4.4
Modeling collaboration preparedness assessment

J. Rosas, L. M. Camarinha-Matos

Information incompleteness and imprecision are typical difficulties when assessing the collaboration preparedness of a candidate to join a collaborative network. Bayesian belief networks and Rough Sets are examples of modeling approaches that can be used in these cases. The use of these approaches depends on the type of collaborative network considered, namely long term or goal oriented, and on the available data necessary to perform the assessment. Combination of different modeling techniques is also useful in this context. In order to illustrate the suggested approach, a number of modeling experiments are described and achieved results are briefly discussed.

1. INTRODUCTION

A number of decision making problems in collaborative networks involve the assessment of network members. Examples include the estimation of the preparedness level of a candidate to join a virtual organization breeding environment (VBE) (Afsarmanesh, Camarinha-Matos, 2005) or the selection of partners to form a virtual organization (VO) in response to a business opportunity.

In such assessment cases, multiple criteria are typically used and the decisions are often based on incomplete and / or imprecise information. This chapter discusses some approaches to handle this problem, namely resorting to Bayesian belief networks and Rough Sets. A combination of various modeling techniques in order to achieve better results is also discussed. In order to illustrate the concepts and suggested approach, a number of modeling examples or experiments are introduced along with the introduction of base concepts and definitions.

The collaboration preparedness concept has lately received some attention. For instance, it is referred that a way to increase the preparedness to work in collaboration is to be part of a VBE, as it provides a common ICT infrastructure, mechanisms and guidelines for collaboration, letting members to be able to agilely grasp business opportunities. In this sense, the level of preparedness would be measured taking in attention several technical, economical and reliability indicators (Camarinha-Matos, Afsarmanesh, 2006). In (Baldo, 2007) a methodology is presented to help finding the appropriate performance indicators to be used when searching for suitable sets of organizations to fulfil specific collaboration opportunities. In (Jarimo et al, 2005), the concept of preparedness is organized in an attribute hierarchy, constituted by node and network preparedness attributes, over which a mathematical optimization methodology for optimal VO configurations is applied as a multi-attribute decision making problem. However, most of the previous works addressing this issue remain at a qualitative and informal level of analysis.

2. COLLABORATION PREPAREDNESS ASSESSMENT

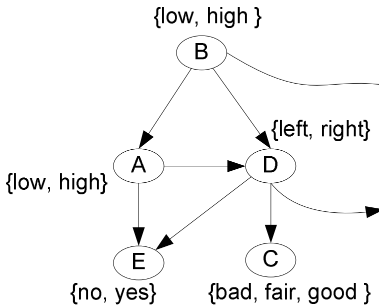
2.1 Estimation of preparedness to join a VBE using Belief Networks

This modeling example proposes the use of Bayesian belief networks in order to predict whether a member has adequate characteristics for collaboration and thus be considered a good candidate to join a VBE. A number of attributes are used to characterize members, such as their prestige, reliability, size and tolerance to risk.

A model based on belief networks is particularly useful when there is little information to perform an accurate assessment. This typically happens whenever there is a new candidate to join a VBE, for which the available information concerning this candidate is usually low as the example described below illustrates.

The Bayesian belief network concept. A Bayesian belief network is a kind of probabilistic model that represents causal relationships on a set of variables (Fig. 1). It is composed of two parts: (i) the structural part, which consists of a direct acyclic graph, in which nodes stand for random variables and edges for direct conditional dependences between them; and (ii) the probabilistic part that quantifies the conditional dependence between these variables.

Each variable can have state values (such as, 'no', 'yes' or 'low', 'high'). If the value of a variable in a node is known, then that node is said to be an evidence node. In Fig. 1, the arc pointing from node A to node E can be perceived as "A causing or influencing E". Each of the children nodes have an associated conditional probability table that quantifies the effects that the parents have on them. For nodes without parents, the corresponding table only contains prior probabilities. Due to these conditional dependences, if a node becomes an evidence node, then the probabilities (or likelihood) of the other nodes change. More on belief networks can be found in (Jensen, 1996).



B	
low	high
0.30	0.70

		D	
A	B	left	right
no	low	0.00	1.00
no	high	0.70	0.30
yes	low	0.85	0.14
yes	high	0.93	0.07

Figure 1 – An example of a Bayesian belief network

For any node of the network in Fig. 1, the computation of conditional probabilities is done using the Bayes' rule, as exemplified in the modeling example below. Belief networks can be used to perform queries in distinct ways:

- To perform predictions. This is useful whenever some causes are known and it is necessary to determine the probability of possible effects/consequences. For instance, when *A*=low and *D*=left, the probability of *E*=yes is given by the query P(*E*=yes | *A*=low, *D*=left).
- To perform diagnostics. For instance, when the fact *C*=bad is known, it is necessary to determine the likelihood of eventual causes, e.g. P(*D*=right| *C*=bad).

It is also possible to make queries on the joint distributions, without providing evidences. For instance, the probability of *C*=fair, without further evidence, is given by P(*C*=fair).

In simple cases, a Bayesian network can be specified by an expert and used to perform inferences. In other cases, the task of defining the network is too complex to be done by hand. Therefore, both the structure (nodes and arcs) and parameters of the local distributions must be learned from data using Machine Learning techniques (Pearl, 1996), (Cheng, Greiner, 2001), (Friedman, 1997). This process can be summarized by the following steps:

1. Acquire sufficient information from data repositories and take it as the learning / training sample data.
2. Use Belief Network Learning in order to obtain the structure of the Belief network.
3. Use probabilistic/statistical methodologies to compute the local probability tables on every node of the belief network.
4. Use examples out-of-the-sample data to test the model.

After this process, and if the network is considered good enough, it can be used to support decision making. Moreover, during the utilization phase of the belief network model, the conditional probabilities can be adjusted (through learning) as more cases and corresponding decisions are observed (Wang & Vassileva, 2003).

For the example described below, due to the difficulty in obtaining historic data concerning situations of collaboration preparedness assessment, the belief network was specified by hand. Nevertheless, this does not undermine the intents of the modeling exercise, as its primary objective is to reveal the potential application of this approach in the context of CNs.

Modeling Example. This example illustrates a situation where a candidate is being considered to join a network, namely a VBE. Let us suppose that, at the very beginning, little information is known about the candidate's profile, though it might present attractive technological skills.

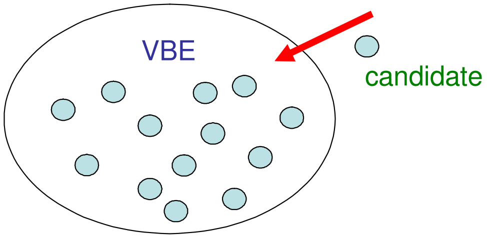


Figure 2 – A candidate wants to get in the network.
Little information on its profile is available

In order to better illustrate the potential use of belief networks, the modeling exercise is built up in two phases, as illustrated in Fig. 3.

