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Chapter 6

Behavior-based VO Supervision and Intervention

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- Shadi, M., Afsarmanesh, H. Task Failure and Risk Analysis in Virtual Organizations. Submitted to *International Journal of Cooperative Information Systems.* World Scientific Publishing.

6.1 Introduction

To respond to the arising opportunities in the market, some autonomous and heterogeneous agents that are registered as members of a Virtual organization Breeding Environment, join forces and form a VO. Research on the success rate of Virtual Enterprises in industries however show that many of the established VOs end up either in failure or operating under the pressure of high risks of failure [80]. Three categories of risks are highlighted in the literature for organizations involved in a virtual organization [8], namely: internal, external, and network-related. Network-related risks are those due to the collaborative relationships among organizations, and are typically caused by the lack of trust, insufficient information sharing, and clash of cultures among others [8]. To support the success of collaboration among the involved organizations in the VOs, we define a framework and provide a set of functionality by which the VO risks can mitigate, to support the VO coordinator.

The definition of our proposed framework is based on the following understanding and modeling of this form of CN. VO is a goal-oriented network, for which during its formation/creation stage, a set of targets/goals are defined, which are achievable jointly by its members. Furthermore, the main sub-goals and their main tasks are specified in the form of a VO contract for achieving these targets. However, VOs are very dynamic and therefore only during the operation/evolution stage of the VO 's life-cycle, these high level sub-goals and their tasks will to be detailed out into a set of specific sub-tasks, each of which to be performed by a specific partner. In our research, we focus on risks that mostly rise during the operation phase of the VOs, when a large number of tasks and sub-tasks are being planned and scheduled (or are being gradually planned), each to be performed either individually by one partner, or jointly by a group of partners. Past research and practice indicates that to support the success of collaboration in VOs, it is necessary that its planned activities are monitored, supervised, and coordinated, in order to also discover and/or predict potential failure risks in their fulfillment. Our novel approach to forecasting and managing potential risks of failure in VOs is founded on the analysis of partners' past and present collaborative behavior in performing the tasks to which they have been committed, as discussed in the Chapter 3. Our approach contributes to developing novel methods and mechanisms to monitor both individual and collective/group behavior of partners in VOs [92].

The factors considered in our research for identifying potential risk in VOs include: low trustworthiness, insufficient communication, and heavy workload, which play a major role in posing a number of risks during the operation phase of the VO's life cycle. Therefore, our approach concentrates on measuring the trust level, the communication level, and the workload level of each agent acting as a VO partner, while also being a member within a VBE. For example, high workload of each VO partner, when considering all of its involvements through the information gathered in the VBE, can be considered as one factor when evaluating causes of failure in that VO. Thus, these levels are used as the criteria for discovering the probability of activity failures in sub-tasks currently assigned to the agents. As mentioned in Chapter 3, in VOSAT the requirements on the above three factors are defined as the controlling norms, which are monitored and their violation does trigger the risk prediction procedure.

As a main factor related to risk, in VOs trust is commonly considered, representing a countering factor for risks that may rise in networks. Owing to an agent's opportunistic behavior and creating uncertainty, low trustworthiness level is resulted influencing the risk of failure. On the contrary, the agent's high trust level positively influences the prediction of its successful completion of assigned sub-tasks as well as its cooperation in the VO.

There is also a direct relationship between collaboration success and communication in the VOs [8]. More success is achieved in the network when there is an effective communication among partners, while insufficient or failing communication among partners in a VO is a typical cause of failure in the VO.

A third risk factor considered in our approach is the current workload of both the staff and percentage of occupied resources belonging to the VO partners. This considers the total current workload of each agent within the entire VBE and in relation to all its commitments. For instance, if a VO partner is simultaneously involved in several VOs, its workload may become too heavy and its resources and staff overloaded, which will be taken into consideration when measuring its potential risk to fail the already committed responsibilities, or when it volunteers to undertake any new responsibilities.

It should be noted that the main goals and sub-goals of the VOs are usually reflected through high level tasks planned for its partners. These are typically included in the VO contracts, which are agreed and signed during the VO 's creation phase among its partners. Nevertheless, considering that VOs are dynamic organizations, typically the sub-tasks related to daily activities to be performed by the partners, are gradually defined during the VO 's operation phase [91]. In our framework, the responsibilities accepted by different VO partners in performing each sub-task constitute promises from partners to perform those sub-tasks. Therefore, our responsibility template represents both tasks/sub-tasks, and their related promises from VO partners to perform them, as well as the inter-relationships among the task/sub-tasks. The causal inter-relationships among sub-goals, tasks and sub-tasks are modeled by a Bayesian Network (BN). Applying the BN, on cases where a VO partner violates one of its related controlling norms, the risk prediction process discovers general potential risks and whether there are other sub-tasks assigned to the partner, that can now also become risky.

For calculating the failure probability of every individual sub-task, the above mentioned factors are considered. For tasks and sub-tasks, promised by a group of partners, applying the Bayesian network, their failure probabilities are calculated, which in turn enables the VO coordinator to identify their associated potential risks, and possibly to decide to intervene and reassign the risky tasks and sub-tasks to other agents in the VO. Our approach also supports and facilitates finding the best-fit candidates for such reassignment.

The rest of this chapter is structured as follows. In Section 2, some related works are discussed. Section 3 addresses supporting the VO coordinator in VOs. Section 4 analyzes the risk factors in VOs, and then a new approach for risk prediction, applying the Bayesian network is introduced in Section 5. The proposed mechanisms for VO planning intervention are addressed in Section 6. The details of VOSAT functionality for an application case are expressed in Section 7, and finally in Section 8, some conclusive remarks are addressed.

6.2 Related Work

Coordinating a Virtual Organization (VO), while being aware of any potential failure risk in fulfillment of its tasks, clearly increases the chance of its success, and thus the effective achievement of its goals and sub-goals. The literature review illustrates different definitions for risks in various environments. Risk in an organization is defined in [97] as the probability of an event that can influence the organizations' objectives, either negatively or positively. In [57], supply chain risk is described as: "variation in the distribution of possible supply chain outcomes, their likelihood, and their subjective value". In our research, we seek to identify risks in the VOs, due to the behavior of VO partners who may violate some of their norms, and consequently threaten the success of the VO.

6.2.1 Risk Factors in VOs

There is an extensive attention to the problem of risk analysis in the context of supply chain management (SCM). Despite some differences between the selection of suppliers in SCM and the configuration of VOs, SCM literature is a good introduction to risk prediction in VOs. Three risk factors related to the supply chains, including the internal, external and network-related risks are identified in [8]. Changes in industry market, political situation, social atmosphere, etc. are categorized as the sources for external risks threatening the involved organizations, while events such as strikes, machine failure, etc. are placed in the internal risks category. All other risks raised from the collaborative relationships among organizations in a VO, are clustered under the network-related risk category. There is a large similarity on internal and external risk factors between the supply chains and virtual organizations. However, the factors related to their network-related risks are different between the virtual organizations and supply chains. In supply chains, every organization is a member within a chain, thus we know each member is dependent on which organizations, and also which organizations follow it in the chain. Moreover, every organization is contracted to perform its own sub-task within the chain, hence the success/failure of each organization depends primarily on receiving the needed output from its predecessor organization in the chain as well as performing its own contracted tasks. The case of VOs however is different, because all its partners are jointly responsible for achieving the goals and sub-goals of the VO, and therefore, the success or failure of every one of its involved organizations is directly dependent on the success or failure of the VO as a whole. This joint responsibility is the main reason why even when one partner cannot perform its sub-task in the VO, other partners volunteer to perform it instead, so that the VO as a whole can succeed. The joint responsibility notion in turn creates complex inter-relationships among the involved partners.

In [8], a list of important sources/causes for network-related risks in VOs is provided, which includes: lack of trust, lack of clarity in the agreements/commitments, partners heterogeneity, loss of communication, lack of information sharing, heavy workload, ontology differences, heterogeneity in structure and design, cultural differences, geographic distance, etc. In other words, any of these sources represents the existence of a risk in the VO, and depending on its severity can contribute to its failure. From this list of risk sources, trust, commitment, and information sharing are investigated further in [96], with specific focus on the creation phase of the VOs, and finding the potential risk of collaboration for the industrial partners and logistics operators that wish to get involved in the formation of a new VO.

In our research, we focus on three factors of trust, communication, and workload of the organizations (considered as agents), in order to predict the probability of failure for each of these agents in fulfilling their individual assigned sub-tasks during the VO operation phase. As such, violation of a trust-related norm by an agent triggers the risk prediction process to consider further involvement of that agent in the responsibility template of the VO. Our algorithm focuses on dynamic measurement of agent's trustworthiness and potential risks associated with it during the operation phase of the VOs, so it differs from approaches applied during the VO creation phase [8] and [96].

6.2.2 Risk Prediction

A number of approaches, some of which parametrized, are employed to model and predict risks, such as the FTA (Fault Tree Analysis), the ETA (Event Tree Analysis) and the ANP (Analytic Network Process). FTA uses the combination of AND and OR gates to build the failure model [40]. It calculates the probability of failing for the top level event(s), based on the data extracted from their lower level events. This method is however limited to a binary prediction, and it only treats instantaneous failures, i.e. it does not include and/or consider any delays in time. Furthermore, a main drawback of FTA is related to building the accurate tree which requires a great effort.

In [96], estimation of the failure risk for individual partners is routed in ETA. ETA addresses all potential consequences resulted by an initiating event, to which the probability of their occurrence can be assigned. In addition to individual risk, collective risk is also addressed in [96], which is evaluated through fault tree analysis. The limitation of the ETA approach is however related to the number of event trees that it generates.

ANP is a multi-criteria decision making method that produces a structured influence network of clusters containing nodes. The network contains source node, intermediate nodes and sink nodes indicating different criteria. The origin of the influence path is shown by a source node, while the destination of influence path is illustrated by a sink node. In [83], the authors compare ANP with other multi-criteria decision making methods. However, the ANP model has also the limitation to require filling up many questionnaires as input.

The benefits of BN to assess risks in natural hazards are illustrated in [93]. A Bayesian Network (BN) consists of a set of nodes representing its variables and a set of directed arcs representing relationships between those variables. If variable A causes B then there is a directed arc from A to B, i.e. A is the parent of B. To each node, a conditional probability is assigned which indicates the probability of the variable associated with the node, given the probability of the variables associated with its parents. Roed et al. in [77] propose a framework considering human and organizational factors in Hybrid Causal Logic (HCL) to perform a risk analysis. This framework is developed based on traditional risk analysis tools (FTA and ETA) accompanied by the Bayesian Network.

