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**Title:**

Introducing a Novel Multi-Objective Optimization Model for Last-Mile Distribution in the Post-Disaster Phase: Combining Fuzzy Inference Systems with NSGA-II and NRGA

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| | |
|---|---|
| ACO | Ant Colony Optimization |
| BD CATNAT Global | Base de Données Catastroph Natural |
| BRERA | Bi-Objective Robust Emergency Resource Allocation |
| CRED | Centre for Research on Epidemiology of Disasters |
| CVRP | Capacitated Vehicle Routing Problem |
| DC | Distribution Centre |
| DRR | Disaster Risk Reduction |
| EA | Evolutionary Algorithm |
| EMBO | Enhanced Monarch Butterfly Optimization |
| EM-DAT | Emergency Events Database |
| FIS | Fuzzy Inference System |
| FSACO | Fish-Swarm Ant Colony Optimization |
| GA | Genetic Algorithm |
| GFDRR | Global Facility for Disaster Reduction and Recovery |
| GLIDE | GLobal Unique Disaster Identifier |
| GP | Goal Programming |

| | |
|---|---|
| HADC | Humanitarian Aid Distribution Centre |
| HL | Humanitarian Logistics |
| HV | Hypervolume |
| HVRP | Heterogeneous Vehicle Routing Problem |
| L-MLCA | League Base Multiple League Championship Algorithm |
| MDHVRPTW | Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows |
| MDVRP | Multi-Depot Vehicle Routing Problem |
| MDVRPTW | Multi Depot Vehicle Routing Problem with Time Windows |
| MID | Mean Ideal Distance |
| MILP | Mixed-Integer Linear Programming |
| MIP | Mixed Integer Programming |
| MLCA | Multiple League Championship Algorithm |
| MOEA | Multi-Objective Evolutionary Algorithm |
| MOEA/D | Multi-Objective Evolutionary Algorithm based on Decomposition |
| mt-CCSVRP | multi-trip Cumulative Capacitated Single-Vehicle Routing Problem |
| NatCatSERVICE | Natural Catastrophe Services |

| | |
|---|---|
| NGO | Non-Governmental Organization |
| NNS | Number of Non-dominated Solutions |
| NRGA | Non-dominated Ranked Genetic Algorithm |
| NSGA-II | Non-dominated Sorting Genetic Algorithm II |
| P-MLCA | Playoff Multiple League Championship Algorithm |
| POD | Point of Demand |
| PSO | Particle Swarm Optimization |
| RNA | Rapid Needs Assessment |
| SA | Simulated Annealing |
| SA-GA | Simulated Annealing - Genetic Algorithm |
| SM | Spacing Metric |
| UAV | Unmanned Aerial Vehicle |
| VCA | Vulnerability and Capacity Assessment |
| VRP | Vehicle Routing Problem |
| VRPTW | Vehicle Routing Problem with Time Window |
| WHO | World Health Organization |

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# 1- Introduction

Natural disasters have become increasingly pressing in recent years, causing significant human and economic losses. Yearly, numerous natural disasters occur globally, resulting in severe economic repercussions, extensive agricultural damage, and the displacement of a significant number of individuals. Certain events, such as the Indian Ocean tsunami in 2004 and the Kashmir earthquake in 2005, have had a profound historical influence on a global scale.

Despite concerted endeavours to alleviate the repercussions of natural disasters, communities persistently grapple with substantial difficulties when it comes to responding to and recovering from these disasters. The domain of natural disasters is extensive, drawing scholars from diverse disciplines who aspire to attain a holistic comprehension of the scientific dimensions and effective approaches for handling the devastating aftermath. This context is so crucial that prominent organizations such as World Health Organization (WHO) and the United Nations have allocated significant resources to investigating natural disasters.

## 1.1- Hazard vs. Disaster

Recognizing the difference between a hazard and a disaster is essential, as these terms should not be used interchangeably. A hazard is "a dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage" (UNISDR 2009). Examples of hazards include earthquakes, floods, hurricanes, and wildfires.