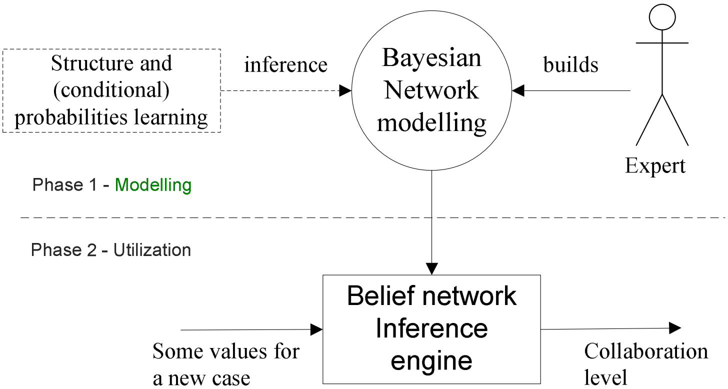


Figure 3 – Phases followed in the modeling exercise

Phase 1. In this phase, the expert structures the belief network by first identifying and specifying its probabilistic variables and corresponding conditional dependencies. He then quantifies these dependencies in the so called conditional probability tables. For this example, the expert creates a kind of prediction model to help estimate the probability of the candidates to be ready to join a collaborative network. When designing the belief network (by hand), a few assumptions related to members' behavior were made in order to guide the design process. These assumptions, among potential many others, should be taken as merely illustrative. Therefore, we conjecture that:

- An organization in a difficult economical condition, in order to benefit from others' competences (that usually it cannot afford to own) and have access to others' business opportunities, is more willing to accept the risks of collaboration. On the other hand, due to its fragile condition, it tends to be less reliable.
- An organization in good economical conditions might be more reliable, but does not feel the same pressure, as the previous case, to collaborate and therefore tend to be more risk conservative considering collaboration/partnerships.
- An organization might become less reliable if it has a weak adaptability to newer situations.
- A small size organization (e.g. a SME) might possess fewer competences and, in order to complement them, accepts to be more exposed to the risks of collaborating with other organizations.
- The prestige of an organization, which is an attribute that is perceived by its peers, is fundamental in collaboration and has a positive contribution to the preparedness level.
- The creativity of an organization, which can be roughly estimated by evaluating its rate of generated innovations, might also be important for collaboration, and adds to the preparedness level.

A belief network, modeled using the above guidelines, is shown in Fig. 4 and can be used to perform some testing as described below. It shall be noted that Belief networks models do not live by themselves, but are rather integrated as sub-components in larger (reasoning) systems.

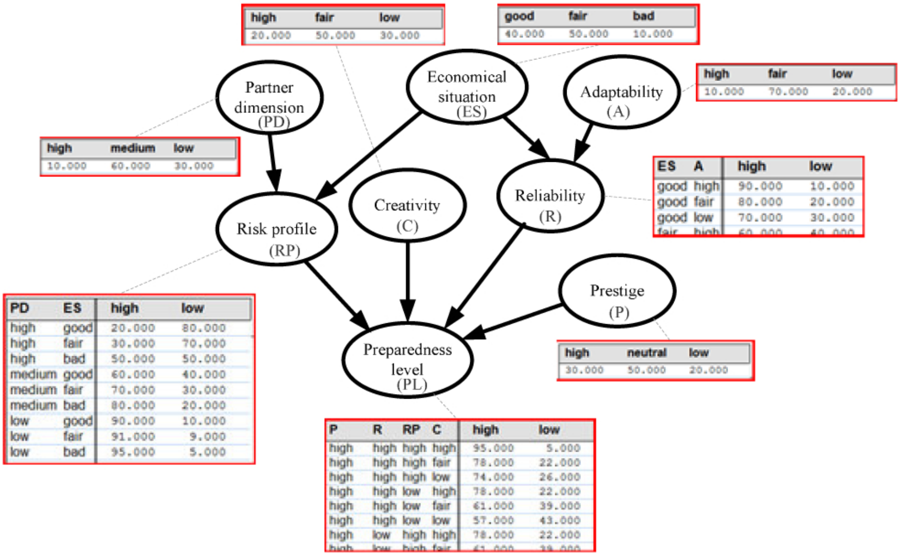


Figure 4 – A Bayesian network example to assess the preparedness level

For this belief network, the joint probability distribution, from which the analysis can be made, is the following (showing only the initials for the nodes names):

$$P(PD,ES,A,RP,R,C,P,PL) = P(PD) \times P(ES|PD) \times P(A|ES,PD) \times P(RP|PD,ES,A)$$
$$\times P(R|PD,ES,A,RP) \times P(C|PD,ES,A,RP,R) \times P(P|PD,ES,A,RP,R,C) \times$$
$$P(PL|PD,ES,A,RP,R,C,P)$$

This function can be simplified by considering the conditional independence statements implied in the belief network. For instance, the 'Partner Dimension' and 'Risk Profile' variables do not influence the 'Reliability', as 'Economical Situation' and 'Adaptability' do. This is because $P(R|PD,ES,A,RP)=P(R|ES,A)$, so PD and RP can be removed from the above expression. The same approach can be applied to the other conditional probabilities, helping remove more variables (the shaded ones) from the above expression. This results in the function:

$$P(PD,ES,A,RP,R,C,P,PL) = P(PD) \times P(ES) \times P(A) \times P(RP|PD,ES)$$
$$\times P(R|ES,A) \times P(C) \times P(P) \times P(PL|RP,R,C,P)$$

As illustration for the given problem, and assuming most of the nodes as evidences (to reduce calculations), the probability of collaboration level *PL=high*, given that *PD=high*, *ES=fair*, *A=fair*, *C=high* and *P=high* is given by

$$P(PL_{high} \mid PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high}) = \frac{P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high})}{P(PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high})}$$

The steps for the calculation of this probability are the following:

$$
\begin{aligned}
& P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high}) \\
&= \sum_{rp\in\{high,low\}} \sum_{r\in\{high,low\}} P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{rp}, R_r, C_{high}, P_{high}) \\
&= P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{high}, R_{high}, C_{high}, P_{high}) \\
&+ P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{high}, R_{low}, C_{high}, P_{high}) \\
&+ P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{low}, R_{high}, C_{high}, P_{high}) \\
&+ P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{low}, R_{low}, C_{high}, P_{high}) \\
&= P(PD_{high}) \times P(ES_{fair}) \times P(A_{fair}) \times P(RP_{high} | PD_{high}, ES_{fair}) \\
&\times P(R_{high} | ES_{fair}, A_{fair}) \times P(C_{high}) \times P(P_{high}) \times P(PL_{high} | RP_{high}, R_{high}, C_{high}, P_{high}) \\
&+ P(PD_{high}) \times P(ES_{fair}) \times P(A_{fair}) \times P(RP_{high} | PD_{high}, ES_{fair}) \\
&\times P(R_{low} | ES_{fair}, A_{fair}) \times P(C_{high}) \times P(P_{high}) \times P(PL_{high} | RP_{high}, R_{low}, C_{high}, P_{high}) \\
&+ P(PD_{high}) \times P(ES_{fair}) \times P(A_{fair}) \times P(RP_{low} | PD_{high}, ES_{fair}) \\
&\times P(R_{high} | ES_{fair}, A_{fair}) \times P(C_{high}) \times P(P_{high}) \times P(PL_{high} | RP_{low}, R_{high}, C_{high}, P_{high}) \\
&+ P(PD_{high}) \times P(ES_{fair}) \times P(A_{fair}) \times P(RP_{low} | PD_{high}, ES_{fair}) \\
&\times P(R_{low} | ES_{fair}, A_{fair}) \times P(C_{high}) \times P(P_{high}) \times P(PL_{high} | RP_{low}, R_{low}, C_{high}, P_{high})
\end{aligned}
$$

The final step is to replace every conditional (or prior) probability in the expression by the values taken from the conditional (or prior) probability tables that are in the belief network. This results in:

$$
\begin{aligned}
& \sum_{rp\in\{high,low\}} \sum_{r\in\{high,low\}} P(PL_{high}, PD_{high}, ES_{fair}, A_{fair}, RP_{rp}, R_r, C_{high}, P_{high}) \\
&= 0.1 \times 0.5 \times 0.7 \times 0.3 \times 0.5 \times 0.2 \times 0.3 \times 0.95 \\
&+ 0.1 \times 0.5 \times 0.7 \times 0.3 \times 0.5 \times 0.2 \times 0.3 \times 0.78 \\
&+ 0.1 \times 0.5 \times 0.7 \times 0.7 \times 0.5 \times 0.2 \times 0.3 \times 0.78 \\
&+ 0.1 \times 0.5 \times 0.7 \times 0.7 \times 0.5 \times 0.2 \times 0.3 \times 0.61 \\
&= 0.001567
\end{aligned}
$$

The calculation of the denominator is similar to the previous steps:

$$
\begin{aligned}
& P(PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high}) \\
&= \sum_{rp\in\{high,low\}} \sum_{r\in\{high,low\}} \sum_{cl\in\{high,low\}} P(PL_{cl}, PD_{high}, ES_{fair}, A_{fair}, RP_{rp}, R_r, C_{high}, P_{high}) \\
&= 0.00209
\end{aligned}
$$

The corresponding probability is therefore

$$
P(PL_{high} | PD_{high}, ES_{fair}, A_{fair}, C_{high}, P_{high}) = \frac{0.001567}{0.00209} = 0.75
$$

Phase 2. In order to test the belief network, the model obtained in the first phase was implemented with the help of the NETICA tool. This is a program used to create diagrams encoding knowledge or representing decision-making problems. The corresponding API (Application Program Interface) provides the same functionality as NETICA application, but designed for programmers to embed in their programs (NorSys, 1997).