In our approach, we use BN to recognize risky tasks to support the success of collaboration in VOs. The BN is created during VO's operation phase, and if task planning is altered, the graph representing BN and Conditional Probability Tables (CPTs) get updated, which is not easy in other mentioned approaches that need more effort to stay up-to-date with changes in task planning.

6.2.3 VO Partner Selection

In our framework, during the VO operation phase, the VO Coordinator needs to select the best-fit partner for two different purposes: to reassign the risky tasks and to distribute indirect rewards; however, in the literature, partner selection is focused on the VO formation .

Based on literature review, regarding the partner selection in VOs, many factors, such as cost, delivery time, quality of services, trust, credit, performance, and reliability are taken into account and, consequently, several multi-criteria approaches are proposed such as Analytic Hierarchy Process, etc. In [53], AHP is used to select the best-fit partner based on their manufacturing cost, the time to market, and their performance. There are also some works, in which partner selection for a VO formation is related to risk analysis. In [96], authors apply the combination of event tree and fault tree to predict the risk of partners' composition to form a VO for a given business.

Concerning the virtual organization, partner selection for task reassignment has a strong connection with the concept of competence modeling. Studies on competence modeling are directed towards enabling structural description of the agents with extra emphasis on profiles, capacities, resources, etc. Today, the idea of competence modeling is developing fast. Works done in [41], and [80] propose approaches to select partners for a VO formation based on the agent profile, in which each member should provide up-to-date information about feasible activities and presentable services to promote itself and to be taken into account during VO partner selection processes. This is often denoted as competence description. In [41], the 4C competency model is introduced, in which agents' competency comprises four elements of Capability, Capacity, Cost, and Conspicuity. The work of Rosas, J. et al [80] is built on top of 4C competency model in which capability, capacity, cost, and conspicuity are considered as hard competencies and abstract behaviors of agents are considered as representative of soft competencies, which can affect the hard competencies. For example, knowledge sharing is considered as a soft competency to which a value is assigned based on the agent's past successful or unsuccessful experiences in sharing information.

In [80], partnership formation in a VO based on the requirements of collaboration opportunities is also investigated.

Different from other researchers, we propose new competency-based model for partner selection to reassign the risky tasks, in which new hard and soft criteria are considered. We applied AHP to solve this multi-criteria problem, because this approach makes it possible for the VO coordinator to customize the process by adding or deleting the criteria. Moreover, applying AHP, both quantitative and qualitative criteria can be considered in the partner selection process.

6.3 Supporting VO Coordinator

The VO coordinator plays a fundamental role in VO management through monitoring the performance of both individual and collective tasks assigned to the VO's partners, analyzing their risks/failures, finding the weak points and finally intervening in order to ensure the VO success. Monitoring the behavior of agents involved in the VO as well as how they fulfill their commitments can provide good indications for predicting some of the weaknesses in near future activity plan, which can cause risks in the VOs. Subsequently, notifying the VO coordinator about such weaknesses and the risks that are associated with them assists the coordinator with taking timely and appropriate strategic actions. Therefore, it is necessary to develop a framework, which enables formalizing responsibilities and promises of agents to perform their sub-tasks in the VOs. It further supports the VO coordinator with monitoring partners' behavior through identification of any potential violation in the set of defined norms for the VO.

The new models and mechanisms proposed in this chapter are also further applied for the development of the VOSAT, shown in Figure 4.1 that provides the VO coordinator with proactive assistance. This assistance include the monitoring of partners' collaborative behavior in relation to performing their tasks, diagnosing risks and early detection of potential failure related to the performance of currently planned tasks, as well as providing decision making suggestions for intervention toward failure prevention and collaboration promotion in VOs, and thus enhancing the success rate of VOs. For instance, as a first example, the VOSAT system can support the VO coordinator during its operation phase, with altering the situation of a risky sub-task, through finding/suggesting alternative suitable partners among those that may volunteer to accept taking over that sub-task. A second example of how VOSAT can assist the VO coordinator during the VO operation phase is through recording and ranking VO partners' performance and collaborative behavior during its entire operation phase, which can then be applied for creating incentives for good behavior in the VOs, or used indirectly for some reward distribution at the VO.

6.4 Risk Analysis Approach

The ability to predict the reasons of particular events is crucial in risk management. Based on the state-of-the-art in the area [8], different causes of risk in VOs can be identified, among which three specific ones are considered in our research, including: lack of trust, lack of communication, and heavy workload. These three play a vital role in posing the risk during the operation phases of the VO 's life cycle, and are addressed in more details below.

6.4.1 Lack of Trust

Trust plays an important role in virtual organizations and in relation to the identification of risk factors. Establishing trust is primarily rooted in the behavior of involved partners. In our approach, as explained in Chapter 5, the trust-related norm defined for the agent is monitored when its socio-regulatory or committing norms are violated. The trust level of an agent is evaluated considering the hierarchical factors applying the AHP comprehensive fuzzy evaluation method. This method is a multi-criteria decision making approach that evaluates the influences of various factors on a certain element through applying fuzzy mathematical methods [63]. For example, construction project management can be evaluated using fuzzy comprehensive evaluation in which three evaluation factors are the degree of controlling project objectives, the need for supporting the owners and the supporting ability of the owners and contractors.

To find the probability of Lack of Trust (LT) for agents, we need to defuzzify their trust level. Defuzzification is the process of generating a crisp value from fuzzy sets and their corresponding membership degrees [81]. There are different methods for defuzzification, among which we adopt weighted average method, as explained in Chapter 5. If the membership function, representing the minimum acceptable level of trust, specified by the VO coordinator, is represented by $Trapezoidal(x; a, b, c, d)$, then we calculate the probability of LT for agent A as follows:

$$p(LT(A) = True) = \left\{ \begin{array}{cc} 1 & Trust_{crisp}(A) < a \\ 1 - \frac{Trust_{crisp}(A) - a}{b - a} & a \leq Trust_{crisp}(A) < b \\ 0 & Trust_{crisp}(A) \geq b \end{array} \right\} \tag{6.1}$$

where $Trust_{crisp}(A)$ shows the crisp value of the A's trust level, applying weighted average defuzzification method (Formula 5.2 in Chapter 5). Assume that the minimum acceptable level defined in trust-related norms is Medium Trust, and $MediumTrust(x) = Trapezoidal(x; 0.2, 0.4, 0.6, 0.8)$, then $a = 0.2$ and $b = 0.4$. In this situation, $Trust_{crisp}(A) < a$ shows that A violates its trust related norm, while $Trust_{crisp}(A) \geq b$ shows that the norm is not violated. When the other condition is met, it shows that the trust-related norm is not violated, while the trust level does not have the ideal value whose membership degree in $MediumTrust$ is 1.

6.4.2 Communication Failure

The second important risk factor in virtual organizations is related to the failures of the required communication with other partners, which are typically followed by failures in virtual organizations [100]. In other words, agents' timely and periodic reporting on the status of progress in activities for which they are responsible (e.g. in relation to performing a sub-task by sending an email to both the task-leader and other involved partners, in relation to a Work Package by sending an email to the VO coordinator, etc.) is vital to the success of the VO.

Communication processes in VOs complements the VO 's structures. In other words, goals of the VO as well as the partners' responsibilities are reflected and clarified through their effective communication. There is in fact a direct relationship between VO's success and partners' communication, which means that more success can be achieved in a collaborative network, as a consequence of better communication. Nevertheless, sometimes communications among agents fail. The Ratio of Failure for an agent in its required Communication (for example the number of meeting that the VO partner should attend), is calculated through the following equation:

$$RFC(A) = (n_f(A))/N_A \tag{6.2}$$

where, A shows the agent for whom we calculate the Ratio of Failure in Communication (RFC), $n_f(A)$ shows the number of A's failed communications in this VO, and N_A shows the total number of required communications by agent A in the VO.

In our approach, the VO Coordinator defines a threshold percentage for tolerating failures in communications in each VO. This threshold, $0 < T_{Com} \leq 1$ is then compared against the RFC of an agent. The constraint is that the RFC should not be larger than the pre-defined threshold. As mentioned before, the communication-related constraint is modeled as a norm, placed in the category of controlling norms; therefore, if the RFC is larger than the pre-defined threshold, its related norm is violated and their difference indicates the percentage of not-tolerated lack of communication by the agent in that VO. This difference represents the probability of Lack of Communication (LC) for the agent A. Consequently, we have:

$$p(LC(A) = True) = \left\{ \begin{array}{cc} RFC(A) - T_{Com} & RFC(A) > T_{Com} \\ 0 & \text{otherwise} \end{array} \right\} \tag{6.3}$$

6.4.3 Heavy Workload

When a partner is involved in two or more VOs simultaneously, there is a risk of resource or staff insufficiency for undertaking all of its responsibilities. There is not much related work referring to this aspect, however in [8] an agent's bidding for tasks in several VOs is considered as a risk source. In our approach, we define a Ratio of work Overload Commitment for each agent $ROC(A)$. To measure $ROC(A)$, all agent's commitments to different VOs in the VBE are taken into consideration, in comparison to the real person-months that the agent has planned to invest in this VBE, as equation below shows:

$$ROC(A) = \frac{(\sum_{i=1}^{n} PM_i(A)) - N_A}{N_A} \tag{6.4}$$

where $PM_i(A)$ shows the Person-Month that agent A commits in current VO_i, n shows the number of VOs in which A is involved, and N_A is the maximum person-month that A has planned for being involved in the VBE, as specified in its profile or competency information at the VBE. We also define Work OverLoad (WOL) for agent A, as follows:

$$WOL(A) = \left\{ \begin{array}{cc} 1 & ROC(A) > 1 \\ \text{ROC(A)} & 0 \leq ROC(A) \leq 1 \\ 0 & ROC(A) < 0 \end{array} \right\} \tag{6.5}$$

In our approach, the VO coordinator considers a threshold percentage for tolerating over-commitment, i.e. $0 < T_{WL} \leq 1$, according to which a workload-related norm is defined. If the $WOL(A)$ is larger than this pre-defined threshold for an agent, then its workload-related norm is violated and the difference between $WOL(A)$ and pre-defined threshold indicates the probability of Heavy Workload (HW) for the agent A:

$$p(HW(A) = True) = \left\{ \begin{array}{cc} WOL(A) - T_{WL} & WOL(A) > T_{WL} \\ 0 & \text{otherwise} \end{array} \right\} \tag{6.6}$$

6.5 Bayesian Network Risk Prediction Approach

In the VO contracts, some general tasks are defined for the partners, in order to fulfill the VO's goals and sub-goals. The aforementioned template called Goals-Tasks-Interdependency-Template (GTIT) for a VO is extracted during its creation phase. The GTIT reflects the pre-defined goals and main tasks hierarchy as well as their inter-relationships to the VO's partners, as they are typically specified in the VO contract. However, during the VO operation stage, each of the main tasks is divided into several sub-tasks, thus day-to-day activities of each partner are specified. Therefore, the GTIT of a VO will dynamically get instantiated and expanded with more details during its operation phase, generating the Partner-Responsibility-Interdependency-Tree (PRIT) that represents current activities of the VO. At any time, there is only one current PRIT for the VO, which can be dynamically updated to reflect new assignment of sub-tasks to the partners, reassignment of main VO tasks/sub-tasks from one partner to another, or higher level changes in the VO's goals and sub-goals.

