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Swarm Intelligence Investigation of a Risk Management Model

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Abstract. The virtual enterprise is undoubtedly exposed to various risks from multiple angles owing to its dynamic operational setting, diverse constituents, and dispersed characteristics. Identifying crucial information that establishes a connection between the owner and the partners represents a potential gap that impedes sound decision-making. Therefore, the significance of such information cannot be overstated in managing the risks associated with a virtual enterprise. Each partner involved in a virtual enterprise is susceptible to various risk factors that threaten the enterprise's overall integrity. As the number of participants, risk factors, and events within a virtual enterprise increase, the search space will experience a significant expansion. The model under investigation pertains to a distributed decision-making process within virtual enterprise risk programming. Numerous control strategies are available for mitigating each risk. This research aims to identify a suitable decision-making methodology that can enhance the overall effectiveness of risk management practices across the organization. The present study uses the Grey Wolf Optimizer (GWO) to acquire valuable solutions. The findings indicate that the algorithm operates highly and that the model augmented the linkage between the owner and the partners. A comparative analysis is performed to evaluate the impact of the algorithm on mitigating risks associated with virtual enterprises, as compared to prior findings. The results indicate a positive effect of the algorithm in reducing such risks.

Keywords. Risk Management, Risk Factors, Virtual Enterprises, Decision-Making Model, Risk Control Strategies, Swarm Intelligence, Grey Wolf Optimizer.

1. Introduction

The contemporary business landscape has witnessed a surge in competition and a pressing demand for prompt responsiveness, owing to the emergence and proliferation of virtual enterprises (VEs) as significant undertakings in the current century. In this context, effective risk management of virtual enterprises assumes paramount significance, as it constitutes the primary determinant of a successful enterprise [1]. The concept of virtual enterprises aims to enhance competitiveness, optimize resource allocation, augment business volume, and leverage the complementary competencies of collaborative business partners [2]. The conventional approach to risk management, centered on individualistic loss prevention, is now being replaced by integrated enterprise risk management. This shift in attitude is the current trend in corporate governance. Risk managers' primary focus is mitigating potential losses or

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adverse impacts of particular risks. From a conventional standpoint, the statement holds. However, in the context of enterprise risk management, a more comprehensive outlook is adopted, which considers both the favorable and unfavorable dimensions of risk, it is shown in the figure (1). Consequently, the emphasis is placed on the strategic and commercial goals of the enterprise [3].

