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Ignorant Critical Path Analysis with Triple Objectives for Event Networks and Its Application in Marine Ranching Emergency Decision

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Abstract: Emergency decision-making in event networks is often constrained by scarce historical data, conflicting expert judgments, and uncertain activity durations and costs. To address this problem, this paper develops an ignorance-event-network optimization framework that integrates GC-rule-based expert evidence fusion with a time-cost-risk multi-objective scheduling model. The GC rule is used to transform expert interval judgments into fused activity parameters and residual uncertainty-risk indicators. On this basis, a competitive multi-objective particle swarm optimization algorithm (CMOPSO) is applied to generate a Pareto set of feasible schedules, and TOPSIS is used to select a representative compromise solution. The framework is validated using a marine ranching ecological-security emergency decision network containing 62 real activities and two virtual start/finish nodes. Compared with the CPM baseline, the selected CMOPSO-TOPSIS schedule reduces project duration from 190.00 days to 156.41 days and slightly reduces the uncertainty-risk objective from 59.283 to 58.791, with total cost increasing from 326.80 to 361.46. The results show that the proposed framework can support transparent trade-off analysis among response duration, cost, and uncertainty risk in data-scarce marine ranching emergencies.

Keywords: multi-objective optimization; critical path analysis; ignorance; marine ranching emergency decision making

1. Introduction

Project management is a cornerstone of the global economy, directing approximately 30 percent of all economic activities [1]. In scenarios with predictable and constant activity durations, methods like the Critical Path Method (CPM) and Project Evaluation and Review Technique (PERT) have been widely used in diverse fields [2,3], from transportation network and energy supply chains [4]. However, contemporary project scheduling is rarely a single-objective task. Instead, it involves navigating a complex landscape of competing goals, such as minimizing both time and cost while managing quality and risk [5]. This has shifted scholarly focus towards multi-objective optimization problem, where solutions are typically represented by a Pareto optimal set that illustrates the trade-offs between conflicting objectives [6].

Several sophisticated multi-objective project optimization models have been proposed to navigate the trade-offs between variables like quality, time, cost, risk, and others [7]. It should be noted that optimization mentioned in this article refers to project scheduling optimization. According to the combination adaptive function and Jaya principle, various algorithms are designed to solve the project management problems in different scenarios [8]. However, a critical gap emerges when projects must be managed under conditions of high uncertainty, or "ignorance".

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In many event networks, particularly for emergencies, the lack of historical data and practical experience means that event durations and costs are not known or predictable. This introduces a high degree of scheduling uncertainty, rendering existing scholarly methods inadequate for formulating reliable predictions or effective project plans. Consequently, the rational sequencing of activities becomes a paramount challenge, necessitating the development of new theories and methods to solve these problems.

Existing time-cost-quality or time-cost-risk scheduling studies generally assume that activity parameters can be obtained from historical records, probability distributions, or stable expert consensus. In marine ranching emergencies, however, these assumptions are often weak because ecological incidents are sudden, response experience is limited, and expert forecasts may conflict. Therefore, the scheduling problem is not only how to optimize a known network, but also how to construct reliable activity parameters before optimization. This study fills this gap in the research.

Many real-world activities are subject to uncertainty, hindering expected outcomes. Marine ranching serves as a prime example. While it offers immense ecological value for sustainable fisheries by restoring marine living resources and boosting coastal fishery production [9], its late development means policies and emergency protocols remain unrefined [10]. This immaturity leads to frequent ecological security issues, yet the lack of practical experience in emergency decision-making prevents effective project management and compromises the full ecological and economic benefits of marine ranching.

To address this gap, this paper develops a multi-objective optimization model for an ignorance event network. First, the Generalized Combination (GC) rule is used to fuse expert predictions and obtain activity-level duration, cost, and uncertainty-risk parameters. Second, a time-cost-risk optimization model is constructed to describe the trade-offs among emergency response duration, project cost, and residual forecast uncertainty. Third, CMOPSO is used to generate a Pareto set of non-dominated schedules, and TOPSIS is adopted to select a representative compromise solution for interpretation. The model is validated by constructing a marine ranching ecological-security emergency decision-making network and comparing the optimized schedule with a CPM baseline.

The rest of the paper is organized as follow. Section 2 presents a literature review of related studies, addressing multi-objective optimization theories, project scheduling under ignorance conditions, applications of Dempster-Shafer evidence theory and the Generalized Combination (GC) rule, multi-objective particle swarm optimization algorithms, and emergency management frameworks for marine ranching ecological security. Section 3 elaborates on the fusion of expert predictions based on the GC rule, detailing the methodology for managing uncertain parameters via evidence theory, including expert forecast preprocessing and evidence fusion procedures. Section 4 formulates a time-cost-risk multi-objective optimization model for event networks, encompassing problem definition, mathematical model construction, and algorithmic optimization through the CMOPSO approach. Section 5 demonstrates the practical application of the model by constructing an emergency decision-making event network for marine ranching ecological security, presenting case study outcomes, comparative analyses with traditional methods, and discussions on optimization effectiveness. Finally, Section 6 concludes the paper, summarizing the contributions and outlining future research directions.

2. Literature Review

2.1. Multi-Objective Optimization

Project scheduling optimization is a key technology for effectively allocating resources and arranging the execution order of project activities [11]. Traditionally, project optimization problem has been considered a single-objective optimization problem [12]. For example, Muritiba et al. [13] addressed the scheduling of multi-mode resource-constrained projects by optimizing the total production scope. Similarly, Bettemir and Birgonul [14] studied a budget variant of the discrete time/cost trade-off problem, optimizing it by minimizing the completion time as a single objective. Although the above research focuses on optimizing a single aspect of project management, project elements are, in fact, closely related. Consequently, focusing on one primary goal invariably affects other objectives. Therefore, project management often involves multiple competing goals, making multi-objective optimization a central focus of scholarly research.

Multi-objective optimization problems generally consist of multiple conflicting objectives, where the conflict between them usually leads to a series of trade-off solutions [15]. These solutions form a Pareto set (PS) in the decision space, and their projections in the objective space form a Pareto front (PF) [16]. Multi-objective optimization is well-suited for solving complex project scheduling problems, and it is widely used in diverse fields such as energy emission and consumption [17], complex manufacturing process, and traffic evacuation [18]. For instance, Zhang et al. [19] proposed an optimal design framework that combines an analysis model, multi-objective optimization, and decision-making to balance the dehumidification performance and energy consumption of a

drying runner. Deng et al. [20] used multi-objective optimization to enhance a new type of sandwich corrugated square pipe, analyzing interaction and main effects by constructing a surrogate model. To address multi-objective optimization problems, scholars have proposed various solutions. Among them, genetic algorithm (GA) is one of the most common. Inspired by genetics and natural selection, GAs are known for their simplicity, strong robustness, and ability to avoid converging to local optima [21].

In the existing multi-objective optimization research, time, cost, and quality are traditional criteria for measuring project performance. For example, Yılmaz and Dede [22] investigated multiobjective time-cost-quality problems in construction projects and evaluated the efficacy of strength Pareto-based Rao algorithms. Recently, risk management has also become a key focus for scholars [23]. For example, some studies have applied financial risk indicators to multi-objective optimization [24], while others have developed hybrid simulation optimization methods combining scenario analysis and risk assessment to manage uncertainty in process planning [25]. These studies show that the traditional time-cost-quality trade-off has been extended toward time-cost-risk decision contexts. However, a gap remains in the research regarding risks that arise from parameter uncertainty, particularly from expert predictions. In emerging projects, overlooking the variability in expert forecasts can significantly increase the risk of project delays. This paper addresses this gap by measuring the uncertainty risk associated with project schedule parameters and integrating it into the time-cost-risk optimization framework.

For this reason, the risk objective in this study differs from conventional quality or safety indicators. It is defined as the residual uncertainty associated with fused duration and cost forecasts. This allows the optimization model to penalize schedules that appear efficient but depend heavily on unreliable expert predictions. The resulting model therefore links parameter fusion and multi-objective scheduling in a single decision framework.

To sum up, multi-objective optimization is of great significance to the problem of goal conflict in project management. It provides optimal solutions by navigating the complexity and trade-offs between objectives like cost, time, and risk. However, the effectiveness of these optimization results is often weakened in emerging projects because the uncertainty in expert predictions is not adequately addressed. Therefore, this paper introduces a method for measuring this uncertainty and integrates it into a multi-objective optimization model to better meet the demands of modern project management.

