Using Data Envelopment Analysis and Fuzzy Logic as Intelligent Risk-based Decision Making Support for Virtual Organizations

Fernanda Sales Bittencourt de Lemos, Adriano Fiorese, Omir Correia Alves Junior and Rafael Giordano Vieira

Abstract Collaboration is key to foster and leverage business. Management techniques regarding organizational issues involved in collaborative working between partners require special attention. Particularly, Virtual Organizations (VO) have raised as cornerstone to enable intelligent attendance to Collaboration Opportunities (CO). Therefore, the VO concept has emerged as one of the most promising forms of collaboration among companies by providing a way of sharing their costs, benefits and risks, in order to attend particular goals. In general, organizational goals are achieved through management processes, whose result depends on the performance of several areas such as planning, design, development and decision making. Particularly, intelligent decision making can be accomplished using techniques that take into account information regarding indicators on the environment being analysed. Therefore, this chapter elaborates on the decision making using Data Envelopment Analysis (DEA) and Fuzzy Logic on partners' selection process complying particularly with the risks involved in VO formation process.

Fernanda S. B. de Lemos
Santa Catarina State University, R. Paulo Malschitzki, Joinville, Brazil 89.219-710
e-mail: fernandasl.bittencourt@gmail.com

Adriano Fiorese
Santa Catarina State University, R. Paulo Malschitzki, Joinville, Brazil 89.219-710
e-mail: adriano.fiorese@gmail.com

Omir Correia Alves Junior
Santa Catarina State University, R. Paulo Malschitzki, Joinville, Brazil 89.219-710
e-mail: omalves@gmail.com

Rafael Giordano Vieira
Santa Catarina State University, R. Paulo Malschitzki, Joinville, Brazil 89.219-710
e-mail: rafaelgiordano12@gmail.com

1 Introduction

In the last years, a wide variety of new organizational forms has emerged as a result of many socioeconomic challenges faced by society [13]. In fact, companies are specializing themselves and collaborating with each others, thus leading them to a more effective competition with other entities or groups in the markets. At the same time, the advances and the use of information and communication technologies (ICT) clearly facilitated the process of collaboration between companies, by providing a way in which the distance is no longer a major problem [7].

Among several forms of collaboration, the so called Virtual Organizations (VOs) have been indicated as appropriate to address these issues, by providing a more dynamic and flexible way to deal with the market demands. A VO consists in a temporary alliance of autonomous, heterogeneous and usually geographically dispersed organizations that come together to share skills (or key competencies) and resources in order to attend to Collaboration Opportunity (CO) [24]. There are four main phases regarding VO life cycle: formation, operation, evolution and dissolution [5]. This chapter focuses at the formation phase, which is seen as critical to ensure the correct VO operation and evolution.

One of the issues regarding the formation of VOs that have to be faced refers to how their partners are selected. In this chapter, a VO is seen as a set of Service Providers (SPs) that have previously agreed to collaborate in a mutual goal. It is also assumed that SPs are members of long-term alliances (like Virtual Breeding Environments – VBEs) [1] so sharing some minimum and common collaboration, working, quality and performance principles.

Several works in the literature have approached the problem of selecting partners for VO composition via an analysis focused on members' competences and capabilities [30, 4, 17]. Nevertheless, there is another critical factor that must be considered for the successful formation of a VO, which refers to measure the risk of each SP, and consequently to the overall VO. However, there is a lack of more systematic and integrated methods to handle the several dimensions of risk, which includes both VO intra and inter-organizational aspects.

In this sense, this chapter aims to elaborate on a method that analyzes and measures the risks for a set of SPs to compose a VO, through the combination of Data Envelopment Analysis (DEA) [8] and Fuzzy Logic [36]. By means of a set of quantitative analysis, VO managers can have better information to decide about which SPs should be effectively discarded or not on a given business CO and, additionally, the identified risks can be managed and mitigated throughout the VO formation process.

The remaining chapter is organized as follows: Section 2 presents the problem context and related work. Section 3 specifies the proposed risk analysis method. Section 4 presents the set of experiments conducted to evaluate the proposed method and also presents the final results. Finally, Section 5 concludes the chapter and outlines some future work.

2 Problem Context and Related Work

Risk management has emerged as an important contribution to most fields related to decision making and control management. When dealing with a network of interrelationships between organizations (e.g., a VO), risk management should be associated with the entire network [18]. It means that, in addition to the traditional environmental and organizational sources of risk, the VOs face a third category, called network risk, which is associated with the interactions between the participants [2].