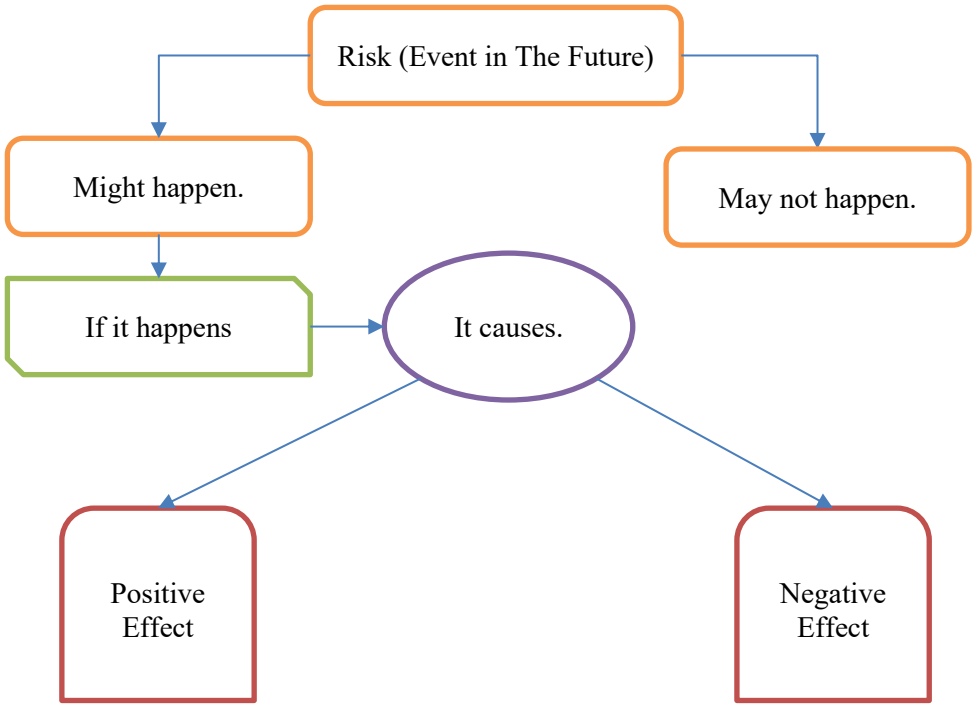

Figure 1. The general form of risk

2. The interaction of artificial intelligence and risk management

Looking at the ERM framework, we can see how AI (and technology in general) may assist with many of its foundational concepts. It can assist in finding previously unknown hazards, improve the precision with which risks are measured, provide novel approaches to risk management, and facilitate more thorough monitoring and control of risks. The use of AI technologies has a profound effect on improving the effectiveness of risk management in virtual enterprises. The deployment of AI techniques, particularly in the areas of stakeholder and business risks, might alter the risk profile [4].

Modern artificial intelligence (AI) solutions can alter how employers communicate with their staff. When deciding on an AI tool, it is crucial to consider the intended system architecture. Employees may be hesitant to adopt these tools for fear of losing their jobs, or clients may not engage with "technologies" that swap humans, such as Chatbots. One compelling case is that AI works freely within specific parameters and relates instances that deviate from the norm to an analyst for consideration [5][6]. Figure (2) shows how AI affects several risk management aspects.

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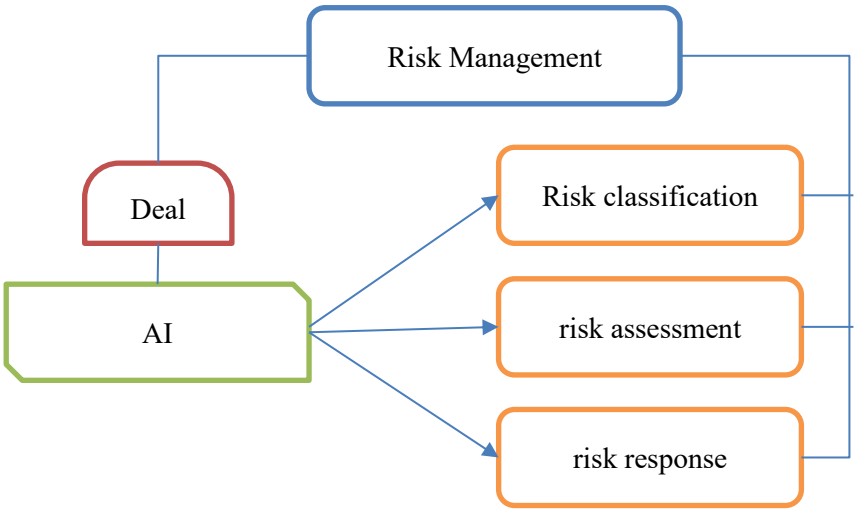

Figure 2. Artificial intelligence and risk management

3. The Optimization problems

In this study, we investigate the proposed model [7] two-tiered paradigm for risk management. As can be seen in Figure (3), this model employs two distinct "Distributed Decision Making" (DDM) layers. The "owner" is the top-level decision maker who must decide how much money to provide to each VE worker. Thus, we have ($x_0, x_1, \ldots, x_m$). as our decision variables. The owner's Budget is denoted by (x_0), and Partner's Budget is characterized by x_m. The primary goal of risk management is to maximize the return on investment for all parties involved, with the expectation that this return will be greater than the owner's target returns on investment (TBi).