On the other hand, a disaster is "a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources"

(UNISDR 2009). While a hazard refers to an event that can happen regardless of human actions, it is crucial to understand that hazards can escalate into disasters if not appropriately addressed. Disasters can arise from sources such as earthquakes, floods and hurricanes or human-induced incidents, like terrorist attacks, industrial accidents, and war.

### 1.2- Disasters Classification

Disasters can be classified mainly based on two aspects: causes and characteristics. Disasters may be divided into two general categories based on their causes: natural and technological disasters. Six sub-categories (geophysical, meteorological, hydrological, climatological, biological, and extraterrestrial) make up the category of natural disasters. On the other hand, technological disasters refer to disasters resulting from human actions. This group consists of three Disaster Subgroups: Industrial accidents, Transport accidents, and Miscellaneous accidents. Each disaster group covers different disaster types (IRDR 2014). Table 1 gives an overview of the grouping of disasters regarding their causes.

Another way to classify disasters is by their onset, which can be sudden or slow. Sudden-onset disasters, such as earthquakes, hurricanes, and terrorist attacks, arise suddenly and have an immediate impact. Slow-onset disasters, such as pandemics, insect infestation, and political crises, emerge gradually over time and may not be immediately apparent. To effectively manage disasters, it is crucial to understand their causes and characteristics (Ergun et al. 2010).

Table 1: Disaster Classification Regarding the Causes

| Disaster Group | Disaster Subgroup | Disaster Main Type |
|---|---|---|
| **Natural** | Geophysical | Earthquake, Mass Movement (dry), Volcanic activity |
| | Meteorological | Extreme Temperature, Fog, Storm |
| | Hydrological | Flood, Landslide, Wave action |
| | Climatological | Drought, Glacial Lake Outburst, Wildfire |
| | Biological | Epidemic, Insect infestation, Animal Accident |
| | Extraterrestrial | Impact, Space weather |
| **Technological** | Industrial accident | Chemical spill, Collapse, Explosion, Fire, Gas leak, Poisoning, Radiation, Oil spill, Other |
| | Transport accident | Air, Road, Rail, Water |
| | Miscellaneous accident | Collapse, Explosion, Fire, Other |

Adapted from IRDR (2014)

## 1.3- Disaster Databases

Disasters can cause harm to individuals, their livelihoods, and the natural surroundings. They have lasting consequences on both the economy and society, leading to heightened poverty, inequality, and vulnerability. Thus, it is crucial to minimize the risk of disasters as much as possible. According to UNISDR (2009), Disaster Risk Reduction (DRR) refers to "The concept and practice of reducing disaster risks through systematic efforts to analyze and manage the causal factors of disasters, including through reduced exposure to hazards, lessened vulnerability of people and property, wise management of land and the environment, and improved preparedness for adverse events." Investing in DRR can achieve advantages such as preserving lives, safeguarding infrastructure and valuable resources, minimizing losses, and strengthening our ability to cope with social and environmental challenges.

Disaster databases support DRR by integrating data analysis and geospatial visualization. Therefore, these databases are crucial in disaster management by providing comprehensive information on disaster events, exposure elements, and hazard susceptibility. They aid in creating efficient policies and procedures that reduce future risks and enhance global, regional, and national community resilience.

Typically, disaster databases are used for the following reasons (Mazhin et al. 2021):

1. Engaging in the implementation of disaster relief, recovery, and reconstruction initiatives. The assessment of financial requirements for recovery and reconstruction can be established by considering both physical damage and its economic counterpart;
2. Evaluating the potential risk of forthcoming disasters. The reliance solely on past damage as a predictive measure for future damage is insufficient. However, it is crucial to utilize primary data from previous disasters to validate, calibrate, and establish vulnerability curves in order to assess and estimate future damage accurately;
3. The assessment of the economic feasibility of investments aimed at mitigating losses;
4. Engaging in the ongoing processes of follow-up, monitoring, and evaluation pertaining to the patterns and trends of human impacts and disasters in order to attain the global objectives established in disaster risk reduction;
5. Performing thematic analysis such as damage assessment in specific sectors.