The result is shown in the Fig. 5, where the gray nodes (Partner dimension and Economical situation) stand for variables that, at that instant, are evidences. The way to use the belief network is to provide some evidences (if available) and place queries for the probability or likelihood of the other unknown values: P(query | evidences).

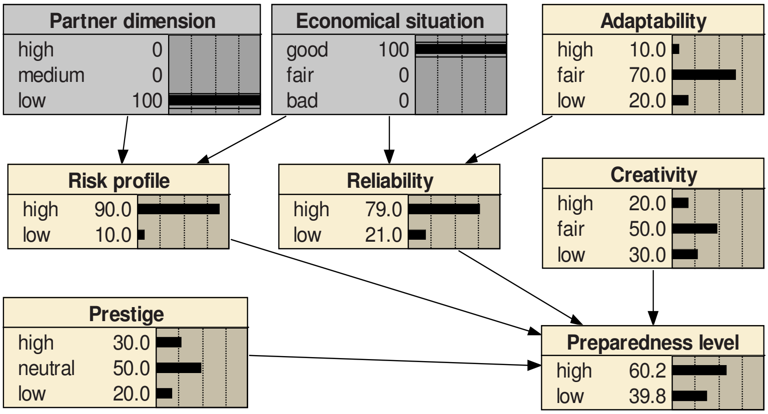


Figure 5 – Belief network with two nodes taken as evidences

This model can now help estimate the probability of a candidate to be prepared for collaboration. For instance, given the evidence that a certain candidate is in good economical situation and is of low dimension (Fig. 5), the probability of that member being prepared for collaboration is given by

P("Collaboration level"=high | "Partner dimension"=low, "Economical situation"=good)=60.2%.

If more information is known about this candidate, the certainty of the performed classification increases. For instance, if it is also known that it has high creativity and high prestige (Fig. 6), then the collaboration level is:

P("Collaboration level"=high | "Partner dimension"=low, "Economical situation"=good, "Prestige"=high, "Creativity"=high)=89.7%.

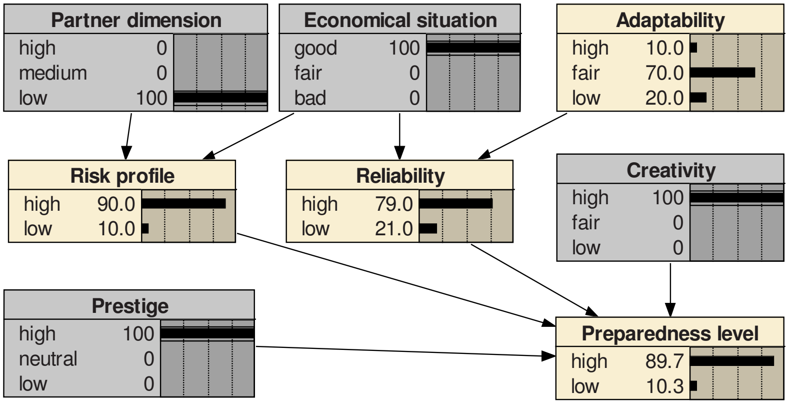


Figure 6 – State of the variables for the second case

Naturally, the more information is available, the more accurate is the classification. Even when the available information is (quite) scarce, belief networks appear to offer a reasonable model, as they can still provide helpful outputs.

Benefits and Limitations. In summary, belief networks are particularly suited for modeling and decision making in contexts of uncertainty and insufficient information. They can be used both for prediction and for diagnosis. They are easy to maintain and modify, particularly if a tool like NETICA is available. The structure and corresponding cause-effects in a belief network are easy to understand. They can be obtained using learning processes (Friedman, 1997).

As main limitation, it might be difficult to collect initial data for building up (learning) the belief network. Most often expert knowledge is used instead. Collecting knowledge for modeling a belief network can be very difficult and time consuming.

2.2 Improving partners' evaluations with Rough Sets

Rough Sets provide a way to do concept approximations for concepts of interest. In the following example, this theory is used to define the concept of "Excellent partner". By applying the Rough Sets theory, this definition is obtained through the utilization of both the indiscernibility relation and the reducts concepts. From the obtained model, it is possible to generate a rule-based decision support system that can be used to perform the classification of CN members.

Contrary to the belief network model previously described, the utilization of Rough Sets is usually applied in situations where there is a significant amount of information. The aspect of uncertainty still exists, but the principal concerns here are the imprecision and vagueness of information. Typically, there is a repository of cases characterized by many attributes, which are specified with imprecision. Moreover, some cases might contradict other cases. Such cases can be found in a VBE composed of members that have been participating in VOs. Assuming that during the lifecycle of the VBE, the collaboration opportunities, formation of VOs, obtained performance and outcomes are recorded in a VBE repository, the Rough

Sets methodology can be applied on this repository for knowledge extraction, as the example below illustrates.

The Rough Sets concept. Rough sets theory is an approach to model and address vagueness according to which imprecision is expressed by a "boundary region of a set", and not by a partial membership as in the fuzzy sets theory. The main idea of the rough sets is the approximation of a set by a pair of sets that are called the lower and the upper approximation of the set (Pawlak, 1999). The lower approximation of a rough set *X* is the collection of objects that can be classified with full certainty as members of the set *X* (Fig. 7). The upper approximation of *X* is the collection of objects that may possibly be classified as members of the set *X*. The boundary region comprises the objects that cannot be classified with certainty as to be neither inside *X*, nor outside *X*, thus the "set difference" between the upper and lower approximation sets.

This theory was proposed in early 1980s by Pawlak (Pawlak, 1991) as a way to deal with the needs in the analysis and classification of large data/decision tables taken from information systems. As a Soft Computing method, whose typical uses are found in the Knowledge Discovery and Data Mining areas, it is applied in situations where the available information is characterized by vagueness, ambiguity and uncertainty – therefore, to characterize concepts not easily defined in a crisp way. Rough Sets is used to synthesize approximations for the concepts of interest, using the referred upper and lower approximations, as illustrated in Fig. 7. More about Rough Sets can be found in (Pawlak, 1991, 1995) and (Pawlak and Skowron, 1999).

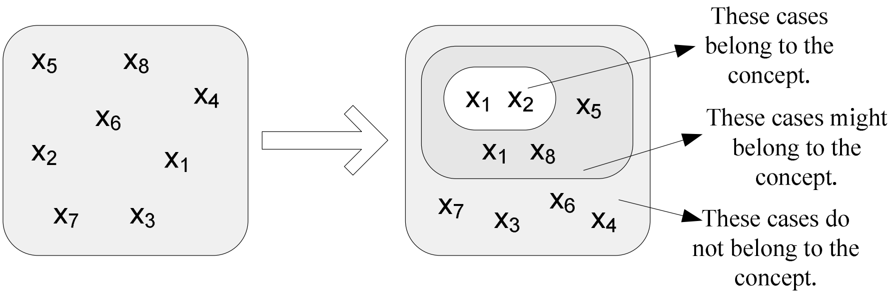


Figure 7 – The Rough Sets' concept approximation approach

Adopted methodology. This section applies the rough sets methodology on an illustrative modeling example. Basically, it begins with historic data taken from a VBE repository. In practice, such data may be organized in a (possibly) large decision table with (possibly) tens of attributes. But, for illustrative purposes and in order to keep this example simple and clear, the used table was made smaller.

