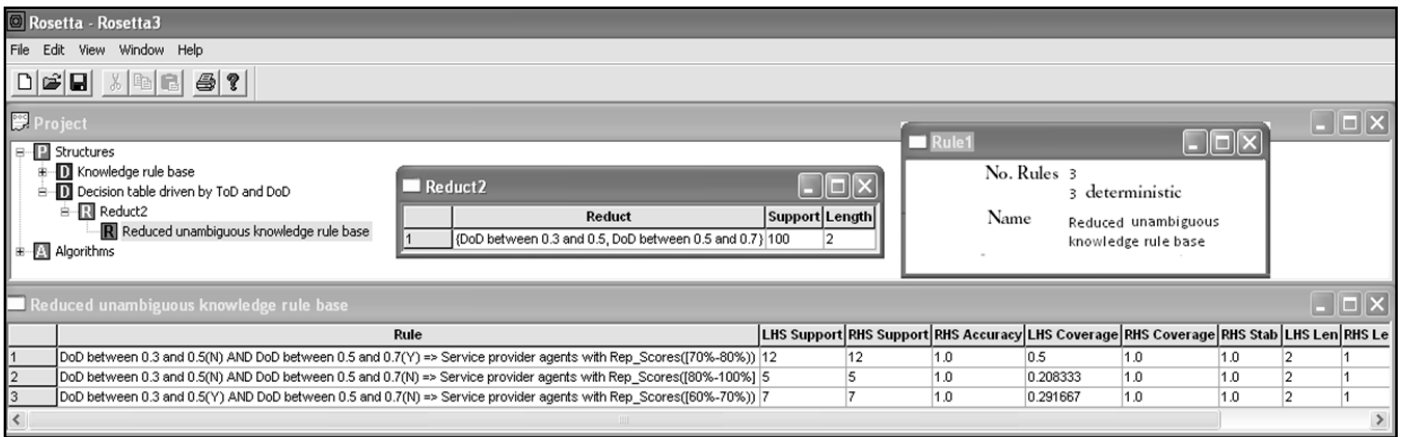

Figure 5 Unambiguous rule base after 2nd reduction

4.5. Result Analysis

In order to classify the goals under various categories of service provider agents, standard voting algorithm [12] was applied on test data using ambiguous as well as unambiguous compact rule base. The results are illustrated in figure 6.
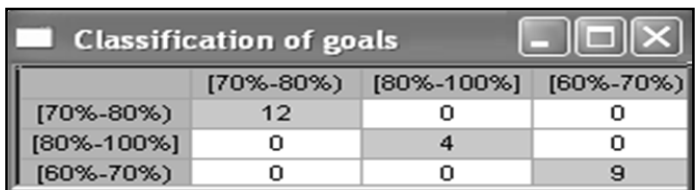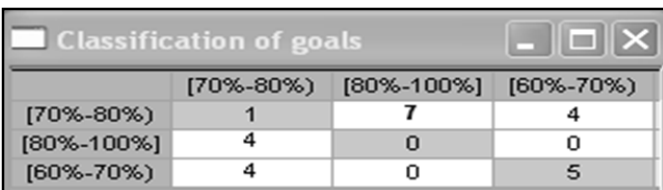

Figure 6 Classification of goals characterized by (a) ambiguous rule base (b) unambiguous compact rule base

The values of the matrix, exhibit the belongingness of goals to various classes of service provider agents. The matrix is traversed row wise from left to right. The diagonal elements signify the goals uniquely belonging to the class of agents. The row 1 in figure 6(a), signifies that a total of (1+7+4=12) goals belong to the category of agents with Rep_Scores [70%-80%), out of which single goal can uniquely be classified under Rep_Scores [70%-80%), 7 goals in the cell$_{1x2}$, cannot uniquely be classified in the class of Rep_Scores [70%-80%) and may belong to the class of Rep_Scores [80%-100%). Similarly remaining non diagonal non-zero values signify the uncertainties involved in the belongingness of numerous goals to various classes of agents.

The unambiguous compact rule base evolved using ToD and DoD, facilitates the goals to be uniquely classified as illustrated in figure6(b). In figure 6(a), only (1+5=6) goals were uniquely classified; 1 goal belonging to the class of Rep_Scores [70%-80%) and 5 goals to the class of Rep_Scores [60%-70%), but in figure 6(b), all 25 goals of test data were uniquely classified. This comprised 12, 4, 9 goals belonging

to the classes of agents with Rep_Scores [70-80%), [80%-100%], [60%-70%) respectively.

Hence specification of ToD and uncertainties in relation thereto facilitate the developer to comprehend the user perception of dependencies and subsequently induction of DoD assists him to resolve the ambiguities in the selection of service provider agents.

5. CONCLUSIONS

The investigation of uncertainties in social dependencies is augmented as an integral part of Software Requirements Specification (SRS) that eventually would provide the developer a sound underpinning in formulating coordination issues in a distributed environment without squandering resources and hence in building MAS of high quality.

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