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Research Article

A strategic and operational framework for pre-disaster management considering sustainability, resilience, and smart city using multi-criteria decision-making and mathematical optimization

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Abstract

With surging population and rising natural disaster threats, disaster management and its continuous improvement have become global concerns. This study presents a strategic framework for enhancing disaster management in preparedness and risk reduction phases, employing MCDM and mathematical optimization methods while incorporating sustainability, resilience, and smart city approaches. Aspects and criteria for disaster management are identified through literature review and expert consultation. SWARA and WASPAS methods determine the importance of Aspects and criteria, region prioritization, and earthquake vulnerability assessment. A non-linear three-objective integer programming mathematical model is formulated to minimize operational costs, maximize camera and sensor coverage, and enhance reliability. This model encompasses supplier selection, warehouse location, inventory control, and IoT equipment allocation to establish a smart city infrastructure in selected regions.The research findings highlight the importance of infrastructure, social, and physical Aspects, along with criteria such as the number of healthcare centers, transportation networks, fire stations, population density, and ICT infrastructure, for prioritizing disaster management efforts. Emergency supplies, warehouses, and suppliers were identified to ensure crisis preparedness . Inventory control policies for order quantity and safety stock determination were employed to reduce costs and enhance crisis response readiness. Furthermore, several normal regions were selected for smart city infrastructure development, and the allocation of various cameras and sensors was optimized considering coverage radius, reliability, and demand variability reduction compared to normal regions. A case study of Isfahan's 15 districts demonstrated the framework's problem-solving capability. Sensitivity analysis revealed that the objective function is influenced by maintenance costs, demand correlation coefficient, and average demand. This research can serve as a foundation for future studies in disaster and crisis management optimization and has the potential for application in disaster management organizations and other regions.

***Keywords*:** Disaster Management; Relief Logistics Network; Smart City; Pre-Disaster; Location-Allocation; Internet of Things; SWARA; WASPAS

1. Introduction

Disaster management is one of the most critical challenges facing the world today. According to studies and forecasts, the global population in urban and rural areas will increase to approximately 21 percent and reach 9.7 billion people by 2050 (United Nations Department of Economic and Social Affairs, Population Division, 2022). A 68 percent growth in the urban population rate is expected over the next three decades, based on the breakdown of the population by urban and rural areas (United Nations Department of Economic and Social Affairs, Population Division, 2022; World Urbanization Prospects, 2019). Natural disasters such as earthquakes, storms, and floods are among the top ten most likely risks in the next decade (The Global Risks Report**,** 2023).
Disaster management is a comprehensive system that encompasses both managerial decisions and operational actions. Evaluating and prioritizing regions serve two crucial purposes in disaster management: prevention and optimal resource allocation (Aksoy and Selim, 2020; Güller et al., 2023; Aktaş, 2022). Earthquakes are among the most catastrophic physical and psychological hazards worldwide. Assessing and prioritizing vulnerability is a prerequisite for earthquake risk assessment, prevention, and mitigation (Alizadeh et al., 2018; Jena et al., 2020; Shakibai et al., 2023; Zare-Bahramabadi et al., 2023). Optimal resource allocation is another critical objective in disaster management research. However, a significant challenge lies in assigning equal importance weights to all relief areas (Aljohani et al., 2023; Liu et al., 2023; Kheildar et al., 2023).
One of the primary strategies for enhancing the efficiency of relief operations and reducing delays and shortages is the pre-disaster location and establishment of distribution centers to distributerelief supplies (Ghasemi et al., 2019; Hajipour et al., 2021). Determining the location of distribution centers and controlling inventory levels, assigning distribution centers to affected areas with minimum costs and distance to demand points are essential actions in the preparedness phase (Du et al., 2020; Baser & Behnam, 2020; Goodarzian et al., 2021).
The emergence of the Internet of Things (IoT) and the concept of smart cities has gained significant traction as a promising solution for enhancing human quality of life in

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economic, social, political, and disaster management Aspects. A city is considered smart when its management and optimization infrastructure is in place (Batty et al., 2012; Rathore et al., 2016). While this concept makes cities more intelligent in their operations, they are not necessarily resilient in disaster management (Khatibi et al., 2022). Consequently, incorporating resilience Aspects into smart city design is crucial to address this challenge. The IoT enables continuous data collection through dispersed devices across regions (Elshamy et al., 2019; Aljohani et al., 2023; Colajanni et al., 2023). The presence of Information and Communication Technologies (ICTs) in disaster situations can significantly impact demand management and relief efforts by reducing demand uncertainty. However, ICTs have been largely overlooked in humanitarian logistics studies (Nodoust et al., 2023).

In disaster management, multicriteria decision-making (MCDM) methods are employed as valuable tools for structuring decision-making systems. Complex decisions in this domain necessitate the simultaneous consideration of multiple criteria, and MCDM can enhance the accuracy and effectiveness of these decisions (Peng, 2015; Aktaş, 2022; Akbarian et al., 2022). Additionally, multi-objective optimization (MOO) techniques are crucial in disaster management. This capability aids decision-makers in making more effective decisions (Tirkolaee et al., 2020; Guo and Zhang, 2022; Mahmoodi et al., 2022; Ming et al., 2022).

The driving force behind this research is to enhance the efficiency of both strategic and operational disaster management decisions. Our study introduces novel approaches to achieve this goal. For the first time, it simultaneously addresses disaster management in both normal and smart regions, specifically in the pre-disaster phase. The integration of IoT technologies, including cameras and sensors, into some normal regions aims to reduce the demand deviation of these areas. Furthermore, the concepts of sustainability and resilience are incorporated into identifying Aspects and evaluation criteria for disaster management. Considering the complexity and diversity of decision-making domains in disaster management, a combination of MCDM and MOO methods is employed to facilitate comprehensive decision-making. The practical findings of this research, conducted in Isfahan County, provide valuable insights for policymakers in the field of disaster management. These innovations contribute to improving disaster management efficiency by providing a framework and utilizing cutting-edge technologies.

In this research, a multi-stage methodology is proposed for strategic and operational decision-making in disaster management, incorporating sustainability, resilience, and smart city concepts. The strategic decision-making stage involves identifying Aspects and criteria using literature review and expert consultation, assessing content validity with Lawshe's method, determining weights with SWARA, and prioritizing earthquake-prone regions with WASPAS. The outcomes of this stage guide resource allocation and prioritization, including action prioritization and earthquake region weighting. The operational decision-making stage involves developing a three-objective nonlinear integer programming (NIP) mathematical model to optimize operational costs, camera and sensor coverage, and system reliability. The model incorporates supplier selection, warehouse location, inventory control policy determination, IoT equipment allocation, coverage radius consideration, and failure rate consideration.

The remaining sections of the research are structured as follows. Section 2 presents a comprehensive review of disaster management literature and MCDM methods, providing a theoretical foundation for the analysis and decision-making process. Section 3 details the research methodology, including the research design, data collection methods, identified Aspects and criteria, and the mathematical model developed for operational decision-making. Section 4 presents the results analysis based on a case study, including the prioritization of earthquake-prone regions and the optimal solutions obtained from the mathematical model. Section 5 concludes the research by discussing the findings, implications, limitations, and directions for future research.

2. Literature Review

This section reviews some of the most significant research conducted in the field of disaster relief logistics, categorized into two main themes: "Literature related to prioritization, evaluation, and decision-making" and "Literature related to mathematical optimization" in disaster management.

A disaster or catastrophe refers to the occurrence of an undesirable and destructive situation in a community or environment. Disasters are typically associated with serious threats to life, safety, security, balance, and the normal functioning of entities. Disasters can be classified into two categories based on their nature and origin: natural disasters and man-made disasters (Shakibaei et al., 2023; Çakar et al., 2021; Yu et al., 2018; Drabek et al., 2003). Disaster management is divided into two main phases: pre-disaster and post-disaster (Carter, 1991; Alexander, 2002; Sawalha, 2020). The disaster management cycle, which includes the stages of mitigation and prevention, preparedness, response, and recovery, is the most common framework for disaster management. Pre-disaster activities include hazard assessment, risk reduction, and preparedness. Post-disaster activities include response, reconstruction, and recovery.

Relief logistics plays a critical role in disaster management by enabling a rapid and effective response to the needs of affected people and areas. Relief logistics encompasses a series of stages, including procurement of relief items, warehousing and inventory management, distribution and transportation, resource management, information transfer, and disaster compensation. These activities are carried out with the aim of creating preparedness and an appropriate response in the face of incidents and assisting affected individuals and areas (Bullock et al., 2017; Canton, 2019; Ye et al., 2020; Zhang et al., 2023). When disaster management measures are properly designed, financial and human losses can be reduced (Ming et al., 2022).

2.1.1 Literature related to prioritization and evaluation

In the face of destructive events such as natural and man-made disasters, the planning and prioritization process is crucial (Fang et al., 2019; Sarma et al., 2020). Due to the limited resources and time available during disasters, it is often not possible to protect all assets. Therefore, assets are prioritized after considering their desired value for protection (Bashiri et al., 2021). By employing MCDM techniques and utilizing expert opinions, the priority of each region and its associated risk are determined (Shakibaei et al., 2023).

Jena et al. (2020), presented an earthquake vulnerability assessment in North Sumatra Province using a multi-criteria decision-making model. The aim of this study was to assess earthquake vulnerability using MCDM through AHP and VIKOR methods using a geographical information system. In this research, social vulnerability, structural vulnerability, and geotechnical vulnerability criteria were assigned weights and prioritized using pairwise comparison. The results showed that the central part of the city has high to very high vulnerability. Özkaya and Erdin (2020), presented an evaluation of smart and sustainable cities using a hybrid MCDM approach. Based on a literature review, the fundamental Aspects of smart cities were evaluated using the criteria of regional competitiveness, transportation, information and communication technology, economy, natural resources, human and social capital, quality of life, and citizen participation. The Analytic Network Process (ANP) was used to weigh the criteria of smart and sustainable cities, and the TOPSIS method was used to prioritize them. According to the results, the smart living and smart governance criteria were evaluated as the most and least important features, respectively.

Malakar and Rai (2022), developed an earthquake vulnerability assessment in the Himalayas using MCDM models based on social, geotechnical, structural, and physical parameters. In this study, the AHP method was employed to determine the weights of the parameters, and the VIKOR and Grey Relational Analysis (GRA) methods were used for prioritization. The analysis reveals that more than 12% of the region may be subjected to high to very high vulnerability, while over 44% of the population and around 43% of buildings are highly vulnerable to earthquake hazards. Aktas (2022), presented a study on prioritizing regions for disaster preparedness planning. In this research, a hybrid multi-criteria decision-making model with criteria of population, disaster points, building damage, expected number of deaths, and expected number of injuries is proposed based on SWARA and WASPAS methods through a case study.