**Mazhin et al. (2021)** identified 25 global and regional databases in their study. Six of them are global disaster databases:

- Emergency Events Database (EM-DAT)
- Natural Catastrophe Services (NatCatSERVICE)
- SIGMA

- GLobal Unique Disaster Identifier (GLIDE)
- Global Facility for Disaster Reduction and Recovery (GFDRR)
- Base de Données Catastroph Natural (BD CATNAT Global)

EM-DAT was maintained by the Centre for Research on Epidemiology of Disasters (CRED) at the Université Catholique de Louvain in 1988 in Belgium. EM-DAT is publicly available and reports the occurrence of more than 22,000 disasters attributed to natural, technological, and biological hazards, as well as their health and economic consequences from 1900 to the present day. In fact, this database is the primary repository for epidemiological data on disasters (CRED - The Emergency Events Database (EM-DAT): The last 25 years in research 2022).

A disaster must meet at least one of the following requirements in order to be added to the database (CRED. 2022 Disasters in numbers. 2023):

- Ten or more documented fatalities
- At least 100 people reported being impacted
- the proclamation of an emergency
- ask for support from abroad

In the year 2022, the Emergency Event Database (EM-DAT) documented a total of 387 disasters worldwide that were associated with natural hazards. The events mentioned above led to a total of 30,704 fatalities, affecting a population of approximately 185 million individuals and resulting in an economic loss exceeding 223.8 billion US dollars.

Floods dominated these events, with 176 occurrences, followed by storms that occurred 108 times. Nevertheless, storms caused the highest economic losses, with 131 billion US$ (58% of total economic losses). In addition, the deadliest disaster types are extreme temperature and flood, contributing to 79% of deaths by natural disasters in 2022.

Compared to the past, in Africa, the human and economic cost of disasters was comparatively higher—16.4% of fatalities were caused by them, compared to 3.8% in the two decades prior. Even though Asia saw some of the most catastrophic events in 2022, the impact of disasters was comparatively lower there. Every kind of disaster occurred almost at the same frequency as during the previous 20 years. With 30,704 deaths overall in 2022, it was three times more than in 2021 but still less than the average of 60,955 deaths between 2002 and 2021.

Globally, 2022 was characterized by a 5% rise in disaster occurrences (Figure 1) and a 19% increase in economic losses. However, the number of fatalities and those impacted were below their 20-year norms (CRED. 2022 Disasters in numbers. 2023).

### 1.4- Disaster Management

United States Comprehensive Emergency Management introduces four distinct stages for disaster management operations to deal with emergencies and disasters: mitigation, preparedness, response, and recovery. This framework is designed to minimize the impact of disasters on people, property, and the environment (Altay and Green 2006). Figure 2 depicts the humanitarian operation steps and the disaster timeline. We briefly overview each phase in the following.