In this chapter, the inter-relationships among sub-tasks, tasks, and goals shown in PRIT as well as the information related to the agents' behavior are used to model a Bayesian network. Applying the Bayesian network, we are able to measure the failure probabilities in fulfilling sub-tasks, tasks, and goals, based on the probabilities of Failures in Behavior (FB) of agents. Failures in Behavior of an agent depends on its lack of trust, lack of communication, and heavy workload. In other words, the Bayesian network includes three kinds of nodes: (1) one for each risk factor related to each agent, (2) one for FB of each agent, and (3) one for failure in each sub-task, task, sub-goal and goals. The probability of FB for each agent is utilized to predict the failure probability of the sub-tasks, for which it is responsible, i.e. in the Bayesian network the node representing the FB of an agent is a parent of the nodes representing failure of sub-tasks assigned to the agent. When and if the trust, communication and workload level of an agent is dramatically changed, it may in turn increase the probability of its failure or success in tasks in which the agent is involved, as well as the failure or success of other dependent tasks, and consequently the failure or success of the entire VO.

During the VO operation phase, when the sub-tasks are defined in details or dynamically changed, the Bayesian network is established and changed accordingly. For instance, when the PRIT of the VO is changed to represent that a new partner has entered to the VO with certain new responsibilities, or when a partner leaves the VO while its responsibilities are delegated to others, the Bayesian network is updated accordingly.

6.5.1 Network Design

Bayesian Networks (BNs) are frequently used to model the knowledge about an uncertain domain. A Bayesian network is a DAG (Directed Acyclic Graph) consisting of nodes representing the variables and edges representing the causal relationships between variables. A directed edge from the variable a to b (a is considered as the parent of b) is interpreted as: a causes b, as shown in Figure 6.1. A Conditional Probability Table (CPT) is assigned to each node, which indicates the probabilities of the variable associated with the node, given the probabilities of the variables associated with its parents. The steps of BN construction follows:

- Identifying the variables
- Determining the variables' values

- Specifying the variables' relations
- Defining Conditional Probability Table for each node

In fact, a Bayesian network is a compact representation of the joint probability distribution, which shows the probability of a specific state of the world. The joint probability of variables $v_1, v_2, \ldots, v_n$ is calculated as follows [54]:

$$p(v_1, \ldots, v_n) = \prod_{i=1}^{n} p(v_i | Parents(v_i)) \tag{6.7}$$

It is useful to obtain any marginal probability (i.e. an unconditional probability,

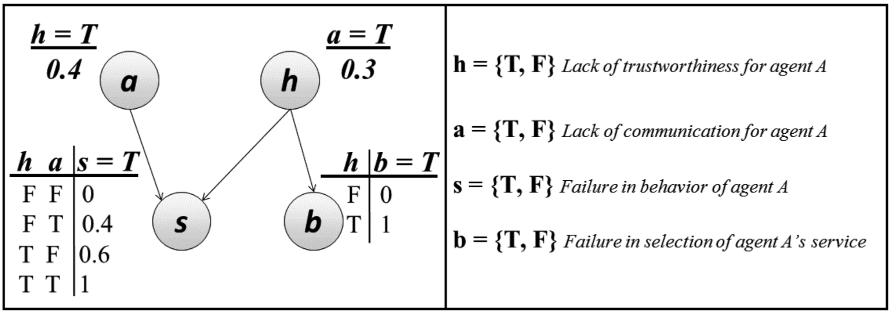


Figure 6.1: An example of a Bayesian network.

such as p(s) in the example below).

A simple example is used here to show how the marginal probabilities in BNs are calculated. Assume that, the failure in the behavior of agent A, which is presented by node s in Figure 6.1, is only dependant on the lack of A's trustworthiness represented by node h, and A's lack of required communication resented by node a. Moreover, lack of A's trustworthiness causes failures in future selection of A's services resented by node b. Figure 6.1 shows, a and h are the parents of s, and h is the parent of b. Based on the Formula 6.7, we have:

$$p(h, a, s, b) = p(h)p(a)p(s|h, a)p(b|h)$$

Considering marginalization [44] (summing out or removing the variables that we do not want) over the joint probability, p(s) is calculated as follows ($\sum_a$ shows the sum over different values of variable a, i.e. True and False):

$$\begin{aligned} p(s) &= \sum_{h,a,b} p(h, a, s, b) \\ p(s) &= \sum_{h,a,b} p(h)p(a)p(s|h, a)p(b|h) \\ p(s) &= \sum_{h} \sum_{a} \sum_{b} p(h)p(a)p(s|h, a)p(b|h) \end{aligned} \tag{6.8}$$

If g_1 and g_2 are two factors, and if variable x exists only in g_2 then $\sum_x g_1 g_2 = g_1 \sum_x g_2$ [44]; therefore, we have:

$$\begin{aligned} p(s) &= \sum_h \sum_a p(h)p(a)p(s|h,a) \sum_b p(b|h) \\ p(s) &= \sum_h p(h) \sum_a p(a)p(s|h,a) \sum_b p(b|h) \end{aligned} \tag{6.9}$$

In this example, all variables have two values, True and False (i.e. T and F). It should be noticed that $\sum_b p(b|h) = p(b = T|h) + p(b = F|h) = 1$ and $\sum_a p(a)p(s|h,a) = p(a = T)p(s|h, a = T) + p(a = F)p(s|a = F)$, so we have:

$$\begin{aligned} p(s) = &\sum_h p(h) \sum_a p(a)p(s|h,a) = \\ &\sum_h p(h)(p(a = T)p(s|h, a = T) + p(a = F)p(s|h, a = F)) = \\ &p(h = T)(p(a = T)p(s|h = T, a = T) + p(a = F)p(s|h = T, a = F))+ \\ &P(h = F)(p(a = T)p(s|h = F, a = T) + p(a = F)p(s|h = F, a = F)) \end{aligned}$$

finally, we have:

$$\begin{aligned} p(s) = &p(h = T)p(a = T)p(s|h = T, a = T)+ \\ &p(h = T)p(a = F)p(s|h = T, a = F)+ \\ &p(h = F)p(a = T)p(s|h = F, a = T)+ \\ &p(h = F)p(a = F)p(s|h = F, a = F) \end{aligned} \tag{6.10}$$

Considering the Formula 6.10, the probabilities of $p(a = T) = 0.3$ and $p(h = T) = 0.4$, and the conditional table of s shown in Figure 6.1, we have: $p(s) = 0.36$.

6.5.2 Conditional Probability Table

As mentioned before, three risk factors are considered to predict the failure risk in an agent's behavior, including Lack of Trust (LT), Lack of Communication (LC), and Heavy Workload (HW). Figure 6.2b shows a part of Bayesian network representing the causal dependencies of these factors along with Failure in Behavior (FB) of the agent A. Results from applying AHP [84] on these three factors are used to build the Conditional Probability Table for the node to represent the potential Failure in the Agent's Behavior, as explained below. The AHP supports assigning different weights to the evaluation criteria according to their paired comparisons specified by the experts. The higher the weight, the more important is the related criterion (See Algorithm 2).

Figure 6.2a shows an example of the VO coordinator's opinion about comparing the influences of each agent's LT, LC, and HW on its FB. For example, in this case the VO coordinator has decided that the weight of LT is 7 times that of the LC, which also indicates that the former is greatly more important than the latter, consequently the weight for the LC in contrast to the LT is 1/7, which equals to 0.14.

To find the weight vector, the sum of entries in the weight matrix columns, shown in Figure 6.2a, is calculated. But then, in order to normalize these values, each entry in column i is divided by the sum of the entries of that column. Finally, the average of the entries of the first, second and third rows are calculated and considered as the weights for LC, LT, and HW, respectively, see Algorithm 2 in Chapter 5. Consequently, the resulted weight vector is: $\{w_{LC} = 0.15, w_{LT} = 0.78, w_{HW} = 0.07\}$. The CPT constitutes the probabilities $p(FB(A) = True|HW(A) = s_1, LT(A) = s_2, LC(A) = s_3))$, where each s_1, s_2, and s_3 has two states, i.e. True, and False. If $s_i = True$, then $I_{s_i} = 1$, otherwise it is 0. The CPT entries are calculated, using the formula below:

$$p(FB(A) = True|HW(A) = s_1, LT(A) = s_2, LC(A) = s_3)) = \\ w_{HW} * I_{s_1} + w_{LT} * I_{s_2} + w_{LC} * I_{s_3}$$

An example of CPT based on the weight vector mentioned above is shown in Figure 6.2c. Now, we can compute the probability of FB of agent A, i.e. $p(FB(A) = True)$, applying marginalization. It is possible, because CPT of node $FB(A)$, the prior probabilities of three risk factors for agent A can be calculated. It should be noticed that the prior probabilities of three risk factors, i.e. $p(HW(A)), p(LT(A))$, and $p(LC(A))$, are calculated based on the Formula 6.6, Formula 6.1, and Formula 6.3), respectively.

