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Decision Making and Robust Optimization for Information Systems Oriented to Emergency Events

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Abstract

The landscape and the factors affecting the development of advanced tools (e.g., artificial intelligence, predictive analytics of outbreaks, knowledge management, vigilance, and reporting systems) with specific concern on supply chain disruptions are described, so as the main topics on health emergencies, preparedness, and mitigation are introduced. This work deals with Multi-Criteria Decision Making (MCDM) tools to address the Suppliers Selection Problem (SSP) and prepare emergency responses by applying Robust Optimization (RO) models, dealing with uncertainty and risk, and coping with computational issues. Definitions and goals are updated, and approaches and models for emergency preparation and responses are adjusted to enlighten the costing and performance indexes. Relevant topics are also integrated: the provisions (and procurement) disruptions and the mitigation of related impacts. After that, an actual situation for deciding on the supplier bid for Information Systems oriented to emergency events is addressed. The decision matrix is built using the referred criteria. Four different MCDM methods/models with the associated software are applied: (i) the simple additive model, (ii) the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) model, (iii) the "e" Fuzzy model, and (iv) - the Elimination and Choice Expressing Reality (ELECTRE) model. The hierarchy of alternatives is built, and the decision process ends by assigning one of the bidder supplier companies. As the differences between the obtained hierarchies are minor, a comparative analysis that addresses the deviation amplitude, the best and the least alternatives, is performed.

Keywords: emergency management, hierarchical models, comparative analysis, supply chain disruptions, supplier selection, vigilance and reporting systems, multi-criteria decision-making

1 Introduction

Emergency events, in particular health emergencies, such as pandemics, bio-terrorism, or natural disasters, may lead to widespread illness, causing significant morbidity and mortality on a global scale, millions of deaths, and major disruptions to economies and daily life worldwide. Such events need prompt recognition and action to minimize harm and improve the outcomes. Developing robust and adaptive response systems based on advanced tools like predictive analysis, Artificial Intelligence (AI), knowledge management, and vigilance and reporting systems significantly enhances emergency preparedness and response capabilities. To ensure effective supplier selection and resource allocation and to face challenges in supply chain disruptions, information systems are needed to implement robust optimization and multi-criteria decision-making (MCDM) models. There are many Advanced Tools for Health Emergencies, and we have several examples of such tools used in real situations.

Artificial Intelligence and Predictive Analytics - AI and PA are pivotal in forecasting outbreaks and managing emergency responses. For instance, machine learning models can analyze vast amounts of data from various sources to predict the spread of infectious diseases, enabling timely interventions. Predictive analytics can forecast resource needs, helping pre-positioning supplies and optimizing logistics.

• Example: During the COVID-19 pandemic, AI algorithms were used to predict hotspots and spread patterns, allowing authorities to allocate resources more effectively [10].

Knowledge Management Systems (KMSs) - Effective KMSs ensure accurate and timely information is available to all stakeholders, enhancing coordination and response efforts. These systems store and disseminate best practices, protocols, and real-time data, supporting decision-making processes.

• Example: The WHO's Global Outbreak Alert and Response Network (GOARN) uses knowledge management systems [19] to coordinate international responses to outbreaks.

Vigilance and Reporting Systems (VRSs) - Robust VRSs monitor health events and report incidents, enhancing situational awareness and supporting proactive measures. These systems integrate data from various sources, providing a comprehensive view of the situation.

• Example: The WHO's Global The CDC's BioSense program collects and analyzes data from hospitals and clinics to detect and monitor health threats [11]. EpiPulse is the European Portal for Infectious Diseases, integrating several previously used applications. It is used by European public health authorities and partner organizations to collect, analyze, share, and discuss data for threat detection, monitoring, risk assessment, and infectious disease outbreak response, such as the case of botulism in 2023 [5] or the one of severe acute respiratory infection in a sentinel hospital in Ireland in 2021-2022 [1].

Supply Chain Disruptions in Health Emergencies - Supply chain disruptions - such as delays, shortages, and logistical constraints - can severely impact emergency response efforts. Understanding the factors contributing to these disruptions, such as geopolitical instability, transportation issues, and demand surges, is essential for developing mitigation strategies.