Taş and Alptekin (2023), developed a smart city assessment for metropolises from a developing country perspective. Initially, smart city indicators were identified in six main categories: livability, economic, environmental sustainability, research and development, accessibility, and cultural interaction, by referring to the research literature. Subsequently, the MEREC method was employed for criteria weighting and the MARCOS method for ranking municipalities. As a result of the study, Istanbul was identified as the top-ranked city based on the proposed methodology. Bitarafan et al. (2023), presented a novel integrated multi-criteria decision-making approach for natural hazard assessment in cities. The primary objective of this study was to identify natural hazards in Tehran for resilience enhancement by introducing a novel integrated MCDM method based on ANP and the Combined Compromise Solution method with Maximum Variance (MV-CoCoSo). The comparative weighting of the identified criteria was then investigated using the ANP method. Based on the obtained results, the disaster consequence criterion, disaster intensity criterion, and occurrence probability criterion were ranked first to third, respectively. Anvari et al. (2023), proposed a model for prioritizing demand points considering lateral transshipment. The aim of this paper was to investigate Integratinglateral transportation and road vulnerability into the humanitarian relief chain, considering the priority of the affected area. Following the identification of criteria and sub-criteria, an MCDM framework was utilized to obtain weights and rank demand points. A mixed-integer programming mathematical model was formulated considering facility location, inventory, road vulnerability, and the amount of lateral transshipment. The results demonstrated that utilizing prioritization criteria and sub-criteria related to lateral transportation and road vulnerability led to a fairer distribution of relief items by reducing the average total distance traveled per relief item.

AbdelAziz et al. (2024), presented a study titled "Application of GIS and IoT-Based Multi-Criteria Decision-making for Disaster Risk Management". The study proposes a two-phase framework to enhance disaster management strategies for floods using Geographic Information Systems (GIS) and Internet of Things (IoT) data from unmanned aerial vehicles (UAVs). The first phase utilizes GIS and four predictive models to identify the province with the highest flood risk. The second phase involves selecting optimal locations for UAV takeoff and landing using GIS and multi-criteria decision-making. The results, demonstrated in a case study of Egypt's Mediterranean coast, indicate that Port Said Province is the most vulnerable to flooding, and 10 suitable locations for UAV takeoff and landing are proposed for this province.

2.2.1 Literature related to mathematical modeling in disaster management

The preparation and mitigation phases are considered the foundational stages in disaster management. Optimization in these phases ensures that there are no surprises during the response phase, minimizing potential casualties and costs (Colajanni et al., 2023). Pre-disaster emergency item location and inventory control, and post-disaster routing and distribution of aid can cover the demand of affected areas and reduce the impact of disasters (Yáñez et al., 2021; Nodoust et al., 2023). Facility location significantly impacts the design of distribution routes between facilities and various demand locations. Since decision-makers in real-world applications often face more than one objective, the problem can be formulated as a multi-objective optimization problem (Tadaros & Migdalas, 2022). Mohammadi et al. (2020) proposed a novel multi-objective optimization model for organizing location and routing in the humanitarian aid chain with the objectives of minimizing total logistic costs and total emergency operation time. Cotes et al. (2019) developed a facility location model for pre-disaster resource preparation to minimizea set of costs. Adrang et al. (2020) in disaster management has focused on optimizing location-routing for medical emergency services, using models like Mixed-Integer Linear Programming (MILP). In the context of "Planning for Medical Emergency Transportation Vehicles during Natural Disasters," bi-objective optimization methods, such as the ε-constraint, have effectively balancedresponse time and costs. Sensitivity analyses further reveal the critical influence of demand uncertainties, emphasizing the need for robust resource allocation strategies during disasters.

Bashiri et al. (2021) presented a two-stage stochastic programming model for the asset protection routing problem during crisis situations. The study considers strategic and tactical decisions to determine the locations of protective warehouses and allocate assets to them based on setup and routing costs. The Frank-Wolfe Progressive Hedging decomposition approach and uncertainty parameters for direction, wind speed, and monthly rainfall are employed to solve the proposed model in a realistic case study in South Hobart. The numerical results demonstrate that more assets can be protected by considering the proposed two-stage stochastic programming model. Cheng et al. (2021) proposed a two-stage facility location mathematical model with a robustness approach under demand uncertainty and disruptions before natural disasters. Environmental changes, such as population shifts and transportation infrastructure issues, can turn today's optimal location decision into poor performance tomorrow. Therefore, it is crucial to consider potential uncertainties in the planning stage. In this study, a column generation and constraint algorithm are developed to solve the proposed model. The results show that the algorithm can achieve higher optimality compared to other models. Stienen et al. (2021) presented a study on warehouse location for humanitarian logistics providers using robust optimization under disaster scenarios. The mathematical model is formulated as a bi-objective model that minimizes transportation costs and response time to a disaster. Robust optimization is employed to find solutions against uncertainty in the location and scale of future disasters.

Mehtab et al. (2022) proposed a multi-objective stochastic robust humanitarian logistics model to assist disaster management in optimal decision-making before and after a disaster. The model provides the location of temporary facilities, the amount of goods to be pre-positioned, and a detailed plan for distributing goods and dispatching vehicles. They considered the uncertainty in demand, access to nodes by a specific transportation mode, and resource status, as well as addressing the issue of fairness in the distribution of goods. The findings indicated that the proposed model can assist decision-makers in optimal resource allocation. Saraji et al. (2022) presented an integrated multi-objective two-stage mathematical model for humanitarian logistics with distributional inequity and dissatisfaction under uncertainty. Focusing on the optimal distribution of relief resources to emergency shelters, the proposed model was designed with the objectives of minimizing operational costs, distribution, and dissatisfaction. Considering the computational complexity, two multi-objective metaheuristic algorithms, namely multi-objective vibration optimization and non-dominated sorting genetic algorithm, were employed to solve the problem, and a comprehensive sensitivity analysis was performed. The results demonstrated that the proposed approach outperforms traditional optimization methods in achieving better Pareto front solutions. Sun et al. (2022) proposed a scenario-based bi-objective robust optimization model that designs the location of medical facilities, transportation of casualties, and allocation of relief goods, considering the prioritization of casualties based on their severity. The objectives of the proposed model are to minimize the delay in accessing medical services and the total operational cost. Considering the uncertain number of casualties under each scenario, they employed a robust approach with uncertainty and the ε-constraint method to solve the bi-objective model and used real-case studies of the Wenchuan earthquake to validate the proposed model.

Sheikholeslami and Zarrinpoor (2023) presented a multi-objective multi-period probabilistic location allocation model for designing a humanitarian logistics network with the objectives of minimizing total cost and maximizing network coverage. The management of perishable relief items and the flow of affected people are considered. They employed a programming approach to address uncertainty and used the competitive and invasive weed optimization algorithm to solve the model. Several test problems were solved to validate the proposed model and a real-world case study was conducted to evaluate its performance. Zarrinpoor et al. (2023) proposed a mathematical optimization model for designing a multi-period emergency response system with the objective of cost minimization. The model considers location, allocation, and distribution decisions, as well as the flow of medical equipment and affected people, using a stochastic approach. The results demonstrated that the robust stochastic approach can effectively control cost and demand uncertainty. Zhang et al. (2023) studied a network design problem for humanitarian aid purposes with demand correlation and limited demand information. They formulated the problem as a two-stage facility location inventory model and employed a metaheuristic algorithm to solve it. Case study results showed that modeling demand correlation can reduce unmet demand.

Javadi and Yadegari (2024) proposed a two-stage stochastic programming model for the location of emergency facilities and reconstruction equipment and the distribution of relief items to demand nodes as quickly as possible. The objective function minimizes the deprivation costs due to lack of access to resources and logistics costs under each scenario. They considered two types of structural and operational uncertainties and employed a robust fuzzy stochastic programming approach to solve the model. The computational results demonstrate the effective performance of this model in reducing the social costs of the humanitarian logistics problem. Chang et al. (2024) presented a two-stage stochastic programming model that optimizes the location of relief item distribution centers and the number of vehicles in the first stage and determines the best vehicle routing and inventory in the second stage. They employed an efficient simulation optimization algorithm to solve the proposed model. Given the immense damage caused by natural disasters, effective disaster management measures are crucial. Therefore, numerous studies have been published to create a unified stream of research in the field of relief logistics, which is strengthened every year with new and interesting ideas. Table 1 summarizes the research background by presenting the characteristics of past research.

Table 1

Literature review on Pre-Disaster Management

Authors / Research Characteristics	Type of Optimization			Objective		Disaster Management Strategies				Certainty / Uncertainty			Relief Goods		Research Paradigms			
	MOO	MCDM	GIS	Single Objective	Multi Objective	Prioritization	Location	Inventory Control	Evaluation	Certainty	Uncertainty	Fuzzy	Single Goods	Multi Goods	Sustainability	Resilience	Ordinary City	Smart City
Alizadeh et al (2018)		✓	✓			✓			✓	✓							✓	
Arif et al (2019)	✓			✓				✓			✓			✓			✓	
Eshghi et al (2020)	✓				✓	✓	✓	✓			✓			✓			✓	
Jena et al (2020)		✓	✓			✓			✓	✓					✓		✓	
Ozkaya and Erdin (2020)		✓							✓	✓					✓			✓
Cheng et al (2021)	✓			✓			✓				✓						✓	
Stienen et al (2021)	✓				✓		✓	✓			✓						✓	
Bashiri et al (2021)	✓			✓			✓				✓						✓	
Hajipour et al (2021)	✓				✓		✓	✓		✓				✓				✓
Khalili-Damghani et al (2022)	✓		✓		✓	✓	✓				✓			✓	✓		✓	
Malakar and Rai (2022)		✓				✓			✓		✓						✓	
Ming et al (2022)	✓			✓			✓				✓						✓	
AKTAS (2022)		✓							✓	✓							✓	
Taki et al (2022)	✓			✓			✓	✓		✓				✓			✓	
Zhang et al (2023)	✓				✓		✓	✓			✓			✓			✓	
GÜLER et al (2023)		✓	✓		✓				✓	✓							✓	
Taş and Alpektin (2023)		✓				✓			✓	✓					✓			✓
Shao et al (2023)		✓				✓			✓			✓			✓			✓
AbdelAziz et al (2023)		✓	✓			✓	✓		✓	✓					✓			✓
Sahraei and Samouei (2023)	✓			✓			✓	✓			✓						✓	

Research gaps, as indicated in Table (1) and as far as we have studied, show that there is no research optimizing disaster management before a disaster by simultaneously considering both normal and smart areas. In this research, various cameras and sensors with different coverage radii and failure rates are used to convert some normal areas into smart areas. Additionally, this study considers sustainability and resilience approaches in identifying the Aspects and criteria of the research. Given the complexity of the research and to enhance the effectiveness of the results, MCDM methods and multi-objective mathematical modeling (MOO) are employed. Overall, disaster management in this research is conducted through strategic and operational measures. The framework presented in this study includes identifying and categorizing Aspects and criteria, determining their importance weights, prioritizing and assessing earthquake-prone areas, selecting suppliers, locating warehouses, determining inventory control policies, and equipping candidate smart city areas with various IoT items including cameras and sensors.

2.3. SWARA and WASPAS decision-making methods

First, the reasons for using and the advantages and disadvantages of the SWARA and WASPAS methods in disaster management are discussed, followed by the presentation of the solution algorithms for each method. These two methods are part of the MCDM techniques, which are widely used in disaster management research due to their flexibility and high accuracy in prioritizing options and determining the weights of criteria. The SWARA method, with its advanced and step-by-step approach, allows for more precise evaluation of the weighting of various factors. The WASPAS method, by combining the weighted sum of criteria and calculating the products, arrives at a final result for prioritizing factors. This method is suitable for issues that require flexibility in determining weights and combining various criteria.

However, due to the extensive calculations involved, these methods may increase computational complexity. In this research, given the high number of factors in disaster management and the importance of decision-making accuracy, these two methods have been utilized in the decision-making phase.

2.3.1. The SWARA decision-making method

The SWARA (Step-wise Weight Assessment Ratio Analysis) method is an MCDM technique aimed at calculating the weights of criteria and sub-criteria. Its functionality is similar to methods such as Best-Worst, Shannon Entropy, and LINMAP. In this method, criteria are ranked based on their value. The main feature of this method is the ability to estimate the relative importance of criteria through expert and stakeholder assessments during the weight determination process.