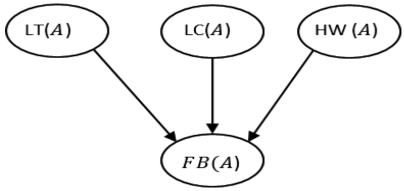
As mentioned above, during the VO operation phase, GTIT is instantiated into PRIT which includes the inter-dependencies among sub-tasks, tasks, sub-goals and goals of the VO. Based on the interdependency-related information in PRIT, a Bayesian network is created, in which each node representing failure in a sub-task can have more than one parent. In other words, the nodes representing the failures in the dependent sub-tasks of a particular sub-task as well as the node representing the failure in behavior of its actor, are its parents in the Bayesian Network. It should be noticed that the CPT for nodes representing failure in tasks, sub-goals and goals is built based on the importance of each node in successful fulfilling of its dependent node. If a node has more than two parents, then we apply AHP to specify the weights for them based on their importance in order to construct its CPT. If the node is fully dependent, for example on one of its parent, that parent is not considered when we apply AHP.

6.5.3 An Example Case

Our proposed approach is discussed here by giving an example. Suppose that a VO is created for fulfilling a project aiming at investigating the impact of certain

	LC	LT	HW
LC	1	0.14	3
LT	7	1	9
HW	0.33	0.11	1

(a)



(b)

$HW(A)$	$LT(A)$	$LC(A)$	$p(FB(A)\|HW(A), LT(A), LC(A))$
True	True	True	1
True	True	False	0.93
True	False	True	0.22
True	False	False	0.15
False	True	True	0.85
False	True	False	0.78
False	False	True	0.07
False	False	False	0

(c)

Figure 6.2: (a) An example of relative values to compare LT, LC, and HW, which are defined by the VO coordinator to measure their importance in failure of agent's behavior, applying AHP, which was also used in Section 5.3 for trust evaluation. For example, here, LT is 7 times more important than LC. (b) The part of BN for the node representing the failure in behavior of A, and (c) An example of the CPT for the node representing the failure in behavior of A.

Scientific Research on the Agriculture (SRA) and three agents ($A_1, A_2, and\ A_3$) are involved in this initiative. One of the VO sub-goal, SG_1, is the *strategy implementation*, which is planned to be fulfilled through performing two high level tasks, e.g. *the cross-scale analysis*, called T_1, and *the better monitoring of SRA investment*, called T_2. During the operation phase of the VO, a number of sub-tasks are generated. For task T_1, two sub-tasks are generated, e.g. *the preliminary stocktake of SRA*, called $ST_{1,1}$, and *the acquisition of time-series data*, called $ST_{1,2}$, where 20% of the success of performing $ST_{1,2}$ depends on the successful results produced by $ST_{1,1}$. For task T_2 also two sub-tasks are generated, e.g. *structural decomposition analysis technology*, called $ST_{2,1}$, and *uptake and SRA*, called $ST_{2,2}$. Furthermore, agent A_1 is responsible for $ST_{1,1}$, and agent A_2 for $ST_{1,2}$, and $ST_{2,1}$, and finally $ST_{2,2}$ is the responsibility of A_3. The CPT related to the nodes representing the failure in agent's behavior has been discussed before in Section 6.5.2, the CPT related to the other nodes is also calculated below based on the importance of the dependent nodes in their fulfillment. For example, if $ST_{1,1}$, and $ST_{1,2}$ are respectively 30% , and 70% important in fulfilling the task T_1, then:

$$p(F_{T_1} = True|F_{ST_{1,1}} = True) = 0.3$$
$$p(F_{T_1} = True|F_{ST_{1,2}} = True) = 0.7$$

Assume that at time t_0 the default of all the prior probabilities of LC, LT, and HW for agents A_1, A_2, and A_3 are 0. If the failure probability of a task or a sub-goal, at a certain point in time is more than a priori specified threshold by the VO coordinator, then the system warns the VO coordinator. For example, if at time t_1, the probability of Lack of Trust for agents A_1, and A_3 change to 0.7, and 0.6 respectively, there is no risky task based on the specified threshold, e.g. 0.5 (see Figure 6.3). Only sub-task $ST_{1,1}$, the responsibility of A_1 is at risk. The aim here, is to find the failure probability in the VO sub-goals and tasks fulfillment, caused for instance by any decrease in the level of trust or communication, or any increase in the workload of the involved agents. However, at time t_2, if the probability of Lack of Trust for an agent A_2 changes to 0.9, then the system needs to warn the VO coordinator or task leaders, advising them to intervene because it shows that some tasks (e.g. in this case, both T_1 and T_2) are at risk (see Figure 6.4). This is because of the important role played by A_2 in performing these tasks. The intervening plans that the VO coordinator can follow may include new negotiation with the task leaders or other partners to ensure that the current weak points are removed, and/or the risky tasks, i.e. tasks with high failure probability are reassigned. Furthermore, the threshold for finding risky sub-goals and tasks can be changed by the VO coordinator at any time, after using this risk prediction mechanism and gaining experiences in the VO during its operation stage.

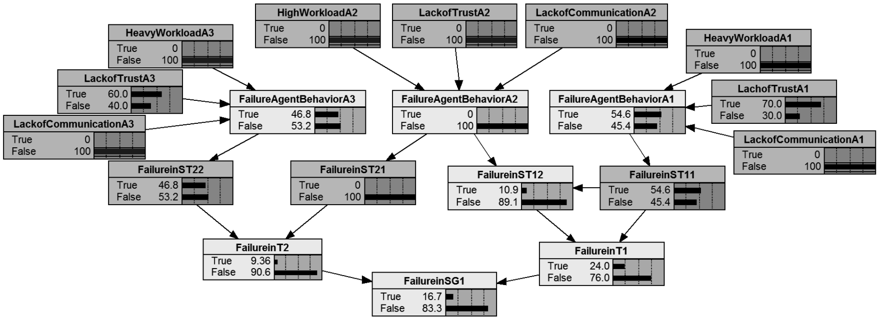


Figure 6.3: The Bayesian network representing the probabilities of nodes at time t_1.

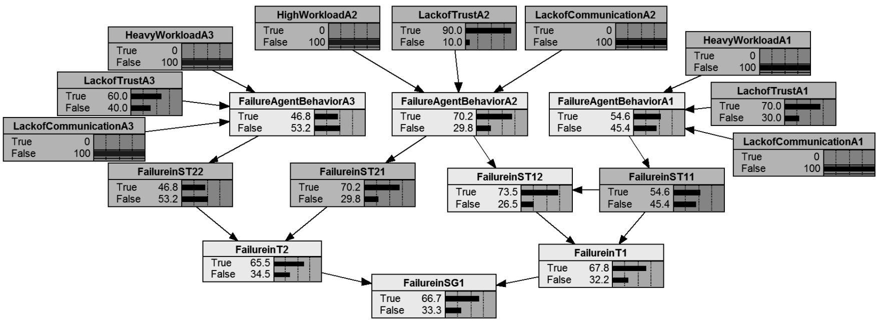


Figure 6.4: The Bayesian network representing the probabilities of nodes at time t_2.

6.6 VO Planning Intervention

During the operation phase of the VO, there are three main types of cases where the VO coordinator gets warned against an agent's performance of its promised sub-task, including when:

- (i) the agent has not fulfilled its sub-task on the specified time.
- (ii) the agent will not be able to fulfill its sub-tasks on the specified time, due to certain specific reasons, mostly outside agent's control.
- (iii) there is a high failure probability predicted (e.g. by our developed system), indicating potential risk for the VO.

In any of the above situations, usually the VO coordinator decides to intervene and solve the situation by reasoning the tasks in risk of failure to other partners in the VO. Therefore, the VO coordinator needs to select the best-fit partner for reassignment. Moreover, VOSAT enables the VO coordinator to rank partners based on a set of their behavior performance criteria for potential distribution of rewards, which both plays a vital role as an incentive for collaborative behavior in future VOs, and for supporting the fairness in profit distribution, and convincing partners to conform to their norms in future. In this research, reward implies any form of profit, prestige, reputation, and future positive recommendations for important roles in future VOs, which we in fact call indirect reward.

6.6.1 Supporting Task Reassignments

According to the literature review, a great number of approaches for partner selection in VOs are based on: (1) cost minimization models and (2) multi-criteria models where several factors in addition to the cost are captured. Recently, competency-based models are also taken into account for this purpose. In [80], two kinds of competencies are investigated, including hard competency and soft competency. The former refers to functions and techniques, which are claimed by the agent, whereas the latter focuses on the behavioral characteristics of the agent. Our approach proposes a new competency-based model addressing both hard and soft kinds of competencies. The proposed soft competencies, and the way they are evaluated in our system differ from those introduced in [80]. The criteria, which are considered in our proposed model includes the following:

- Cost: The price of the services and activities provided by the agent.
- Work Overload (WOL): The simultaneous involvement of agents in different VOs, gathered in the VBE, which is a key factor in partner selection. We have defined ratio of work overload commitment for each agent to find the agent's workload (see Formula 6.5 in Section 6.4.3).

- Committing Norm Abidance Degree (CNOD): It is measured based on the approach discussed in Chapter 4, Section 4.3.1.
- Socio-regulatory Norm Abidance Degree (SNOD): It is measured based on the approach discussed in Chapter 4, Section 4.3.2.
- Cooperative Traits (CT): It has three sub-criteria, including Interaction Rate, Co-work Quality, and Not Being Opportunistic, measured based on the recommendations received from other agents involved in join-responsibilities together with the agent.
- Communication Rate: The Ratio of Successful Communications (RSC) of the agent measured by $RSC(A) = (n_s(A))/N_A$, where $n_s(A)$ is the number of successful communication of an agent A and N_A shows the total number of required communications by this agent in the VO.

The first two criteria mentioned above are categorized as hard competencies, while the last four imply the soft competencies. Our approach to the most-fit partner selection process involves two stages. In the first stage, all those partners who qualify, i.e. are both able to perform the currently at risk task and have the required resources, are selected. Then at the second stage applies AHP to rank the partners based on the criteria hierarchy shown in Figure 6.5.

6.6.2 Indirect Reward Distribution

To effectively manage VOs, partners should be provided by fair distribution of both profits and losses, as well as any award that can be distributed in the business. Typically, the type of collaboration identifies the degree of benefit sharing. However, collaborating parties can also be motivated and incentivised by using some schemes for sharing profit, property rights and ownership control. This section focuses on indirect reward distribution to promote future collaborations, and the stimulation of the current collaboration.