As in the belief networks example, the experiment is developed in two separate phases, as shown in Fig. 8. In the first phase, an expert builds an information table from the repository. Then he selects the decision attribute (e.g. Partner grade) for the concept of interest, which in this case is the concept of "Excellent Partner". The result is the concept approximation for "Excellent Partner" or, in other words, its Rough Set definition. Finally, the obtained concept can be transformed into a set of decision rules.

In phase 2, the rough sets technique is applied to evaluate the members of the VBE to see whether they can be considered excellent partners or not.

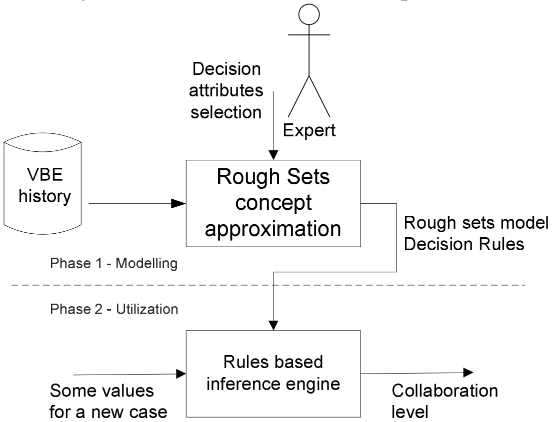


Figure 8 – Phases of the rough sets modeling experiment

Modeling example. When selecting a new member for a VO, it is not possible to foretell whether this candidate will turn out to be a good partner or not. A VBE manager would typically pick up the candidate's profile and, based on the history of previous selections, use his/her best judgment to make the decision. However, this manager could benefit if there was a model, obtained from the history of previous collaboration cases that would provide some support to his /her decision.

The modeling example follows the two phases as mentioned above.

Phase 1. The table in Fig. 9 shows a number of records taken from a VBE repository of past collaborations. It is assumed that during the lifetime of the network, members participated in several VOs. As time passed, they were given a "Partner grade" quantifying their performance as partners in collaborative projects. Therefore, each member was classified as an "excellent", "good" or "fair" partner.

CN1$

	Past Activity	Prestige	Reliability	Risk _profile	Respect other partners	technological background	Localization distance	Partner dimension	Economic situation	Partner grade
1	high	high	good	high	high	high	far	big	good	excellent
2	low	fair	good	low	fair	medium	near	big	fair	fair
3	high	low	bad	prudent	high	low	far	medium	good	fair
4	low	low	fair	high	fair	low	near	small	fair	fair
5	low	high	good	low	high	high	near	big	fair	good
6	high	fair	good	prudent	fair	high	far	medium	good	excellent
7	low	low	bad	prudent	high	low	near	small	good	fair
8	high	fair	fair	high	fair	medium	near	big	fair	good
9	high	fair	good	prudent	high	low	far	medium	good	good
10	low	high	bad	high	fair	high	near	small	fair	fair
11	low	fair	fair	low	high	high	near	big	good	fair
12	low	high	good	prudent	fair	low	far	medium	fair	fair
13	low	high	good	prudent	high	medium	near	small	fair	fair
14	low	fair	fair	prudent	fair	medium	far	big	good	fair
15	high	high	good	prudent	high	high	near	medium	fair	good
16	low	high	good	prudent	fair	low	near	small	fair	fair
17	low	high	fair	low	high	low	far	big	good	fair
18	high	fair	good	prudent	fair	medium	near	medium	fair	good
19	low	high	good	prudent	high	low	near	small	fair	fair

Figure 9 – Examples with characteristics and grading for the members of a VBE.

When observing the partners characteristics, and corresponding grades, one would wonder if there was any pattern in the values, or any dependencies that might be of interest. Just by looking at the table, it seems that it is possible to discover some patterns in the data. Therefore, it is worth exploring whether these patterns provide some insights on how to classify a candidate.

In this phase, the utilization of Rough Sets to identify the aspects that are important for candidates' classification is described. The Rough Sets theory not only identifies these attributes, but it also provides a classification model, in the form of a rule-based decision system for further utilization. This model can then be used to classify the candidates for new VOs.

The exercise is performed using the ROSETTA tool (Komorowski et al., 2002), as illustrated in Fig. 10. It begins with the sample data given as input and selecting the decision variable "Partner Grade" amongst the table's attributes, as Fig. 9 illustrates. Then, using the concept of indiscernibility, the reducts are determined. In order to illustrate this concept, any two or more cases in Fig. 9 are considered indiscernible if for a chosen set of attributes, they share the same values. Considering the attributes set {'past activity', 'prestige', 'risk profile, 'respect other partners', 'technological background'}, then cases 12 and 16 are indiscernible, as spotted by the squares in the referred figure. Reducts are, therefore, minimum sets of attributes that preserve the contents of the decision table, while removing the redundant attributes. The indiscernibility relation, in turn, allows the elimination of the redundant cases. The resulting decision table, composed of the reduct's attributes and the non-redundant cases, expresses the same knowledge as the original table. For the proposed modeling example, one of these reducts is the set {Past activity, Prestige, Risk profile, Respect other partners, Technological background}, which according to the Rough Sets technique, are just the necessary attributes to classify a candidate. As such, a VBE manager can pay more attention to these characteristics of the candidates when considering and classifying the VBE members.

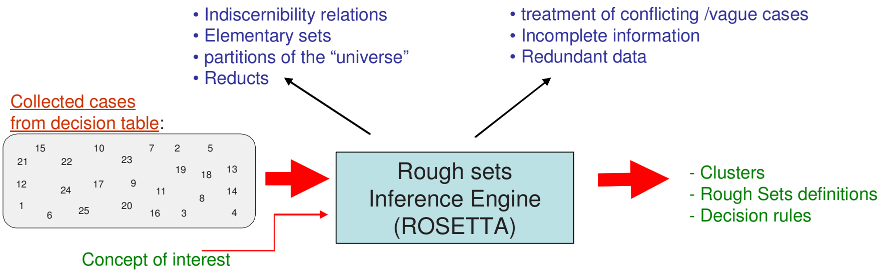


Figure 10 – Using the Rough Sets methodology in concept approximation

The results of applying this technique are shown in Fig. 11. The cases 1, 23 and 6 correspond to "Excellent" partners. This means that any new candidate with similar characteristics (i.e., with the same values in the attributes of the reducts) will be definitely considered as an excellent partner. Regarding partners 15 and 21 it is uncertain whether they are excellent or just good partners. This means that, there will be uncertainty when classifying new cases with similar attribute values. The outer region represents partners that do not belong to the concept of “Excellent partner”.