Step 1: Ranking the Criteria Initially, the criteria are listed in order of importance.

Step 2: Determining the Relative Importance of Each Criterion (s_J)

In this step, the relative importance of each criterion compared to the previous criteria is determined. This value is denoted by s_J.

Step 3: Calculating the Coefficient k_J

The coefficient k_J, which is a function of the relative importance of each criterion, is calculated using Equation 1:

$$k_J = S_J + 1 \tag{1}$$

Step 4: Calculating the Initial Weight of Each Criterion

In this step, it should be noted that the weight of the first criterion, which is the most important, is considered to be equal to 1.

$$Q_J = \frac{Q_{J-1}}{k_J} \tag{2}$$

Step 5: Calculating the Final Normalized Weight

In the final step, the final weight of the criteria, which has been normalized using a simple linear method, is calculated using the following equation:

$$q_j = \frac{Q_j}{\sum Q_j} \qquad ; j = 1 \dots n \tag{3}$$

2.3.2. The WASPAS decision-making method

This method combines equal shares from the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to evaluate options. It is highly efficient and accurate for complex problems. WASPAS operates based on weighting techniques such as BWM, SWARA, and AHP.

Step 1: Forming the Decision Matrix and Quantifying the Criteria

In the first step, the decision matrix (A) is formed with the relevant options and criteria.

Step 2: Forming the Dimensionless Decision Matrix

The decision matrix is transformed using the linear dimensionless method, converting all criteria to positively-oriented indices.

Step 3: Calculating the Relative Importance of Options Based on the WSM Method

The relative importance of option *I* is denoted as Q_i in the following equation, where n_{ij} is defined as the normalized value:

$$Q_i = \sum_{j=1}^{n} n_{ij} w_j \qquad ; \sum_{j=1}^{n} w_j = 1 \tag{4}$$

Step 4: Calculating the Relative Importance of Options Based on the WPM Method

According to the Weighted Product Model (WPM), the weight of option *I* is defined as Q_p in the following equation:

$$Q_p = \prod_{j=1}^{n} (n_{ij})^{W_j} \qquad ; \sum_{j=1}^{n} w_j = 1 \tag{5}$$

Step 5: Calculating the Common Measure $\boldsymbol{Q_i}$

$$Q_i = 0.5 * Q_p + 0.5 * Q_l \tag{6}$$

Step 6: Calculating the Relative Importance of the Option Using the $\boldsymbol{\lambda}$ Formula

$$Q_i = \lambda * Q_p + (1-\lambda) * Q_l \qquad \mathrm{i} = 1, \dots, \mathrm{m} \;\; ; \;\; 0 \le \lambda \le 1 \tag{7}$$

To calculate the optimal λ based on the standard deviation of criteria, the following formula is used:

$$\lambda = \frac{\delta^2 Q_p}{\delta^2 Q_l + \delta^2 Q_p} \tag{8}$$

$$\delta^2 Q_l = \sum_{j=1}^{n} \sum W_j^2 \delta^2 n_{ij} \tag{9}$$

$$\delta^2 Q_p = \sum_{j=1}^{n} [\frac{\prod_{j=1}^{n} (n_{ij})^{W_j} W_{ij}}{(n_{ij})^{W_j} (n_{ij})^{(1-W_j)}}]^2 \delta^2 n_{ij} \tag{10}$$

$$\delta^2 n_{ij} = (0.05 * n_{ij})^2 \tag{11}$$

3. Methodology

This research is designed to enhance the effectiveness of strategic and operational disaster management decisions prior to disasters. The research methodology is outlined in three phases. The first phase involves defining research objectives, identifying and classifying Aspects and criteria using literature review and forming an expert panel to establish the decision hierarchy matrix. It is noteworthy that this research utilized the insights of 20 experts specializing in disaster management, urban planning, and decision science and mathematical optimization. Finally, the Lawshe method was employed to assess content validity. In the second phase, after evaluating the performance of various MCDM methods, the SWARA method is employed to determine the weight of importance of Aspects and criteria. Subsequently, information is gathered from the 15 municipalities of Isfahan to evaluate and prioritize the municipalities using the WASPAS method. It is worth mentioning that the weight of importance of the municipalities is used in determining the candidate smart city areas by the mathematical model. In the third phase, the objectives and variables of the problem are first translated into mathematical language. In the next step, the parameters and constraints of the problem are defined to create a mathematical model. Finally, solution methods, sensitivity analysis, and analysis of the results obtained from the mathematical model in conjunction with MCDM are discussed. It is noteworthy that the outputs of the third phase of the research include the selection of suppliers, location of support warehouses, determination of emergency item inventory, and allocation of IoT items including various sensors and cameras to the candidate smart city areas. Figure 1 illustrates the research methodology.

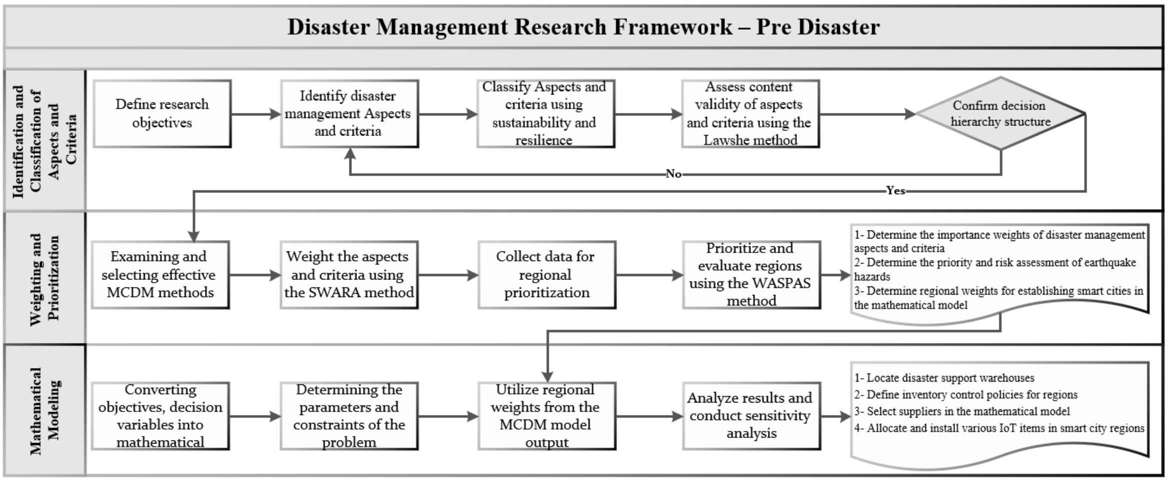

Fig. 1. Research methodology framework

3.1. Decision hierarchy matrix

In this section, the identified decision matrix and decision tree of the research, which includes five main Aspects and nineteen criteria considering sustainability and resilience approaches, are presented as shown in Table 2 and Figure 2. The decision tree illustrates the high complexity of the decision-making process.

Table 2
The identified Aspects and Criteria of the disaster management decision matrix in the current research

Aspects	Criteria	Researchers
Physical	**Threat History (TH)**	Bitarafan et al (2023), Anvari et al (2023), Gharib et al (2018)
	Construction Area (CA)	Anvari et al (2023), Malakar and rai (2022), Yariyan et al (2020), jena et al (2020)
	Building Density (BD)	Shao et al (2023), Anvari et al (2023), Peng (2015)
Environmental	**Number of Fault (NF)**	Malakar and rai (2022), Naderi et al (2021), Yariyan et al (2020), jena et al (2020)
	Energy Consumption (EC)	AbdelAziz et al (2024), Shao et al (2023), Taş and Alptekin (2023), Ozkaya and Erdin (2020), lim et al (2019)
	Ratio of Green Coverage (GC)	Shao et al (2023), Anvari et al (2023)
	Waste Per Capita (WC)	Taş and Alptekin (2023), Shao et al (2023), Ekin and Sarul (2022)
Social	**Populations (PO)**	Taş and Alptekin (2023), Shao et al (2023), Anvari et al (2023), AKTAS (2022), Yariyan et al (2020), Gharib et al (2018), Anand et al (2017), Peng (2015)
	Population Density (PD)	GÜLER et al (2023), Taş and Alptekin (2023), Anvari et al (2023), Yariyan et al (2020), Malakar and rai (2022)
	Educated Population Index (EP)	Malakar and rai (2022), Ekin and Sarul (2022), jena et al (2020), غفاری و همکاران (1396)
	Touristic Protentional (TP)	Taş and Alptekin (2023), Ekin and Sarul (2022), Malakar and rai (2022), jena et al (2020), Ozkaya and Erdin (2020)
Economical	**Per Capita GDP (CG)**	GÜLER et al (2023), Taş and Alptekin (2023), Shao et al (2023), Anand et al (2017), Peng (2015)
	Average Income People (IP)	Anvari et al (2023), Taş and Alptekin (2023), lim et al (2019), Anand et al (2017)
	Region's Budget (RB)	Taş and Alptekin (2023), lim et al (2019) Current Research Experts
	Distribution of People's Economic activity (PE)	Taş and Alptekin (2023), Anand et al (2017)
Infrastructure	**ICT Infrastructures (II)**	Shao et al (2023), Ekin and Sarul (2022), Ozkaya and Erdin (2020), lim et al (2019)
	Transportation Network (TN)	AbdelAziz et al (2024), Ekin and Sarul (2022), Malakar and rai (2022), Ozkaya and Erdin (2020), jena et al (2020), Anand et al (2017)
	Fire Stations (FS)	Anvari et al (2023), Malakar and rai (2022), Yariyan et al (2020)
	Healthcare Centers (HC)	Anvari et al (2023), Malakar and rai (2022), Yariyan et al (2020), jena et al (2020)

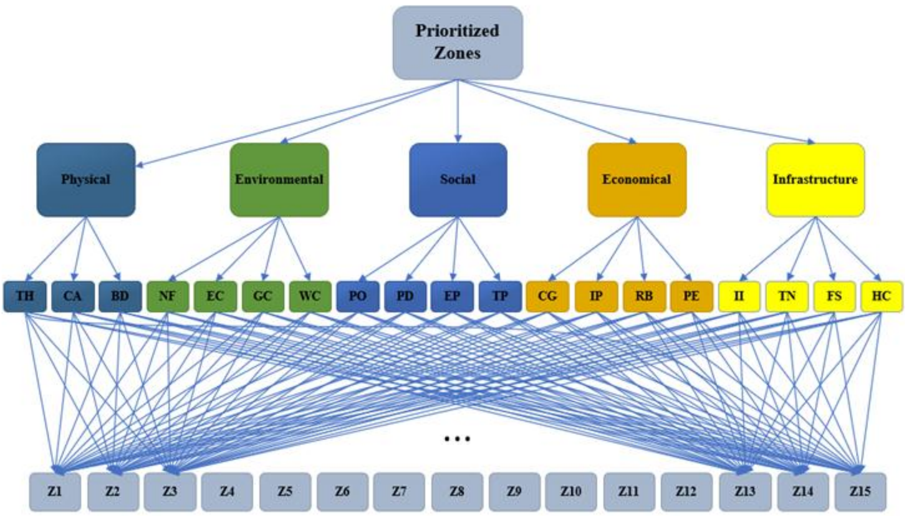

Fig. 2. Decision tree research in disaster management

3.2. Study area

Isfahan Province, holding the highest rank in urbanization and the third rank in population in Iran, is of significant importance due to its large population, political and economic relevance, and industrial and nuclear infrastructure. The study area encompasses the 15 districts of Isfahan County, as depicted in Figure 3. In 2016, the Geological Survey of Iran reported that 2,300 kilometers of the province's plains are at risk of land subsidence. Isfahan Province holds the record for the largest area affected by land subsidence. Therefore, this geographical region has been studied due to its importance and the high risk associated with the combination of earthquakes and land subsidence. Implementing the proposed framework of this research for earthquake disaster management and the effectiveness of disaster management strategies before a catastrophe will be of great importance for prevention and preparedness. Furthermore, this framework can be extended and implemented in other regions as well.