Reward distribution may depend on many criteria; however, two main criteria are identified in our research (see Figure 6.6):

- Assigned responsibility Performance. This criterion has three sub-criteria: Socio-regulatory Norm Obedience Degree (SNOD), Committing Norm Obedience Degree (CNOD) and Cooperative Traits (CT) that apply to agent's performance in joint-responsibilities. CT has itself three sub-criteria, including: Interaction Rate, Co-work Quality, and Not Being Opportunistic.
- Voluntary Performance. This criterion is scored by the VO Coordinator, based on monitoring every agent's participation in cases, such as exception handling, risk mitigation, and/or problem solving and decision making, which assists the VO coordinator, and enhances the VO's rate of success and survival.

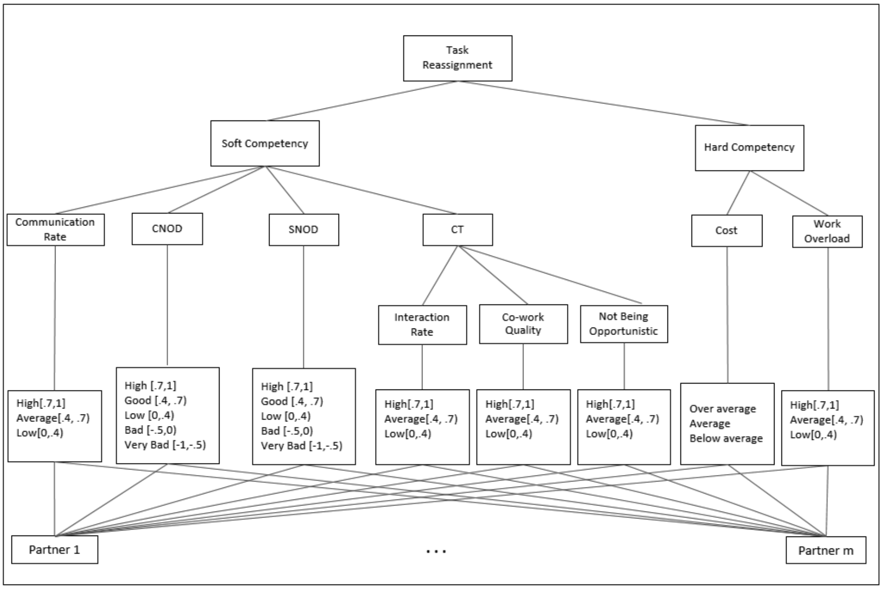


Figure 6.5: The criteria hierarchy to evaluate partners for task reassignment.

To distribute rewards among the VO partners, it is needed to rank them based on their exposed behavior. The mostly used method in the field of decision-making in virtual organization is Analytic Hierarchy Process [56]. AHP (defined in the next section) is a technique for multi-criteria decision making, which our approach for indirect reward distribution is rooted in. The first reason for choosing AHP for reward distribution is that in our model, there are a number of criteria and sub-criteria for ranking partners, which can be evaluated through the hierarchical structure of the AHP. The second is that when applying AHP, both quantitative and qualitative factors of our model can be taken into account.

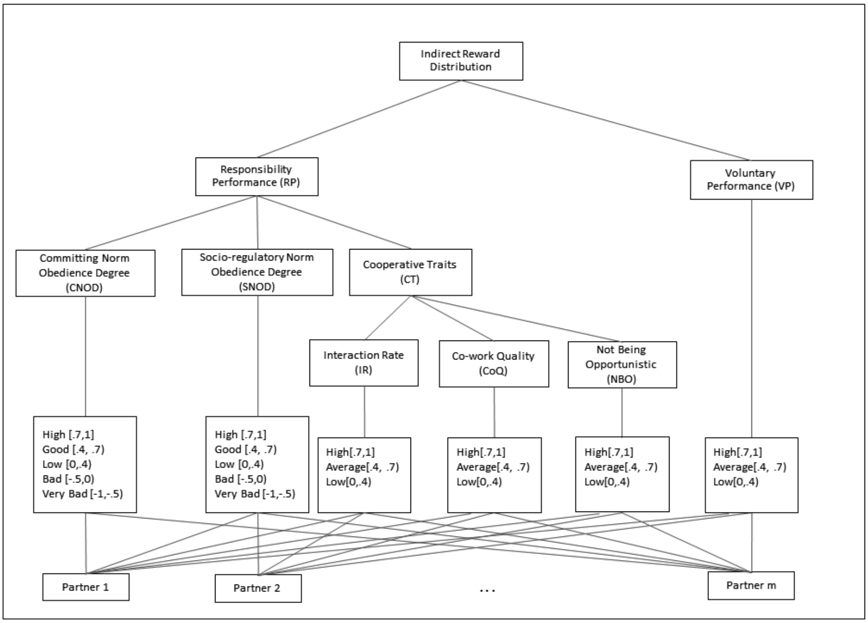


Figure 6.6: The criteria hierarchy to evaluate partners for reward distribution.

6.6.3 Analytic Hierarchy Process (AHP)

The AHP is a versatile and effective approach for multi-criteria decision making since the required scores and consequently the final rankings, are obtained based on the paired parallel evaluations of both the criteria as well as the alternative set defined by the user. Generally, the AHP computations are directed by the decision maker's experience, hence AHP can be considered as the means to derive a multi-criteria ranking from the decision maker's evaluations.

The AHP includes three sequential steps: (1) to determine the criteria weights vector, (2) to determine the matrix of alternatives scores and (3) to rank the alternatives.

First Step: This part applies the same method which was also used in Section 5.3 for trust evaluation, but provides more description. The approach initiates the creation of a paired comparison matrix A. The matrix A is an $m \times m$ matrix, where m is the number of evaluation criteria considered to be compared. Let us assume that each a_{jk} indicates the relative importance of the j^{th} factor to k^{th} factor, so there are three possibilities:

- $a_{jk} > 1$, if the j^{th} factor is more important than the k^{th} factor
- $a_{jk} < 1$, if the j^{th} factor is less important than the k^{th} factor
- $a_{jk} = 1$, if the two criteria have the same importance

There are two constraints: $a_{jk} * a_{kj} = 1$ and $a_{jj} = 1$ for all j. Table 6.1 indicates suggestive numerical scales for relative importance between any two factors [84]. After building the matrix A, it is possible to derive a normalized paired compar-

Status	**Value**
Equally important	1
Slightly more important	3
More important	5
Greatly more important	7
Fully more important	9
For comparison between margins mentioned above	2, 4, 6, 8

Table 6.1: Relative importance where comparing every two factors [84].

ison matrix from it, by making the sum of the entries on each column equal to 1. Therefore, each entry in column i is divided by the sum of the entries of that column. Ultimately, the criteria weight vector w (that is an m-dimensional column vector) is constructed by averaging the entries on each row of the normalized matrix (see Algorithm 2 in Section 5.3 of Chapter 5).

Second Step: The score matrix of the alternatives is a $m \times n$ matrix S, where m is the number of evaluation criteria considered to be compared and n is the number of alternatives. Each entry s_{ij} of S represents the score of the i^{th} alternative in relation to the j^{th} criterion. To gain such scores, at first a paired comparison matrix $B(j)$ is made for each m criterion, $j = 1, \ldots, m$. The matrix $B(j)$ is a $n \times n$ matrix, where n is the number of alternatives evaluated. Each entry b_{ih} of the matrix $B(j)$ represents the evaluation of the i^{th} alternatives compared to the h^{th} alternatives concerning the j^{th} criterion. $b_{ih} > 1$, if i^{th} alternative is better than the h^{th} alternative, while if $b_{ih} < 1$, then i^{th} alternative is worse than the h^{th} alternative. If two alternatives are evaluated as equivalent with reference to the

j^{th} criterion, then the entry is 1. Table 6.1 is used again to convert the decision maker's paired evaluations into numbers. The same procedure used for the paired comparison matrix A explained in the first step (normalization and averaging the entries on each row), is applied for each matrix $B(j)$. After normalization and averaging the entries on each row of matrix $B(j)$, we have a vector, which is called $s(j)$. The vector $s(j)$ contains the scores of the evaluated options concerning the j^{th} criterion. As the final step, the score matrix S is determined as

$$\begin{bmatrix} s(1) \\ s(2) \\ \dots \\ s(m) \end{bmatrix}$$

Third Step: Finally, to rank alternatives, the score matrix S computed in the second step is multiplied by the weight vector W, itself computed in the first step, i.e. $V = W \times S$, where $V(i)$ shows the global score assigned to the i^{th} alternative.

We have proposed Algorithm 4 for AHP-based ranking alternatives based on the criteria hierarchy (see in Figure 6.5 as an example). We will start from the root and follows a downward path to a leaf. The value of a leaf is a vector $s_{1\times n}$, which is the result of applying Algorithm 2 in Section 5.3 of Chapter 5, on the comparison matrix of alternatives (agents) for the corresponding criterion (current node). The value of internal node is $W_p \times S_p$, where W_p is the weight vector for p's children (p is the current node), and S_p is the score matrix for p. The values of p's children are placed in matrix S_p as its rows. The details of applying Algorithm 4 for a case study is discussed in the next section.

Algorithm 4: AHP for Ranking Alternatives

```
Input: p, the criterion in root of the hierarchy
Output: a ranking vector
Function Score(p) is
    if p is leaf then
        B_{n×n} := Get the comparison matrix of alternatives for criterion p
        s_{1×n} := run Algorithm 2 for matrix B
        return s
    else
        W_p := get weight vector for p's children
        for i := 1 to number of p's children do
            i^{th} row of matrix S_p := Score(p.child(i))
            return W_p × S_p
        end
    end
end
```

6.7 Application Case

In Chapter 4 to 6, we have addressed the main challenges for modeling and approaching the work-related behavior of VO partners, how their behavior can affect increasing the risk factors and failure of the VOs, as well as how to allocate such potentially risky situations, and to incentivize the partners to behave better and more collaboratively.

In this chapter, we will present an application case for the VOSAT, in which we have applied our proposed solutions to a VO that is organized for an R&D project, with 6 partners, addressing the topic of highly customized buildings. This goal of the project is divided into some sub-goals, for which four Work Packages (WPs) are specified and assume that all WPs start in month 1 of the project. The descriptions of these WPs are provided in the project's DoW (Description of Work), as briefly described in Table 6.2. Each WP consists of several tasks,

WP Number	**WP Title**	**WP Leader**	**Delivery month**
1	Requirements Analysis and Scenario Development	A4	12
2	System Architecture for collaboration	A2	18
3	Highly Customized Specification of Intelligent Building	A3	32
4	Exploitation and Dissemination	A6	36

Table 6.2: WP description of the R&D project example.

where each task represents a subset of the WP activities, planned to be jointly performed by a number of its 6 partners. We define six agents in VOSAT, called A1, A2, A3, A4, A5, and A6 that are involved in the VO formed for this R&D project. A short description of each task is also specified in the DoW, as also briefly shown in 13 task descriptions in Table 6.3.