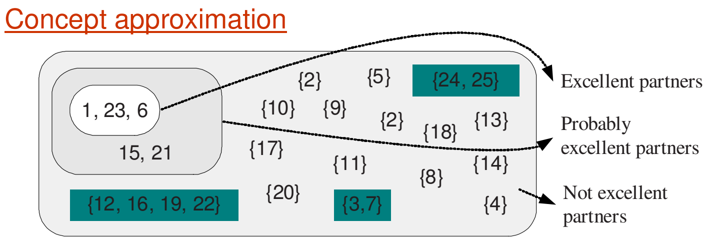


Figure 11 – The lower and upper approximations for the concept “excellent partner”. Other clusters in this figure might represent other concepts

With Rosetta tool, we can convert these concepts into decision rules (Fig.12), which can be integrated in a larger reasoning system.

```
Past Activity(high) AND Prestige(high) AND Risk _profile(high) AND
Respect other partners(high) AND technological background(high)
     => Collaboration level(excellent)

Past Activity(low) AND Prestige(high) AND Risk _profile(low) AND
Respect other partners(high) AND technological background(high)
     => Collaboration level(good)

Past Activity(low) AND Prestige(high) AND Risk _profile(prudent) AND
Respect other partners(fair) AND technological background(low)
     => Collaboration level(fair)

Past Activity(high) AND Prestige(high) AND Risk _profile(prudent) AND
Respect other partners(high) AND technological background(high)
     => Collaboration level(good)
     OR Collaboration level(excellent)
                                        this rule is fired for the
                                        cases in the boundary
Past Activity(low) AND Prestige(fair) AND Risk _profile(low) AND
Respect other partners(fair) AND technological background(medium)
     => Collaboration level(fair)
```

Figure 12 – Decision rules for the concept of “Excellent partner”

Phase 2. Before performing the tests with the model obtained in previous phase, the corresponding decision rules must be converted into some computable format. The ROSETTA tool can perform such conversion and these rules were translated to Prolog predicates, as shown in Fig. 13.

If a query is performed for case o1, the model classifies it as “excellent”, and so any candidate similar to this case. Similarly, for case o10 the model yields a “fair” classification. These cases correspond to unambiguous classifications.

Prolog shell

```
| ?- 'collaboration level'(o1, Class, _, _, _).
Class = excellent

| ?- 'collaboration level'(o10, Class, _, _, _).
Class = fair ;

| ?- 'collaboration level'(o15, Class, _, _, _).
Class = good ;
Class = excellent
```

Case in the boundary

Rough Set predicates

```
'collaboration level'(X, excellent, 1, 1.0, 1.0) :-
        'past activity'(X, high),
        prestige(X, high),
        'risk _profile'(X, high),
        'respect other partners'(X, high),
        'technological background'(X, high).

'collaboration level'(X, fair, 1, 1.0, 1.0) :-
        'past activity'(X, low),
        prestige(X, fair),
        'risk _profile'(X, low),
        'respect other partners'(X, fair),
        'technological background'(X, medium).
```

Figure 13– A partial view of the decision rules tried in a Prolog shell

Now, let us consider member o15 as a potential partner. Some information available about its profile is shown in Fig. 14.

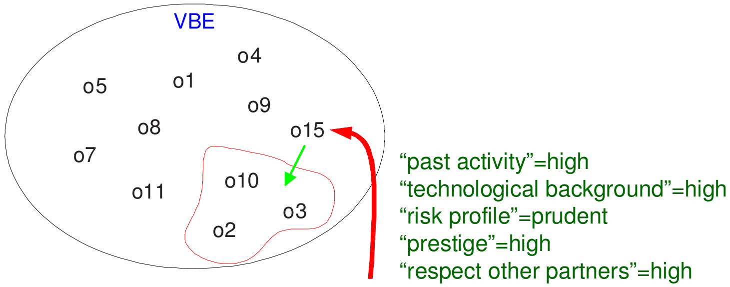


Figure 14 – Member o15 is a candidate for a new VO

The classification for the case o15 is not like the others tested before. For this case, the decision rules cannot unequivocally classify whether it is a "good" or "excellent" partner, as it yields these two results. However, there is a reason for this kind of classification. Although case o15, in a previous collaboration, was classified as "good" (as the table of Fig. 9 shows), its profile resembles the profiles of other cases that were classified as "excellent". Due to the incongruence between the o15's profile, its corresponding classification and the classifications given to similar cases, the model places case o15 in the boundary between the upper and lower approximation of the Rough Set obtained in phase 1. Perhaps there was a mismatch in the classification, or maybe something did not go totally well in a previous collaboration with member o15, which might mean that it did not performed as well as what was expected, given its (perceived) profile.

Benefits and limitations. In summary, the Rough Sets approach allows dealing with problems characterized by incomplete information, which may also be redundant, and even ambiguous and vague. Using the Rough Sets approach allows the construction of a concept from a possibly large historic record table (with thousands of rows and tens of attributes). The resulting concept uses only a minimal set of the original attributes, which allow decision making with fewer decision variables.

A comparison between Rough Sets and other decision tree classifier algorithms as ID3 was presented in (Hassanien 2004). Rough Sets test results were much better in terms of the number of rules and classification accuracy. In decision trees, more robust features are required to improve the performance of decision tree classifiers. Moreover, ID3 cannot handle contradictory data, whereas Rough Sets deal well with it (through their approximations to the concepts). ID3 is also very sensitive to small modifications on the data. This does not occur with Rough Sets.

One limitation found in this experiment is that, if the information about some candidate is not sufficient to assign values to the reduct's attributes, then the classification cannot be performed, because no decision rule will be fired. This drawback is better handled using Bayesian Belief Networks, as illustrated in the modeling approach previously presented.

3. MODELING A PARTNERS SUGGESTION MECHANISM

3.1 The concept of collaboration preparedness

The last modelling experiment illustrates how different modeling methodologies, "crisp" and "soft", can be combined in the resolution of a problem and how we can benefit from such combination in collaborative networks modeling.

The next modeling exercise is focused on <u>a situation where a collaboration opportunity is identified and a virtual organization (VO) has to be formed</u>. Therefore, possible sets of VBE members are suggested for the corresponding consortium formation. The process of partners' suggestion is traditionally based on a matching performed between the requirements of the collaboration opportunity and the competences provided by the potential candidates.

In this modeling experiment, this matching process is improved by considering the concept of organization's character. An organization's **character** can be defined as a composition of a set of traits. A **trait** represents relatively stable predisposition to the manifestation of a certain pattern of behaviour. As illustrated in the example below, these traits are often described in a rather imprecise, incomplete and uncertain way. In this example, the assumption is that if an organization's behaviors can be predicted from its traits, then collaboration preparedness assessment can also be performed using these traits. Additionally to character's preparedness, the concept of competences fitness should also be considered in a collaboration readiness assessment concept, as described in section 3.3.

3.2 Partners' suggestion based on the concept of preparedness

For modeling a partner's suggestion mechanism using the principle of collaboration preparedness based on organization's character, we reuse the belief network model described in section 2.1, which is combined with the concept of competences fitness, as described below. For each suggestion of candidates (or rough *VO* coalition), a model of the *VO* together with its business process plan for the collaboration opportunity is simulated in a simulation engine for obtaining estimated performance measurements.

This framework was implemented using a rule-based knowledge base, developed in Prolog. The belief network inference engine is provided by NETICA tool, whose access is done through its API. For undertaking the experiment, some concepts of Project Management modeling and Simulation techniques were also used. Therefore, a combination of various modeling techniques is used in this example, as shown in Fig. 15.