2.2. Project Scheduling Problem in Ignorance Situation

Project scheduling under uncertainty is a significant area of research. Much of this research focuses on the uncertainty of activity duration. For example, Joo et al. [26] addressed the single-machine, multi-level job scheduling problem with uncertain processing time. However, uncertainty also arises from other factors, such as resources and costs. Delgoshaei et al. [27] considered uncertain system cost in dynamic cell manufacturing, while Peng et al. [28] generated robust baseline schedule for resource-constrained projects under uncertainty. Similarly, Batista and da Fonseca [29] provided a powerful scheduling program for power grids facing uncertain application requirements and resource availability.

While existing literature extensively explores uncertain scenarios using multi-objective optimization, a specific gap remains. General uncertainty usually means that activity duration, resource demand, or cost is variable but can still be described by historical samples, probability distributions, fuzzy sets, or robust intervals. By contrast, the ignorance situation considered in this paper refers to emerging emergency projects in which historical samples are insufficient and parameter estimates mainly rely on expert judgments. In this context, the main difficulty is not only parameter variability but also the possible conflict and unreliability of the expert information itself. To address this gap, we first use GC rules to fuse expert opinions, generating activity parameters and uncertainty-risk indicators. We then construct a multi-objective optimization model that balances time, cost, and uncertainty risk to obtain a more reasonable emergency schedule.

2.3. Application of Evidence Theory and Generalized Combination Rule in Uncertainty Integration

In the context of complex environments or information scarcity, how to effectively integrate multi-source, incomplete, and even conflicting information has become a key issue in modern project management and risk scheduling. In high-risk fields such as maritime transportation, port security, and energy supply chains, decision-making uncertainty often stems from discrepancies in expert judgments, limited data samples, or frequent unexpected events. To obtain more reliable parameter inputs and decision support in these “cognitive blind spots”, the Dempster–Shafer theory of evidence (D-S theory) and its derivatives have increasingly attracted scholarly attention.

D-S theory is based on a probabilistic framework, using belief and plausibility functions to model uncertainty, providing theoretical support for expert opinion integration and fuzzy event recognition. However, when dealing with highly conflicting evidence, D-S theory often produces biased or counterintuitive results. To address this

limitation, researchers have proposed various improvements—among them, the Generalized Combination (GC) rule has demonstrated superior adaptability in adjusting evidence weights and redistributing belief values. By introducing conflict management mechanisms and reliability discounting strategies, the GC rule effectively mitigates fusion failures caused by divergent expert opinions, thus proving valuable in tasks such as project scheduling and risk identification.

In the maritime and port sectors, evidence fusion models have been applied to various uncertainty recognition and management tasks. For instance, Jiang et al. [30] developed a comprehensive safety assessment system for ports along the Maritime Silk Road, integrating cross-validated expert opinions to support emergency management with systematic parameters. The theoretical foundation behind such methods can be traced back to the extended applications of D-S theory. Similarly, Zhao et al. [31] emphasized in their analysis of container handling safety that expert interviews and historical incident data could be structured into fuzzy matrices, which can then be dynamically updated and harmonized using evidence fusion rules to enhance operational predictability and compliance.

In the field of transportation risk analysis, Said et al. [32] combined the analytical hierarchical process (AHP) and supply chain operations reference (SCOR) models to identify key risk points in the road transportation segment of oil supply chains. They argued that in scenarios involving multiple stakeholders and highly coupled risk factors, relying solely on a single evaluation tool is insufficient to accurately capture the system's state—thus making multi-source evidence fusion mechanisms particularly critical. Gul [33] further validated the feasibility of such fusion mechanisms in practical applications by developing a fuzzy evidence-based risk assessment framework for occupational safety in port operations, which significantly improved the system's responsiveness to evolving hazards.

Furthermore, in the context of the "Ice Silk Road" national strategy, Liu et al. [34] highlighted the strategic importance of fusion models from the perspective of international trade layout. They noted that in polar shipping routes characterized by environmental instability and long-term data deficiency, simulating collective expert decisions and integrating uncertain data is essential for forming effective strategic plans. Similarly, Wang et al., [35] in their theoretical modeling of marine cultural development across ten major port cities, encountered challenges related to differences in knowledge sources and ambiguous evaluation criteria—scenarios that further exemplify the relevance of evidence fusion in macro-level strategic planning.

2.4. Application of Multi-Objective Particle Swarm Optimization in Complex Scheduling

With the increasing complexity of port transportation systems and multimodal logistics networks, scheduling problems have evolved from traditional single-objective optimization to multi-objective trade-offs involving time, cost, and environmental impact. Against this backdrop, the Competitive Multi-Objective Particle Swarm Optimization (CMOPSO) algorithm has emerged as a powerful tool for solving complex scheduling problems due to its strong global search capability and adaptability to nonlinear scenarios. By incorporating competitive mechanisms, non-dominated sorting, and crowding distance evaluation, CMOPSO can effectively generate well-distributed Pareto-optimal solutions and handle conflicts and synergies among multiple objectives. It is particularly well-suited for applications in port operations, maritime scheduling, and green logistics where efficiency and sustainability must be balanced.

Although many multi-objective algorithms can be used for scheduling, including NSGA-II, NSGA-III, multi-objective Rao algorithms, and other evolutionary methods, CMOPSO is selected here because it matches the structure of the proposed problem. The decision variables are real-valued activity durations bounded by Table A2 in Appendix A, and each candidate solution must be evaluated through CPM-based network scheduling and three objective functions. CMOPSO's particle-update mechanism is suitable for continuous decision variables, while its competitive learning and non-dominated archive maintenance help preserve diverse Pareto schedules. Accordingly, CMOPSO is adopted as a problem-compatible solver for the present time-cost-risk scheduling model, rather than as a universal benchmark choice for all multi-objective scheduling problems.

In the field of multimodal transport route optimization, Shen et al. [36] proposed a scheduling model involving collapsible vehicle racks. By incorporating a multi-objective optimization algorithm, they designed comprehensive round-trip routes that effectively balanced transport costs, equipment utilization, and backhaul inefficiencies. This approach is particularly suitable for dynamic routing scenarios and uneven load distributions, highlighting CMOPSO's flexibility in route composition and resource allocation. Similarly, Kim et al. [37] examined container shipping operations and developed an optimization model that simultaneously minimized shift costs and maximized spatial utilization. Their model, powered by CMOPSO, enabled more intelligent and economical scheduling of shipping schedules and berth assignments, demonstrating strong practical utility in real-world port operations.

Mahmud et al., [38] in their study of green port management practices at Asian ports, noted that modern port performance is no longer evaluated solely by throughput, but must also consider carbon emissions, energy efficiency, and operational stability. Under such multi-objective demands, CMOPSO enables rapid exploration and convergence toward optimal solution sets, providing port operators with a range of balanced scheduling options that reconcile environmental responsibility with operational efficiency. On the issue of port resilience, Mohsendokht et al. [39] emphasized that in the face of disruptions such as natural disasters or supply chain interruptions, port systems must be able to dynamically reconfigure schedules and resource allocation under uncertainty. These time-sensitive and adaptive tasks place higher demands on algorithmic convergence speed and solution diversity—areas in which CMOPSO has proven to deliver high scheduling recovery efficiency in empirical studies.

Beyond operational scheduling, swarm-intelligence-based optimization also shows potential in policy design and network planning. However, the choice of algorithm should depend on the decision-variable type, objective structure, and evaluation cost of the problem. In this study, CMOPSO is used to obtain a diverse Pareto set for continuous activity-duration adjustment, while the final reported schedule is selected through TOPSIS to reflect decision-maker preferences. Comparative tests with other multi-objective algorithms are therefore retained as an important direction for future work.

2.5. Emergency Management and Optimization Scheduling for the Ecological Security of Marine Ranching

As global marine resource development moves into deeper waters, marine ranching has gradually emerged as a critical vehicle for advancing the blue economy among coastal nations. Nevertheless, its complex system structure is vulnerable to high ecological phenomena and extreme environmental events. The occurrence of sudden events such as red tides, disease outbreaks, or anthropogenic pollution can inflict irreversible damage on marine ecosystems. Therefore, establishing an efficient and coordinated emergency management system for ecological security has become essential to ensuring the sustainable operation of marine ranching.