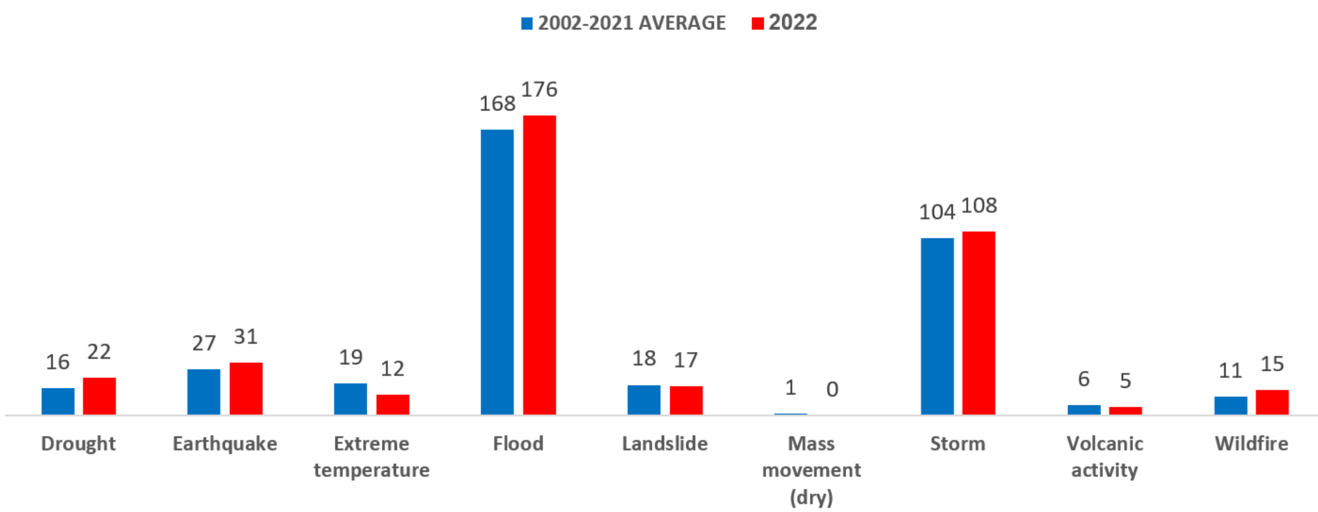



Figure 1: Disaster Type Frequency in 2022 Compared to the Yearly Average from 2002 to 2021