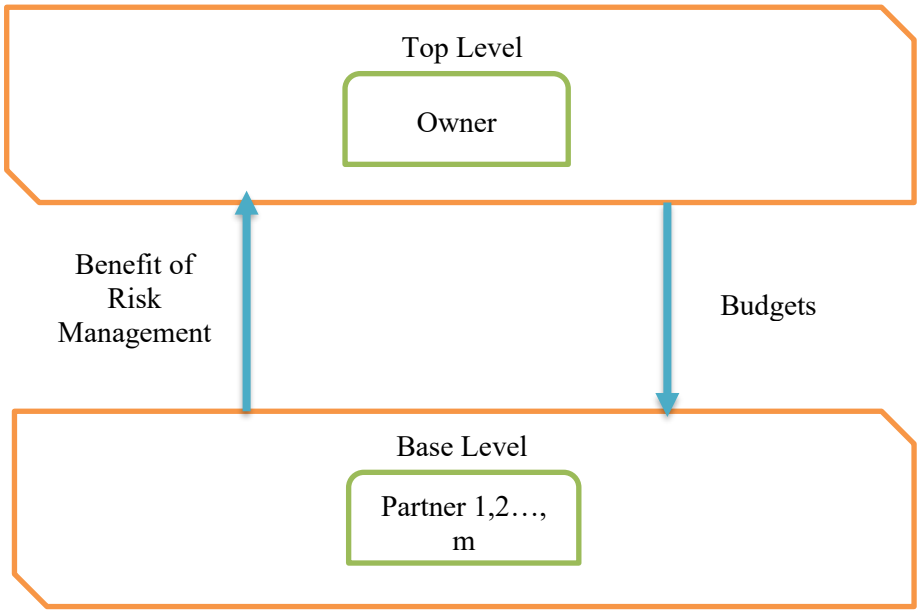

Figure 3. The Risk Management Model For VE

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Eq. (1)–Eq. (3) present the investment budget constraint and the interval of decision variables, respectively, and constitute the basis of the mathematical description of the problem.

$$\max\left[L_0^{initial} - L_0(x_0) - x_0\right] + \sum_{i=1}^{M} Benefit_i(x_i) \quad (1)$$

$$\sum_{i=1}^{M} x_i \le B_{max} \quad (2)$$

$$Benefit_i(x_i) > TB_i, i = 1,2,\dots,M \quad (3)$$
$$X_i \in [0, B_I], i = 1,2,\dots,M$$

were,

$L_0^{initial}$: *is* the initial risk loss for the owner

x_0 : *is the owner's budget*

$L_0(x_0)$: *is the risk loss level of the owner*

$Benefit_i(x_i)$: *is the benefit to the partner i of risk management*

x_i : *is the budget of partner i, where* $i = 1,2,\dots$ M

B_{max} : *is the upper bound of total budget for risk management in the VE*

TB_i : *is the target benefit to manage risk from partner i, specified by the owner*

B_i : *is the upper bound of the budget for partner i*

At the base level, there are M partners who represent the decision-makers. Partner selects the best strategies. y_{ij} as a risk control to maximize the risk management's benefit within the constraints of the Budget x_i. The cost of risk management cannot exceed the Budget. x_i, as shown in Equations (4) and (5).

$$\max Benefit_i(x_i) = L_i^{initial} - \sum_{j=1}^{N_i} p_{ij} l_{ij}(y_{ij}) - x_i \quad (4)$$

$$\sum_{j=1}^{N_i} C_{ij}(y_{ij}) \le x_i \quad (5)$$

$$y_{ij} \in \{0,1,\dots,W_{ih}\}, j = 1,2,\dots,N_i$$

were,

p_{ij} : *is the probability of a risk occurring for risk factor j for partner i.*

$l_{ij}(y_{ij})$: *is the risk loss from risk factor j of partner i under strategy* y_{ij}

$C_{ij}(y_{ij})$: *is the cost of partner i is under the risk control strategy of risk factor j*

W_{ih} : *is the available strategy no. for risk factor j for partner i*

4. The Swarm Optimization

The optimization problem of this model is a non-linear and "integer programming problem" with a two-level configuration for which no productive method exists. Furthermore, the vast problem size will lead to excessive computational time consumption as the number of partners and risk factors increases. Hence, this work introduces a two-level metaheuristic technique (TLMT) algorithm for resolving the optimization problem; this is done utilizing the Grey Wolf Optimizer (GWO), initially invented by [8].