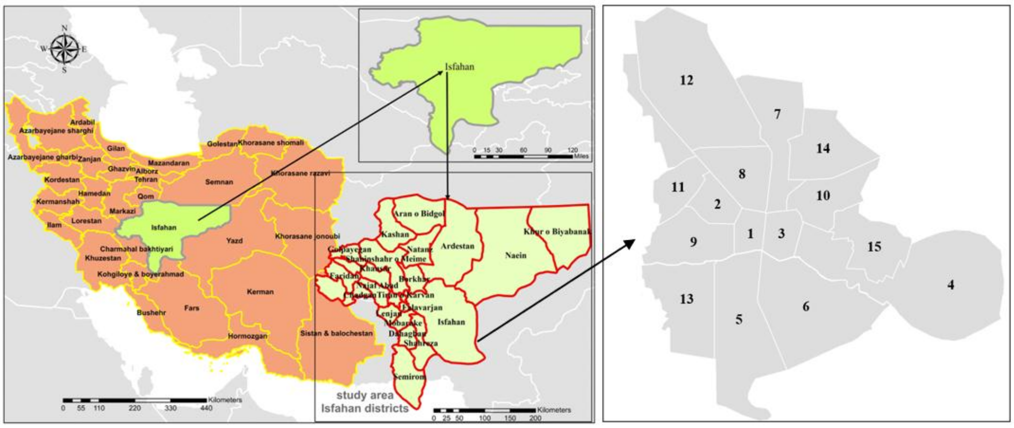

Fig. 3. Hierarchical map of the division of urban areas of Isfahan

3.3. Expert group

The expert group for this study comprises specialists in the following fields relevant to the research:

Disaster Management Specialist (E1): An individual with experience and knowledge in disaster response, emergency planning, and management strategies.

Mathematical Optimization Specialist (E2): An expert skilled in problem-solving, mathematical modeling and analysis.

Decision Science Specialist (E3): A specialist familiar with problem-solving, validation of weighting processes, prioritization, and evaluation.

Urban Planning Specialist (E4): A professional with an understanding of the infrastructure and unique characteristics.

3.4. Data collection

A comprehensive data collection process is essential for conducting the research outlined in the previous stages. In the first stage, identifying the Aspects and criteria of the research involved studying and extracting criteria from reputable and up-to-date disaster research to categorize and create the decision hierarchy matrix. In the second stage, for prioritizing and evaluating the areas, data from the National Statistics Organization of Iran and experts from the Management and Planning Organization of Isfahan Province were utilized.

3.5. Mathematical model of the research

This section of the paper presents a mathematical model for a humanitarian relief logistics network, incorporating the smart city approach for pre-disaster management. The proposed model includes supplier selection, the location of support warehouses, inventory control policies for relief items, and allocating Internet of Things (IoT) devices such as various cameras and sensors based on the coverage radius from buildings in the candidate smart city areas. Figure 4 illustrates the conceptual model of the relief logistics network.

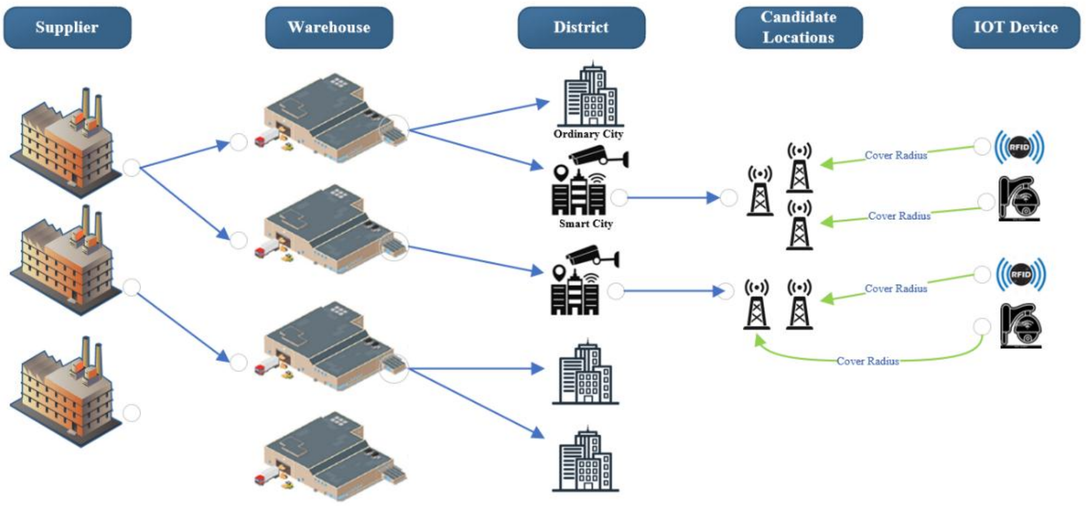

Fig. 4. Conceptual model of disaster management – Pre-disaster

According to Figure 3, during the pre-disaster stage, strategic operational actions are undertaken to ensure preparedness and risk reduction during the disaster event. In this context, suppliers are selected to provide the necessary relief items, and warehouses are located for storing these items. After procuring the relief items from the selected suppliers, the warehouses are allocated to potential disaster-prone areas. It is worth noting that areas are categorized into regular areas and candidate smart city areas. Therefore, in the candidate smart city areas, in addition to warehouse location and item allocation, the allocation of IoT devices, including various cameras and sensors, is also considered. This allocation of IoT devices is based on the coverage radius from potential buildings in the candidate areas. Additionally, the minimum number of candidate smart city areas is determined by the decision-making model of the research. Subsequently, the mathematical model of the research specifies the exact number of smart city areas based on the importance weight of each area, operational costs, coverage radius, and reliability. This pre-disaster smartification and equipping enable the accurate collection of demand information, casualty statistics, and damage reports in the event of a disaster. Overall, the goal of this mathematical optimization model is to minimize operational costs, which include supplier selection, warehouse location, inventory control with ordering policies, equipping high-priority areas with smart city infrastructure, and increasing coverage and reliability to support strategic decision-making before a disaster occurs.

3.6. Assumptions for problem modeling

- The following assumptions are considered for modeling the problem:

- Potential points within the study area's regions are used for the construction or selection of warehouses.
- The selection of suppliers to provide the necessary relief items for each region is performed by the mathematical model.
- Relief items are categorized into two groups: food and hygiene products.
- Each warehouse can receive relief items from only one supplier.
- It is possible to send relief items from one warehouse to different regions.
- The minimum number of smart city candidate areas is determined by the expert or management.
- Control tools, including sensors and cameras, are used as IoT items for implementing the smart city.
- The sensors and cameras vary in terms of coverage radius, implementation cost, and reliability.
- Sensors and cameras are allocated in each region based on their coverage radius with the objective of maximizing coverage.
- To assess the reliability rate of IoT tools in each region, a failure rate is considered for each device.
- Potential installation sites for sensors and cameras are specified separately for each region.
- The importance coefficients of regions are obtained by prioritizing them using the WASPAS method.
- The presented model is single-period.
- The demand in each region is approximated and follows a normal distribution with mean μ_{pj} and standard deviation σ_{pj}.

- For the allocation of IoT items in each region, a budget is considered based on the region's importance.

According to the assumptions, the symbols, parameters and variables used in the mathematical model are expressed as follows:

Model Sets

J	Set of regular and smart regions in the study $j, j' \in J$
K	Set of potential warehouses $k \in K$
L	Set of suppliers $l \in L$
P	Set of relief items $p \in P$
S	Set of sensor types $s \in S$
C	Set of camera types $c \in C$
D	Set of potential installation locations for IoT items $d \in D$
UU_j	Set of potential installation locations for IoT items in region J
B	Set of buildings in the regions $b \in B$

Model Parameters

φ_j	Priority importance coefficient of region $j \in J$
fk_k	Fixed cost of selecting and establishing a warehouse at location $k \in K$
fE_j	Fixed cost of selecting and establishing a smart city infrastructure in region $j \in J$
fS_{Sj}	Cost of installing a sensor in the candidate smart city region $j \in J$
fC_{cj}	Cost of installing a camera in the candidate smart city region $j \in J$
g_{kl}	Fixed cost of constructing a route between warehouse $k \in K$ and supplier $l \in L$
t_{plk}	Transportation cost of product $p \in P$ between warehouse $k \in K$ and supplier $l \in L$
t'_{pkj}	Transportation cost of product $p \in P$ between warehouse $k \in K$ and region $j \in J$
a_{pk}	Ordering cost of product $p \in P$ from warehouse $k \in K$
h_{pk}	Holding cost of product $p \in P$ in warehouse $k \in K$
μ_{pj}	Mean demand of product $p \in P$ in region $j \in J$
σ_{pj}	Standard deviation of product $p \in P$ in region $j \in J$
$\rho_{jj'}$	Correlation coefficient of demand between regions $j \in J$ and $j' \in J$
γ_{pj}	Coefficient of demand variability reduction σ_{pj} in selected smart city regions $j, j' \in J$
l_{pkl}	Lead time for product $p \in P$ from warehouse $k \in K$ to supplier $l \in L$
c_{pk}	Inventory capacity of product $p \in P$ in warehouse $k \in K$
ω	Minimum number of regions to be equipped with IoT, such that $\omega \leq |J|$
Z_α	Probability of the cumulative distribution function
NS_j	Number of sensors in each region $j \in J$
NC_j	Number of cameras in each region $j \in J$
Dis_{dbj}	Distance from the candidate installation location of IoT items to buildings in each region for coverage radius
RS_s	Coverage radius of each sensor $s \in S$
RC_c	Coverage radius of each camera $c \in C$
λS_s	Failure rate of each sensor $s \in S$
λC_c	Failure rate of each camera $c \in C$
Bu_j	Budget for creating smart city infrastructure in each region $j \in J$
ac_{cdbj}	
as_{sdbj}	1, if sensor c installed at location d building b in region j covers. 0, otherwise

Decision Variables

X_{jk}	1, if region $j \in J$ is allocated to warehouse $k \in K$. 0, otherwise
Y_{kl}	1, if warehouse $k \in K$ is allocated to supplier $l \in L$. 0, otherwise
F_k	1, if a warehouse is selected at location $k \in K$. 0, otherwise
F'_j	1, if buildings in region $j \in J$ are equipped with IoT tools. 0, otherwise
XC_{cdj}	1, if camera c is installed at candidate location d in region j. 0, otherwise
XS_{sdj}	1, if sensor c is installed at candidate location d in region j. 0, otherwise
Rec_{cdj}	Reliability of camera c at location d and region j
Res_{sdj}	Reliability of sensor s at location d and region j
D_{pk}	Actual mean demand of product $p \in P$ for warehouse $k \in K$
U_{pk}	Actual demand variance of product $p \in P$ for warehouse $k \in K$
L_{pk}	Total lead time of product $p \in P$ for warehouse $k \in K$
S_{pk}	Safety stock of product $p \in P$ in warehouse $k \in K$
R_{pk}	Reorder point of product $p \in P$ in warehouse $k \in K$
I_{pk}	Total inventory of product $p \in P$ in warehouse $k \in K$
Q_{pk}	Economic Order Point $p \in P$ in warehouse $k \in K$