Yuen et al., [40] in their studies on sustainable practices and carbon reduction incentives in the shipping industry, argued that only within a framework that balances economic efficiency with environmental performance can true green transformation be achieved. This perspective is equally applicable to emergency scheduling in marine ranching. Effective emergency management must not only aim for the shortest response time and lowest operational cost but also minimize ecological disruption and carbon emissions. Integrating sustainable shipping concepts into the management system of marine ranching implies that emergency scheduling should move beyond reactive measures toward proactive prevention, achieved through early risk identification, intelligent resource allocation, and the design of system resilience.

Specifically, emergency scheduling models need to incorporate multiple dimensions, including multi-source information integration, ecological risk assessment, and resource reallocation. In their 2018 study on the impact of maritime emissions trading systems (METS) on fleet deployment, Zhu et al. [41] developed a scenario-based stochastic programming model to dynamically optimize fleet structure and carbon output. This modeling logic can be analogously applied to marine ranching: based on the type of emergency, resource distribution, and environmental sensitivity, an event network model can be constructed and solved using intelligent algorithms such as CMOPSO. The objective is to optimize scheduling paths, enable rapid resource mobilization, and minimize response time, thereby enhancing overall system resilience and adaptability.

Furthermore, Yuen et al. [42] suggested that the effectiveness of corporate social responsibility (CSR) implementation in maritime enterprises is influenced by the degree of alignment with their core strategic orientation. When sustainable practices are deeply integrated with a firm's competitive strategy, performance outcomes are maximized. Translating this "strategy-practice fit" theory into the context of marine ranching suggests that the emergency ecological security system should not function merely as a technical response platform; rather, it must be embedded into the institutional framework of marine ranching development, achieving a dual drive of "ecological resilience" and "operational efficiency".

To address the problem of weak innovation capability among marine ranching enterprises, Wan et al. [43] developed a supernetwork-based collaborative innovation model grounded in supernetwork theory. Their study analyzes the operating mechanisms of the relationship coordination network, resource-sharing network, and cooperative innovation network within the supernetwork framework. Consistent with this strand of research, this paper treats marine ranching emergency response as a networked decision process. The proposed GC-CMOPSO framework further extends this idea by integrating expert-evidence fusion, time-cost-risk optimization, and Pareto-based schedule selection, thereby providing a computational approach for emergency response planning under ignorance conditions.

3. Fusion of Expert Predictions Based on GC Rule

In traditional event network planning, activity parameters like duration and cost are treated as fixed values. However, in practice, these parameters are often uncertain. To understand and quantify this uncertainty, organizations typically rely on expert predictions [44]. In emerging fields or novel projects a lack of historical data and relevant experience can lead to significant uncertainty in expert judgements—a state we refer to as the ignorance scenario in this paper. The ignorance situation can distort parameter estimates, rendering them unreliable for optimization. Consequently, the resulting network plan may deviate significantly from reality, losing its practical value and undermining the purpose of the optimization. In light of this, it is imperative to develop methods to manage and reduce the uncertainty. Existing research shows that GC rules can effectively integrate diverse expert opinions to produce more objective information. Based on this, this study combines GC rules with multi-objective optimization theory to overcome the ignorant situation of expert prediction, thereby, producing an optimized event network plan that is both robust and practically applicable.

The GC rule is an improved version of D-S evidence theory. As a generalization of subjective probability Bayesian theory, D-S evidence theory is widely used in decision-making and risk assessment [45,46]. However, a significant limitation of the D-S theory is that it often produces counterintuitive results when faced with highly conflicting evidence. To address this, scholars have proposed several improvements. These improvements generally fall into two categories. Some scholars have studied the modification of the fusion rules of evidence theory [47,48], such as the evidence crossover strategy and the flexible fusion rules [46,48]. Others have proposed new improvement methods from the perspective of evidence combination preprocessing [49], such as the method of modifying the weight of evidence to improve reliability [50,51]. Among them, the GC rule, proposed by Du and Zhong [52], is particularly effective. It integrates D-S theory with evidence reasoning, using a rational discounting of evidence weight and reliability to resolve key issues like indiscrimination and global ignorance. Therefore, based on GC rules, this paper solicits opinions from experts in related fields on the construction process of each process, and the duration and cost of optimizing each process in the event network. This step takes the duration of the event network as an example. The steps are as follows.

For clarity, the GC-rule-based fusion process in this study is organized into three stages: expert-input preparation, evidence fusion, and optimization-input generation. The inputs are expert interval judgments for each activity's duration and cost, together with the corresponding reliability and evidence weights. The fusion stage converts these judgments into a combined belief distribution and then into a pignistic probability distribution. The outputs used by the optimization model are the fused expected duration, the fused expected cost, and the residual uncertainty of duration and cost forecasts for each activity.

Step 1: Expert forecast and data pre-processing. Experts in related fields can estimate the duration of the activity based on their own experience and present their findings through basic probability assignment (BPA). The basic function of BPA is:

$$\begin{cases} m(\theta) = 0 & \theta = \varnothing \\ m(\theta) \geq 0, \sum_{\theta \subset \Theta} m(\theta) = 1 & \theta \neq \varnothing \end{cases} \tag{1}$$

Among them, it is known as a focal element if $m(\theta)$>0 is satisfied. According to Shafer's definition, BPA function refers to the integration of belief distribution and evidence weight. $(\theta, p_{\theta,i})$ is assumed to be the support degree of evidence. i stands for expert number. We can obtain:

$$bi = \left\{ (\theta, p_{\theta,i}), \forall \theta \subseteq \Theta, \sum_{\theta \subseteq \Theta} p_{\theta,i} = 1 \right\} \tag{2}$$

Furthermore, the weight w_i and reliability r_i of the evidence are all between 0 and 1, resulting in the following reliability distribution:

$$m_{\theta,i} = m_i(\theta) = \begin{cases} 0 & \theta = \varnothing \\ w_i r_i p_{\theta,i} & \theta \subset \Theta \\ w_i r_i p_{\theta,i} + w_i(1 - r_i) & \theta = \Theta \\ 1 - w_i & \theta = P(\theta) \end{cases} \tag{3}$$

Step 2: Evidence fusion. According to the generalized evidence theory, the reliability distribution reflects the trust level of experts in the proposition. It is necessary to fuse the evidence through the use of the evidence fusion rules in order to get a comprehensive inference about the construction period. Here is the result of the fusion:

$$m_{\theta,e(i)} = [m_1 \oplus m_2 \oplus \cdots m_i](\theta) = \begin{cases} 0 & \theta = \varnothing \\ \dfrac{\widehat{m}_{\theta,e(i)}}{\sum_{\vartheta \subseteq \Theta} \widehat{m}_{\vartheta,e(i)} + \widehat{m}_{P(\Theta),e(i)}} & \theta \neq \varnothing \end{cases} \tag{4a}$$

$$\begin{aligned} \widehat{m}_{\theta,e(i)} &= [\sum_{B \cap C = \theta, B, C \subset \Theta} m_{B,e(i-1)} m_{C,i} + m_{\theta,e(i-1)} m_{\Theta,i} + m_{\theta,i} m_{\Theta,e(i-1)}] \\ &+ [(1 - w_i) m_{\theta,e(i-1)} + m_{P(\Theta),e(i-1)} m_{\theta,i}] \theta \subset \Theta \end{aligned} \tag{4b}$$

$$\widehat{m}_{\Theta,e(i)} = m_{\Theta,e(i-1)} m_{\Theta,i} + [m_{P(\Theta),e(i-1)} m_{\Theta,i} + (1 - w_i) m_{\Theta,e(i-1)}] \tag{4c}$$

$$\widehat{m}_{P(\Theta),e(i)} = (1 - w_i) m_{P(\Theta),e(i-1)} \tag{4d}$$

where $0 \le \widehat{m}_{\theta,e(i)} \le 1$ for $\theta \subset \Theta$, $\theta = \Theta$, $\theta = P(\Theta)$, thus, the reliability of the final combination is as follows:

$$\mathrm{p}_{\theta,e(2)} = \begin{cases} 0 & \theta = \varnothing \\ \dfrac{\widehat{m}_{\theta,e(2)}}{\sum_{\vartheta \subseteq \Theta} m_{\vartheta,e(2)}} & \theta \subseteq \Theta, \theta \neq \varnothing \end{cases} \tag{5}$$

Step 3: Calculation of final probability. Fusion inference information obtained through the process (2) must be transformed into a probability so it can be used for decision-making. Signal probability is a common method to determine the probability that corresponds to each subset. Calculated with the help of the signal probability formula $BetP(\theta_n) = \sum_{\theta_n \in \theta \subset \Theta} p_{\theta,e(I)} / |\theta|$, the probability $BetP(\theta_n)$ is calculated, i.e., the probability that the hypothesis θ_n may be true, and the final result $BetP(\theta_*) = \max(BetP(\theta_1), \cdots Betp(\theta_N))$ is determined.