4.1. *Grey Wolf Optimizer*

The Grey Wolf Optimizer takes ideas from wild wolves, who always look for new and improved methods of catching their prey. The algorithm follows the process used by nature. The members of the wolf pack are divided into four categories according to the kind of wolf function that aids in advancing the hunting process, following the hierarchy established to arrange the various responsibilities within the wolf pack. As can be seen in Figure 4, the four categories are labelled Alpha, Beta, Delta, and Omega. To this day, the Alpha remains the most effective hunting method discovered [9] .

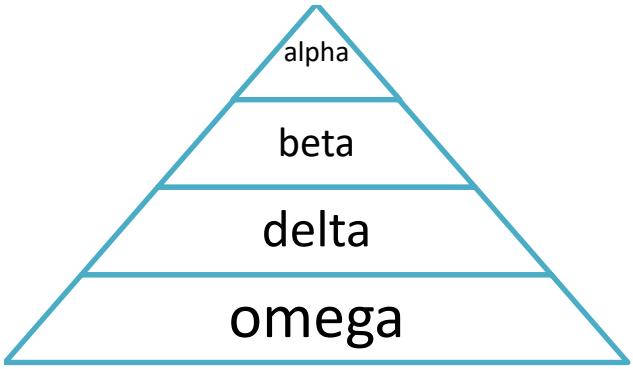

Figure 4. Gray wolf hierarchy (dominance decreases from top to bottom)

4.2. Mathematical Model and Algorithm

4.2.1. Encircling Prey

Equations (6) and (7) represent the mathematical modeling of prey-encircling behavior

$$\vec{D} = \left|\vec{C} \cdot \vec{x}_P(t) - \vec{x}(t)\right| \quad (6)$$

$$\vec{x}(t+1) = \vec{x}_P(t) - \vec{A} \cdot \vec{D} \quad (7)$$

Where t denotes the current frequency, $\vec{A}$ and $\vec{C}$ are the vector coefficients, $\vec{x}_P$ is the prey location vector, and $\vec{x}$ denotes the location vector of the gray wolf [8].

4.2.2. Hunting

We assume that Alpha (best solution candidate), beta (second best solution), and delta (third best solution) have more information about the likely location of prey; thus, we store the top three solutions obtained so far and force other search agents (which includes omegas) to update their sites based to a better search position [8].

$$\vec{D}_\alpha = \left|\overrightarrow{C_1} \cdot \vec{x}_\alpha - \vec{x}\right|, \vec{D}_\beta = \left|\overrightarrow{C_2} \cdot \vec{x}_\beta - \vec{x}\right|, \vec{D}_\delta = \left|\overrightarrow{C_3} \cdot \vec{x}_\delta - \vec{x}\right| \quad (8)$$

According to the alpha, beta, and delta locations in the two-dimensional search space, the other wolves update their location, and the final location will be in a random place within a circle marked by the Alpha, beta, and delta locations in the search space [8].

4.2.3. Search for Prey (Exploration)

Gray wolves frequently use the alpha, beta, and delta locations to narrow their search. They spread out to look for prey and then come back together to make a coordinated attack. We employ $\vec{A}$ Random values higher than 1 or less than -1 allow the search agent to stray from the prey, thereby mathematically modelling divergence. This places a higher value on detection and enables global searching via the GWO algorithm [8].