• Example: During the early stages of the COVID-19 pandemic, global supply chain disruptions led to shortages of personal protective equipment (PPE) and medical supplies [18] highlighting the need for robust supply chain management. Later, the world economy and health system were seriously affected by the disruptions in the vaccine procurement supply chain [2].

Multi-criteria Decision-Making (MCDM) Tools - MCDM tools are essential for addressing the Suppliers Selection Problem, particularly in the context of emergency preparedness. These tools evaluate multiple criteria, ensuring a comprehensive assessment of potential suppliers. The four MCDM methods widely used for supplier selection are:

(A) Simple Additive Weighting (SAW): sums weighted criteria scores to rank alternatives.

- (B) TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution): identifies solutions closest to the ideal and farthest from the worst-case scenarios.
- (C) Fuzzy Model: uses fuzzy logic to handle uncertainty and subjective judgments in criteria evaluation.
- (D) ELECTRE (Elimination and Choice Expressing Reality): Compares alternatives based on outranking relationships.
 - Example: The pharmaceutical laboratories produce new generations of medicines, and the managers and decision-makers use advanced tools to integrate the decision methods in their supply chain activity [12].

Robust Optimization Models (ROMs) - ROMs handle uncertainty and risk in decision-making processes. It considers uncertainties in demand, supply, and transportation time to provide solutions that remain effective under various scenarios. These models are crucial in ensuring the reliability and performance of emergency response systems.

• Example: A robust optimization model for resource allocation and location planning was built based on the lessons learned in China during the COVID-19 pandemic [6].

2 Robust tools to address the Suppliers Selection Problem

Uncertainty or incomplete data usually occurs in complex optimization problems considering long planning horizons. Diverse and complementary procedures are often developed, such as the mean average value (e.g., the expected value problem, EVP) or the worst-case scenario. The typical sensitivity analysis studies correspond to a reactive approach to optimal decision-making, as they aim to clarify the impact of data uncertainty on the optimal values for the project variables.

The robust value is thus addressed, and the associated finance and economic estimators are defined. This way, non-overlapping is guaranteed - IS technical estimators are treated through two sets of non-overlapping mutually independent criteria: the suppliers' capacity and quality, as addressed later in Section 3.

The multi-period robust approach is beneficial because the emergency system must respond to unpredictable and rapid deviations from operating conditions. Otherwise, it would be inefficient or even inoperable.

The implementation plans are carried out with a distant insight into the future, but only the first step is compromised in the project phase. Any deviations from the initial decision will be subject to further corrections due to the successive re-appreciation of initial assumptions. The RO approach considers the estimation of scenario probabilities and the associated penalties in case of any deviations.

Usually, diverse scenarios are developed following the uncertain environment, and the decision process is separated into two or even multiple phases, allowing proactive actions focused on data variability and fluctuations.

The **robust NPV** is the objective function for the robust model. It aims to maximize the expected Net Present Value (NPV), with robustness promoted by weighting and penalizing the expected value for the variability of the solutions, dvtn, the expected non-satisfied demand, Qns, and the expected capacity slackness, slk, as in formula (1):

$$[max]\Phi' = \sum_{r=1}^{NR} prob_r \xi_r - \lambda \ dvt \sum_{r=1}^{NR} prob_r.dvtn_r - \lambda \ qns \sum_{r=1}^{NR} \frac{prob_r}{NC.NT} (\sum_{j=1}^{NC} \sum_{t=1}^{NT} Qns_{jtr}) - \lambda \ slk \sum_{r=1}^{NR} \frac{prob_r}{M.NC.NT} (\sum_{i=1}^{M} \sum_{j=1}^{NC} \sum_{t=1}^{NT} slk_{ijtr})$$

$$(1)$$

Estimators,	Net Present	nt Benefit-Cost Paybao		Internal
Scenarios	Value	Ratio	(years)	Return Rate (%)
1	40.91	1.82	0.50	100
2	36.78	1.74	1.09	61.8
3	32.90	1.66	1.59	44.6
4	29.25	1.58	2.26	34.9
5	25.82	1.52	3.01	28.6
6	22.59	1.45	3.51	24.3
7	19.55	1.39	4.33	21.1
8	16.69	1.33	5.21	18.6
9	13.99	1.28	6.14	16.7
10	11.45	1.23	7.13	15.1
11	33.01	1.66	1.45	46.2
12	22.98	1.46	3.27	25.4