Step 4: Calculation of time. The generalized evidence theory produces the probability distribution for the duration of a process: $BetP(\theta_*) = \max(BetP(\theta_1), \cdots Betp(\theta_N))$ and according to the mathematical expectation, the duration of the work task is calculated, namely $\widetilde{d_v} = \sum_{n=1}^{N} \theta_n BetP(\theta_n), l, m \in V$.

The detailed calculation flow for the fused duration is therefore: expert interval forecast → BPA construction → reliability-weighted evidence adjustment → GC-rule evidence fusion → $BetP$ probability transformation → expected-value calculation. For activity v, the fused duration d_v is calculated as the weighted expectation of all candidate duration values under BetP. The same flow is repeated for cost to obtain the fused cost c_v. The belief and plausibility bounds retained during the fusion process are further used to calculate the uncertainty terms TU_v and TU'_v, which are later used in the risk objective.

Step 5: Repeat the preceding steps to obtain the fusion result for project cost.

Consequently, the GC-rule module provides four activity-level inputs for the subsequent optimization: fused duration, fused cost, duration uncertainty, and cost uncertainty. In the case study, the fused duration, cost, bounds, compression coefficient, and uncertainty-risk parameters are reported in Table A2 in Appendix A and are used as the direct input data for the CMOPSO optimization.

4. A Time-Cost-Risk Multi-Objective Optimization Model for Event Networks Based on GC Rule and Algorithmic Design

4.1. Problem Description

This section introduces the construction of the time-cost-risk multi-objective optimization model. This model mainly solves the minimization of event network execution time, cost and uncertain risk. After determining the event duration and cost through GC rules, this section introduces the modeling process of duration minimization, cost minimization and risk minimization. The general structure of the event network model is shown in Figure 1, and the definitions for all symbols used are provided in Table 1.

The model addresses the following three objectives:

1. Minimizing total duration: The primary goal is to reduce the overall duration of the event network. This is achieved by optimizing the sequence of activities subject to the network's logical time constraints. Reducing the total duration is a key indicator of successful project planning.
2. Minimizing total cost: While compressing the project schedule is desirable, it typically requires additional resources and management oversight, thereby increasing costs. To model this trade-off, we introduce a cost-increase coefficient linked to duration compression. This allows the model to find an optimal balance between project speed and budget.
3. Minimizing uncertainty risk: The initial parameter estimates from experts, even after fusion with GC rules, retain a degree of uncertainty. This model quantifies the risk arising from this potential variability in duration and cost parameters. This risk is the third objective to be minimized, leading to a more robust and reliable project plan.

In this model, duration and cost are not treated as deterministic inputs. They are first estimated from expert judgments through the GC-rule-based evidence fusion process described in Section 3. The fused values are then used as expected activity parameters, while their lower and upper bounds define the feasible compression or extension interval. The third objective, uncertainty risk, measures the residual uncertainty that remains after expert-evidence fusion. Therefore, time and cost enter the model as fused uncertain parameters, whereas risk explicitly quantifies the unreliability of these fused predictions.

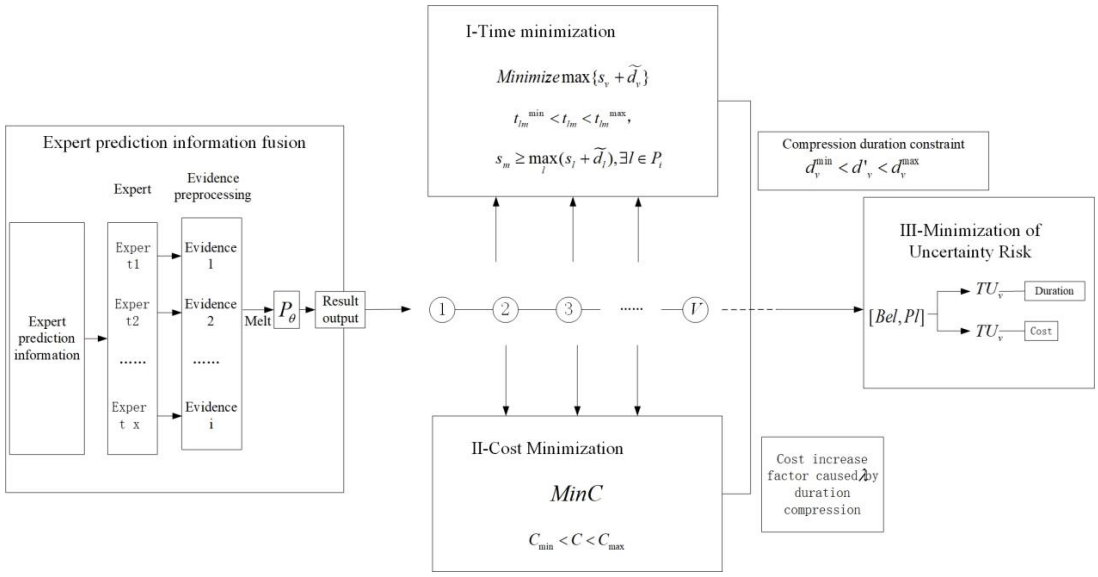


Figure 1. Model structure.

Table 1. Symbol representation.

Symbol	Meaning	Symbol	Meaning
$V = \{0, 1, \cdots, V, V+1\}$	Activity collection	TU_v	Uncertain risk of time limit for a project forecast
TU'_v	Uncertain risk of cost for a project forecast	$\widetilde{d_v}(v \in V)$	Duration of each process
d_v^*	Actual duration of activity v after compression	$d_v^{\min}$	Operation duration compressed Lower limit
$d_v^{\max}$	Extended working period Upper limit	P_v	Immediate preceding activity set of activity v
s_v	The start time of an activity v.	R	Upper limit of expert prediction parameters
Q_{vk}	The demand of activity v for resource k	$C_{\min}$	Lower limit of total cost
C	Total cost	$\widetilde{c_v}$	Cost of activity v
λ_v	Coefficient of cost increase caused by compression of construction period	x_{vk}	Decision variable, indicates whether activity v uses resource k
$C_{\max}$	Total cost ceiling	$\overline{N_k}$	supply of resources K
Bel	Lower limit of expert prediction parameters	Pl	Upper limit of expert prediction parameters
y_v	Decision variable, indicates whether the activity is on the critical path.		

4.2. Model Construction

This section mainly introduces the construction process of the model, including three aspects. First, combined with the second section, experts predict that the duration of each process under ignorance situation is $\widetilde{d}_v$. Based on this, the first problem to be solved by this model is to minimize the duration of the event network. The total duration of the project under resource constraints can be expressed as follows.

$$T = \max\{s_v + d_v^*\} \tag{6}$$

s.t.

$$s_m \geq \max_l(s_l + d_l^*), l \in P_m, m \in V \tag{7}$$

$$\sum_v \sum_k Q_{vk} x_{vk} \leq \overline{N_k}, v \in V \tag{8}$$

$$x_{vk} \in \{0,1\}, v \in V \tag{9}$$

In the above formulas, Formula (6) is the objective function, which minimizes the total project duration. This is achieved by minimizing the finish time of the final event in the network. Formulas (7)–(9) show the relevant constraints. Formula (7) defines the precedence constraint, ensuring that an event only begins after its immediate predecessor is completed. Formula (8) indicates the resources constraint, ensuring that resources used at any time do not exceed the maximum available limit. Formula (9) represents a binary decision variable, indicating whether an event needs resource k or not.

The CPM calculation is used to transform a candidate duration vector into a project-level schedule. For each candidate solution, the activity-on-node network is traversed according to the precedence relationships in Table A1 in Appendix A. The earliest start and finish times are computed forward through the network, and the latest start and finish times are computed backward from the terminal node. Activities with zero total float are identified as critical activities, and the binary variable y_v is set to 1 for critical activities and 0 otherwise. In this way, CPM is used both as a baseline comparison method and as an internal scheduling calculation for evaluating the time, cost, and risk objectives.