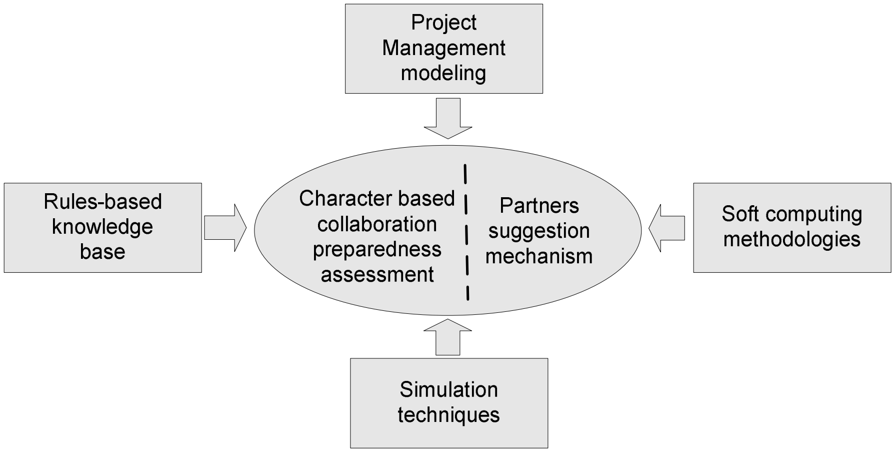


Figure 15 – Theories and tools used in this experiment

3.3 An axiomatic model for partners' suggestion

The first step is to define basic sets, such as organizations, competences and traits, which are necessary for the specification of the partners' suggestion axioms. To adequately distinguish the concepts, it is assumed that all single attributes are named in small letters, while sets are named in capital letters. These sets are defined as:

- $O=\{o_1, o_2, \ldots\}$ – the set of organizations of a VBE.
- $T=\{t_1, t_2, \ldots\}$ – the set of traits identifiers that can be used to characterize an organization's character.
- $V_i=\{v_{i,1}, v_{i,2},\ldots\}$ – the set of values that trait t_i can assume.
- $OP=\{op_1, op_2, \ldots\}$ – the set of comparison operators. The operator op_i performs comparisons between the values of the set V_i (e.g. 'near(v_1,v_2)').
- $C=\{c_1, c_2,\ldots\}$ – the set of competences required for the achievement of a given collaboration opportunity (CO).

Just as an example, these sets can be instantiated with the following values: O={net1, org2, university3}, T={flexibility, creativity, reliability}, $V_{reliability}$={low, fair, high}, C={DBA, logistics, ICT, CAD},and OP={'<', '>', '=', about, near, reliability_op, prestige_op}.

For the purposes of this experiment, the collaboration opportunity (CO) already appears organized as a business process plan, which is constituted by a set of activities, each one having time and precedence constraints, and requiring specific competences for their execution.

These activities are specified in a PERT-like approach. The duration of each activity is specified by three estimated values: the most optimistic (to), the most likely (tm), and the most pessimistic (tp). From these values and following the PERT approach, the duration of an activity is calculated by the formula Te = (to +

4*tm + tp) /6, with standard deviation s = (tp - to)/6, which already incorporates the underlying uncertainty for the activity durations (Martinich, 1997).

For the definitions presented below, we abstract from many details that, although important, are irrelevant for our illustrative purposes in this experiment. For instance, our definition of collaborative business process plan is rather simplistic and is better explained in (Camarinha-Matos et al, 2005).

Definition 1 (**Activity**) – An activity, a component of the collaborative business process plan for the CO, is defined as a tuple Act=(id, d, C) in which:

- *id* - is the name of the activity.
- $d=(to, tm, tp)$ - is a tuple that specifies the time duration, using a *PERT* modelling approach. The attributes *to*, *tm* and *tp* stand for the most optimistic, the most likely and the most pessimistic time duration, respectively.
- $C=\{c_1,c_2\ldots\}$ - corresponds to the set of competences required for the satisfaction of the goals of the activity.

Definition 2 (**Collaborative business process plan**) – A collaborative business process plan for a given CO is defined as a project based plan composed of a set of activities and corresponding precedences. This plan is defined as a tuple $Plan=(co, A, Prec)$, in which

- co is the collaboration opportunity.
- $A=\{(act_1,d_1,C_1),\ (act_2,d_2,C_2),\ldots\}$ - is a set of activities as specified in *definition 1*.
- $Prec=\{(a_i,a_k)|\ a_i,a_k \in A\}$ - is the set that specifies the precedences between the activities of set *A*.

Definition 3 (**Organization's Character**) – An organization's character can be seen as a composition of a set of traits that determine the way it behaves. It can be modeled as a tuple $OC=(o, TV)$, in which:

- o - is the organization being characterized;
- $TV = \{(t_i, v_{i,k}) \mid t_i \in \mathrm{T}, v_{i,k} \in V_i\}$ – is the trait set constituted of tuples, each one composed of a trait and a corresponding trait value.

Definition 4 (**Character-related Preparedness Conditions**) – The preparedness conditions related to the organization's character are represented by a set *PC* of preparedness items. Each item is a tuple that specifies the condition or value required for a given character trait of an organization. The preparedness conditions set is defined as:

$PC = \{ (t_i, v_{i,k}, op_i, p_i) \mid t_i \in T, v_{i,k} \in V_i, p_i \in [0,1], op_i \in OP \}$, in which

- t_i - is the trait name;
- $v_{i,k}$ - is the trait (linguistic) value, such that $v_{i,k} \in V_i$;
- op_i - is the comparison operator that is used for comparing the values of V_i ;
- p_i - expresses the desired probability/likelihood of the attribute t_i having the value $v_{i,k}$.

Definition 5 **(Competences fitness)** – An organization fits in some collaboration scenario if it possesses the adequate (or required) competences.
The competences' adequacy depends on whether the context is a *VBE* (bringing competences that fit the general scope of the VBE) or a *VO* (providing or complementing required competences for the achievement of the *VO goals*).

Definition 6 **(Preparedness for collaboration)** – An organization is considered prepared to collaborate if it both satisfies a set of character's conditions (definition 4) and possesses adequate competences (definition 5).

With the definitions above it is now possible to state the axioms for the partners' suggestion model. Such axioms are formally presented below, together with their corresponding descriptions. The process of partners' suggestion in VO creation is a complex task (Camarinha-Matos et al, 2005), (Camarinha-Matos, Afsarmanesh, 2006). In this modeling experiment we consider only a simplified version of this process by defining a few axioms that establish the correspondence, or matching, between the CO's necessary competences and the competences provided by candidate partners. This process is illustrated in Fig. 16.

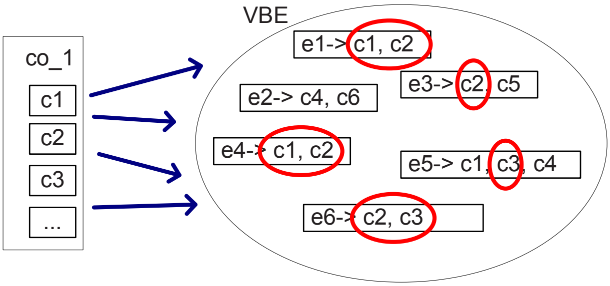


Figure 16 – Illustration of the matching between the CO needed competences and the candidates' competences

Axiom 1 – Any VO is an acceptable suggestion for a given *CO*, if it satisfies the requirements *C* of the *CO* and also complies with a specified preparedness conditions *P*.

$$\forall_{co} \forall_{P} \forall_{VO} ((suggest\_vo(co, P, VO) \leftarrow \exists_{C} (requirements(co, C) \wedge satisfy(C, VO) \wedge preparedness(VO, P)))$$

For this axiom, the predicate "requirements" grabs the needed competences from the *CO* and puts them into the set *C*.

Axiom 2 - A *VO* satisfies a set of required competences *C* if, recursively, for each competence in *C* there is an organization in the *VO* that satisfies it.

$$(\forall_C \forall_{VO} ((satisfy\ (c_i.\mathrm{C}, (o_j, c_i).VO) \leftarrow$$
$$s\mathrm{atisfy}\ (\mathrm{C}, \mathrm{O}) \wedge c\mathrm{ompetence}\ (o_j, c_i)) \vee \mathrm{satisfy}(\{\}\ ,\{\})$$

In this axiom, the operator '.' unifies or *grabs* the first element of the set (assuming sets modeled as lists). For instance, c_i represents the first element of C. The 'competence' predicate verifies whether a competence c_i is owned by organization o_j.

Axiom 3 – A *VO* satisfies the given preparedness conditions *P* if all its members are prepared according to *P*.

$$\forall_P \forall_{VO} ((preparedness(VO, P) \leftarrow$$
$$\forall org((belongs(org, VO) \rightarrow is\_prepared(org, P)))$$

In axioms 3 and 4, the predicate *belongs* performs the usual set membership operator.