4.2.4. Attacking Prey (Exploitation)

Gray wolves end the hunt by attacking the prey when it stops moving. To model the approach to the prey, we reduce the value of $\vec{a}$, and it is noted that the oscillation range of $\vec{A}$ also decreases by $\vec{a}$. In other words, $\vec{A}$ is an arbitrary value in the interval [-2a,2a]; as a reduces from 2 to 0 throughout iterations, and when random values of $\vec{A}$ are at [-1,1], the search operator's following location can be anywhere between its current location and that of the prey [8]. Figure (5) represents a flowchart of the GWO algorithm.

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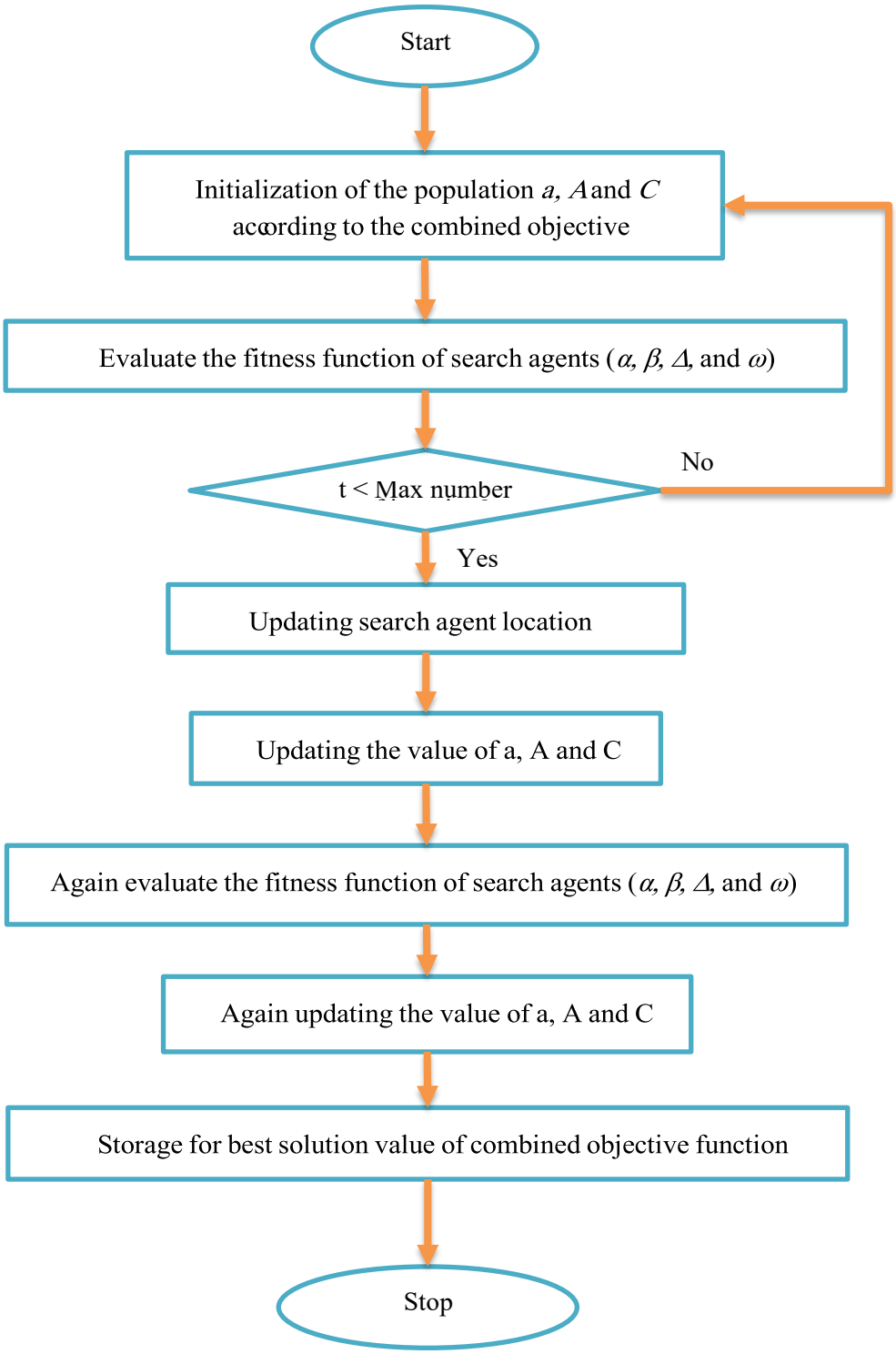