Second, from Section 2.2, it is clear that the normal cost predicted by experts for each process is $\widetilde{c}_v$. At the same time, the overall construction period is determined by the time duration on the critical path, so the decision variable y_v is set to indicate whether the event is on the critical path. Based on the existing research, the compression of the construction period will lead to the increase of the cost. If the cost increase coefficient caused by the compression of the construction period is set as $\lambda_v (v = 1, 2, \cdots, V)$, and the catch-up cost on the critical path caused by the compression of the construction period is recorded as $\lambda_v y_v (\widetilde{d}_v - d_v^*)^2$, the objective function of the cost is:

$$C = \sum_{v=1}^{V} [\tilde{c}_v + \lambda_v y_v (\widetilde{d}_v - d_v^*)^2] \tag{10}$$

$$C_{\min} < C < C_{\max} \tag{11}$$

$$d_v^{\min} < d_v^* < d_v^{\max} \tag{12}$$

Formula (10) is the cost objective function, which minimizes the total project cost. Formula (11) sets the budgetary constraints. It ensures that the total cost remains within a defined range, having both an upper limit (to control cost increases from schedule compression) and a lower limit. Formula (12) defines the duration limits for each activity, establishing the maximum extent to which any single activity's construction period can be compressed or extended.

Finally, in order to minimize the uncertain risk, this paper introduces the third objective. To achieve this, we first introduce a measurement of uncertainty risk. Due to conflicting evidence and uncertainty in evidence theory, the fused reliability function is uncertain. This paper calculates the total uncertainty of the generalized evidence theory using Yang and Han's [53] distance-based total uncertainty measurement method (TU). Given the confidence interval of the evidence e_i, which is $[Bel(a_i), Pl(a_i)]$. The uncertainty of a_i will be small if the

confidence interval is far from the most uncertain situation; otherwise, the uncertainty of a_i will be large. Therefore, in this paper, the distance between confidence interval and [0, 1] is calculated by using the distance formula between interval numbers [53], namely:

$$d([a_1,b_1],[a_2,b_2])=\sqrt{\left[\frac{a_1+b_1}{2}-\frac{a_2+b_2}{2}\right]^2+\frac{1}{3}\left[\frac{b_1-a_1}{2}-\frac{b_2-a_2}{2}\right]^2} \tag{13}$$

Replace $[a_1,b_1]$ with $[Bel(a_i),Pl(a_i)]$, replace $[a_2,b_2]$ with $[0,1]$ and it can be concluded that the distance resulting from this can be regarded as the distance to the most uncertain situation. The interval number is a fuzzy data, and the value of the ratio between $\left[\frac{Bel(\theta_i)+Pl(\theta_i)}{2}-\frac{1}{2}\right]^2$ and $\left[\frac{Bel(\theta_i)-Pl(\theta_i)}{2}-\frac{1}{2}\right]^2$ depends on the shape of fuzzy data model. In this paper, we assume that confidence intervals are uniformly distributed, so the ratio between them is 1/3. By subtracting the interval distance between normalization and average belief from 1.

The uniform-distribution assumption is adopted as a neutral baseline because no empirical distribution of expert forecast intervals is available for the marine ranching emergency case. This assumption avoids introducing additional distributional parameters that cannot be reliably calibrated under ignorance conditions.

$$TU=1-\frac{1}{\mathrm{n}}\sqrt{3}\sum_{i=1}^{n}d([Bel(\theta_i),Pl(\theta_i)],[0,1]) \tag{14}$$

Among them, in addition to the normalization factor $\sqrt{3}$, the total uncertainty is calculated by Formula (15). It is also possible to calculate the uncertainty caused by the cost of each process.

$$TU'=1-\frac{1}{\mathrm{n}}\sqrt{3}\sum_{i=1}^{n}d([Bel(\theta_i'),Pl(\theta_i')],[0,1]) \tag{15}$$

According to the above analysis, the total risk of the project is equal to the sum of the duration of personal leave on the critical path and the uncertainty of all activity cost forecasts. Personal leave here refers to inability to work due to force majeure. At this time, using decision variables y_v, the objective function of uncertain risk is:

Formula (16) defines the uncertainty-risk objective. The term TU_v represents the uncertainty associated with the duration prediction of activity v and is counted through the critical-path indicator y_v, because duration uncertainty affects the project completion time mainly through critical activities. The term TU_v' represents the uncertainty associated with the cost prediction and is summed over all activities, since cost uncertainty accumulates across the entire emergency decision-making network.

$$R=\sum_{v=1}^{V}(y_vTU_v+TU_v') \tag{16}$$

Through the model construction of the above three aspects, the multi-objective optimization model of time-cost-uncertain risk finally constructed is as follows.

$$Z=\{\min(T),\min(C),\min(R)\} \tag{17}$$

$$\begin{cases} T=\max\{s_v+d_v^*\} \\ C=\sum_{v=1}^{V}\tilde{c}_v+\lambda_v y_v(\widetilde{d}_v-d_v^*)^2 \\ R=\sum_{v=1}^{V}(y_vTU_v+TU_v') \end{cases}$$

$$s.t.\begin{cases} C_{\min} < C < C_{\max} \\ s_m \geq \max_l (s_l + d_l^*), l \in P_m, m \in V \\ R < R_{\max} \\ \sum_v \sum_k Q_{vk} x_{vk} \leq \overline{N_k}, v \in V \\ x_{vk} \in \{0,1\}, v \in V \\ d_v^{\min} < d_v^* < d_v^{\max} \\ TU = 1 - \frac{1}{\mathrm{n}} \sqrt{3} \sum_{i=1}^{n} d([Bel(\theta_i), Pl(\theta_i)], [0,1]) \\ TU' = 1 - \frac{1}{\mathrm{n}} \sqrt{3} \sum_{i=1}^{n} d([Bel(\theta_i'), Pl(\theta_i')], [0,1]) \end{cases}$$

4.3. Algorithm Optimization

The previous section constructed a time-cost-risk multi-objective optimization model under fused expert uncertainty. We use CMOPSO rather than NSGA-II or NSGA-III because the proposed model is a real-coded, nonlinear, multi-objective scheduling problem with continuous activity-duration adjustment. CMOPSO combines the fast search behavior of particle swarm optimization with a competitive learning mechanism and Pareto-based environmental selection, which is suitable for generating a diverse set of non-dominated schedules within a limited number of function evaluations. In this study, non-dominated sorting is used only as a Pareto-solution maintenance mechanism within CMOPSO; it does not mean that NSGA-II or NSGA-III is adopted.

Step 1: initialization of the particle swarm population and velocity vectors. It is assumed that there are N particles in the swarm P. Each particle has an n-dimensional position, $X_i = \left[x_{i,1}, x_{i,2}, \cdots x_{i,n} \right]$ and n-dimensional velocity vector, $V_i = \left[v_{i,1}, v_{i,2}, \cdots v_{i,n} \right]$. We generate all particle swarm $X = \left[X_i, X_2, \cdots X_N \right]$ and all velocity vectors $V = \left[V_1, V_2, \cdots V_N \right]$ in a random form.

Step 2: The competition mechanism based learning strategy. First, non-dominated sorting and crowding distance-based sorting are employed to select elite particles, with the number of elites set to γ. Specifically, the non-dominated sorting is first performed on the swarm P to obtain the fronts $F_1, F_2, \cdots, F_k$, where k is the maximum index of fronts. Then, the minimum number t is found such that $\left| F_1 \cup F_2 \cup \cdots F_t \right| \geqslant \gamma$, where γ is the number of elite particles to be selected. Finally, all particles belonging to $F_1 \cup F_2 \cup \cdots F_{t-1}$ are selected as the elite particles and the remaining particles are selected from F_t according to the crowding distance of each particle in F_t. Subsequently, pairwise competitions are conducted among particles in the elite particle set, and the winners are utilized to update the velocity and position of particles in the current swarm. For each pairwise competition, given a particle X_p in the swarm, two elite particles X_a and X_b are randomly selected from the elite particle set. Calculate the angles between X_a, X_b, and X_p separately. The elite particle with the smaller angle becomes the winner and is used to guide the movement direction of particles in the current particle. Assuming the position of the winning particle is X_w. We can update the velocity and position of particle X_p using the following formula:

$$V_p' = r_1 V_p + r_2 \left(X_w - X_p \right) \tag{18}$$

$$X_p' = X_p + V_p' \tag{19}$$

where r_1, r_2 ∈ [0, 1]. After the above steps, we obtained a new particle swarm P through competitive learning strategy.