Axiom 4 - An organization *org* is prepared according to the given preparedness conditions *P* if for each preparedness item *t* in *P*, there is a corresponding belief *b* in *org*'s character, such that *b* complies with *t*.

$$\forall_{org} \forall_P ((is\_prepared(org, P) \leftarrow$$
$$\forall_t ((\mathrm{belongs}(\mathrm{t}, \mathrm{P}) \wedge (\exists_b belief(org, \mathrm{t}, \mathrm{b})) \rightarrow c\mathrm{omplies}(\mathrm{t}, \mathrm{b})))$$

The predicate *complies* compares the desired probability or likelihood of the trait in item *t* with the obtained belief *b*, using the comparison operator inside *t* (see definition 4).

The predicate *belief* deserves more attention. It provides the probability that the preparedness item *t*, in axiom 4, has a corresponding trait in the organization's character. Let us suppose that *t* = (reliability, high, '>', 70) and let us observe the vbe_1 in table 1 of section 3.5. The predicate *belief* would provide values for belief *b* in the axiom, as illustrated by the following cases:

- For enterprise *e1*, the belief that reliability=*high* is *b*=100%, because *e1* has the trait 'reliability' defined with value "high" in its character profile. It would be represented by an evidence node in the belief network of Fig. 6.
- For enterprise *e3*, the belief that reliability=*high* is *b*=0%, because *e3* has low reliability in its character profile. It would be represented by an evidence node in the belief network of Fig. 6, but with different evidence (low reliability).
- For enterprise *e2*, the belief is *b*=53.6%. This is because, the reliability of this enterprise is unknown and, therefore, this value is obtained using the query *b*=P('reliability=high'| known_traits(*o_2*)) on the belief network of Fig. 6. The predicate '*known_traits*(*org*)', provides the known values of an organization's traits.

These axioms can be translated into Prolog predicates, as shown in Fig. 17.

```
suggest_vo(CO_id, P, VO):-
  co(CO_id,Act,Links),  requirements(co(CO_id,Act,Links),Lcomp),
  satisfy(Lcomp,VoList),  preparedness(VoList,P),   VO=vo(VoList).

satisfy([],[]).
satisfy ([Comp|Tail],Orgs):-
  satisfy (Tail,Orgs2),  competence(Org,Comp),  append([(Org,Comp)], Orgs2,Orgs).

preparedness( VO,P):-
  forall( member( (Org,C), VO) , is_prepaired(Org, P)).
|
is_prepaired(Org,PrepList):-
  forall( (   member((Trait,Value,Comparator,Probability), PrepList),
              belief(Org,Trait,Value, Probability2)
          ),  complies(Comparator,Probability2, Probability)).
```

Figure 17 – Prolog predicates for partners' suggestion axioms

These axioms can be invoked using the query below. The shaded argument is the preparedness pattern required for the suggested organizations. The characters and competences of organizations are modeled as facts in the memory of the Prolog's inference engine.

```
suggest_vo(co_1,{(creativity,high,'>',60), (preparedness_level,high,'>',70)}",VO).
```

3.4 The simulation component

Simulation is employed in this modeling example to work as a kind of verification process for the VOs obtained using the axioms modeled above. Hence, it is used to 'animate' the inferred VOs along the corresponding CO's business process, in order to measure the performance of each VO and, eventually, select the ones that appear more suitable for the given CO.

The simulation component was specified using a similar axiomatic approach as just described for the partners suggestion presented above. Hence, this component is composed of a set of axioms that were also translated into Prolog. During a simulation cycle, the generated events and corresponding states are kept as facts in the knowledge base. The complete axiomatic model for the simulator (e.g., the predicates *has_events* and *start_activities* used in axiom 5) is not presented here. The axiom 5 specifies a simulation recursively in the following way:

Axiom 5 – At any simulation instant *T*, if there are pending events, finish the corresponding activities, start new ones and advance simulation to next time step. Otherwise, display the simulation results.

$$\forall_T (run(T) \leftarrow (has\_events(T) \rightarrow finish\_activities(T) \wedge start\_activities(T)) \wedge run(T+1) \vee (\neg has\_events(T) \rightarrow write\_simulation\_state(T))$$

The simulation can be started at any initial time by invoking this axiom using the term "run(initial_time)", e.g., "run(0)".

3.5 The structure of the partners' suggestion mechanism

The way the partners' suggestion mechanism works is illustrated in Fig. 18. The business process needed to satisfy the CO, the required preparedness conditions and preparedness level are provided at the beginning. Then the partners' suggestion function selects candidates according to competences' fitness. This might provide several solutions, as illustrated in the example below. Then, taking into account the character of the candidate organizations, the mechanism refines the suggestions to only select candidates that appear to be more prepared to the context of the CO, accordingly to the required preparedness conditions. For instance, if the CO is characterized by strict deadlines, selected candidates must be highly reliable, and so, less reliable candidates would not be selected. The suggested set(s) of candidates would be organized as a VO, taking into consideration the CO's business process. Finally, the VO and CO's business process are given to the simulation module. More on this process is illustrated through the example below.

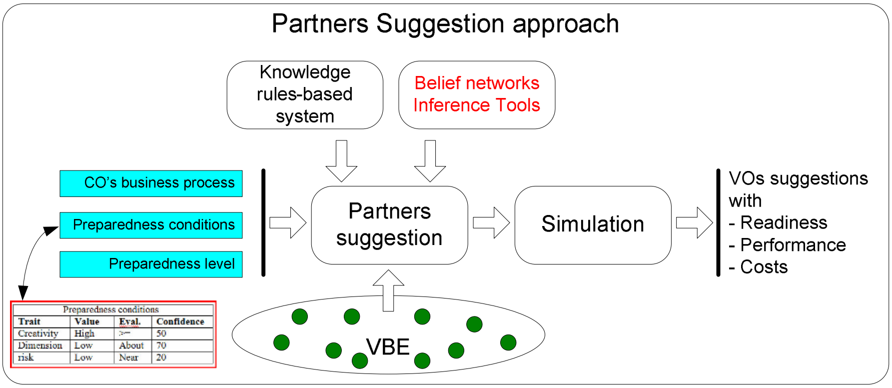


Figure 18 – Structure and components of the partner's suggestion mechanism

3.6 Application example

For the purpose of a modeling example, we can consider the existence of a virtual organization breeding environment (VBE) composed of a group of enterprises (or organizations). These enterprises, together with corresponding competences and character traits, are defined as shown in table 1. One important aspect to emphasize here is that some traits are undetermined.

Table 1 - Competences and traits of the VBE's members.

VBE_1 composition								
		Organization traits						
Enterprise	***Competences***	***PD***	***ES***	***RP***	***R***	***C***	***P***
e1	***c1, c2***	high	high	?	high	high	high
e2	***c4, c6***	med	?	high	?	low	high
e3	***c2, c5***	med	fair	high	low	high	high
e4	***c1, c2***	?	high	high	low	?	?
e5	***c1, c3, c4***	high	bad	high	high	high	low
e6	***c2, c3***	high	fair	high	?	?	?
...	***...***						

(PD: partners dimension; ES: economical situation; RP: risk profile; R: reliability; C: creativity; P: prestige).

Let us assume that at a given instant, a collaboration opportunity was identified, for which the corresponding business process plan is shown in Fig. 19.

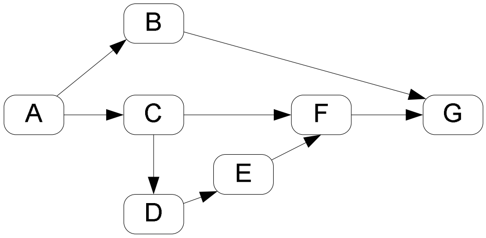


Figure 19 – Example of a business process plan for a given collaboration opportunity

The details of this plan, as specified by definitions 1 and 2, are shown in table 2.