Figure 5. flowchart of the GWO algorithm

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5. Numerical Example

In this section, we report the outcomes of an experiment designed to test the efficacy of the used model for the risk management process in virtual enterprises based on the GWO algorithm. Ten (N=10) potential threats to the partner's safety are identified, and four (W=4) mitigation methods are provided. For each potential threat, either one of these options will be implemented, or nothing will be done.

The method will always use the same population size (Pop. Size = 200) and maximum iteration count (Max. iter = 1000), and the owner's potential loss will be expressed as a convex decreasing function up to its Budget (Eq. (9)).

$$L_0(x_0) = 200\exp(-0.02x_0) \quad (9)$$

The risk loss function of the partners is a convex decreasing function, as shown in Eq. (10).

$$L_{ij}(y_{ij}) = 200\exp(-\chi_{ij}y_{ij}) \quad (10)$$

The parameters χ_{ij} Are used to describe the effect of various risk factors on risk loss; their values are:

$$\chi_{ij} = \{0.94, 0.87, 0.83, 0.73, 0.63, 0.50, 0.37, 0.33, 0.23, 0.1\}$$

The strategy's cost is considered an increasing concave function of the related system, as approximated by Eq. (11).

$$C_{ij}(y_{ij}) = 100[1 - \exp(-\varepsilon_{ij}y_{ij})] \quad (11)$$

The parameters ε_{ij} Are set based on the risk factors. A higher effect strategy correlates to a higher cost and a lower risk loss.

$$-\varepsilon_{ij} = \{0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1\}$$

The experiment's results are compared to those of similar works to judge the algorithm's efficacy. From the research paper [7], below is a comparison between the GWO and TLPSO algorithms. The experimental input data is displayed in Table (1).

Table 1. Parameters used in the experiment

Algorithm	Bmax	TBi	L0	Li	Pop. Size	Max.it	Number of partners
GWO	350	1300	2000	2000	200	1000	1
TLPSO					Unavailable!	unavailable!	

The outcomes for both methods are shown in Table (2); the SHO algorithm fared better than the TLPSO algorithm regarding return benefit rate and Budget. It's worth noting that the research above didn't look into how long the algorithm takes or how much risk is lost after risk management is applied.

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Table 2. The comparison of two algorithms

algorithm	GWO	TLPSO
Benefit of VE	3280	3126.53
Benefit of partner	1399	1362.55
Budget for owner	69	172.37
Budget for partner	277.9	177.43
Total Budget	347	349.8
Strategies selected by partner	3 3 3 3 3 0 0 0 0 0	0 0 0 0 0 3 0 0 3 2
Risk loss	372	unavailable!
Time(sec)	5	unavailable!

6. CONCLUSION

This study highlights the importance of information in risk management decision-making by examining the function of Artificial Intelligence and Swarm Algorithms in the operations of virtual enterprises. The DDM theory and a Swarm Intelligence algorithm explore an essential risk management decision process model. The following optimization problem is then addressed by employing the model. The findings of the experiments show that the Grey Wolf Optimizer (GWO) efficiently navigates the problem's search space and that the adopted approach significantly reduced the risk level in the practical experiments of the model. It's important to remember that more partners mean more variables, making the problem harder to solve. Research in the future will focus on expanding the model by including other methods for dealing with potential dangers.

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