Step 3: Generate new particle swarm through environmental selection strategy. Merge particle swarm A and B to form C. A denotes the parent particle swarm from the previous generation. B denotes the offspring particle swarm newly generated by the PSO operator. They are merged into the combined swarm C for environmental selection. Then use non dominated sorting and crowding distance-based sorting to select N particles from C,

forming a new population for optimization in the next cycle. The specific method for selecting advantageous particles is the same as Step 2.

Step 4: Determine whether the optimization meets the termination criteria. If not, proceed to the next cycle of competitive learning. Otherwise, stop the optimization and return the current particle swarm as the final result.

Based on the above process, the overall workflow of the proposed method is shown in Figure 2. The left part presents the GC-rule-based fusion of expert duration and cost forecasts. The middle part shows how the fused parameters are imported into the time-cost-risk model and evaluated through CPM-based scheduling. The right part illustrates the CMOPSO Pareto search process, in which non-dominated sorting (NDS) and crowding distance are used as archive and ranking mechanisms within CMOPSO rather than as NSGA-II or NSGA-III procedures. After the final non-dominated solution set is obtained, TOPSIS is used to select one representative compromise schedule under equal weights for duration, cost, and uncertainty risk.

In the numerical experiment, the population size was set to 100, the maximum number of function evaluations was set to 20,000, and MATLAB R2021b was used for implementation. The decision variables are the actual activity durations after compression or extension, bounded by the minimum and maximum duration values in Appendix B. After CMOPSO generates the final non-dominated solution set, TOPSIS with equal weights for duration, cost, and risk is used to select a representative compromise solution for reporting and comparison.

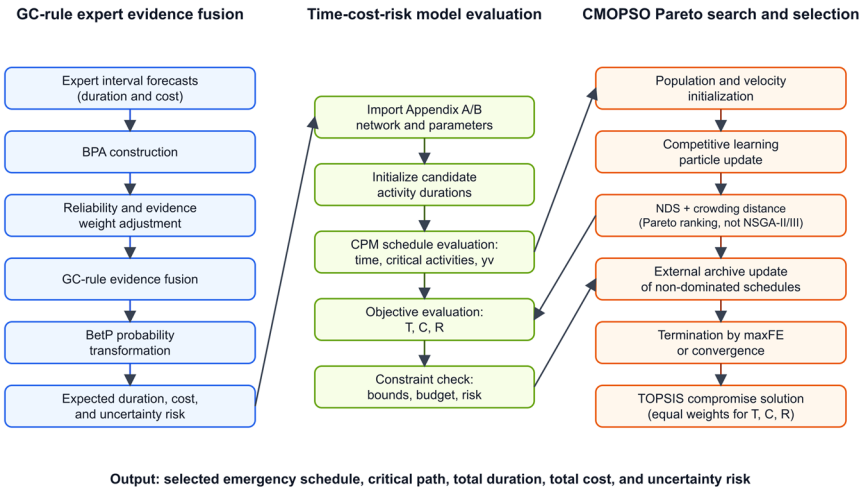


Figure 2. Workflow of GC-rule data fusion, CMOPSO Pareto search, and TOPSIS compromise selection.

5. Construction of Marine Ranching Ecological Security Emergency Decision-Making Event Network

5.1. Construction of Emergency Network for Ecological Security of Marine Ranching

With the increasing economic potential of marine resources, marine development has become a global focus. However, problems such as marine aquaculture pollution and overfishing are causing significant ecological harm [54]. Marine ranching offers a promising solution by combining resource enhancement with ecological restoration, yet research into emergency management for marine ecological security incidents remain limited [10]. Therefore, establishing an efficient and reasonable ecological security emergency decision-making network is crucial for the sustainable development of marine ranching.

Emergency decision-making is the process of selecting an optimal solution from a set of alternatives under conditions of suddenness, seriousness and urgency [55], which has been widely considered in industrial management, infrastructure management and other fields [56]. This field has drawn on various theories, including D-S evidence theory [57], signal detection theory [58], and large group emergency decision-making models [59]. Drawing on existing frameworks [60,61], this paper proposes that an emergency decision-making for marine ranching ecological security can be divided into eight stages: (1) Organization design, (2) planning, (3) resource scheduling, (4) monitoring and forecasting, (5) pre-processing, (6) security incident detection and analysis, (7) processing and (8) rehabilitation.

Figure 3 depicts the relationship between the stages of the marine ranching ecological security emergency decision-making network. First, experts are invited to form an expert group to design the ecological security emergency network, which serves as the foundational framework for all subsequent activities. Second, it is the emergency preparation of ecological security events phase, which is bifurcated. One branch focuses on technical

development, where historical incident data is analyzed to extract critical factors, culminating in the creation of an expert-advised emergency plan library. The other branch involves the identification and cataloging of necessary emergency resources into a dedicated information system. Third, through the collection, analysis and collation of monitoring information, combined with the emergency plan library to select the appropriate emergency plan and the dissemination of accurate early warning information. Fourth, after accepting the early warning results, the harm degree of ecological security events is analyzed, and the resources are scheduled to solve the ecological security events of marine ranching. The final phase comprises a comprehensive post-incident evaluation, which includes an assessment of the emergency response capability, a review of personnel responsibilities, and the formal archiving of the event. Appendix A shows the subdivision steps of the marine ranching ecological security emergency decision network. According to the data predicted by invited experts, this paper uses evidence theory to estimate parameter values under GC rules, as shown in Appendix B.

Figure 3 is used as the conceptual basis for decomposing the marine ranching ecological-security emergency process into computable network activities, and is adapted from Du and Cao [8]. The optimization experiment does not directly treat each box in Figure 3 as one decision variable. Instead, the workflow is encoded as the activity-on-node network listed in Appendix A. Appendix A contains 64 network nodes, including the virtual start node 0 and the virtual finish node 63. The 62 substantive activities are numbered 1–62, and their fused duration, cost, bound, compression coefficient, and uncertainty-risk parameters are reported in Appendix B. Therefore, paths reported in Section 5.2.1 include nodes 0 and 63 for network connectivity, whereas Appendix B contains numerical parameters only for the 62 real activities.

The expert prediction data used in this case were provided by experts and scholars from marine ranching-related fields, including marine ranching planning, ecological-security assessment, emergency management, and marine resource management. These experts were invited to estimate the duration and cost ranges of the activities in the emergency decision-making network according to their professional experience and understanding of marine ranching operations. Their judgments were then transformed into BPA values and fused using the GC rule described in Section 3. Appendix B reports the fused activity parameters used in the optimization model rather than the raw expert-by-expert judgment matrix. This presentation keeps the case study concise while preserving the network structure and numerical inputs required to reproduce the optimization experiment.

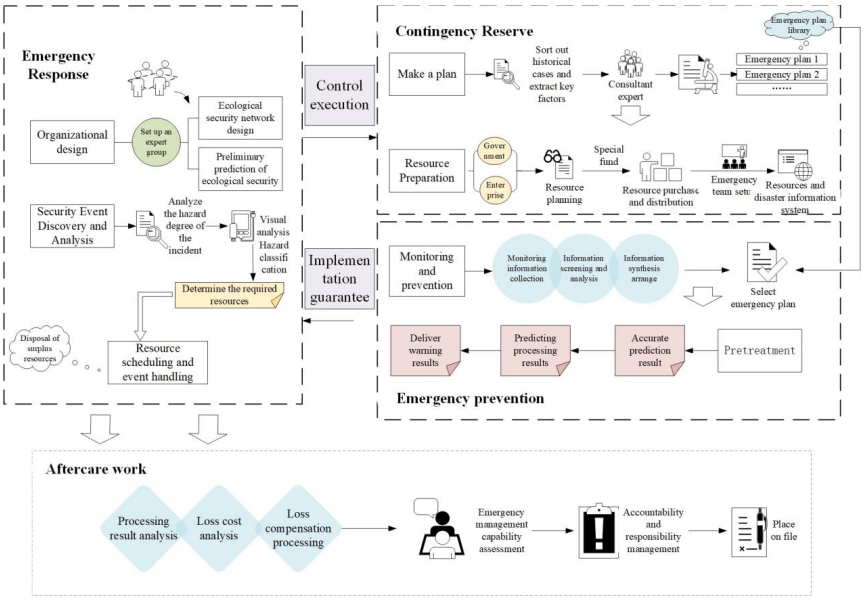


Figure 3. Schematic diagram of emergency decision-making network for ecological security of marine ranching.