3.6.Research model formulation

The research model aims to select suppliers, locate warehouses, determine inventory control policies, and equip candidate smart city areas with various cameras and sensors. The objectives are to minimize operational costs, maximize coverage, and maximize the reliability of the regions. The model is formulated as follows:

$$Min\ Cost = \sum_{k\in K} f_k F_k + \sum_{j\in J}\sum_{d\in D}\sum_{s\in S}\sum_{c\in C}\frac{fS_{Sj}XS_{sdj} + fC_{cj}XC_{cdj} + fE_jF'_j}{\varphi_j} + \sum_{k\in K}\sum_{l\in L} g_{kl}Y_{kl} + \sum_{l\in L}\sum_{k\in K}\sum_{j\in J}\sum_{p\in P} t_{pkl}\mu_{pj}X_{jk}Y_{kl} + \sum_{k\in K}\sum_{j\in J}\sum_{p\in P} t'_{pkj}\mu_{pj}X_{jk} + \sum_{k\in K}\sum_{p\in P} h_{pk}I_{pk} + \sum_{k\in K}\sum_{p\in P}\frac{a_{pk}D_{pk}}{Q_{pk}} \tag{12}$$

$$Min\ (Max\left(\sum_{j\in J}\sum_{d\in D}\sum_{s\in S}\sum_{b\in B} XS_{sdj}as_{sdbj} + \sum_{j\in J}\sum_{d\in D}\sum_{c\in C}\sum_{b\in B} XC_{cdj}ac_{cdbj}\right)) \tag{13}$$

$$Max\ Reliability = \prod_{j\in J}(1 - \prod_{d\in D}\prod_{s\in S}(1 - Res_{sdj}))(\ 1 - \prod_{d\in D}\prod_{c\in C}(1 - Rec_{cdj})) \tag{14}$$

$s.t.$:

$$X_{jk} \le \sum_{l\in L} Y_{kl}\,, \qquad \forall j \in J, k \in K \tag{15}$$

$$\sum_{k\in K} X_{jk} = 1, \qquad \forall j \in J \tag{16}$$

$$\sum_{l\in L} Y_{kl} \le F_k\,, \qquad \forall k \in K \tag{17}$$

$$\sum_{j\in J} F'_j \ge \omega \tag{18}$$

$$\sum_{c\in C}\sum_{d\in UU_j}\sum_{b\in B} XC_{cdj}\, ac_{cdbj} \ge F'_j, \qquad \forall j \in J \tag{19}$$

$$\sum_{s\in S}\sum_{d\in UU_j}\sum_{b\in B} XS_{sdj}\, as_{sdbj} \ge F'_j, \qquad \forall j \in J \tag{20}$$

$$\sum_{c\in D}\sum_{d\in UU_j} XC_{cdj} \le NC_jF'_j, \qquad \forall j \in J \tag{21}$$

$$\sum_{s\in S}\sum_{d\in UU_j} XS_{sdj} \le NS_jF'_j, \qquad \forall j \in J \tag{22}$$

$$Rec_{cdj} = \exp(-\lambda C_c)\, XC_{cdj}\,, \qquad \forall c, d, j \tag{23}$$

$$Res_{sdj} = \exp(-\lambda \mathrm{S}_s)\, XS_{sdj}\,, \qquad \forall s, d, j \tag{24}$$

$$\sum_{c\in D}\sum_{d\in D} XC_{cdj}\, fC_{cj} + \sum_{s\in D}\sum_{d\in D} XS_{sdj}\, fS_{Sj} + fE_jF'_j \ \le \mathrm{Bu}_j, \qquad \forall j \in J \tag{25}$$

$$Q_{pk} = \sqrt{\left(\frac{2a_{pk}\sum_{j\in J}\mu_{pj}X_{jk}}{h_{pk}}\right)}, \qquad \forall k \in K, p \in P \tag{26}$$

$$D_{pk} = \sum_{j\in J} \mu_{pj}X_{jk}\,, \qquad \forall k \in K, p \in P \tag{27}$$

$$U_{pk} = \sum_{j\in J}\sum_{j'\in J} \rho_{jj'}(\sigma_{pj}(1 - \gamma_{pj}F'_j))(\sigma_{pj'}(1 - \gamma_{pj'}F'_{j'}))X_{jk}X_{j'k}\,, \qquad \forall k \in K, p \in P \tag{28}$$

$$L_{pk} = \sum_{l\in L} l_{pkl}Y_{kl}\,, \qquad \forall k \in K, p \in P \tag{29}$$

$$S_{pk} = Z_\alpha\sqrt{U_{pk}L_{pk}}, \qquad \forall k \in K, p \in P \tag{30}$$

$$R_{pk} = S_{pk} + L_{pk}D_{pk}, \qquad \forall k \in K, p \in P \tag{31}$$

$$I_{pk} = \frac{Q_{pk}}{2} + S_{pk}, \qquad \forall k \in K, p \in P \tag{32}$$

$$I_{pk} \le c_{pk}F_k, \qquad \forall k \in K, p \in P \tag{33}$$

$$D_{pk}, U_{pk}, S_{pk}, R_{pk}, I_{pk}, Q_{pk}, Rec_{cdj}, Res_{sdj} \ge 0 \tag{34}$$

$$X_{jk}, Y_{kl}, X_{cdj}, X_{sdj}, F_k, F'_j \in \{0,1\} \tag{35}$$

Equation (12) represents the operational costs in the first phase of the model. These costs include the costs of warehouse location, the costs of transferring items between suppliers, warehouses, and regions, and the costs of allocating various sensor and camera equipment to establish infrastructure in candidate smart city areas. Equation (13) is formulated to maximize the coverage of various sensors and cameras installed in priority areas. Equation (14) aims to maximize the reliability of IoT equipment. Equation (15) indicates that the supply of raw materials from suppliers and their distribution to regions can only be done through selected warehouses. Equations (16) and (17) show that each region can receive emergency supplies from only one warehouse. Equation (18) indicates the minimum number of regions equipped with smart city infrastructure. Equations (19) and (20) address the allocation of various cameras and sensors based on the coverage radius in candidate smart city areas. Equations (21) and (22) control the number of cameras and sensors allocated to each region. Equations (23) and (24) are formulated to control the reliability of IoT equipment in each region, installation sites, and the types of allocated sensors and cameras. Equation (25) considers the budget control for equipping regions with smart city infrastructure. Equation (26) shows the optimal order point of the product for the selected warehouses. Equations (27) and (28) calculate the total demand and the total variance of demand for regions for each warehouse, respectively. It also shows the change in the standard deviation rate of demand when a normal region is converted to a smart region. Equation (29) shows the total lead time of products for the selected warehouses. Equations (30) and (31) show the safety stock and reorder point of products, respectively. Equation (32) shows the amount of each product available in the selected warehouses. Equation (33) indicates that the amount of inventory stored in each warehouse must be less than the capacity of that center. Equations (34) and (35) indicate the type of decision variables.

3.7. Single-objective optimization using the weighted sum method

The weighted sum method was employed to transform the multi-objective problem into a single-objective framework. This technique involves assigning a weight to each objective based on its relative importance, and then aggregating these weighted objectives into a single composite objective function. By doing so, the complexities of handling multiple conflicting objectives are reduced, allowing for a more straightforward optimization process. This method facilitates the decision-making process by providing a clear, quantifiable criterion for evaluating potential solutions, ensuring that the final decision aligns with the overall strategic goals of disaster management.

4. Analysis of Results

This section presents the analysis of research results divided into two parts: "Analysis of Decision-Making Methods Results" and "Analysis of Mathematical Model Results."

4.1. Analysis of decision-making methods results

In this section, the results obtained from distributing expert questionnaires to determine the importance weights of Aspects and criteria, and prioritizing areas, are presented. It is noteworthy that the experts in this study included 20 specialists in disaster management, urban planning, and multi-criteria decision-making issues. Initially, the results from weighting the research Aspects and criteria using the SWARA method are presented. Subsequently, the results from prioritizing the 15 municipal districts of Isfahan city using the WASPAS method in disaster management are discussed. Finally, the prioritization results from this stage are utilized as inputs in the mathematical model for locating and identifying candidate smart city areas and analyzing earthquake-prone regions.

4.1.1. Analysis of SWARA Method Results

In this section, the results of the hierarchical decision-making matrix of the research, which includes 5 Aspects and 19 criteria, are evaluated and weighted using the SWARA method. It should be noted that to determine the importance of Aspects and criteria in the expert questionnaires, Saaty's scale was used. The values related to the decision-making matrix of Aspects are presented in Table (3), and the values related to the decision-making matrix of criteria are presented in Table (4) as provided by the research experts.

Table 3
Decision matrix of disaster management Aspects

Aspects / Experts	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**
Physical	7	9	9	7	9	7	9	9	7	9
Environmental	9	9	9	9	9	9	9	9	9	9
Social	5	7	9	9	9	5	7	9	9	9
Economical	5	7	9	7	9	5	7	9	7	9
Infrastructure	9	9	9	9	9	9	9	9	9	9
Aspects / Experts	**E11**	**E12**	**E13**	**E14**	**E15**	**E16**	**E17**	**E18**	**E19**	**E20**
Physical	9	7	7	9	9	9	7	7	9	9
Environmental	9	5	9	9	9	9	5	9	9	9
Social	9	9	9	9	9	9	9	9	9	9
Economical	9	9	7	9	9	9	9	7	9	9
Infrastructure	7	7	7	9	9	7	7	7	9	9

Table 4
Decision matrix of disaster management Criteria

Criteria/ Experts	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18	E19	E20
TH	7	7	9	5	5	5	7	9	9	3	5	7	7	7	5	9	9	9	9	7
CA	5	7	9	7	7	9	9	9	7	5	7	7	5	9	7	7	7	9	9	5
BD	9	9	9	7	7	7	7	9	9	5	7	7	7	7	9	9	9	9	9	9
NF	9	5	9	9	5	7	5	7	9	9	5	5	7	7	9	7	9	7	9	9
EC	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
GC	7	5	7	7	5	7	7	7	9	3	5	5	5	7	7	7	7	9	9	7
WC	7	7	9	5	5	9	9	9	9	5	7	7	7	7	9	9	9	9	9	7
PO	9	5	9	9	9	7	7	9	9	5	5	5	7	7	9	7	7	9	9	9
PD	7	9	9	9	5	7	7	7	7	5	5	7	7	7	5	7	9	9	9	7
EP	5	7	7	7	7	5	7	7	7	5	7	7	7	7	9	9	9	9	9	5
TP	7	9	9	7	7	5	7	9	9	5	7	7	7	7	7	9	7	7	7	7
CG	5	7	9	7	7	9	9	7	9	9	5	5	7	7	5	7	9	7	7	5
IP	5	7	7	7	7	5	7	7	9	3	5	7	5	7	5	5	7	7	7	5
RB	3	7	9	7	7	5	3	7	9	5	5	7	5	7	9	5	9	9	9	3
PE	5	7	7	5	5	5	3	7	9	5	7	7	5	7	5	7	9	7	7	5
II	7	7	9	5	5	9	9	9	9	5	7	5	7	7	5	7	9	7	9	7
TN	9	9	9	9	9	9	7	9	9	9	9	9	9	9	9	9	9	9	9	9
FS	9	9	9	9	9	7	7	9	9	9	9	9	7	5	9	9	9	9	9	9
HC	9	9	9	9	7	7	5	9	9	7	7	9	5	3	9	9	9	9	9	9

In this section, calculations related to the average sum of ranks, determination of relative importance, computation of the coefficient k_J, and computation of the coefficient Q_J, which represent the final weight and rank of the research Aspects and criteria, are compiled in Table (5) and Table (6). It is worth mentioning that these calculations correspond to steps two to five of the SWARA method.