The concept of risk is vast and can be handled in several perspectives [20, 23]. In brief, risk can be defined as the probability the occurrence of an event that causes a negative or positive impact on the organization's goals when it takes place [32]. Specifically in this work, the risk is characterized by the potential for one or more members, which are able to compose a VO, do not to perform correctly the tasks assigned to them with respect to the requirements thus jeopardizing the VO composition. It implies directly in a need to identify and measure the risks associated with VOs, through a systematic and well-defined process.

In the research review, a number of risk analysis methods has been identified as potentially suitable for VOs, namely Failure Mode and e Effects Analysis (FMEA), Fault Tree Analysis (FTA), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Event Tree Analysis (ETA), Bayesian Networks, Causal Network Event Analysis (CNEA) and Ishikawa Diagram [32, 12, 29, 28, 26]. Two methods were selected as the most suitable ones for this work: Data Envelopment Analysis (DEA) [8] and Fuzzy Logic [36]. DEA is able to handling multiple entries and model them in form of productivity, which is interesting in the context of this work, given that KPIs are used for evaluate the risk of the SPs and the risk is associated to their abilities to comprise the requirements. Further, using a fuzzy system allows risk experts define their own rules, adjusting them according to the interests of the organization.

In this way, there is a number of works related to risk analysis for VOs. In [2, 3], thirteen general risk sources in VOs were identified, which four of them were selected for this work due to their relevance: *trust*, *communication*, *collaboration* and *commitment* [2]. In this work, they are modeled as Key Performance Indicators (KPIs), and their values are provided accordingly [17]. Also, it is assumed that every SP has a set of historical values for each one of these KPIs, regarding to past VO participations.

In [15], the problem of risk mitigation in VO was discussed, and four processes were identified to improve the level of VOs performance reliability. In [19] two sources of risks were specified (external and internal), and risk occurrence likelihood in the life span of a VO was calculated based on them. [21] and [14] considered the fuzzy characteristics and the project organization mode of VOs to propose Multi Strategy Multi Choice (MSMC) risk programming models. In [25] was presented a competence model to support efficiently the process of partner's selection, which works in the context of Service-Oriented Virtual Organization Breeding Environments. [16] showed the relationships between most appropriate decision mechanisms to improve the overall performance of risk management in VOs. In addition, two mechanisms of decision making have been introduced, one of them being centralized and the other distributed.

Specifically in a context where SPs are involved, in a previous work [31] it was presented a method for risk analysis in VOs, which uses the same criteria used to perform risk analysis in this work. That method, called MARTP, initially performs an analysis of individual risk for all pre-selected SPs, using Event Tree Analysis (ETA) [12]. Then, it calculates and analyzes the overall risk of VO, considering the SPs collectively, using Fault Tree Analysis (FTA) [12].

3 Merging DEA and Fuzzy Logic

The VO formation is triggered by the emergence of a CO, and thereafter consists of several steps. More specifically, the SPs' Search and Selection step is key for the success of VO formation [2] and can be divided into two stages. The first stage is responsible for selecting, among all VBE participants, SPs that fulfill the CO requirements. Then, at the second stage, these selected SPs are submitted to the risk analysis, which is the focus of this work.

In the example shown in Figure 1, it is supposed the formation of a VO requiring three different services (A, B and C). Thus, given a VBE with a set of several SPs, those that offer the services A, B and C are joined into clusters (C_A, C_B and C_C). Then, the first stage of the proposed method selects an SP for each service (SP_A, SP_B and SP_C) according procedures presented by [17]. The second stage receives the historical values of all SPs both selected and not selected for the three services, which it is needed due to DEA compare all the SPs of a same service. Next, these values are submitted to linear regressions for providing the necessary data for DEA to determine the efficiency of the selected SPs.

Besides the efficiency of SPs based on their historical KPI values, the method also considers the importance of each service. The importance means the impact a failure has on the operation of VO as a whole, and its value is defined by the VO manager [6]. Then, given these information, fuzzy logic is used to calculate the risk of the VO failure due to a failure of a particular SP. Finally, the VO risk is calculated by averaging the individual risk of its SPs. The entire procedure for calculating the risk of each SP will be presented in the following subsections.