5.2. Result Analysis

5.2.1. Analysis of the Effect of Optimizing the Time Limit, Cost and Risk of the Event Network by the Model

For the marine ranching ecological security emergency decision-making network, we optimized three objectives: minimum project duration, minimum project cost, and minimum uncertainty risk. The input activity network and parameter table were reconstructed according to Appendix A, including 62 real activities and two virtual nodes representing the start and finish of the network. The CMOPSO algorithm was implemented in MATLAB R2021b with a population size of 100 and a maximum of 20,000 function evaluations. All three objectives were treated as minimization objectives.

The final population contained 100 non-dominated candidate schedules. Figure 4 shows the Pareto frontier in the three-dimensional objective space, where each point represents a feasible non-dominated scheduling scheme with a different trade-off among project duration, project cost, and uncertainty risk. To select a representative compromise solution from the Pareto set, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was applied with equal weights for the three objectives. The TOPSIS-based compromise solution had a project duration of 156.41 days, a project cost of 361.46, an uncertainty-risk value of 58.791, and a TOPSIS closeness coefficient of 0.701.

We further compared the optimized schedule with the baseline schedule obtained by the traditional Critical Path Method (CPM). The detailed CPM and CMOPSO-TOPSIS critical paths and objective values are summarized in Table 2.

Table 2. Comparison between the CPM baseline and the CMOPSO-TOPSIS compromise schedule.

Indicator	CPM Baseline	CMOPSO-TOPSIS Compromise Schedule
Critical path	0 → 1 → 2 → 4 → 5 → 8 → 9 → 10 → 11 → 12 → 13 → 14 → 19 → 20 → 28 → 29 → 30 → 31 → 41 → 42 → 43 → 44 → 47 → 48 → 49 → 50 → 52 → 56 → 57 → 58 → 59 → 60 → 61 → 62 → 63	0 → 1 → 2 → 4 → 5 → 6 → 7 → 9 → 10 → 11 → 17 → 18 → 20 → 28 → 29 → 30 → 31 → 41 → 42 → 43 → 44 → 45 → 48 → 49 → 51 → 52 → 56 → 57 → 58 → 59 → 60 → 61 → 62 → 63
Duration (days)	190.00	156.41
Cost	326.80	361.46
Uncertainty risk	59.283	58.791

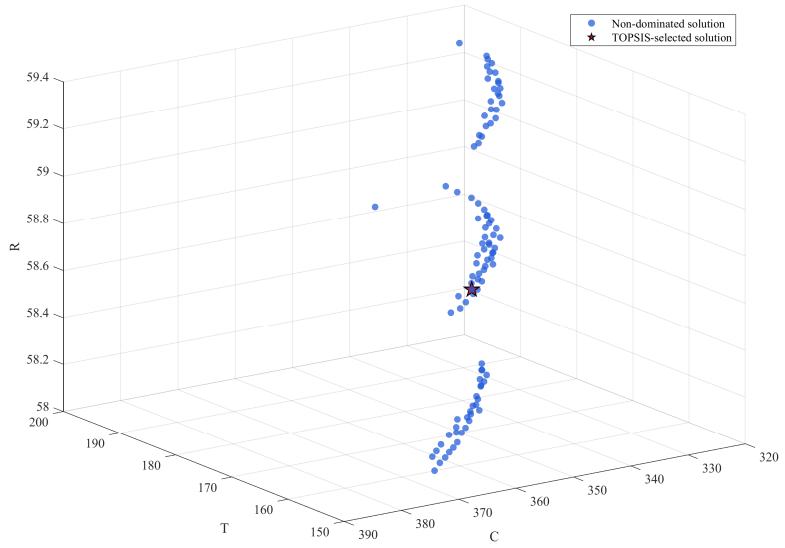


Figure 4. Pareto frontier generated by CMOPSO and the TOPSIS-selected compromise solution.

5.2.2. Analysis of the Significance of Time Limit-Cost-Risk Optimization to the Emergency Decision-Making Process of Marine Ranching Ecological Security

The urgency of ecological emergencies requires not only a short response duration but also a transparent way to balance cost and uncertainty. The proposed GC-CMOPSO framework supports this requirement by converting expert judgments into fused activity parameters, generating a non-dominated solution set, and then using TOPSIS to identify one representative compromise schedule for interpretation.

1. Critical stage identification with uncertainty quantification: The TOPSIS-selected schedule identifies a critical sequence that passes through expert organization, emergency decision-making, resource scheduling, monitoring and prevention, and post-incident processing activities. Compared with the CPM baseline under the original fused durations, the selected CMOPSO schedule reduces total duration from 190.00 days to 156.41 days, a reduction of 17.68%. The uncertainty-risk objective decreases from 59.283 to 58.791, a reduction of 0.83%. These results indicate that the improvement is mainly reflected in response-time compression, while uncertainty-risk reduction is more conservative.

2. Data-driven high-risk activity prioritization: The risk values in Appendix B should be interpreted as forecast-uncertainty indicators rather than observed probabilities of delay. Based on the combined duration-cost uncertainty values, activities 60, 24, 49, 27, 48, 20, 14, 61, 59, 15, 29, and 13 have relatively high uncertainty and should receive priority monitoring. This provides decision makers with a practical checklist for allocating management attention and contingency resources to activities where expert predictions are less reliable.

3. Robust optimization for ecological resilience: GC rules reduce the direct influence of conflicting expert judgments, while CMOPSO explores alternative schedules under the three objectives of duration, cost, and uncertainty risk. The algorithm does not produce a single universally best schedule. Instead, it produces a Pareto set, from which the reported solution is selected by TOPSIS under equal weights. If a decision maker gives stronger preference to cost control or risk avoidance, the same Pareto set can support a different final choice.

Overall, the results show that the proposed model can generate a Pareto frontier and make the trade-offs among duration, cost, and uncertainty risk explicit. The selected compromise solution shortens the project duration with an acceptable increase in total cost from 326.80 to 361.46, while slightly reducing the uncertainty-risk objective. Therefore, the contribution of the model is not only to obtain a shorter critical path, but also to provide a reproducible decision process for selecting emergency schedules under scarce historical data.

6. Conclusions

This paper addresses the challenge of event-network optimization when activity durations and costs are uncertain because historical data are scarce and expert judgments may conflict. The proposed framework first uses the GC rule to fuse expert judgments into activity-level duration, cost, and uncertainty-risk parameters. It then formulates a time-cost-risk multi-objective optimization model and solves it with CMOPSO to generate a Pareto set of feasible schedules. Finally, TOPSIS is used to select a representative compromise schedule for reporting.

The practical utility of the model was examined through a marine ranching ecological-security emergency case. The reconstructed network contains 62 real activities and two virtual start/finish nodes. Compared with the CPM baseline, the selected CMOPSO-TOPSIS schedule achieves a shorter completion time while increasing total cost from 326.80 to 361.46 and slightly reducing the uncertainty-risk objective from 59.283 to 58.791. This case demonstrates how the framework can support emergency scheduling decisions in data-scarce marine ranching contexts.

Despite its contributions, this study has several limitations that warrant consideration. First, activity parameters come from fused expert GC rules and rely on panel composition. Future work shall specify expert selection criteria and empirically validate parameters using emergency records. Second, uniform distribution is adopted for uncertainty calculation, and only logical activity dependencies are considered. Custom distributions (Beta/lognormal) and Copula/Bayesian networks can be adopted to model probabilistic correlations. Third, the 62-activity case only verifies basic applicability. CMOPSO's computational performance on large networks needs testing against other multi-objective algorithms, with sensitivity analysis on weights to check robustness for data-scarce, high-uncertainty emergency scheduling.

Author Contributions

Y.Y.: conceptualization, data curation, methodology, writing—original draft preparation; M.B.: supervision, validation; Q.Z.: supervision, validation. All authors have read and agreed to the published version of the manuscript.

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Data are contained within the article.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors declare that no generative AI and AI-assisted technologies are used.

Appendix A

Table A1. Emergency decision-making network for ecological security of marine ranching (64 network nodes, including virtual start node 0 and virtual finish node 63).