Table 1: Economic estimators for the scenarios under analysis

2.1 The economic estimators

The economic estimators used in the appreciation of the best solution for multi-period instances follow:

(A) The total cost is assumed to be 50 M€ for a planning period of 10 years, based on the estimated cost of 25 M€ for design-build-operate (DBO) in a 5-year horizon [8]:

$$C_{total} = 50, \forall r \tag{2}$$

The expected value of **non-robust NPV**, *Ecsi*, corresponds to the NPV estimator obtained from the payments matrix (uniform probability) in Annex:

$$Ecsi = \sum_{r=1}^{NR} prob_r \xi_r \tag{3}$$

The NPV at each scenario, r, considers the net present payments minus the investment cost (of 50 M \in) on a 10-year horizon:

$$\xi_r = \sum_{t=1}^{NT} P_t - 50, \forall r$$
(4)

(B) The **benefit-cost ratio** on a percentage base is:

$$\%Benef = 100 \frac{Ecsi + C_{total}}{C_{total}} \tag{5}$$

(C) The **payback or return of investment** (ROI), in years, is obtained from the relations:

$$payback = t' - 1 + \frac{C_{total} - \sum_{t=1}^{t'-1} Ecash(t)}{Ecash(t')}$$
(6)

$$Ecash(t) = \sum_{j=1}^{NC} \sum_{r=1}^{NR} (prob_r.ret_{jtr}.W_{jtr})$$
(7)

(D) The **internal rate of return** (IRR) is obtained through the discount return values to the initial time period, *Ecash_0*, and this estimator is taken as:

$$\sum_{t=1}^{NT} E cash_0(t) \le C_{total} \tag{8}$$

$$Ecash_0(t) = Ecash(t)\frac{(1+intrat)^t}{(1+IIR)^t}$$
(9)

Alternatives	Penalties for Non-Satisfied Requirements	Design, Build & Operate			
	$\lambda\partial$	DBO			
	range	range			
A_1	5 - 7	Low			
A_2	11 - 13	Intermediate			
A_3	5 - 7	Low			
A_4	17 - 19	Full			
A_5	17 - 19	Full			
$\overline{A_6}$	11 - 13	Intermediate			

Table 2: The six alternatives and related service levels

Table 1 presents economic estimators associated with the best solution obtained in each multiperiod instance. There is a short space of growth for such estimators. Thus, the successive increase of requirements leads to a deterioration of economic estimators (*Benefit/Cost, Payback, IRR*).

The estimators in Table 1 are obtained from the payments matrix in the Annex, with the 12 economic scenarios assuming equal (uniform) probability. Although these economic estimators are based on the total return of 100 M \in , an overestimation of robust value is promoted. In this manner, the robustness of the reported solution is verified in the range of penalization parameters (Table 2) under analysis.

Some project partners were challenged to play the role of applicants or suppliers, that is, the alternatives (A_1-A_6) , to better emulate the tendering application; the applicants are asked to outline the service level (Table 2) in conjunction to simulate the decision matrix (Table 3). Beyond surveying the multiple criteria under analysis, interviews were conducted to properly clarify the attributes within each criterion, terminology, or standards of reference - among other items of interest. Without formal agreement(s) within this study, the contributors' anonymity shall prevail. The selected profiles follow:

- A₁ Higher Education Institution, Public Sector, Romania;
- A₂ Higher Education Institution, Public Sector, Portugal;
- A_3 Higher Education Institution, Public Sector, national node of European network;
- A₄ IT Multinational, Private Sector;
- A₅ IT Multinational, Private Sector;
- A₆ Civil Protection Institution, Public Sector, Portugal.

The alternatives' set is thus representing the best IS configurations for different service levels, namely:

- Full service the equipment and the sizes required to fully provide the emergency IS to be implemented (significant penalization parameters associated with the activities of design-build-operate, DBO).
- Low service the relaxation of most demand requirements occurs, assuming the ideal requirements cannot be fully satisfied. The IS requirements are evaluated facing their economic suitability (zero or very low penalization).

• Intermediate levels - intermediate levels for the relaxation of IS requirements, assuming the requirements hardness increases with the penalization parameter (interim values for such parameters).