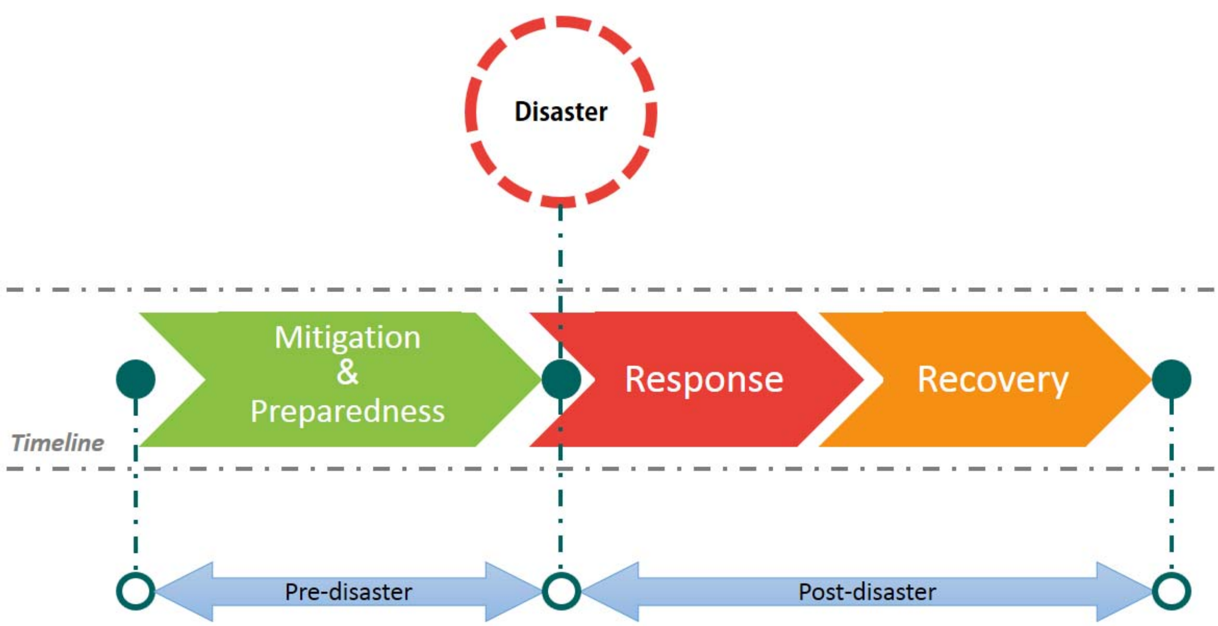



Figure 2: Timeline of a Disaster and Stages of Humanitarian Operation

### 1.4.1- Mitigation

Risk analysis, also known as Vulnerability and Capacity Assessment (VCA), is a critical initial phase in disaster management. Hazards and their potential consequences on communities and activities, as well as the ability of organizations to avoid and respond to disasters, are all identified during this stage (Wisner and Adams 2002). Once this phase has been completed, further risk assessment and risk management solutions can be considered. The identification of mitigation strategies is a part of this process. Mitigation is widely regarded as the fundamental element of disaster management and includes any activity or consistent effort to decrease the hazard risk. To be more specific, mitigation aims to either reduce a hazard's likelihood of happening or its negative impacts if it happens (Coppola 2015; Prasad and Francescutti 2017; Altay and Green 2006).

The National Research Council's Board on Natural Disasters has proposed four mitigating strategies (Prasad and Francescutti 2017):

1. Identify the probable location and the type of any possible hazards;
2. Identify the population's characteristics as well as the structures that are sensitive to the hazards;
3. Establish a specific standard for different risk levels;
4. Utilize mitigation strategies that are reasonable and established on cost-benefit analysis.

Note that each country should coordinate mitigation and preparedness as pre-disaster operations at various levels by organizations concerned with all disaster phases to achieve the ultimate goal of vulnerability reduction (Wisner and Adams 2002).

To be more focused on the mitigation phase, there are two types of mitigation (Coppola 2015):

1. *Structural mitigation*: Risk reduction done via the creation or modification of the physical environment through the use of designed solutions (e.g., Resistant construction; Implementing detection systems);
2. *Nonstructural mitigation*: Risk reduction done via changes in human behaviour or natural processes that occur without constructing structures or solutions (e.g., programs for raising public awareness and education; behavioural modification).

### 1.4.2- Preparedness

The concept of disaster preparedness covers proactive measures undertaken before a disaster to ensure a sufficient response to its effects, as well as the subsequent relief and recovery efforts aimed at mitigating its consequences (Coppola 2015). Note that although we discuss mitigation and preparedness separately here, they should be viewed as interconnected and frequently overlapping parts of the fundamental goal of vulnerability reduction, and they share many actions in practice.

In this phase, there are four levels of planning: National plans, Regional plans, District plans, and Local plans. To create a hierarchy of coordinated plans from national to local levels, plans created at one level should be related to plans created at other levels (Wisner and Adams 2002).

WHO offers a methodology for disaster planning that may be applied at any of the four levels mentioned above. They have numerous characteristics in common, so the following sequence of the planning process will be carried out for each of them(Wisner and Adams 2002):

1. **Determine the hazards and evaluate their impacts**;
2. **Analyze the probable requirements.** Creating a list of everything that has to be done before, during, and after the emergency is required;
3. **Review the requirements.** In order to think of potential items that may have been neglected, this phase entails including as many individuals as possible in the planning process;
4. **Establish the operating processes and evaluate the current priorities**;
5. **Make the responsibilities known.** Now is the moment to define roles so that everyone knows their duties. They can then create their own programs to fulfill their individual responsibilities;
6. **Prepare a list of the local resources and capacity**;
7. **Review steps 2 through 5,** at which point you should analyze your resources and requirements and build reserves;
8. **Recognize critical areas.** These are the areas where likely responses will be put under the highest pressure and where reinforcement is necessary in advance;
9. **Verify your priorities.** It is essential to check the priorities determined in Step 4 and addressed in the following phases in light of the knowledge of both requirements and resources;
10. **Finalize the plan**;
11. **Workout the plan.** Plans should be periodically reviewed, revised, and tested to ensure that those in charge of carrying them out are up to date;
12. **Assess the plan.** The success of the plan's implementation should be assessed if an emergency arises so that lessons may be learned and utilized.