Table 5
Determining the weight of importance of Aspects by SWARA

Average sum of Aspects ratings				
C1	C2	C3	C4	C5
0.867	0.811	0.878	0.911	0.956
Determining the relative importance of Aspects s_J				
C5	C4	C3	C1	C2
0.956	0.91	0.88	0.87	0.81
0.04		0.03	0.01	0.06
Calculation of coefficient k_J				
K1	K2	K3	K4	K5
1	1.04	1.03	1.01	1.06
Calculation of Q_J - weight and final rating of Aspects				
Q1	Q2	Q3	Q4	Q5
1.000	0.957	0.927	0.916	0.868
0.214	**0.205**	**0.198**	**0.196**	**0.186**
Infrastructure	**Economical**	**Social**	**Physical**	**Environmental**

Table 6
Determining the weight of importance of Criteria by SWARA

Average sum of Criteria ratings																		
TH	CA	BD	NF	EC	GC	WC	PO	PD	EP	TP	CG	IP	RB	PE	II	TN	FS	HC
0.78	0.82	0.96	0.82	0.73	0.77	0.76	0.91	0.97	0.64	0.71	0.77	0.71	0.76	0.82	0.87	0.94	0.93	0.96
Determining the relative importance of Criteria s_J																		
PD	BD	HC	TN	FS	PO	II	CA	NF	PE	TH	CG	GC	WC	RB	EC	IP	TP	EP
0.97	0.96	0.96	0.94	0.93	0.91	0.87	0.82	0.82	0.82	0.78	0.77	0.77	0.76	0.76	0.73	0.71	0.71	0.64
0.01		0.00	0.01	0.01	0.02	0.04	0.04	0.00	0.00	0.04	0.01	0.00	0.01	0.00	0.02	0.02	0.00	0.07
Calculation of coefficient k_J																		
K1	K2	K3	K4	K5	K6	K7	K8	K9	K10	K11	K12	K13	K14	K15	K16	K17	K18	K19
1	1.01	1.00	1.01	1.01	1.02	1.04	1.04	1.00	1.00	1.04	1.01	1.00	1.01	1.00	1.02	1.02	1.00	1.07
Calculation of Q_J - weight and final rating of Criteria																		
Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19
1.00	0.99	0.99	0.98	0.97	0.95	0.91	0.87	0.87	0.87	0.83	0.82	0.82	0.81	0.81	0.79	0.78	0.78	0.73
0.060	**0.060**	**0.060**	**0.059**	**0.058**	**0.057**	**0.055**	**0.052**	**0.052**	**0.052**	**0.050**	**0.050**	**0.050**	**0.049**	**0.049**	**0.048**	**0.047**	**0.047**	**0.044**
PD	**BD**	**HC**	**TN**	**FS**	**PO**	**II**	**CA**	**NF**	**PE**	**TH**	**CG**	**GC**	**WC**	**RB**	**EC**	**IP**	**TP**	**EP**

In Table (7), the final calculations of the Aspects and criteria of disaster management research, considering the hierarchical matrix according to the SWARA method, are compiled.

Table 7
Importance weight of Aspects and criteria in disaster management

Aspect	Aspect Weight	Criteria	Criteria Weight	Hierarchical weights of criteria
Physical	0.196	**Threat History (TH)**	0.050	0.010
		Construction Area (CA)	0.052	0.010
		Building Density (BD)	0.047	0.009
Environmental	0.186	**Number of Fault (NF)**	0.052	0.010
		Energy Consumption (EC)	0.048	0.009
		Ratio of Green Coverage (GC)	0.050	0.009
		Waste Per Capita (WC)	0.049	0.009
Social	0.198	**Populations (PO)**	0.057	0.011
		Population Density (PD)	0.060	0.012
		Educated Population Index (EP)	0.044	0.009
		Touristic Protentional (TP)	0.047	0.009
Economical	0.205	**Per Capita GDP (CG)**	0.050	0.010
		Average Income People (IP)	0.052	0.011
		Region's Budget (RB)	0.049	0.010
		Distribution of People's Economic activity (PE)	0.052	0.011
Infrastructure	0.214	**ICT Infrastructures (II)**	0.055	0.012
		Transportation Network (TN)	0.059	0.013
		Fire Stations (FS)	0.058	0.013
		Healthcare Centers (HC)	0.060	0.013

4.2.1. Analysis of WASPAS method results

This section presents the results of prioritizing the 15 districts of Isfahan city, obtained using the WASPAS method. These results are evaluated and ranked based on the importance weights of Aspects and criteria, which were weighted in the previous stage using the SWARA method. It is important to note that the decision matrix for this stage has been compiled using actual data from Isfahan municipality, broken down by districts. The normalized decision matrix values are provided in Table (8).

Table 8
Decision matrix by disaster management districts

Aspect	Criteria	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15
Physical	Threat History	0.556	0.333	0.556	0.778	1.000	1.000	0.778	0.778	0.556	0.556	0.333	0.333	0.556	0.556	0.778
	Construction Area (m^2)	0.307	0.258	0.429	0.531	0.652	1.000	0.586	0.726	0.396	0.588	0.122	0.358	0.357	0.195	0.398
	Building Density (Hm^2)	0.720	0.331	0.789	0.217	0.054	0.142	0.491	0.729	0.512	0.669	0.352	0.455	0.265	1.000	0.425
Environmental	Number of Fault	0.556	0.778	0.556	0.778	0.333	0.333	1.000	0.778	0.556	0.556	0.556	0.556	0.333	0.333	0.333
	Energy Consumption (Lit/Day)	0.330	0.288	0.460	0.558	0.629	0.468	0.704	1.000	0.314	0.867	0.245	0.569	0.553	0.688	0.509
	Ratio of Green Coverage (m^2)	0.060	0.224	0.083	1.000	0.424	0.416	0.311	0.149	0.142	0.254	0.048	0.272	0.199	0.158	0.087
	Waste Per Capita (Day/Kg)	0.417	0.268	0.600	0.558	0.829	0.591	0.644	1.000	0.300	0.909	0.220	0.551	0.507	0.640	0.428
Social	Populations	0.330	0.288	0.460	0.558	0.629	0.468	0.704	1.000	0.314	0.867	0.245	0.569	0.553	0.688	0.509
	Population Density (m^2)	0.170	0.247	0.173	0.141	0.187	0.186	0.133	0.141	0.233	0.173	0.321	1.000	0.252	0.095	0.226
	Educated Population Index (%)	0.979	0.918	0.959	0.969	1.000	0.979	0.959	0.959	0.938	0.938	0.897	0.959	0.979	0.897	0.907
	Touristic Protentional	0.522	0.435	0.652	0.739	0.565	0.870	0.522	0.565	0.391	1.000	0.478	0.696	0.652	0.217	0.696
Economical	Per Capita GDP	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Average Income People (Month)	0.330	0.288	0.460	0.558	0.629	0.468	0.704	1.000	0.314	0.867	0.245	0.569	0.553	0.688	0.509
	Region's Budget	0.115	0.042	0.396	0.438	0.767	1.000	0.273	0.349	0.185	0.385	0.099	0.324	0.365	0.218	0.263

	Distribution of People's Economic	0.326	0.291	0.441	0.556	0.586	0.468	0.702	1.000	0.318	0.855	0.241	0.570	0.492	0.678	0.522
Infrastructure	ICT Infrastructures (Km)	0.415	0.198	0.525	1.000	0.592	0.469	0.186	0.629	0.292	0.331	0.117	0.289	0.219	0.238	0.206
	Transportation Network (Km)	0.546	0.439	0.638	0.944	0.839	0.977	0.771	0.832	0.400	0.894	0.288	1.000	0.798	0.479	0.655
	Fire Stations	1.000	1.000	0.667	0.667	0.667	1.000	0.000	0.667	0.333	1.000	0.333	0.667	0.333	0.333	0.333
	Healthcare Centers	1.000	0.000	1.000	0.167	0.667	0.667	0.167	0.167	0.000	0.167	0.000	0.167	0.333	0.167	0.167

In this section, the calculations for determining the relative importance using the WSM (Weighted Sum Model) and WPM (Weighted Product Model) methods, along with the computation of the common criterion Q_i, are performed to rank the districts prior to the final ranking using the WASPAS method. The results of these calculations are compiled in Table (9). It is important to note that these calculations correspond to steps three through five of the WASPAS method.

Table 9
Ranking of disaster Regions by WSP and WPM methods

Rank / Regions	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15
WSP	0.103	0.079	0.114	0.126	0.126	0.131	0.108	0.139	0.076	0.133	0.062	0.115	0.096	0.094	0.092
WPM	0.840	0.000	0.873	0.888	0.888	0.897	0.000	0.901	0.000	0.897	0.000	0.876	0.847	0.825	0.831
$\boldsymbol{Q_i}$	0.471	0.040	0.493	0.507	0.507	0.514	0.054	0.520	0.038	0.515	0.031	0.495	0.472	0.460	0.462
Rank	**9**	**13**	**7**	**5**	**4**	**3**	**12**	**1**	**14**	**2**	**15**	**6**	**8**	**11**	**10**

After the preliminary ranking to enhance the accuracy and effectiveness of the decision-making process, the final ranking is performed using the WASPAS method. This involves calculating λ and a generalized equation to determine the overall relative importance. The results of this final step are presented in Table (10). It should be noted that this calculation corresponds to step six of the WASPAS method

Table 10
Final ranking of disaster Regions by WASPAS method

Rank / Regions	Z1	Z2	Z3	Z4	Z5	Z6	Z7	Z8	Z9	Z10	Z11	Z12	Z13	Z14	Z15
$\boldsymbol{\lambda}$	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999
$\boldsymbol{Q_i}$	0.098	0.081	0.114	0.126	0.126	0.125	0.112	0.139	0.078	0.133	0.065	0.115	0.096	0.094	0.092
Rank	**9**	**13**	**7**	**4**	**3**	**5**	**8**	**1**	**14**	**2**	**15**	**6**	**10**	**11**	**12**

4.2. Analysis of mathematical model results

In this article section, we initially validate the mathematical model based on random parameters with a uniform distribution and subsequently perform sensitivity analysis. After validating the mathematical model, the model is implemented in a real case study in the province of Isfahan.

4.2.1. Numerical example analysis

To validate the mathematical model, a small-scale numerical example is considered as shown in Table (11). The data for the small-scale numerical example is generated randomly based on a uniform distribution. Table (12) illustrates the range of parameters for the problem based on the uniform distribution. In this numerical example, the importance coefficients of the regions are as follows: 0.805, 0.725, 0.897, 0.746, 0.835, and 0.855.