2.2 Argument for outsourcing

To have an effective and efficient platform to assist decisions for emergency preparation and responses, the following three cases should be analyzed: i) to design and build it in-house; ii) to procure the platform and use it as a service; and iii) a combination of the two. The general practice for deciding between the above considers criteria such as budget constraints, project control and oversight, skills availability, scalability requirements, quality and standards, data security and confidentiality, cultural and operational aspects, time to market, scalability, and risk mitigation. Outsourcing of services has been widely used for decades, mainly to reduce costs. Lately, outsourcing has become a strategic tool for organizations in the private sector and public institutions. It allows for the implementation of new technologies and processes. A recent study [16] made for the National Health Service of the United Kingdom took a qualitative approach with a multiple-case study concept and identified a set of factors to be considered when outsourcing. These factors are grouped into seven areas: Environmental, Financial, Legal, Risks, provider availability, Social Factor, and Trust Factor. Based on this general approach, former studies [20], [21] and the report of the European Commission on the Covid-19 platform tender for the HERA-Health Emergency Response Agency [4] strongly recommend the acquisition of a fully outsourced platform as a service (PaaS) to be delivered securely over the web using the latest digital and cloud technology. When referring to platforms in emergency situations, particularly in healthcare, outsourcing the software development for large platforms will allow a significant decrease in the time to market, such a platform coming online at least one year earlier than in-house solutions, as the service provider can use and further develop existing solutions. Moreover, the service provider will take on all the risks relating to the technology and security while the service can be extended to supply risk sensing and intervention advice. In addition, it is also reported [8]:

- Based on the collected data and with a supply and value chain map documented in reports and dashboards, risks can be rapidly assessed, and early warning will allow the drawing up of actionable risk mitigation strategies.
- A relatively stable demand across the years is assumed, with a reduction of around ten percent for each service, for each year as the service provider becomes more efficient in delivering the service and can partially share this benefit.
- Discounts related to sustained demand over the years can be achieved, too.
- By outsourcing some of the risk assessment, the supply and demand models will be leveraged, with the cascading effect coming from the supply chain mapping and network analysis. This outsourcing does not significantly influence the cost.
- The lack of upfront capital investment and reduced need for in-house talent to operate the platform ensures the cost-benefit provided by managed services; a service provider can bring accelerators from existing assets and scale up more easily as and when required.

3 MCDM tools to address the Suppliers Selection Problem and prepare emergency responses

Multi-criteria decision-making (MCDM) techniques for the Supplier Selection Problem (SSP) deal with the specificity of the field it is used for. To address SSP challenges, the model must account for comprehensive time and resource constraints, a particularly demanding task due to the extensive and intricate nature of robust models. These models typically handle binary decisions (e.g., "Yes or No?"), nonlinear processes (e.g., user interface rules, distribution of storage capabilities), uncertainties (e.g., system demands, energy costs, resource availability), and interactions among stakeholders along the supply chain.

3.1 The decisional matrix

This research was conducted by considering general criteria used by the EC in projects and tenders like those of the HERA [8] and based on the expertise of companies and public authorities dealing with emergency preparedness and response. The stakeholders' main criteria, such as ensuring a comprehensive assessment that balances financial stability, professional experience, cost-effectiveness, and overall quality, are synthesized in Table 3.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C7	C_8	C_9	C_{10}	C ₁₁	C_{12}	C_{13}	C_{14}
Supplier	Turn	Cap1	Cap2	Rel	Pric	Rob	Tech	Stor	Qual	GDPR	Flex	Sec	Inter	Maint
A_1	5	6	6	10	5	5	9	10	5	8	5	10	10	7
A_2	6	7	5	9	8	8	9	5	9	10	9	10	9	9
A_3	8	5	10	8	5	5	9	8	8	9	10	9	9	9
A_4	9	9	7	8	8	9	10	10	9	10	10	10	8	10
A_5	9	9	10	9	6	6	9	5	9	6	8	10	7	9
A_6	2	5	3	10	8	6	8	7	9	10	8	10	9	8
Weights	0.04	0.06	0.06	0.04	0.1	0.1	0.08	0.08	0.06	0.08	0.1	0.07	0.06	0.07

Table 3: The decision matrix (raw data)

In Table 3, suppliers are evaluated by 14 criteria (C_1-C_{14}) defined around three areas, namely, capacity, price and robust value, and quality:

Capacity criteria:

- C_1 Rank According to Turnover This criterion evaluates the supplier's financial health based on their annual turnover. Higher turnover indicates a more financially stable company that can handle project costs and potential financial risks better.
- C_2 **Professional Capacity** Number of qualified persons available for the project. It assesses the number of human resources the supplier allocates to the project. More HR availability suggests a better capability to meet project demands and deadlines.
- C_3 Expertise / Experience Number of Similar Projects implemented. It measures the supplier's experience in handling similar projects. A higher number of similar projects indicates greater expertise and reliability in executing the project successfully.
- C_4 **Reliability** This criterion measures the supplier's consistency in delivering projects on time and within budget and their track record for meeting project specifications.

Price and Robust Value (the economic criteria):

- C_5 Cost of the supplier's proposal (10%) Typically, this is a percentage weight in the overall evaluation, with lower prices being more competitive. However, the lowest price isn't always the best; it should be balanced with quality and capacity.
- C_6 Robust value (10%) Evaluates the typical economic estimators on investment projects. The cost criterion C_5 is complemented to obtain higher robustness. Data for the economic criteria (C_5 - C_6) in Table 3 is estimated in line with the service levels (Table 2) and investment estimators (Table 1), as described in Section 2.2.

Quality criteria:

- C_7 **Technology** Evaluates the technology's age and market presence. Newer, widely adopted technologies might offer better performance and support.
- C_8 Data storage and processing capability Evaluate the overall capability of the system to build scenarios quickly and to assist the decision maker.
- C_9 Quality Plan Assesses the quality plan's comprehensiveness and robustness. A welldefined quality plan ensures the project meets required standards and client expectations.
- C_{10} **Data Protection** Checks if the supplier complies with GDPR regulations and has additional data protection measures. Compliance ensures the protection of personal data according to legal standards.

- C_{11} **Flexibility** Evaluates how adaptable the supplier is to changes or to unforeseen circumstances in the project. High flexibility indicates a better ability to handle project variations. It also considers the level of reliability of the IT technology used for the platform prototype in terms of day-to-day use as well as in the possibility of making full use of artificial intelligence (e.g., algorithms) to optimize the platform experience [8], [3].
- C_{12} **Data Security** Assesses the security measures for data storage and operational processes. Secure data handling minimizes the risk of data breaches and loss.
- C_{13} User Interface Evaluates the user interface's design, operational facility, and usability. A good interface enhances user experience and can increase productivity and satisfaction.
- C_{14} Maintenance Quality of the Service Level Agreement (SLA). This criterion assesses the SLA regarding maintenance services. This includes expected downtime, redundancy measures, and the availability of intervention when issues arise. A robust SLA ensures high system availability and quick problem resolution.

The SSP is solved according to the best price-quality ratio, and the suppliers are ranked following the formula (10), adapted from [8].

$\begin{vmatrix} Score \\ for \\ supplier \end{vmatrix} = \begin{vmatrix} P \\ Robu$	rice $+$ stness $*$ 20% $+$	Total quality score for all * awarded criteria	80%	(10)
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The Price criterion is critical [8], and the Robustness of the solution is also highly important, the related weighted average being established at 20% of the total Price and Robustness and 80% of the total Quality score. This paper deals with the total quality score as a bundle of the Capacity and Quality criteria, considering that the financial and professional capacity of the supplier will essentially influence the quality of the platform. In detail, the weights for individual criteria are established by using the Universal Specialists Test ([3], [9], [17]) in the framework of the EC tender practice (adapted from [8]), specifically: Organization capacity (C_1 - C_4) – 20%, Economic criteria (C_5 , C_6) – 20%, Methodologies (C_7 - C_{10}) – 30%, IT platform flexibility (C_{11}) – 10%, and Quality & measures (C_{12} - C_{14}) – 20%.

Should the outcome of the formula (10) lead to two or more suppliers with the same result, the supplier awarded the highest marks for quality will be deemed the most economically advantageous one.

3.2 Results & comments

Using MCDM methods allows for a structured and systematic approach to decision-making where multiple objectives need to be balanced. The flexibility and robustness of MCDM methods make them suitable for complex problems with competing criteria, providing decision-makers with a clear rationale for their choices. Each method has its strengths and is suitable for decision problems of many different types.