6.7.1 VO Creation Phase

When this project starts, we have only the description of WPs and their related tasks. Each WP fulfills a sub-goal in the project for which several tasks are defined. To fulfill each task shown in Table 6.3, in VOSAT we define a joint-promise that is made by a group of partners, and as their signed contract indicates. The list of 13 joint-promises made in this VO, which is entered into the VOSAT at the VO creation phase, is as follows (below, $T1.1$ is the task number 1.1 in Table 6.3):

1. Joint-Pr ({A1, A2, A4, A6}, A4, T1.1, M10, T, 0)

Task	Description	Involved Agents	Leader	Deadline
1.1	Analyze the requirements of emerging and new co-innovation support services	A1, A2, A4, A6	A4	10
1.2	Analyze the requirements of stakeholders involved in mass customization of service-enhanced intelligent building	A2, A3, A4, A6, A5	A4	11
1.3	Design a set of scenarios around the intelligent building to be used for pilot implementation	A1, A2, A3, A4	A4	12
2.1	Specify services needed to provide information and knowledge	A1, A2, A6	A2	15
2.2	Design the interfaces adjustable for different stakeholders	A1, A6	A2	18
2.3	Define a reference model supporting service provision and innovation	A1, A2, A3	A2	18
2.4	Identify the needed approaches to compose services	A1, A2	A2	18
3.1	Design services for customers and local suppliers.	A1, A2, A3, A6	A3	30
3.2	Develop a tool for specification of intelligent building.	A1, A3	A3	31
3.3	Design dynamically customizable business services to enhance the intelligent building	A1, A2, A3	A3	31
3.4	Develop a tool to order service-enhanced intelligent building	A1, A6	A3	32
4.1	Develop website and brochure	A1, A2	A6	36
4.2	Disseminate scientific joint-publications	A2, A3	A6	36

Table 6.3: Task description of the R&D project example.

2. Joint-Pr ({A2, A3, A4, A6, A5}, A4, T1.2, M11, T, 0)
3. Joint-Pr ({A1, A2, A3, A4}, A4, T1.3, M12, T, 0)
4. Joint-Pr ({A1, A2, A6}, A2, T2.1, M15, T, 0)
5. Joint-Pr ({A1, A6}, A2, T2.2, M18, T, 0)
6. Joint-Pr ({A1, A2, A3}, A2, T2.3, M18, T, 0)
7. Joint-Pr ({A1, A2}, A2, T2.4, M18, T, 0)
8. Joint-Pr ({A1, A2, A3, A6}, A3, T3.1, M30, T, 0)
9. Joint-Pr ({A1, A3}, A3, T3.2, M31, T3.1, M30)
10. Joint-Pr ({A1, A2, A3}, A3, T3.3, M31, T, 0)
11. Joint-Pr ({A1, A6}, A3,T3.4, M32, T3.3, M31)
12. Joint-Pr ({A1, A2}, A6,T4.1, M36, T, 0)
13. Joint-Pr ({A2, A3}, A6,T4.2, M36, T, 0)

6.7.2 VO Operation Phase

At the VO operation phase, and based on the negotiated contract, some plans are made by the involved partners in each task together with the task leader, in which each sub-task is assigned to one specific agent. The list of sub-tasks, which are specified at the beginning of the VO operation phase, is shown in Table 6.4. The negotiation process among agents for defining sub-tasks is performed in the operation phase.

Table 6.4: List of Sub-tasks Specified at VO operation phase.

Begin of Table			
Sub-Task	**Description**	**Responsible Agent**	**Deadline**
1.1.1	Analyze the requirements for different scenario of intelligent building, considering advanced integrated services	A1	10
1.1.2	Identify different levels of knowledge maturity and acceptability	A2	10
1.1.3	Identify different level of infrastructure support	A4	10
1.1.4	Extend a business glossary for intelligent building	A6	10

Continuation of Table 6.4			
Sub-Task	**Description**	**Responsible Agent**	**Deadline**
1.2.1	Identify and characterize stakeholders involved in mass production	A2	11
1.2.2	Identify user expectation from services	A3	11
1.2.3	Identify user potential attraction to new service models	A4	11
1.2.4	Identify contractual conditions	A6	11
1.2.5	Identify cost models and privacy needs	A5	11
1.3.1	Design a set of scenario for intelligent building	A1	12
1.3.2	Identify the business services involved in the designed scenario in sub-task 1.3.1	A2	12
1.3.3	Identify the needed functional and organizational support aspects for the designed scenarios	A3	12
1.3.4	Characterize the role of stakeholders in the designed scenarios	A4	12
2.1.1	Identify services needed to share the catalogues and brochures related to intelligent building	A1	15
2.1.2	Identify services needed to provide information to share process description	A2	15
2.1.3	Identify services needed to share company profiles	A6	15
2.2.1	Design the interfaces adjustable for different stakeholders to provide easily access needs	A1	18
2.2.2	Design the interfaces adjustable for different stakeholders to provide easily visualization needs	A6	18
2.3.1	Analyze the endogenous elements of the co-innovation environment	A1	18
2.3.2	Analyze the exogenous elements of the co-innovation environment	A2	18
2.3.3	Design a general logical architecture for service provision in this project, based on the elements established in sub-task 2.3.1, 2.3.3 and the identified functionality set in WP1	A3	18
2.4.1	Identify the collaborative solution space and service provision space	A1	18

Continuation of Table 6.4			
Sub-Task	**Description**	**Responsible Agent**	**Deadline**
2.4.2	Identify the needed approaches for service composition	A2	18
2.4.3	Establish the relationship between business services and technical services	A2	18
3.1.1	Dynamically profile the customers based on the user profiles defined in WP1	A6	30
3.1.2	Specify the customers' criteria and constraints in relation to ordering the intelligent building	A1	30
3.1.3	Specify the environment/regional criteria	A2	30
3.1.4	Generate a set of sub-products for intelligent building with their related specification	A3	30
3.2.1	Design a data platform of all sub-product alternatives for intelligent building, based on extended profiles designed in Task 3.1	A3	31
3.2.2	Design an interface for customer to order its intelligent building	A1	31
3.3.1	Design a novel approach to achieve the business services suitable to enhance the ordered intelligent building	A1	31
3.3.2	Design a recommendation tree for offering alternatives to the customer	A2	31
3.3.3	Design an adaptive dialogue structure on top of the recommendation tree	A3	31
3.4.1	Design the interface for ordering service-enhanced intelligent building.	A1	32
3.4.2	Develop a tool to order service-enhanced intelligent building.	A6	32
4.1.1	Develop the website	A2	36
4.1.2	Develop the brochure	A1	36
4.2.1	Disseminate two scientific joint-publications	A2	36
4.2.2	Disseminate three scientific joint-publications	A3	36
End of Table			

Each plan include a set consisting of tuples of the form (A_i, p_i, d_i), in which A_i is an agent who should perform p_i before deadline d_i, as a part of the joint-promise made in the contract to realize p before d. The 13 sets of plans made in this example, representing the sub-task divisions in Table 6.4 are as follows (below, $ST_{1.1.1}$ shows the sub-task 1.1.1 from Table 6.4):

1. $Plan(A_1, ST_{1.1.1}, 10), Plan(A_2, ST_{1.1.2}, 10), Plan(A_4, ST_{1.1.3}, 10),$ $Plan(A_6, ST_{1.1.4}, 10)$
2. $Plan(A_2, ST_{1.2.1}, 11), Plan(A_3, ST_{1.2.2}, 11), Plan(A_4, ST_{1.2.3}, 11),$ $Plan(A_6, ST_{1.2.4}, 11), Plan(A_5, ST_{1.2.5}, 11)$
3. $Plan(A_1, ST_{1.3.1}, 12), Plan(A_2, ST_{1.3.2}, 12),$ $Plan(A_3, ST_{1.3.3}, 12), Plan(A_4, ST_{1.3.4}, 12)$
4. $Plan(A_1, ST_{2.1.1}, 15), Plan(A_2, ST_{2.1.2}, 15)$ $Plan(A_6, ST_{2.1.3}, 15)$
5. $Plan(A_1, ST_{2.2.1}, 18), Plan(A_6, ST_{2.2.2}, 18)$
6. $Plan(A_1, ST_{2.3.1}, 18), Plan(A_2, ST_{2.3.2}, 18),$ $Plan(A_3, ST_{2.3.3}, 18)$
7. $Plan(A_1, ST_{2.4.1}, 18), Plan(A_2, ST_{2.4.2}, 18),$ $Plan(A_6, ST_{2.4.3}, 18)$
8. $Plan(A_6, ST_{3.1.1}, 30), Plan(A_1, ST_{3.1.2}, 30),$ $Plan(A_2, ST_{3.1.3}, 30), Plan(A_3, ST_{3.1.4}, 30)$
9. $Plan(A_3, ST_{3.2.1}, 31), Plan(A_1, ST_{3.2.2}, 31)$
10. $Plan(A_1, ST_{3.3.1}, 31), Plan(A_2, ST_{3.3.2}, 31),$ $Plan(A_3, ST_{3.3.3}, 31)$
11. $Plan(A_1, ST_{3.4.1}, 32), Plan(A_6, ST_{3.4.2}, 32)$
12. $Plan(A_2, ST_{4.1.1}, 36), Plan(A_1, ST_{4.1.2}, 36)$
13. $Plan(A_2, ST_{4.2.1}, 36), Plan(A_3, ST_{4.2.2}, 36)$

Promise Monitoring

Considering the formalization of the joint-promise, as formulated in Chapter 4 (Section 4.2.1), each plan results in some promises, which are monitored in VOSAT. Consequently, based on this formalization at VO operation phase joint-promises are decomposed into some promises, which are monitored by VOSAT.

Assume a scenario, in which at month 15, it is inferred by VOSAT that A_6, who has become a trustworthy partner in the past, has not fulfilled one of its promises without any early notification to the task leader or VO coordinator. In other words, VOSAT identifies that the action $Fulfill(A_6, ST_{2.1.3})$ is not realized, while its related deadline is passed.