3.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) [8] is an approach for evaluating the *relative efficiency* of a set of peer entities called Decision-Making Units (DMUs) [10]. The DMU concept is defined to allow flexibility in its use over a wide range of possible applications, and in general is regarded to any entity that can be evaluated in terms of its abilities to convert inputs into outputs [9]. These evaluations take a variety

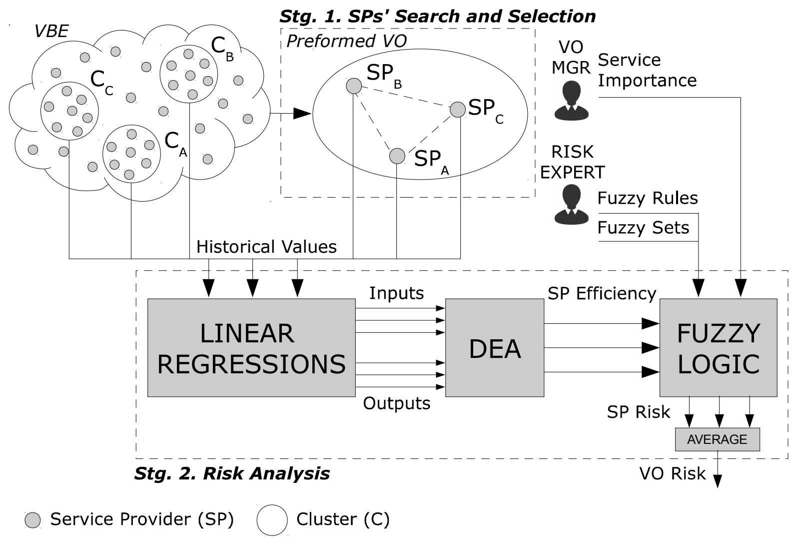

Fig. 1: Overview of the proposed method.

of forms, such as cost per unit, profit per unit, and so on, which are stated as one of the most common efficiency measure, called *productivity*, and can be calculated through the ratio *output/input*. This ratio is usually referred to as “partial productivity measure”, distinguished from “total productivity measure”. This latter, takes into account multiple inputs and multiple outputs and it is composed by the ratio between the weighted sum of the outputs, and the weighted sum of the inputs, making need to determine the weights of each input and output.

In order to avoid the necessity to inform these weights, DEA measures the *relative* efficiency of the DMUs. In this sense, the efficiency of the DMUs is relative to that is more productive, that is, the difference between it and the most efficient DMU. This is calculated by solving a Linear Programming (LP) problem. Thus, consider n DMUs to be evaluated. Each DMU consumes m different inputs to produce s different outputs. More specifically, DMU_j consumes a quantity x_{ij} of the input $i \in [1,m]$ and produces quantity y_{rj} of the output $r \in [1,s]$. Also assume $x_{ij} \geq 0$ and $y_{rj} \geq 0$. Finally, considering that n optimizations are required, one for each DMU_o over analysis, where $o = 1,2,...,n$, the LP that solve this problem is P.1 [10].

$$
\text{(P.1)} \qquad
\begin{aligned}
&\max z_o = \sum_{r=1}^{s} u_r y_{ro} - \mu_o \\
&\text{subject to} \\
&\sum_{i=1}^{m} v_i x_{io} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - \mu_o \leq 0 \\
&u_r, v_i \geq 0, \mu_o \in R
\end{aligned}
$$

where z_0 is the relative efficiency of DMU$_o$, u_r and v_i are, respectively, the input and output weights, and μ_o is a real scale factor.

As already mentioned, the role of DEA in this work is to calculate the efficiency of the SPs selected to form a new VO. In this way, the SPs are regarded as DMUs and therefore they must consume some input to produce some output. In order to define what are those inputs and outputs, it is important to highlight that the efficiency of an SP should be measured regarding to its risk level, which is characterized by its potential to not comply with the VO requirements (Section 2). That is, the lower the risk of an SP to fail with its responsibilities, the greater should be its efficiency. Since the input and output variables are the basis for calculation of the SPs' efficiency, the relation between the risk level and efficiency is established by defining these variables accordingly risk analysis criteria. In this work, this is done by an analysis of the historical series of the SPs.

3.1.1 Determining input/output values

According to [32], variability of a data set is a major component responsible for the difficulty in predicting future events, being considered a risk factor. Therefore, the greater the variability of the historical values of an SP, the greater the unpredictability on its future values, increasing the risk associated to this SP. The input and output values are related to the KPI predictability of the SP and, in this work, they are measured by repeated calculations of linear regressions over the historical values, obtaining the so called estimated values, as seen in Figure 2.