### 1.4.3- Response

Response activities get started as soon as a hazard occurrence arises. Given that it is carried out under conditions of extreme stress, under strict time constraints, and with little information, the response is by far the most complicated of the four emergency management phases. Unnecessary delays during the response immediately lead to tragedy and damage. The main goals of the response phase are to save lives, alleviate suffering, and safeguard assets and the environment. Before the emergency is deemed to be over, it can last days or weeks (Coppola 2015).

When a disaster onsets, the emergency response starts with an assessment to respond appropriately to needs. Generally, there are two types of assessment (Coppola 2015):

1. *Situation assessment*: This evaluation, also known as a damage assessment, aims to determine what occurred due to the hazard. The geographic extent of the disaster and its effects on people and structures may be determined using situation assessments. In essence, it serves as a gauge for the hazard's effects;
2. *Needs assessment*: The purpose of this evaluation is to identify the urgent requirements of the impacted population, including those for food, water, shelter, and medical attention. The assessment helps prioritize resource allocation and ensure that the most critical needs are addressed first.

By far, some international standards and codes of conduct for humanitarian response have been created to improve the performance and accountability of this stage. One of these standards is "**The Sphere Project Humanitarian Charter and Minimum Standards in Disaster Response**". The right of people to protection and aid is protected by this standard, which outlines the fundamental values that guide humanitarian action. Additionally, minimum requirements are established for humanitarian intervention in nutrition, temporary shelter, water supply and sanitation, and health medical attention (Wisner and Adams 2002).

### 1.4.4- Recovery

We proceed to the recovery phase after relief efforts during the response phase. After the immediate effects of the disaster are over, recovery entails long-term activities to stabilize the community and reestablish some sense of normalcy (Altay and Green 2006). Recovery efforts are the most varied and expensive and go well beyond just restoring what was there before (Coppola 2015). The whole rebuilding of the impacted region in accordance with the demands of its inhabitants calls for an integrated development strategy (Wisner and Adams 2002).

Disasters cause various social problems, including homelessness, financial losses, communications problems caused by damaged infrastructure, hunger, malnutrition caused by breakdowns in the food supply chain, unemployment caused by job losses, and more (Coppola 2015).

There are two separate phases of recovery, and each has quite diverse activities: short-term and long-term (Coppola 2015):

1. *Short-term recovery* phase starts following the hazard incident while emergency response efforts are still underway. Short-term recovery efforts aim to stabilize impacted individuals' lives to get them ready for the hard work of reconstructing their lives;
2. *Long-term recovery* often starts seriously when the disaster's emergency phase is over. The community or nation starts to rebuild and repair during long-term recovery.

Sustainable livelihood security is the goal of both recovery phases. It focuses on encouraging people's capacity development through access to food, cash, and other primary resources and corresponding reduced vulnerability to disasters. In addition to physical assistance, recovery strategies should, however, include actions to deal with the economic and social turmoil brought on by the disaster. Loss of life may produce terrible implications for fractured families long after the events of the disaster have passed; as a result, services must be in place to give social assistance to individuals who have been impacted (Prasad and Francescutti 2017).

It should be noted that failure to recover, or partial recovery, makes people more likely to be more vulnerable to the following stressful situations (Wisner and Adams 2002). The tasks that are typically included in each of these four stages are listed in Table 2.