Table 11
Numerical example parameter values for model validation

J	J'	K	L	P	S	C	d	b
6	2	4	3	2	2	2	3	4

Table 12
Interval limits of problem parameters

Parameter	Value	Parameter	Value
$\boldsymbol{f_k}$	$\sim U(2000{,}4000)\$$	NS_j	$\sim RoundU(1{,}20)$
$\boldsymbol{fE_j}$	$\sim U(1000{,}1500)\$$	NC_j	$\sim RoundU(1{,}20)$
$\boldsymbol{fS_{Sj}}$	$\sim U(100{,}250)\$$	dis_{bdj}	$\sim U(20{,}50)m^2$
$\boldsymbol{fC_{Cj}}$	$\sim U(300{,}900)\$$	RS_s	$\sim U(20{,}50)m^2$
$\boldsymbol{g_{kl}}$	$\sim U(150{,}180)\$$	RS_C	$\sim U(15{,}60)m^2$
$\boldsymbol{t_{pkl}}$	$\sim U(12{,}15)\$$	UU_{dj}	$\sim RoundU(1{,}1)$
$\boldsymbol{t'_{pkj}}$	$\sim U(12{,}15)\$$	$landaC_c$	$\sim U(0.03{,}0.1)$
$\boldsymbol{a_{pk}}$	$\sim U(150{,}300)\$$	$landaS_s$	$\sim U(0.02{,}0.15)$
$\boldsymbol{h_{pk}}$	$\sim U(15{,}20)\$$	c_{pk}	$\sim U(1600{,}2000)ton$
$\boldsymbol{\mu_{pj}}$	$\sim U(500{,}750)kg$	ω	3
$\boldsymbol{\sigma_{pj}}$	$\sim U(40{,}80)kg$	Z_α	1.96
$\boldsymbol{\rho_{jj'}}$	$\sim U(0.5{,}0.7)$	γ_{pj}	$\sim U(0.1{,}0.3)$
$\boldsymbol{l_{pkl}}$	$\sim U(10{,}15)h$	$Totla\_budget_j$	$\sim U(90000{,}100000)\$$

After solving the numerical example with the specified Aspects using the Baron solver, the following decisions were obtained. It is important to note that the research mathematical model is a three-objective model, aiming to minimize operational costs, maximize coverage, and maximize the reliability of smart city regions. In the end, the weighted sum method was employed to find the final solution and to convert the research model into a single-objective format.

In this numerical example, the value of the first objective function, which includes minimizing the operational costs of warehouse location, equipping priority regions with smart city infrastructure, and operational costs of inventory procurement and maintenance, was found to be \$284,115.627. The value of the second objective function, aimed at maximizing the coverage of IoT items including various cameras and sensors, was determined to be 27 meters. The value of the third objective function, related to the reliability of cameras and sensors used in disaster management regions, was concluded to be 0.865. The overall value of the objective functions, using the weighting method, was calculated to be 56,825.626. In this numerical example, three suppliers were considered, and suppliers number 1 and 2 were selected to provide food and hygiene products. Subsequently, out of four potential warehouses, warehouses numbered 2, 3, and 4 were selected. Additionally, out of six regions, regions numbered 1, 2, and 5 were chosen to establish smart city infrastructure with the allocation of IoT items. It is noteworthy that the IoT items, including sensors and cameras, will be installed in potential locations within the smart regions, taking into account the coverage radius. Figure (5) illustrates the allocation between suppliers, warehouses, and regions in the first numerical example.

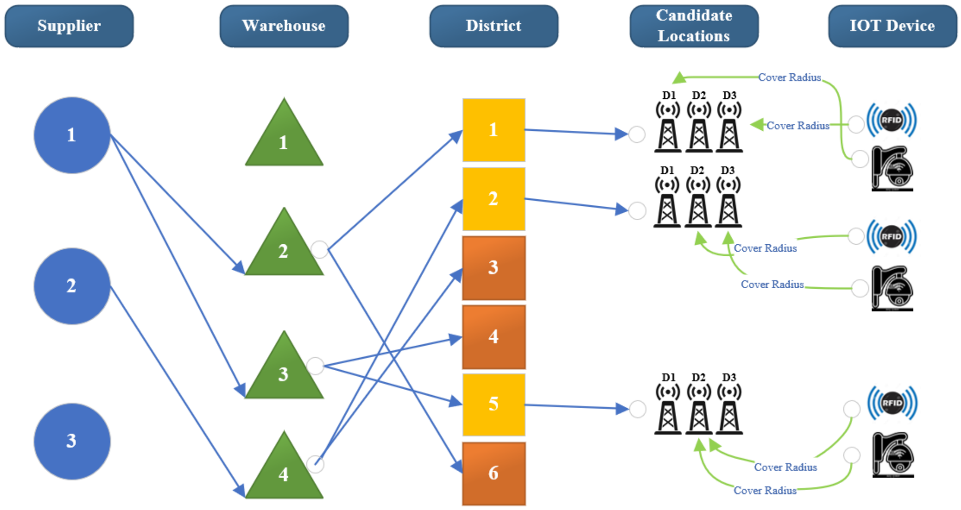

Fig. 5. Conceptual model of allocation between suppliers-warehouses-regions and IoT items in smart regions - first numerical example

Based on Figure (5), it can be observed that warehouse number 1 and supplier number 3 were not utilized. Table (13) presents the optimal order quantity, inventory levels, safety stock, and reorder points for each selected warehouse. Additionally, Table (14) details the variables related to the smart cities, including the types of sensors and cameras installed, their respective installation locations within each region, and their reliability.

Table 13
Values of demand variables and inventory control according to the location of warehouses

Variable	Product	Warehouse 2	Warehouse 3	Warehouse 4
D	1	1343.924	1385.310	1136.046
	2	1275.709	1156.880	1053.585
Q	1	174.393	197.689	155.320
	2	162.498	183.543	149.350
S	1	726.841	643.455	585.490
	2	515.794	657.544	613.969
R	1	17426.276	15845.732	16209.930
	2	18500.284	14868.593	12810.943
I	1	814.037	742.300	663.150
	2	597.043	749.316	688.644

Table 14
The values of the variables of the smart city infrastructure candidate Regions

Variable	Type of IOT	Zone 1 (j_1)			Zone 2 (j_2)			Zone 5 (j_5)		
		d_3	d_2	d_1	d_3	d_2	d_1	d_3	d_2	d_1
XC_{cdj}	Camera 1 (c_1)	-	-	-	1	-	-	-	-	-
	Camera 2 (c_2)	-	-	1	-	-	-	-	1	-
XS_{sdj}	Sensor 1 (s_1)	-	-	-	-	-	-	-	1	-
	Sensor 2 (s_2)	1	-	-	-	1	-	-	-	-
Rec_{cdj}	Camera 1 (c_1)	-	-	-	0.94	-	-	-	-	-
	Camera 2 (c_2)	-	-	0.95	-	-	-	-	0.95	-
Res_{sdj}	Sensor 1 (s_1)	-	-	-	-	-	-	0.96	-	-
	Sensor 2 (s_2)	0.86	-	-	-	0.86		-	-	-

4.2.2. Sensitivity analysis on the numerical example

After reviewing the outputs of the mathematical model, this section focuses on the sensitivity analysis of the problem. By altering some of the most critical parameters, the variations in the total cost are examined. Table (15) shows the total costs of the mathematical model for changes of +20%, +10%, -10%, and -20% in the parameters of ordering cost, mean demand, and correlation coefficient.

Table 15
Sensitivity analysis of mathematical model - first numerical example

Total Objective	$\rho_{jj'}$	Total Objective	μ_{pj}	Total Objective	a_{pk}
49,255.000	-20%	47287.958	-20%	56453.322	-20%
52,583.115	-10%	52818.552	-10%	56644.657	-10%
56,825.626	Base	56825.626	Base	56825.626	Base
59,985.293	+10%	60823.855	+10%	56997.751	+10%
66,172.618	+20%	65019.512	+20%	57162.214	+20%

Based on the results obtained from Table (15), it is observed that with the increase in ordering costs, the total operational costs have risen. Additionally, an increase in the average demand leads to an increase in the optimal order quantity and inventory levels, consequently raising the total costs. Lastly, a high correlation in demand results in an increase in total costs. Figure (6) illustrates the changes in total costs in response to variations in holding costs, average demand, and demand correlation coefficient.

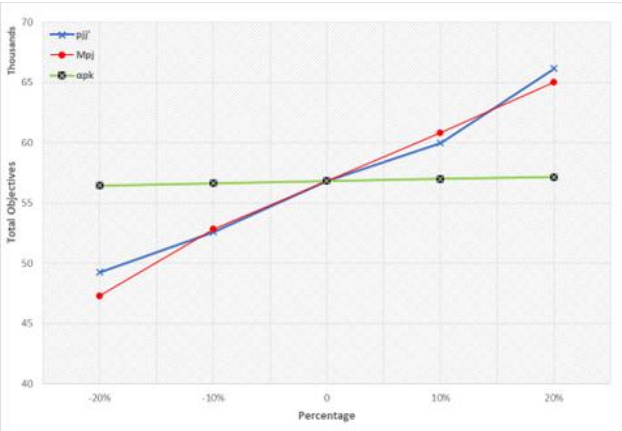

Fig. 6. Sensitivity analysis of the research model in the first numerical example

4.3. Case study

In this numerical example, 15 regions of Isfahan city are considered as the primary areas with the potential to be equipped as smart cities. All 15 regions of this city are also considered as potential warehouses, with the capability to be supplied by 8 potential suppliers. It is worth mentioning that the importance of each region is evaluated and prioritized based on sustainability and resilience Aspects and criteria, focusing on the establishment of smart city infrastructure using SWARA and WASPAS methods. Additionally, in each region, several potential locations are considered for installing cameras and sensors. In this case study, two types of cameras and sensors are considered for each region. This distinction in types of cameras and sensors is due to the coverage radius and reliability characteristics of each equipment. The installation cost of these smart city equipment for each type of camera and sensor in each region is considered in the ranges of [4500 and 3000] and [3000 and 1500] dollars, respectively. The coverage radius and reliability for camera types 1 and 2 are 51 and 29 meters, and 0.95% and 0.91%, respectively. Similarly, the coverage radius and reliability for sensor types 1 and 2 are 47 and 49 meters, and 0.90% and 0.91%, respectively. The cost for establishing a warehouse for storing items in the selected regions is between [10000 and 8000] dollars. The total population of this province, according to the latest census, is 2,189,098 people, with a demand rate considered to be 1%. Table (16) shows the population of the regions in this city. To determine the smart city regions, the output of the WASPAS decision-making model evaluation, as per the weighting results in Table (10), is used in the mathematical model.