More specifically, for each risk KPI of a specific SP, it is calculated a linear regression for the first two participations in a VO, in order to estimate the value of the third, and then for the first three, estimating the fourth, and so on, until the $m-1$ participations, where the value of the last participation is estimated. The procedures for obtaining the input and output values will be presented as follows:

Let $K = \{K_1, K_2, K_3, K_4\}$ the set of KPIs earlier mentioned (trust, communication, collaboration and commitment), respectively. Let also $H_{ki} = \{h_1, h_2, ..., h_m\}$ the set of historical (real) KPI values and $X_{ki} = \{x_1, ..., x_{m-1}\}$ the set of estimated values of the KPI i for the SP k on the m past VO participations, Figure 2 illustrates that process.

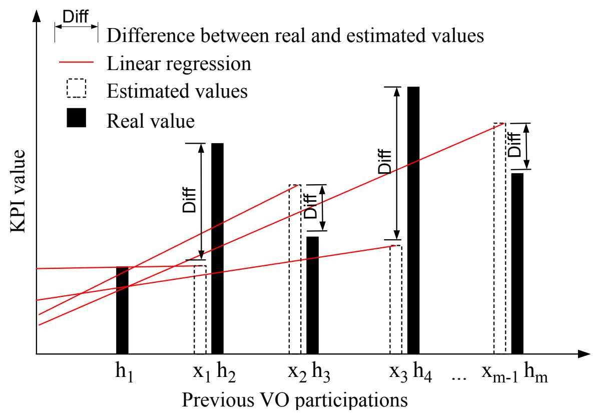

Fig. 2: Calculating input and output values through linear regressions

The efficiency of an SP takes into account the difference between the real and estimated values, that is, the efficiency should be increased when the SP performance is greater than the expectation. Thus, from the point of view of inputs and outputs adopted by DEA, the average of the estimated values can be considered as inputs and the average of the actual values as outputs.

However, considering only the average is not sufficient, because an SP can have high average but also large fluctuations in their historical KPI values, which makes it a riskier SP. Therefore, the final calculation of the inputs and outputs also takes into account the standard deviation of the data. Since the purpose of the DEA is to maximize the ratio outputs/inputs, the standard deviation of historical values (outputs) is subtracted from the mean. Therefore, the greater the deviation, the smaller the resulting value, and consequently the worse the efficiency. Likewise, the average of the estimated values (input) is added to the standard deviation.

Moreover, aiming to increase the efficiency of increasing historical, average historical values are proportionally increased to the $(m+1)th$ expected value (obtained by calculating the linear regression for all historical values). Thus, when historical values are increasing, the expected value (and consequently the efficiency) will be higher than for decreasing data. Since $\overline{X_{ki}}$ and $\overline{H_{ki}}$ correspond, respectively, to the average of the estimated and real values for KPI i from SP k, the input and output variables to be used by DEA are given by Equations 1 and 2, respectively.

$$I_{ki} = \overline{X_{ki}} + \sigma(X_{ki}) \tag{1}$$

$$O_{ki} = (\overline{H_{ki}} + \overline{H_{ki}} * x_{m+1}) - \sigma(H_{ki}) \tag{2}$$

Then, these input and output values are used for solving, for each service, the linear programming problem earlier presented, providing the efficiency of each selected SP. The SPs' efficiency is then used as input for the fuzzy system presented on the next step.

3.2 Fuzzy Logic

This step aims to calculate the individual risk of the selected SPs, i.e., the risk of the entire VO fails due to a failure of a specific SP. This analysis takes into account two factors: 1) efficiency of the SP; 2) impact of the failure of an SP on the VO as a whole. As determined in the preceding step, the higher the efficiency of the SP, the lower its risk of failure. Also, if the service provided by that SP is not crucial to the VO, i.e., the impact of a failure is not so great on the success of the VO as a whole, the lower the risk of the VO failure due to that SP.

It can be noted that both factors are derived from human evaluation, where the first is calculated by DEA from historical values (which were assigned by the partners in past participations in VOs), and the second should be informed by the VO Manager (as shown in Figure 1). Fuzzy logic [36] is specially helpful when involving human assessment, which is the case for risk management, where humans usually evaluate the risk by using linguistic expressions like "high" or "low" [11]. Moreover, the handling of linguistic expressions in the definition of the expert rules or of the available information have been one of the main applications of fuzzy theory [35]. This becomes important since defining expert rules is key for solving a wide range of real world problems, which in most cases needs a systematic representation of human knowledge [33].