Trust-related norm Monitoring

As mentioned in Chapter 5, when a promise of an agent is not met then its trust-related norm is triggered, which results in invocation of AHP Fuzzy Comprehensive Evaluation method, Algorithm 3 in Chapter 5, to compute the trust level of A_6. In this case, we assume that: (1) the Promise Importance (PI) for all promises is one, (2) there is no Quality Specification Criterion in DoW, and (3) the value of IR, CoQ, NOB, SNOD, and ICB for all agents, as criteria in trust evaluation, equals the default value 0.5. It means that at month 15, A_6 fulfills two promises (for performing $ST_{1.1.4}$ and $ST_{1.2.4}$) and violates one promise ($ST_{2.1.3}$), so considering Table 4.3, and Formula 4.8, we have:

$$CNOD(A_6) = \frac{\sum_{j=1}^{|f_1(A)|} PF(p_j) \times PI(p_j) \times QF(p_j)}{\sum_{j=1}^{|f_1(A_6)|} max(PF(p_j)) \times PI(p_j)} = 0.33$$

Considering the weights in Figure 5.3, Algorithm 3 returns the comprehensive evaluation vector B for A_6, and its crisp trust level is measured applying the wighted average method (see Formula 5.2 in Chapter 5), as follows:

$$B = [0, 0, 0, 0.195, 0.804, 0], \quad Trust_{crisp}(A_6) = 0.4314$$

If the minimum level of trust is determined as Medium Trust, which is defined as $MediumTrust(x) = Trapezoidal(x; 0.2, 0.4, 0.6, 0.8)$ (see Section 5.3 in Chapter 5), then the trust-related norm of A_6 is not violated, because $MediumTrust(0.4314)$ is greater than zero, which shows that the trust of A_6 is set to **Medium Trust**. Consequently, the Task Leader may negotiate with A_6 to make new promise to fulfill the the current sub-task ($ST_{2.1.3}$) with delay at month 18, if that can be afforded in the VO.

But then assume that, the new deadline for sub-task $ST_{2.1.3}$, e.g., month 18, also passes, and again A_6 does not fulfill this task and again has not informed in advance. Moreover, poor A_6 does not fulfill its promise for sub-task $ST_{2.2.2}$ either. In this case, its trust-related norm gets triggered again. The new value of $CNOD(A_6) = -0.2$ is calculated. In this situation, applying Algorithm 3, and Formula 5.2, we will have:

$$B = [0, 0, 0.56, 0, 0.44, 0], \quad Trust_{crisp}(A_6) = 0.136$$

This results illustrates that the trust-related norm of A_6 is now violated, because the trust of A_6 is now set to **Low Trust**, and $MediumTrust(0.136) = 0$. Therefore, it is needed to immediately apply the risk prediction for the other VO activities.

Moreover, assume that agent A_1 does not fulfill $ST_{2.1.1}$ and $ST_{2.3.1}$, while $ST_{2.4.1}$ is invalidated, which means that it is not fulfilled, because of some reasons out of A_1's control. Consequently, $CNOD(A_1) = 0.14$, considering the promise fulfillment value in Table 4.3 in Chapter 4. Assume that all other criteria affecting its trustworthiness has default value 0.5, so applying AHP fuzzy comprehensive evaluation method, we have:

$$B = [0, 0, 0, 0.559, 0.44, 0], \quad Trust_{crisp}(A_1) = 0.304$$

The trust-related norm of A_1 is not violated, because $MediumTrust(0.304) > 0$, which shows that the trust of A_1 is set to **Medium Trust**.

Failure Probabilities

In risk prediction approach, beside the probability of the lack of trust, probabilities of lack of communication and heavy workload are also considered. The output of the risk prediction function is the probabilities of the tasks/sub-goals and goals in the Bayesian network.

Considering $Trust_{crisp}(A_6) = 0.136$, and $Trust_{crisp}(A_1) = 0.304$, the probability of Lack of Trust for these agents are calculated based on the formula below ($MediumTrust(x) = Trapezoidal(x; 0.2, 0.4, 0.6, 0.8)$),

$$p(LT(A) = True) = \left\{ \begin{array}{cc} 1 & Trust_{crisp}(A) < 0.2 \\ 1 - \frac{Trust_{crisp}(A) - 0.2}{0.4 - 0.2} & 0.2 \leq Trust_{crisp}(A) < 0.4 \\ 0 & Trust_{crisp}(A) \geq 0.4 \end{array} \right\}$$

Therefore, we have:

$$P(LT(A_1) = True) = 1 - \frac{0.304 - 0.2}{0.4 - 0.2} = 0.48 \qquad P(LT(A_6) = True) = 1$$

The failure probabilities of sub-tasks and tasks in Work Package 3 of this VO, in which A_6 is involved, are shown in Figure 6.7. As illustrated, the failure risk of task $T_{3.4}$ is more than the threshold of 0.5 (it is specified by the VO coordinator), so the task leader decides to reassign the sub-task $ST_{3.4.2}$, which was the responsibility of A_6, to another partner.

Task Reassignment

As mentioned before, for task reassignments, we consider two main factors of Soft Competency and Hard Competency. The former consists of four sub-factors, i.e. Communication Rate (CR), CNOD, SNOD, and CT, where CT itself has three sub-factors of Interaction Rate (IR), Co-work Quality (CoQ), and Not Being Opportunistic (NBO). The latter (hard competency) includes two sub-factors, i.e. Cost, and Work Overload (WOL), as can be seen in Figure 6.5. Assume that only agents $A1$, $A2$, $A3$, and $A4$ are able and interested to perform the sub-task 3.4.2, and values of their performance criteria at month 18 are shown in Table 6.5. Assume that the scores of SNOD, CNOD, IR, CoQ, and NOB for A_6 are

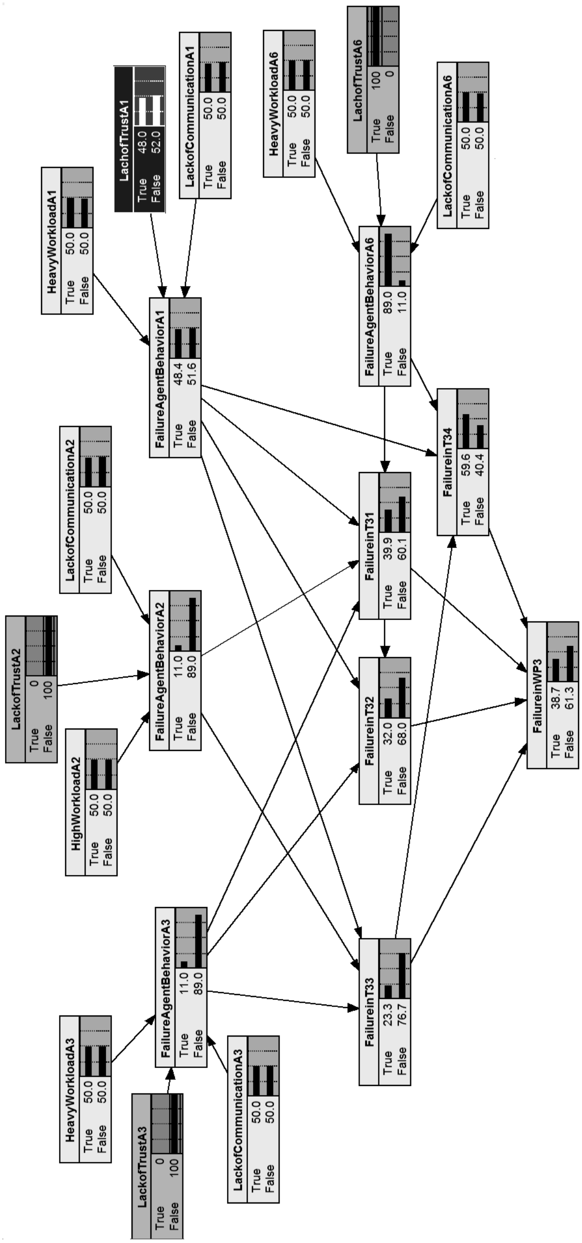


Figure 6.7: The Bayesian network related to the failure in tasks of WP3.

Agent	CR	CNOD	SNOD	IR	Co-Q	NBO	Cost	WOL
A_1	low	Low	Good	Ave	Ave	Ave	High	High
A_2	Ave	High	Good	Ave	Ave	Low	Ave	Ave
A_3	Ave	Good	Good	Ave	Ave	Low	High	Ave
A_4	Ave	High	Good	Ave	Ave	Low	Ave	High

Table 6.5: Agents' performance at month 18 in Task Reassignment's criteria.

.5,-0.2,0.3,0.2,0.4, respectively. Based on the *rating levels* shown in Figure 6.6, these values are respectively converted to Good, Bad, Low, Low, and Ave.

Here, the purpose is to find the best-fit partner among potential candidates, applying AHP. The *first step* is to determine the weights for criteria shown in Figure 6.5. An example of weights for these criteria is shown in Table 6.6.

Factors	Weights	Medium-level factors	Weights	Low-level factors	weights
Soft Competency	0.8	CR CNOD SNOD	0.1484 0.4258 0.2312		
		CT	0.1945	RI Co-Q NBO	0.1919 0.6337 0.1744
Hard Competency	0.2	Cost WOL	0.6667 0.3333		

Table 6.6: An example of weights for Task Reassignment's criteria.

The *second step* is to establish the pairwise comparison matrix for each criterion. It means that for each criterion, such as CNOD, it is needed to compare the value of that criterion for all agents (here $A_1 \ldots A_4$). Figure 6.8, shows that how the comparison matrices for comparing $A_1 \ldots A_4$ for each criterion are established. As Table 6.5 illustrates, IR of all four agents is Average; therefore all entries of comparison matrix for IR is 1 (see Figure 6.9). As Table 6.5 shows, the qualitative value of $CNOD(A_2)$ is High, while the qualitative value of $CNOD(A_3)$ is Good. Now, based on Figure 6.8 b, the $m_{2,3}$ in comparison matrix of CNOD is 2, which means that the CNOD degree of A_2 is 2 times better than the CNOD degree of A_3. It is clear that, the $m_{3,2} = \frac{1}{2}$, which shows that how much the CNOD degree of A_3 is better than CNOD degree of A_2 (see Figure 6.10).