This paper applies the most common MCDM methods to solve SSP: SAW, TOPSIS, FUZZY model, and ELECTRE method [12]. The ranking of the suppliers obtained by applying each of these methods is presented in Table 4.

The inconsistencies in the result given by the ELECTRE method can be eliminated using one of the methods known from the literature, like the computation of the integrated surclass (downgrade/outclass) index or the modified concordance-discordance matrix ([12], [14], [15], [13]). However, the final ranking can be established by combining the results of the four methods (as illustrated in Table 4). Thus, the inconsistency in the ELECTRE ranking can be ignored. Moreover, the practice of the EC [8] gives sufficient guidance in such supplier selection procedure. Following these considerations, we propose the following ranking for the case analyzed in the paper: A_4 , A_2 , A_5 , A_3 , A_6 , A_1 - as ranked by SAW and TOPSIS in Table 4 in agreement with what the outcome of the majority voting confirms in the same table. SAW and TOPSIS rankings are the only ones confirmed by the majority voting of all models. Each of their rankings is granted individually for a specific profile A_k ($k \in \overline{1, 6}$) with an agreement of at least 50%, and at most 75% of the majority voting. Considering the

Table 4: Ranking by all four models (SAW, TOPSIS, ELECTRE, and FUZZY) and the results of majority voting establishing the hierarchy $1 : A_4, 2 : A_2, 3 : A_5, 4 : A_3, 5 : A_6, 6 : A_1$ with the confidence weights of 0.75 for the 1^{st} , 2^{nd} , 5^{th} , and 6^{th} places, and confidence weights of 0.50 for the 3^{rd} and 4^{th} places

	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Maj.	Confidence
Profile	SAW		TOPSIS		ELECTRE		FUZZY		Vot.	Weight
A_1	0.7346	6	0.0466	6	2	4	11.1964	6	6	0.75
A_2	0.8572	2	0.0302	2	3	2	10.4117	3	2	0.75
A_3	0.8202	3	0.0356	3	0	6	10.6406	4	3	0.50
A_4	0.9620	1	0.0121	1	3	2	10.0263	1	1	0.75
A_5	0.8126	4	0.0364	4	5	1	10.3714	2	4	0.50
A_6	0.7868	5	0.0413	5	2	4	11.0500	5	5	0.75

agreement percentages of the majority voting as confidence parameters, the hierarchy A_4 , A_2 , A_5 , A_3 , A_6 , A_1 coincides with the ascending order of the rankings, but not necessarily with descending order of agreement percentages (as confidence parameters) - a fact evidenced in the last column of Table 4.

4 Conclusions

In this study, we tackled the complex problem of supplier selection by employing (a combination of) Multiple Criteria Decision Making (MCDM) methods and robust optimization. The primary goal was to determine the most suitable supplier for a platform used in emergency preparedness and adequate response delivery by considering various critical criteria influencing decision-making in this domain. Data for the practical case study was gathered from different stakeholders, including suppliers and specialists, to act in the case of emergency situations.

RO's importance is widely recognized among other approaches within the Multi-Criteria Decision Aiding/Making (MCDA/M) area. RO allows stochastic treatments beyond the EVP, with robustness achieved in models and solutions. The economic estimators and technical parameters are adjusted in line with the risk treatment's targets in such an approach.

We applied several MCDM techniques, including SAW (Simple Additive Weighting), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), ELECTRE (Elimination and Choice Translating Reality), and Fuzzy Logic. These methods allowed us to handle different aspects of supplier selection, such as evaluating suppliers' performance based on multiple criteria (organizational capacity and quality aspects) and ranking the alternatives to support the decision-making process.

The integration of these methods resulted in a robust and well-rounded supplier selection framework. The final outcome was a prioritized list of suppliers, reflecting a balanced consideration of all relevant criteria. The combination of MCDM methods with robust optimization, enhanced by the use of the Universal Specialist Test [17] and of the surclass (downgrade/outclass) index contributed to a comprehensive and consistent decision-making process.

In conclusion, our approach demonstrates the efficacy of integrating multiple decision-making methodologies and optimization techniques in complex supplier selection problems. This comprehensive framework can be applied to various industries and decision-making scenarios. It offers a robust tool for organizations to optimize their supplier selection processes and enhance their overall supply chain performance.

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