Therefore, fuzzy logic is used in this work for establishing, through a set of expert rules, a relation between the two factors earlier presented. To accomplish that, first of all, it is necessary define fuzzy sets and label them using the called *linguistic variables*, which should be done preferably by a risk expert in order to get more accurate results. However, in this work they will be empirically defined and based on literature review [34].

The following linguistic variables were defined: *provider efficiency*, *service importance* and *VO risk*. Each variable can take five values: Very Low (VL), Low (L), Moderate (M), Very High (VH) and Extremely High (EH). Table 1 presents the set of 25 rules used in this work (result of all combinations of values for the three linguistic variables), which represents the influence of the relationship between the SP efficiency and the service importance for the VO as a whole. The rules have the form of the following example: *"If the provider efficiency is very low and the service importance is extremely high, then the VO risk is extremely high"* ("EH" in first line, last column).

The set of rules have been defined, it is also necessary to define the membership function and the defuzzification method. That done, the fuzzy system is able to make inferences over the entries, which are numeric values that represent the SP efficiency

Table 1: Set of fuzzy rules proposed in this work

Service Importance	Provider Efficiency				
	EH	VH	M	L	VL
	VO Risk				
Extremely High (EH)	M	VH	VH	EH	EH
Very High (VH)	L	M	VH	VH	EH
Moderate (M)	L	L	M	VH	VH
Low (L)	VL	L	L	M	VH
Very Low (VL)	VL	VL	L	L	M

and the service importance, and determine the VO risk for that SP. According [11], the triangular membership function (represented in Figure 3) is one of the most used, and thus applied in this work for all fuzzy sets. For the same reason, the Center of Gravity (CoG) method was used for defuzzification process [27].

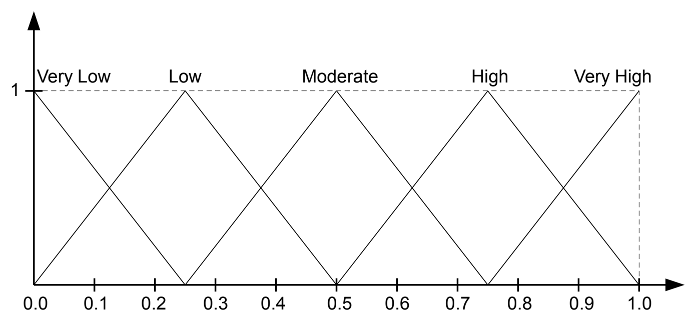

Fig. 3: Membership function for all the fuzzy sets.

Since the fuzzy parameters are defined, then the process of inference can be started. This process should be performed n times, one for each selected SP, and for each run the outcome corresponds to the risk R_i of the VO failure due to a SP_i failure. Finally, the overall VO risk , i.e., the risk of the VO failure due to one or more SPs, is calculated by Equation 3.

$$R_{VO} = \sum_{i=1}^{n} \frac{R_i}{n} \tag{3}$$

4 Results and Discussion

This section aims to evaluate the proposed method and compare it with the MARTP [31]. This analysis is performed through simulation process and is focused on how both methods measure the risk of SPs that have different historical trends. For example, it is expected that an SP that has more constant historical KPI values and a reasonable average, present less risk than an SP whose performance is decreasing. Therefore, it is interesting to analyze whether the methods reflect the expectations or not.

For this purpose, the simulation scenario is composed by SPs with historical KPI values based on different probability distributions [22]: *linear*, *triangular*, *exponential increasing*, *exponential decreasing*, *beta increasing* and *beta decreasing*. The SPs historical values are generated by using the "shape" of these distributions (Figure 4) , which is obtained from a *frequency distribution* calculation.

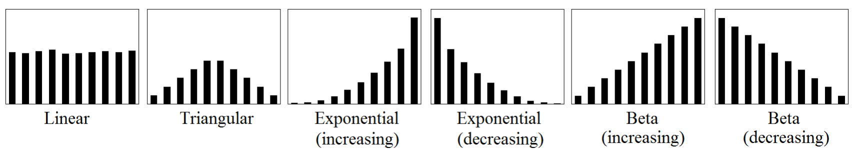

Fig. 4: Shape of the probability distributions used for forming the SPs' historical values.

The simulation considers the services *A*, *B* and *C* (i.e, three clusters (see Section 3)) each with six SPs (one for each distribution). Hence, six potential VOs are formed by one SP of each service, as in Figure 5.