The *third step* is to apply Algorithm 4, given the weight vectors calculated in the first step, and comparison matrices from the second step. Applying Algorithm 4, the score of CT is calculated as Figure 6.9 shows. Algorithm 4 is used for AHP-based ranking alternatives (agents) based on the criteria hierarchy. It starts from the root of the hierarchy and follows a downward path to a leaf. In this example,

$Value_{c_k}(A_i)$	$Value_{c_k}(A_j)$	$m_{i,j}$	$m_{j,i}$
High	Average	5	$\frac{1}{5}$
High	Low	7	$\frac{1}{7}$
Average	Low	3	$\frac{1}{3}$

(a) Comparison of two partners A_i and A_j, based on their values in criterion c_k. It should be noticed that c_k is CR, IR, CoQ, or NBO, which have three ratings values (Low, Average, and High). In other words, $Value_{c_k}(A_i)$ shows the c_k's value of partner A_i. When $Value_{c_k}(A_i)$=$Value_{c_k}(A_j)$, the related entries of comparison matrix for c_k (i.e. $m_{i,j}$ and $m_{j,i}$) are 1, which are not shown here.

$Value_{c_k}(A_i)$	$Value_{c_k}(A_j)$	$m_{i,j}$	$m_{j,i}$
High	good	2	$\frac{1}{2}$
High	Low	4	$\frac{1}{4}$
High	Bad	6	$\frac{1}{6}$
High	Very Bad	9	$\frac{1}{9}$
Good	Low	2	$\frac{1}{2}$
Good	Bad	4	$\frac{1}{4}$
Good	Very Bad	7	$\frac{1}{7}$
Low	Bad	2	$\frac{1}{2}$
Low	Very Bad	5	$\frac{1}{5}$
Bad	Very Bad	3	$\frac{1}{3}$

(b) Comparison of two partners A_i and A_j, based on their values in criterion c_k. It should be noticed that c_k is CNOD, or SNOD, which have five ratings values (Very bad, Bad, Low, Good and High). When $Value_{c_k}(A_i)$=$Value_{c_k}(A_j)$, the related entries of comparison matrix for c_k (i.e. $m_{i,j}$ and $m_{j,i}$) are 1, which are not shown here.

$Value_{c_k}(A_i)$	$Value_{c_k}(A_j)$	$m_{i,j}$	$m_{j,i}$
High	Average	$\frac{1}{5}$	5
High	Low	$\frac{1}{5}$	7
Average	Low	$\frac{1}{5}$	3

(c) Comparison of two partners A_i and A_j, based on their values in criterion c_k. It should be noticed that c_k is cost or work overload, which have three ratings values (Low, Average, and High). When $Value_{c_k}(A_i)$=$Value_{c_k}(A_j)$, the related entries of comparison matrix for c_k (i.e. $m_{i,j}$ and $m_{j,i}$) are 1, which are not shown here.

Figure 6.8: An example of judgments for comparing two partners A_i and A_j in their different performance' criteria.

for each leaf of the hierarchy, a vector 1×4 is returned, which is the result of applying Algorithm 2 in Section 5.3 of Chapter 5 on the comparison matrix of agents for the corresponding criterion. For example, considering the Figure 6.5, IR, CoQ and NOB are leaves of the hierarchy for task reassignment. The score values related to the children of CT, i.e. IR, CoQ, and NOB are placed in matrix S as its rows, respectively represented by S[0], S[1], and S[2] in Figure 6.9. Then the weight vector determined for IR, CoQ, and NOB is multiplied to matrix S, which results in $Score(CT)$.

```
<terminated> Ranking_Task [Java Application] C:\Program Files\Java\jre7\bin\javaw.exe (Nov 28, 2016, 7:26:29 AM)

 Comparison Matrix for IR
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00

 S[0]=score(IR) = [ .25  .25  .25  .25 ]

 Comparison Matrix for COQ
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00
  1.00   1.00   1.00   1.00

 S[1]=score(COQ) = [ .25  .25  .25  .25 ]

 Comparison Matrix for NBO
  1.00   3.00   3.00   3.00
  0.33   1.00   1.00   1.00
  0.33   1.00   1.00   1.00
  0.33   1.00   1.00   1.00

 S[2]=score(NBO) = [ .50  .17  .17  .17 ]

 W"=[ 0.192 0.634 0.174]

 Score(CT)=W"xS=[ 0.294 0.235 0.235 0.235]
```

Figure 6.9: The result of AHP for Score (CT).

The result vector $Score(CT)$ is used in the forth row of the score matrix of soft competencies. The calculation of $Score(Softcompetency)$ is shown in Figure 6.10.

Finally, $Score(TaskReassignment)$ showing the ranking rates of A_1, A_2, A_3, and A_4 is calculated as follows (see Figure 6.11):

$$Score(TaskReassignment) = [0.151, 0.326, 0.219, 0.303]$$

The elements of the vector above from left to right, shows the ranking of agents A_1,..., A_4. therefore, it means that A_2 is the best-fit partner to reassign the sub-task 3.4.2.

```
Comparison Matrix for CR
 1.00   0.33   0.33   0.33
 3.00   1.00   1.00   1.00
 3.00   1.00   1.00   1.00
 3.00   1.00   1.00   1.00

S[0]=score(CR) = [ .10  .30  .30  .30 ]

Comparison Matrix for CNOD
 1.00  0.25  0.50  0.25
 4.00  1.00  2.00  1.00
 2.00  0.50  1.00  0.50
 4.00  1.00  2.00  1.00

S[1]=score(CNOD) = [ .09  .36  .18  .36 ]

Comparison Matrix for SNOD
 1.00  1.00  1.00  1.00
 1.00  1.00  1.00  1.00
 1.00  1.00  1.00  1.00
 1.00  1.00  1.00  1.00

S[2]=score(SNOD) = [ .25  .25  .25  .25 ]

S[3]=score  (CT)=[ 0.294 0.235 0.235 0.235]

W'=[ 0.148 0.426 0.231 0.194]
Score(Soft Competency)=W'xS=[  0.168  0.303  0.226  0.303]
```

Figure 6.10: The result of AHP for Score (Soft Competency)

```
Comparison Matrix for COST
 1.00  0.20  1.00  0.20
 5.00  1.00  5.00  1.00
 1.00  0.20  1.00  0.20
 5.00  1.00  5.00  1.00

S[0]=score(Cost) = [ .08  .42  .08  .42 ]

Comparison Matrix for WOL
 1.00  0.20  0.20  1.00
 5.00  1.00  1.00  5.00
 5.00  1.00  1.00  5.00
 1.00  0.20  0.20  1.00

S[1]=score(WOL) = [ .08  .42  .42  .08 ]

W=[ 0.667 0.333]

Score(Hard competency)=WxS=[ 0.083 0.417 0.194 0.306]
...............................................
S[0]= Score(Soft Competency)=[  0.168 0.303 0.226 0.303]
S[1]=Score(Hard competency)= [  0.083 0.417 0.194 0.306 ]
W0=[ 0.800 0.200]

Score(Task Reasignment)=W0xS=[  0.151  0.326  0.219  0.303]
```

Figure 6.11: The result of AHP for Score (Task Reassignment).

Reward Distribution.

In order to promote collaborative behavior in partners, one approach suggested in Section 6.6.2 is to reward good work-related behavior of VO partners. Such rewards very much depend on what is valued at the VO and its organizations, and it may vary from monetary rewards for enterprises in some example industry VOs, to certain awards recognizing the organizations' contribution in some example socially concerned VOs. To support the VO coordinator to distribute reward among six partners, AHP is applied for criteria hierarchy, shown in Figure 6.6. Assume that, the agents' performance at the VO dissolution phase, is shown in Table 6.7. For applying the AHP, at first we need to calculate weights for criteria,

Agent	Responsibility Performance					Voluntary Performance
	SNOD	CNOD	IR	CoQ	NOB	
A_1	Good	Low	Average	High	Low	Low
A_2	High	High	Average	Average	Low	Average
A_3	High	Good	Average	High	Low	High
A_4	Good	High	Average	High	Low	Average
A_5	Low	Good	High	Low	Low	High
A_6	Good	Bad	Low	Low	Average	Low

Table 6.7: Examples of the agent's performance at dissolution phase of the VO.

based on the VO coordinator's opinion. An example of the weights are shown in Table 6.8. Considering Figure 6.8 a for IR,CoQ, NBO, VP, and Figure 6.8 b for

Factors	Weights	Medium-level factors	Weights	Low-level factors	weights
Responsibility Performance	0.8	CNOD SNOD	0.4258 0.2312		
		CT	0.1945	RI Co-Q NBO	0.1919 0.6337 0.1744
Voluntary Performance	0.2				

Table 6.8: An example of weights for Reward Distribution's criteria.

CNOD and SNOD, which are all criteria considered in reward hierarchy in Figure 6.6, the result of applying Algorithm 4 is as follows:

$$Score(RewardDistribution) = [0.094, 0.182, 0.208, 0.177, 0.158, 0.063].$$

The elements of the vector above from left to right, shows the ranking of agents A_1,..., A_6. The best partner in this VO is A_3.

6.8 Conclusion

This Chapter addresses an application of VOSAT, as introduced in Chapter 4, and detailed out further in Chapters 5 and 6, emphasizing agents' work behavior and supporting the prediction of risks in task-related planning during the operation phase of VOs. Considering the importance of success in achieving the goals of VOs, identifying the sources of risk in relation to the performance of planned daily activities of VO partners is critical for the risk analysis process and guaranteeing the success of the VOs. The VOSAT framework provides the mechanisms to gather important information and to reason about partners' trust-related norms as well as their influence on the VO risk analysis. Apart from trustworthiness, two other factors, the interaction level and the workload level of each agent, are also considered for calculating the potential failure probability of individual sub-tasks, and in turn identifying the potential sources of risks in VOs. Our proposed model for measuring the risk of failure also considers the joint-tasks and the VO sub-goals. Furthermore, it does not only consider the failure of the involved agents in one sub-task, but also captures the interrelationship and causality among the sub-tasks and tasks. Therefore, based on the Partner-Responsibility-Interdependency-Tree (PRIT), which is developed during the VOs operation phase, a Bayesian network is created and kept up to date, which makes it possible to find failure probability of VO's sub-goal/goals, depending on the agents' work related behavior and dependent on the tasks/sub-tasks at each point of time. This results in identifying the weakest points of planned activities as well as and the high risk tasks in the VOs. Then VO coordinator can decide on a follow up action, such as reassignment of the risky tasks to handle the situation. In VOSAT, an approach is also considered for a fair indirect reward distribution, to encourage partners to behave better and more collaboratively.