Project Stage	Number	Name	Tight Work
Start work	0	-	1
Emergency response-organizational design	1	Set up an expert group	2
	2	Develop a network design for marine ecological security in the event of an emergency	3, 4
	3	Early warning projects for ecological security	21, 32
	4	Decision-making engineering in the event of an ecological emergency	5
Emergency preparedness-making a plan	5	Historical case reference and comparison	6,8
	6	Extract information from events	7
	7	Identify the key factors of success and failure	9
	8	Consultee with experts	9
	9	Formulate an emergency plan	10
	10	Develop a library of emergency plans	11
Emergency preparation-resource scheduling-pretreatment	11	Conventional and unconventional resource planning	12, 15, 17
	12	The government's emergency reserve plan	13, 18
	13	Establish a special fund to ensure the ecological security of marine ranching	14
	14	Purchase a certain proportion of emergency resources in accordance with the plan	19
	15	Planning for emergency resources in marine leading enterprises	16
	16	Reserve emergency resources in accordance with government instructions	18, 19
	17	Distribution and reserve of emergency resources among nearby residents	18, 19
	18	All members of the society have joined forces to form a standing professional rescue team	20
	19	Plan the supply of resources	20
	20	Establish a regular resource standing system	28, 41
	21	Establish a disaster information network system	22, 25, 26
Emergency prevention-monitoring and forecasting	22	Monitor the collection of information	23
	23	Monitor information data screening	24
	24	Analyze dynamic forecast data	27
	25	Collect information and feedback from surrounding residents	27
	26	Collect early warning information from external sources	27
	27	Comprehensive arrangement of information	28, 32
	28	According to the emergency plan, select the appropriate plan for implementation in advance	29
Dealing with beforehand	29	Process result analysis	30
	30	Forecast the development results in more detail	31
	31	Re-measure emergency events and treatment outcomes	41
	32	Construction of the Early Warning Framework for Emergency Events	33
Emergency response-discovery and analysis of safety incidents	33	Reception of early warning results	34
	34	Information analysis	35, 36, 37
	35	Forecast the development trend	38
	36	Analyze the scope, mode, duration and harm degree of the incident	38
	37	Analyze the consequences of secondary disasters	38
	38	Integrate early warning analysis results and visual analysis	39
	39	Determine the classification and rating of emergency events	40
	40	Result output	41
	41	Plan security event resources	42
Emergency response-resource scheduling-processing process	42	Resource classification	43
	43	Inquire about related resources	44
	44	Resource scheduling	45, 46, 47
	45	Governmental resource supply and supplementary purchases	48
	46	Schedule enterprise resources	48
	47	Evacuation of nearby residents	48
	48	Arrangements for surplus resources	49
Complete treatment and aftercare	49	Detection and analysis of processing results	50, 51
	50	Detection of relevant safety indexes	52
	51	Analyze safety results	52
	52	Organize the processing results and data	53, 56
	53	Analyze related expenses and losses	54, 55, 56
	54	Pay related expenses	61
	55	Compensation for aftercare work	61
	56	Material analysis	57
	57	Reappearance of the emergency process	58
	58	Evaluate events	59
	59	Assessing the capability of emergency management	60
	60	Establish responsibility for an event	61
	61	Accountability and management of related responsibilities	62
	62	Arrange event warehousing	63
Finish work	63	-	END

Table A2. Expert prediction results after GC rule fusion for calculation (62 real activities, numbered 1–62).

Code Name	Duration	Minimum Duration	Maximum Duration	Project Cost	Upper Cost Limit	Lower Cost Limit	Cost Factor of Compress -ed Duration	Cost Forecast Risk	Forecast Risk of Construction Period
1	10	8	15	1	3	1	1.3	0.589	0.643
2	8	6.4	12	1	2	0.7	1.8	0.327	0.607
3	5	4	7.5	1.5	3.5	1	1.2	0.625	0.558
4	15	12	22.5	4	7	3	1.5	0.477	0.613
5	8	6.4	12	1.5	3	0.7	1.3	0.693	0.602
6	5	4	7.5	1.1	2.1	0.3	1.2	0.593	0.674
7	7	5.6	10.5	5	5.5	1.2	1.6	0.642	0.518
8	14	11.2	21	6	8	3.8	1.7	0.554	0.561
9	10	8	15	5	7	1.2	1.4	0.519	0.658
10	7	5.6	10.5	2.4	3.2	1.6	1.5	0.668	0.602
11	5	4	7.5	2.4	3	1.6	1.5	0.625	0.556
12	8	6.4	12	2	2.5	2	1.3	0.665	0.479
13	9	7.2	13.5	2.2	3	1.5	1.6	0.654	0.646
14	6	4.8	9	2.2	2.5	1.5	1.6	0.692	0.627
15	6	4.8	9	1.6	1.6	0.8	1.5	0.709	0.597
16	6	4.8	9	1.7	2.1	1.25	1.6	0.629	0.602
17	10	8	15	5	9	4	1.6	0.552	0.607
18	8	6.4	12	3	4.5	1.7	1.5	0.642	0.602
19	8	6.4	12	5	6.5	2.9	1.4	0.527	0.624
20	10	8	15	12	20	6.5	1.5	0.667	0.657
21	7	5.6	10.5	10	21	5.5	1.4	0.679	0.615
22	3	2.4	4.5	2	8	1.8	1.5	0.579	0.630
23	4	3.2	6	5	8.5	2.9	1.7	0.629	0.586
24	7	5.6	10.5	6	11	4.4	1.6	0.585	0.783
25	3	2.4	4.5	3.5	4.5	2.2	1.7	0.601	0.631
26	5	4	7.5	2.5	5.8	1.9	1.5	0.458	0.390
27	4	3.2	6	1.4	2.4	0.9	1.5	0.627	0.727
28	4	3.2	6	3	4	1.9	1.3	0.655	0.570
29	4	3.2	6	6	7.5	3.5	1.2	0.642	0.660
30	5	4	7.5	5	6.5	3	1.3	0.605	0.595
31	8	6.4	12	10	13.5	8.1	1.4	0.619	0.619
32	2	1.6	3	2	5.5	1.6	1.6	0.679	0.611
33	4	3.2	6	6	11.5	4.6	1.4	0.598	0.633
34	5	4	7.5	8	15	6	1.6	0.665	0.616
35	3	2.4	4.5	8	14	6	1.3	0.618	0.583
36	3	2.4	4.5	9	15	6	1.5	0.437	0.607
37	5	4	7.5	6	10.5	4.6	1.5	0.558	0.410
38	4	3.2	6	6	8.5	3	1.7	0.651	0.575
39	2	1.6	3	1.8	2.2	0.9	1.5	0.656	0.438
40	5	4	7.5	7	11.5	4.2	1.6	0.581	0.649
41	2	1.6	3	3.5	5	1.8	1.4	0.613	0.678
42	2	1.6	3	3	5.5	1.6	1.5	0.745	0.546
43	3	2.4	4.5	10	13	7	1.4	0.655	0.577
44	4	3.2	6	12	18	7.5	1.5	0.639	0.598
45	3	2.4	4.5	5	6.5	3	1.5	0.549	0.630
46	2	1.6	3	6	11	4	1.4	0.604	0.568
47	4	3.2	6	2	5	1.6	1.5	0.659	0.639
48	4	3.2	6	6	14	6	1.7	0.593	0.755
49	4	3.2	6	9	15	5	1.5	0.679	0.689
50	3	2.4	4.5	8	16	6	1.5	0.734	0.558
51	2	1.6	3	1.5	3.5	1.1	1.6	0.652	0.611
52	2	1.6	3	3.5	5.5	1.8	1.4	0.668	0.598
53	0	0	0	30	65	12	1.5	0.628	0.639
54	5	4	7.5	10	15	7	1.4	0.602	0.597
55	5	4	7.5	5	9.5	3	1.4	0.551	0.615
56	4	3.2	6	7	9	4	1.5	0.598	0.623
57	3	2.4	4.5	8	16	6.5	1.4	0.672	0.612
58	1	0.8	1.5	5	8	3.5	1.5	0.621	0.658
59	5	4	7.5	5	8.5	2.5	1.4	0.648	0.661
60	6	4.8	9	7	13	5	1.5	0.673	0.711
61	2	1.6	3	2.5	5.5	1.2	1.5	0.679	0.634
62	2	1.2	3	4	6	3	1.2	0.534	0.621

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