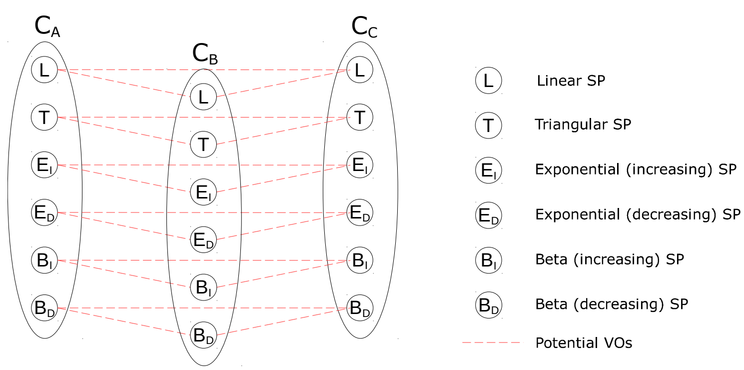

Fig. 5: Potential VOs formed by SPs of services *A*, *B* and *C*.

Since all SPs are generated and joined into potential VOs, both the methods are applied for analyzing the risk level of the SPs and the VO formed by them, whose results is shown in Table 2. There, the cells correspond to the risk of the SPs and the VOs, as well as the mean and standard deviation. The results were obtained by considering importance as 30%, 50% and 70% for services A, B and C, respectively. Values outside this range proved unrepresentative for the proposed analysis.

Furthermore, aiming to statistically enable the set of computationally generated SPs, the set of historical KPI values of each SP is the result of the average of K sets of historical values generated based on a distribution. In order to maintain the representativeness of the data set, it was employed the sample size calculation of [22] to determine the minimum sample size $K = 42$, considering a confidence level of 95%.

Table 2: Risk level for VOs composed by SPs with historical values based on different distributions for both methods under analysis.

	MARTP				**Proposed Method**			
Distribution	SP_A	SP_B	SP_C	**VO**	SP_A	SP_B	SP_C	**VO**
Linear	0.56	0.00	0.00	0.19	0.00	0.00	0.00	0.00
Triangular	0.13	0.13	0.00	0.09	0.40	0.61	0.68	0.56
Exponential (Incr.)	0.45	0.22	0.00	0.22	0.25	0.47	0.65	0.45
Exponential (Decr.)	1.00	1.00	1.00	1.00	0.62	0.75	0.75	0.70
Beta (Incr.)	0.00	0.00	0.00	0.00	0.20	0.20	0.43	0.27
Beta (Decr.)	0.51	0.51	0.58	0.53	0.56	0.75	0.75	0.68
Mean	0.44	0.31	0.26	0.34	0.33	0.46	0.54	0.44
Standard Deviation	0.35	0.38	0.43	0.37	0.23	0.30	0.29	0.27

Hence, from the results shown in Table 2, it can be seen that in average, both methods have resulted in different risk levels (either to the SPs as to VOs as a whole) when considered different historical behaviors. As expected, the distributions exponential and beta (decreasing) obtained higher averaged risk level in relation to the other historical behaviors for both methods (1.00 and 0.53, respectively for MARTP method; 0.70 and 0.68, respectively for the proposed method), which is easily explained by the provision of their values (i.e., values start high and are decreasing along the time series). It appears that the opposite is also true, i.e., the distributions exponential and beta (increasing) presented lower averaged risk level for both methods (0.22 and 0.00 to the MARTP method; 0.45 and 0.27 for the proposed method). The triangular distribution in turn showed differences in the risk level for both methods (0.09 to the MARTP method and 0.56 for the proposed method).

Finally, given that the proposed method has the variability of historical KPI data as a criterion to measure risk, the SPs that were modeled by linear distribution showed a risk level much lower compared to other SPs (0.00). This result is consistent, because these SPs showed good performance and stability during all previous VO participations, so there is no reason for them to have an increase in their risk levels.

However, except for this particular case, it is important to note that 0% or 100% rarely exist in practice, and the method proposed in this work demonstrates to take this aspect into account. One can clearly see the dissonance between the mean values of risk presented by both methods. While the method proposed in this work provides more balanced average values, the MARTP computes most values as 0 or 1, which explains the larger standard deviations for it. Moreover, it can be seen that, for the proposed method, the SP risk increases as its service importance also increases (mean of 0.33, 0.46 and 0.54 for service importance 30%, 50% and 70%, respectively).