Table 16
Population of the municipal Regions of Isfahan city

District No.	Population	District No.	Population
1	79,091	9	75,168
2	69,120	10	207,803
3	110,368	11	58,841
4	133,731	12	136,376
5	150,865	13	132,469
6	112,129	14	164,850
7	168,732	15	121,961
8	239,756		

For solving the case study using the Baron solver, the mathematical model decisions are as follows. The value of the first objective function, which aims to minimize operational costs, including warehouse location costs, equipping priority areas with smart city infrastructure using IoT items such as various cameras and sensors, and operational costs of purchasing and maintaining inventory, amounted to 6,361,300 million dollars. The value of the second objective function, which aims to maximize the coverage of IoT items including various cameras and sensors, reached 210 meters. Additionally, the value of the third objective function, which pertains to the reliability of the cameras and sensors utilized in disaster management areas, was concluded to be 0.89%. The overall value of the objective functions, using the weighted Sum method, amounted to 1,590,325 million dollars. In this numerical example, 8 suppliers were considered, with suppliers' number 5, 6, and 7 selected to supply food and hygiene products. Among the 15 potential warehouses, warehouses number 10, 11, 12, and 13 were chosen. Additionally, out of the 15 regions, regions number 6, 4, 8, 9, 14, and 15 were selected to establish smart city infrastructure by allocating IoT items. The IoT items, including sensors and cameras, will be installed in potential locations within the smart regions, considering their coverage radius. Figure (8) shows the positions of the suppliers, warehouses, and smart city regions

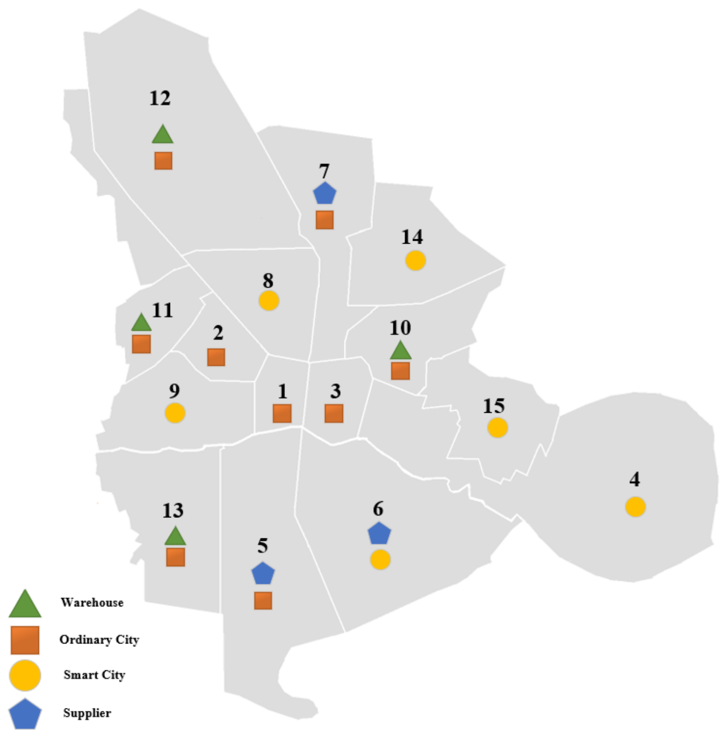

Fig. 7. Location of suppliers, warehouses and Regions equipped with smart city infrastructure in case study

According to Figure (7), it is observed that out of the 15 potential warehouses, only the warehouses in regions numbered 10, 11, 12, and 13 have been established. Additionally, the supply of goods to these regions and warehouses is exclusively managed by suppliers numbered 5, 6, and 7. In terms of smart city development, regions numbered 4, 6, 8, 9, 14, and 15 have been equipped with cameras and sensors.

Table 17
Values of demand variables and inventory control according to the location of warehouses - case study

Variable	Product	Warehouse 10	Warehouse 11	Warehouse 12	Warehouse 13
D	1	8605.5	6713.2	9445.8	1938.1
	2	9189.4	6752.1	8280.8	1789.6
Q	1	389.8	346.6	431.3	215.9
	2	471.1	405.2	387.0	188.4
S	1	41840	38687	51077	11725
	2	46717	34302	43157	11045
R	1	132590	134530	169390	39250
	2	152300	109120	139880	37500
I	1	42035	38860	51292	11833
	2	46953	34505	43351	11139

Table 18
The values of the variables of the smart city infrastructure candidate Regions- case study

Variable	Type of IOT	Zone 4 (j_4)			Zone 6 (j_6)			Zone 8 (j_8)			Zone 9 (j_9)			Zone 14 (j_{14})			Zone 15 (j_{15})		
		d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3
XC_{cdj}	Camera 1 (c_1)	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1
	Camera 2 (c_2)	1	-	1	-	-	-	-	1	-	-	1	-	1	-	1	1	1	-
XS_{sdj}	Sensor 1 (s_1)	1	-	1	-	-	-	-	1	-	-	1	-	-	-	1	-	1	-
	Sensor 2 (s_2)	-	-	-	1	1	1	-	-	-	1		1	1	1	-	-	-	1
Rec_{cdj}	Camera 1 (c_1)	-	0.93	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.93
	Camera 2 (c_2)	0.91	-	0.91	-	-	-	-	0.95	-	-	0.91	-	0.91	-	0.91	0.91	0.91	-
Res_{sdj}	Sensor 1 (s_1)	0.90	-	0.90	-	-	-	0.96	-	-	-	0.90	-	-	-	0.90	-	0.90	
	Sensor 2 (s_2)	-	-	-	0.93	0.93	0.93	-	-	-	0.93	-	0.93	0.93	0.93	-	-	-	0.93

5. Discussion and Conclusion

This study aimed to develop a framework for disaster management before the catastrophe and during the strategic preparedness phase. This framework was created by integrating multi-criteria decision-making methods, mathematical optimization, and considering sustainability, resilience, and smart city approaches. In other words, this disaster management, prior to the catastrophe, is implemented through prioritizing regional policies, locating and stocking service warehouses, and determining candidate areas for smart city infrastructure with the allocation of various types of cameras and sensors. In the following sections, the discussion and analysis of the research results are presented, divided into decision-making models and mathematical models.

In the first part, an evaluation and prioritization framework for regions was developed based on five criteria and nineteen Aspects using the sustainability, resilience, and smart city approach through a review of disaster literature and expert opinions. Following this, after examining multi-criteria decision-making methods, two effective methods, SWARA and WASPAS, were selected for weighting and evaluating the chosen regions. Results from the SWARA method indicated that infrastructure, social, and physical Aspects were ranked first to third in terms of importance with weights of 0.214, 0.205, and 0.198 respectively. Additionally, Aspects such as the number of medical service centers, transportation network, fire stations, population density, and ICT infrastructure ranked in the top five among the nineteen Aspects. Subsequently, data was collected on the fifteen administrative regions of Isfahan municipality to prioritize them using the WASPAS method based on the identified criteria and Aspects. The results of this prioritization and evaluation demonstrated that regions 8, 10, 5, 4, and 6 out of the fifteen regions were of higher importance. Moreover, these prioritization weights of the regions are utilized by the mathematical model in determining smart regions. In conclusion, the first part of this research concludes that the framework presented has a strong capability in strategic decision-making and analysis in disaster management based on sustainability and resilience approaches. In other words, an executive action plan clearly prioritizes and evaluates actions.

In the next section of this research, a three-objective mathematical model for natural disaster management has been proposed based on the Aspects of sustainability and resilience, aiming to optimize resource allocation and smart infrastructure deployment. This model addresses supplier selection, warehouse location, inventory determination, and allocation of IoT equipment such as cameras and sensors in selected regions to establish smart city infrastructure. Numerical results from modeling and case studies demonstrate that the proposed model can provide optimal decisions aligned with various objectives. For instance, in a case study with moderate Aspects, operational costs were minimized by $6,361,300, IoT item coverage was maximized to 210 meters, and reliability was maximized to 0.89. In this numerical example, eight potential suppliers were selected for provisioning food and hygiene items to warehouses in regions 10, 11, 12, and 13 among regions 5, 6, and 7. Furthermore, six regions numbered 6, 4, 8, 9, 14, and 15 were chosen based on their prioritized importance weights for creating smart city infrastructure and allocating IoT items, considering operational costs, coverage rates, and reliability. This smart city deployment involves installing various sensors and cameras in potential locations within selected regions, considering their coverage radius. Sensitivity analysis on a numerical example indicated that total costs are influenced by maintenance expenses, demand correlation coefficient, and demand average. These results underscore the model's capability to achieve a balance among conflicting objectives, directly leading to improved resource management and enhanced efficiency in both ordinary and smart urban areas.

Review of Innovations and Applications of the Research

This study, compared to previous research, has presented significant innovations by integrating aspects of sustainability and resilience and addressing smart cities as a novel approach to disaster management in the preparedness phase before a disaster. This study develops disaster management strategies for mitigation and preparedness by providing an evaluation, prioritization, and location-allocation framework using multi-criteria decision-making (MCDM) methods and mathematical modeling. It should be noted that, according to the literature on disaster management in the pre-disaster phase, the simultaneous use of MCDM and multi-objective optimization (MOO) methods has been seldom addressed. Given the complexity of managing this domain, substantial effectiveness can be achieved. Additionally, in tandem with warehouse location and emergency supply allocation within a studied area, several regions are selected and equipped with various sensors and cameras as candidate regions for implementing smart infrastructure for disaster management. This approach aims to reduce the demand variance across regions and increase accuracy. Below, three studies on disaster management in the pre-disaster phase are discussed, and the developments achieved in the present research are explained.

In the study by Zabihi et al. (2023), a sustainable intelligent system for disaster management was presented using artificial intelligence and multi-criteria decision-making. In this regard, a comprehensive system with three sections, including monitoring, prediction, and control, was designed. In this research, hydrological data is initially evaluated using statistical analysis to classify flood phenomena in different climates of Iran based on rainfall parameters, and then the data is clustered using machine learning. Güler et al. (2023) conducted a study titled "Prioritization of Earthquake Risk through Two-Stage Cluster Analysis and Multi-Criteria Decision-Making Methods." In this study, twenty-nine provinces in Turkey were clustered for earthquake risk prioritization through a two-stage cluster analysis. The indices determined in the two-stage cluster analysis were defined and weighted using the SWARA method. After evaluating the criteria, the ELECTRE method was used to rank the earthquake risk of the provinces. Shao et al. (2023) proposed a sustainable development assessment framework for a smart city using a fuzzy integrated decision-making approach. In this research, an evaluation system based on constructed criteria, urban infrastructure, environmental, social, and economic factors was initially suggested. The DEMATEL technique was used to determine the interrelationships between the indices and obtain their weights. Additionally, the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) with an aspiration-level approach was used to analyze the sustainable development performance of a smart city.

In the present study, mathematical modeling and decision-making techniques have been utilized, which can significantly enhance the effectiveness of decisions considering the complexity of natural disaster issues. Furthermore, after evaluating the regions based on sustainability and resilience approaches, the study addresses the implementation of operational decisions such as warehouse location, inventory control, and the allocation of cameras and sensors to increase the efficiency of data collection post-disaster. This research aims to provide a comprehensive and implementable framework applicable to various study areas. The proposed framework enables the simultaneous evaluation of regions using sustainability and resilience approaches, along with the execution of strategic decisions such as supplier selection, warehouse location, emergency inventory control, and the allocation of IoT items like cameras and sensors based on coverage radius. This integration not only improves preparedness and response capabilities but also optimizes resource allocation, ensuring that critical areas receive the necessary support and infrastructure to mitigate the impacts of disasters effectively. The combined use of multi-criteria decision-making (MCDM) and multi-objective optimization (MOO) methods provides a robust approach to handling the intricacies of disaster management, facilitating the development of strategic plans that enhance both immediate response and long-term resilience.

Challenges and Limitations

During the execution of this research, several challenges were encountered, such as data limitations, the complexity of modeling, and the need for coordination among various management and operational sectors. Despite these challenges, the results indicate the high potential of the model in enhancing disaster management and increasing the resilience of urban areas. Future research should focus on integrating uncertainties into modeling, particularly related to demand and budget, by incorporating advanced techniques such as probabilistic or scenario-based approaches. Utilizing metaheuristic algorithms can enhance the accuracy and flexibility of decision-making in disaster management. Additionally, developing dynamic and adaptive models, alongside analyzing social and psychological resilience, will improve the efficiency of crisis management systems. Expanding the application of emerging technologies in smart cities and testing models on an international level would ensure that the proposed framework is implemented more comprehensively and practically, enhancing disaster response capabilities across diverse conditions.

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