Table 2 – Example of time and precedences

Time and precedences for project "co_1"					
Activity	Necessary Competences	Durations			Precedences
		Most Optimistic	Most Likely	Most Pessimistic	
A	c3	8	16	20	-
B	c2	10	20	30	A
C	c1	12	18	24	A
D	c2	12	16	18	C
E	c4	6	9	12	D
F	c1	10	15	20	C, E
G	c3	5	7	9	B, F

As specified by axiom 2, the suggestion mechanism for partner's selection is initially based on the traditional matching of competences or, in other words, competences fitness. These suggestions are then enhanced when the mechanism uses the preparedness conditions. In the simulations phase, the organizations characters are also important. For instance, a very reliable member expectedly tends to perform better its assigned activities. Consequently, we can tell that activity durations are influenced according to the entities that perform it, and that a reliable organization tends to faster and promptly perform its assigned activities.

Therefore, the simulation model computes the activities' durations that run at each instant, using the following rule of thumb: "If the member that performs an activity has high probability of having high 'collaboration level', the duration Te of the assigned activity will slightly decrease, and it will increase otherwise".

Now using the partners' suggestion model for the given CO, only the correspondent business process is provided, at the first try, without specifying any preferences for the candidate members (Fig. 20). As referred before, the mechanism is invoked by the predicate 'suggest_vo' of axiom 1.

Figure 20 – Suggestions without preparedness restrictions

The initial VO suggestions, as shown in table 3, are based on a simple competences' matching approach, according to axiom 2. For each suggestion, the simulation module provides the duration of the simulated business process plan, helping spot the best suggestions. In order to restrict the number of provided suggestions, it is imposed that each member can be assigned to only a single competency otherwise the number of suggestions would be much bigger.

Table 3 – Example of VO suggestions

Virtual Organization Possibilities								
Solution	e1	e2	e3	e4	e5	e6	e7	Duration
1	c1	c4	c2		c3			38
2	c1	c4		c2	c3			39
3	c1	c4			c3	c2		39
4	c2	c4		c1	c3			40
5		c4	c2	c1	c3			40
6		c4		c1	c3	c2		41
7	c1	c4	c2			c3		38
8	c1	c4		c2		c3		39
9	c1			c2	c4	c3		38
10	c1			c2	c4	c3		39
11	c2	c4		c1		c3		40
12		c4	c2	c1		c3		40
13	c2			c1	c4	c3		40
14			c2	c1	c4	c3		40
15	c2	c4			c1	c3		40
16		c4	c2		c1	c3		40
17		c4		c2	c1	c3		41

In the previous solution, we did not consider any preparedness conditions. Some suggestions may in fact be composed of members with low reliability and the VO might fail in achieving its goals. On the other hand, as shown in Fig. 21, if we now provide desirable preparedness conditions to the suggestion mechanism (see definition 6 and axiom 4), the suggestions would be those in table 4. As the preparedness conditions restrict the number of suggestions, each partner can now be assigned with more than one competence.

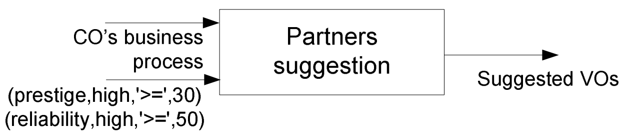


Figure 21 – Suggestions influenced by preparedness conditions

For this case, the mechanism selected only organizations with both high reliability and prestige. Organizations with these traits undefined are also selected, provided that the likelihood of having a high value is at least 30% and 50% respectively. As mentioned in a previous section, this likelihood is determined by the predicate *belief* of axiom 4, using the belief network of Fig. 6.

Table 4 – Another example of VO suggestions

Virtual Organization Possibilities								
Solution	e1	e2	e3	e4	e5	e6	e7	Duration
1	c1 c2	c4				c3		38
2	c1	c4				c3 c2		39

Finally, the mechanism can be told to only consider organizations with a high preparedness level, this time without specifying any preparedness conditions, as they are implicit in the preparedness level. The likelihood of any organization to have a high level of preparedness is determined using the *belief* predicate and associated belief network mentioned before. If we impose a collaboration level of value "high" with likelihood of 60% (Fig. 22), then just one suggestion shows up (table 5).

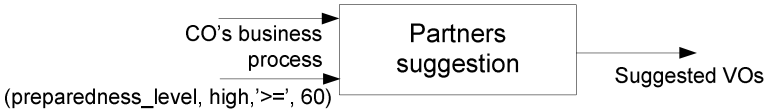


Figure 22 – Selection of organizations with high preparedness level

With the corresponding solution:

Table 5 – Another example of VO suggestions

Virtual Organization Possibilities								
Solution	e1	e2	e3	e4	e5	e6	e7	Duration
1	c1	c4	c2		c3			38

After performing the simulation for this suggestion, the Gantt diagram appears as it is shown in Fig. 23. This diagram illustrates how the business process plan's activities are executed and how they were assigned to the VO members. For instance, activities 'b' and 'd' were assigned to enterprise 'e3'.

For the offered suggestion, the project duration is 38, which is the minimum possible duration. Nevertheless, duration does not make the whole story, as it could be longer. The point is that the suggested VO is composed of partners with higher likelihood of a "high" collaboration level, which accounts for a lower risk of working together.

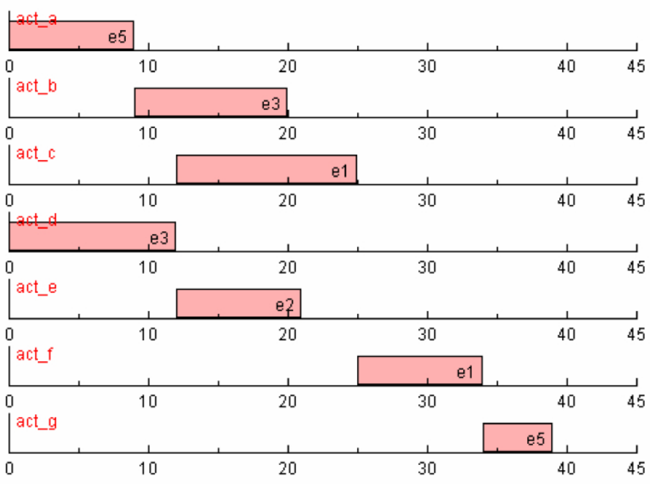


Figure 23 – Simulation of the collaboration opportunity with the suggested VO (Source-code obtained from Chris Beck, University of Toronto, 1995)

3.7 Results analysis

Through this modeling experiment, it was shown that, to a certain degree, through a combination of different methodologies may result in improved solutions for the example presented. Based on a traditional approach, the partners' suggestion model proposed several VOs, some of which presented longer project durations during the simulation phase. With the inclusion of preparedness conditions, the partners' suggestions model yielded improved results.

Several aspects of this experiment require further research. The collaboration preparedness was based on the utilization of a belief network, which was used to predict the collaboration level of a candidate. In practice, the correct approach for an adequate preparedness assessment should be based on several indicators. Furthermore, the situations and contexts in which collaboration occurs must be considered, which is also an aspect being currently researched, and not included in this experiment.

4. CONCLUSIONS AND FURTHER CHALLENGES

Although not yet widely used in the collaborative networks research area, soft computing / computational intelligence methods are potentially useful when dealing with reasoning and decision making under situations of incomplete and imprecise information. Given the nature of these networks, composed of autonomous, distributed, and heterogeneous nodes, this is a frequent situation.

The set of modeling experiments discussed in this chapter illustrate how Bayesian belief networks and Rough Sets can be applied to assess the preparedness of a candidate to join a collaborative network. Furthermore, in some problems it is convenient to combine various modeling techniques in order to capture different facets of the problem at hands, as illustrated by the last example of partners' suggestion for a VO.

It shall be noted that the introduced examples have only an illustrative purpose and therefore several simplifications were made. The application of the suggested methods to more realistic scenarios certainly needs further research and evaluation.

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