5 Conclusion and future work

In general, risk analysis has become an inherent problem in Virtual Organization (VO) formation since bad choices can lead to impairment as a whole. Therefore, the delimitation of strategies for risk assessment are key to ensure the success of the VO. In this way, the main contribution of this work is to propose and develop a hybrid method that combines Data Envelopment Analysis (DEA) and Fuzzy Logic to quantify and measure the risk in a number of Service Providers (SPs) that are going to compose a VO.

In order to assess the performance of the proposed method, simulations were performed involving pre-selected sets of SPs. The simulations explored the comparison between the proposed method and the method previously proposed in [31]. The results shown that:

- the proposed method may be more or less critical for the assessment of SPs in a given VO, and this analysis is strongly dependent on the importance of the service assigned to each SP. In this sense, the VO manager plays a key role in the evaluation of the VO process, since it is the one that informs which service will have greater or lesser importance;
- the DEA has shown a good alternative for analyzing the risk in large sets of SPs, given its ability to compare a given SP with all the others that offer the same service category. It allows to know, among all other possibilities, if a given SP is a good choice or not, thus providing a more realistic assessment of the whole process;
- the proposed method provides more balanced results for the averaged risk of the VOs, as well as more resilient analysis regarding the variation in the historical behaviors of each SP in relation to MARTP method. This aspect becomes desirable in practice because there are many scenarios where SPs will present different distributions in its historical values.

Likewise, the proposed method presented many advantages compared to other methods in the literature. The first one is the ability to prioritize services according to their real importance to the success of the VO. In this case, the use of the fuzzy theory become advantageous, by supporting the manipulation of inaccurate data provided by humans. In real circumstances, one can modify the fuzzy rules to fit them to the interests of the VO. The criterion for determining the inputs and outputs of the method (which considers the variation in historical values of each SP) comprises another contribution of this work. Thus, the risk of a SP is related not only to their level of performance, but also its predictability. It should also be noted that the SPs are all members of a long-term alliance (VBE), which tends to tremendously facilitate collaboration between them and their measurement and performance management, which are key elements in the proposed method.

The method was evaluated in a simulated manner and using hypothetical data. In fact, it is very difficult to obtain data from companies and VOs, especially those related to its performance and historical behavior. Therefore, as a future work, it has been designed to test the method in real scenarios in order to compare it with other methods that have the same goal. It is also intended to test the method using different fuzzy rules in order to assess any changes in its behavior. Finally, we aim to integrate the proposed method in a framework for VO formation process.

References

1. Afsarmanesh, H., Camarinha-Matos, L.M.: A framework for management of virtual organization breeding environments. In: Proceedings of the 6th Working Conference on Virtual Enterprises (PRO-VE'05), pp. 35–48. Valencia, Spain (2005)
2. Alawamleh, M., Popplewell, K.: Risk sources identification in virtual organisation. In: K. Popplewell, J. Harding, R. Poler, R. Chalmeta (eds.) Enterprise Interoperability IV, pp. 265–277. Springer London (2010). DOI 10.1007/978-1-84996-257-5_25
3. Alawamleh, M., Popplewell, K.: Analysing virtual organisation risk sources: an analytical network process approach. International Journal of Networking and Virtual Organisations **10**(1), 18–39 (2012)
4. Baldo, F., Rabelo, R.J., Vallejos, R.V.: A framework for selecting performance indicators for virtual organisation partners search and selection. International Journal of Production Research **47**(17), 4737–4755 (2009)
5. Camarinha-Matos, L., Afsarmanesh, H.: The virtual enterprise concept. In: L. Camarinha-Matos, H. Afsarmanesh (eds.) Infrastructures for Virtual Enterprises, *IFIP The International Federation for Information Processing*, vol. 27, pp. 3–14. Springer US (1999)
6. Camarinha-Matos, L.M., Afsarmanesh, H.: On reference models for collaborative networked organizations. International Journal of Production Research **46**(9), 2453–2469 (2008)
7. Camarinha-Matos, L.M., Afsarmanesh, H., Galeano, N., Molina, A.: Collaborative networked organizations – concepts and practice in manufacturing enterprises. Computers & Industrial Engineering **57**(1), 46 – 60 (2009). DOI http://dx.doi.org/10.1016/j.cie.2008.11.024
8. Charnes, A., Cooper, W., Rhodes, E.: Measuring the efficiency of decision making units. European Journal of Operational Research **2**(6), 429 – 444 (1978)
9. Cooper, W.W., Seiford, L.M., Tone, K.: Introduction to data envelopment analysis and its uses: with DEA-solver software and references. Springer (2005)
10. Cooper, W.W., Seiford, L.M., Zhu, J.: Handbook on data envelopment analysis. Springer, US (2011)
11. Dikmen, I., Birgonul, M.T., Han, S.: Using fuzzy risk assessment to rate cost overrun risk in international construction projects. International Journal of Project Management **25**(5), 494 – 505 (2007)
12. Ericson, C.A., et al.: Hazard analysis techniques for system safety. John Wiley & Sons (2005)

13. Esposito, E., Evangelista, P.: Investigating virtual enterprise models: literature review and empirical findings. International Journal of Production Economics **148**, 145–157 (2014)
14. Fei, L., Zhixue, L.: A fuzzy comprehensive evaluation for risk of virtual enterprise. In: 10th International Conference on Internet Technology and Applications, pp. 1–4. Corfu, Greece (2010)
15. Grabowski, M., Roberts, K.H.: Risk mitigation in virtual organizations. Journal of Computer-Mediated Communication **3**(4), 704–721 (1998)
16. Huang, M., Wang, X., Lu, F.Q., Bi, H.L.: A coordination of risk management for supply chains organized as virtual enterprises. Mathematical Problems in Engineering **2013** (2013)
17. Junior, O.C.A., Rabelo, R.J.: A KPI model for logistics partners' search and suggestion to create virtual organisations. Int. J. Netw. Virtual Organ. **12**(2), 149–177 (2013)
18. Jüttner, U.: Supply chain risk management: understanding the business requirements from a practitioner perspective. International Journal of Logistics Management, The **16**(1), 120–141 (2005)
19. Li, Y., Liao, X.: Decision support for risk analysis on dynamic alliance. Decision Support Systems **42**(4), 2043–2059 (2007)
20. March, J.G., Shapira, Z.: Managerial perspectives on risk and risk taking. Management Science **33**(11), 1404–1418 (1987)
21. Min, H., Xue-Jing, W., Lu, F., Xing-Wei, W.: Multi-strategies risk programming for virtual enterprise based on ant colony algorithm. In: Proceedings of the 1st International Conference on Industrial Engineering and Engineering Management, pp. 407–411. Singapore (2007)
22. Montgomery, D.C., Runger, G.C.: Applied statistics and probability for engineers. Wiley, Hoboken, NJ (2011)
23. Moskowitz, H., Bunn, D.: Decision and risk analysis. European Journal of Operational Research **28**(3), 247–260 (1987)
24. Mowshowitz, A.: Virtual organization. Communications of the ACM **40**(9), 30–37 (1997). DOI 10.1145/260750.260759
25. Paszkiewicz, Z., Picard, W.: Modelling competences for partner selection in service-oriented virtual organization breeding environments. arXiv preprint arXiv:1111.5502 (2011)
26. Rhee, S.J., Ishii, K.: Using cost based fmea to enhance reliability and serviceability. Advanced Engineering Informatics **17**(3), 179–188 (2003)
27. Roychowdhury, S., Pedrycz, W.: A survey of defuzzification strategies. International Journal of Intelligent Systems **16**(6), 679–695 (2001)
28. Rychlik, I., Rydén, J.: Probability and risk analysis: an introduction for engineers. Springer (2006)
29. Saaty, T.L.: Decision makingthe analytic hierarchy and network processes (AHP/ANP). Journal of systems science and systems engineering **13**(1), 1–35 (2004)
30. Sari, B., Sen, T., Kilic, S.: AHP model for the selection of partner companies in virtual enterprises. The International Journal of Advanced Manufacturing Technology **38**(3-4), 367–376 (2008)
31. Vieira, R.G., Junior, O.C.A., Fiorese, A.: A risk analysis method for selecting service providers in P2P service overlay networks. In: Proceedings of the 16th International Conference on Enterprise Information Systems, pp. 200–211. Lisboa, Portugal (2014)
32. Vose, D.: Risk analysis: a quantitative guide. John Wiley & Sons (2008)
33. Wang, L.X.: A Course in Fuzzy Systems and Control. Prentice-Hall, Inc., Upper Saddle River, NJ, USA (1997)
34. Wang, Y.M., Chin, K.S., Poon, G.K.K., Yang, J.B.: Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. Expert Systems with Applications **36**(2), 1195–1207 (2009)
35. Yager, R.R., Zadeh, L.A.: An introduction to fuzzy logic applications in intelligent systems. Springer (1992)
36. Zadeh, L.: Fuzzy sets. Information and Control **8**(3), 338 – 353 (1965). DOI http://dx.doi.org/10.1016/S0019-9958(65)90241-X