Table 2: Some Crucial Activities in the Field of Disaster Operations Management

| |
|---|
| **Mitigation**<br>**(Goal: preventing the occurrence of disasters and mitigating their severity)** |
| • Building of disaster force-controlling barrier, deflection, and retention systems<br>• Building regulations and laws to make structures more disaster-resistant<br>• Construction of community shelters to protect human lives from a disaster's consequences<br>• Systems for detection (such as biological detection systems, imaging satellites, and weather stations)<br>• Robust infrastructure for life safety (such as public health and transportation infrastructure)<br>• Regulatory measures (e.g., zoning and land use restrictions to forbid habitation in high-risk regions)<br>• Public awareness and education campaigns<br>• Changing behaviour (e.g., through tax incentives, subsidies, and other financial incentives for safe behaviours)<br>• Insurance to minimize the monetary effects of disasters |
| **Preparedness**<br>**(Goal: preparing individuals to respond effectively in the event of a disaster)** |
| • Developing a comprehensive disaster plan, including the roles and responsibilities, evacuation procedures, communication protocols, and resource allocation<br>• Conducting training and exercises, including simulations, tabletop exercises, and full-scale drills<br>• Setting up emergency operations hubs<br>• Conducting research and development to improve disaster management practices and technologies<br>• Developing partnerships with community organizations, businesses, and other stakeholders to ensure a coordinated response to disasters<br>• Establishing warning systems such as sirens, text alerts, and social media notifications<br>• Stockpiling supplies to have adequate supplies of food, water, medical equipment, and other essential items |

| |
|---|
| • Conducting public education campaigns |
| **Response** **(Goal: saving lives, rescuing people, and reducing extra human and economic damages)** |
| • Search and rescue victims<br>• Evacuation of threatened populations<br>• Provide emergency medical care to affected people<br>• Damage assessment caused by the disaster<br>• Resumption of critical infrastructure<br>• Establishing shelters and offering widespread care<br>• Ensuring the safety of responders and affected people<br>• Setting up communication channels, coordinating resources, and sharing information<br>• Fatality management |
| **Recovery** **(Goal: returning the disaster-affected area to normal conditions)** |
| • Disaster debris cleanup<br>• Provision of temporary, transitional, or permanent housing<br>• Rebuilding damaged infrastructures (e.g., roads, bridges, and hospitals)<br>• Resumption of social services<br>• Cultural and psychosocial rehabilitation programs<br>• Financial assistance and promoting economic growth in the affected area<br>• Ongoing dialogue with the public about recovery efforts<br>• Reassessment of hazard risk |

Adapted from Altay and Green; Coppola (2006; 2015)

## 1.5- Humanitarian Logistics

Thomas and Kopczak (2005) define Humanitarian Logistics (HL) as the systematic and efficient planning, implementation, and control of the movement and storage of goods, equipment, and relevant information from the point of origin to the point of consumption. The primary objective of this process is to minimize the suffering experienced by vulnerable individuals. Humanitarian Logistics involves some key activities:

- *Procurement:* It involves acquiring necessary relief items such as food, water, and medical supplies from suppliers or through donations;
- *Transportation:* It involves transportation of procured relief items to the affected areas by various modes of transportation;

- *Warehousing:* It involves storing the relief items in warehouses or distribution centres before being distributed to the affected population. Warehousing involves managing the inventory of relief items and maintaining adequate stock levels to meet the ongoing needs of the disaster response;
- *Distribution:* It involves planning and executing the delivery of relief items to various demand points while considering factors like demand uncertainty, transportation constraints, and the prioritization of needs. Fairness and equity in allocating relief items to the affected population should also be considered.

Effective humanitarian logistics planning and execution can save lives, alleviate suffering, and support the recovery of communities impacted by disasters (Thomas and Kopczak 2005).

In scholarly discourse, the concept of humanitarian logistics is often referred to by various synonymous terms, including humanitarian supply chains (Ertem et al. 2010; Yadav and Barve 2018), disaster relief operations, disaster relief supply chains, and emergency management. These terms are commonly used interchangeably in literature (Habib et al. 2016).

## 1.6- Humanitarian Logistics vs. Commercial Supply Chains

While sharing some similarities, humanitarian logistics and commercial supply chains have distinct differences in their objectives, priorities, and challenges (Thomas and Kopczak 2005).

The main goal of humanitarian logistics is to provide relief and assistance to affected populations during emergencies and disasters, focusing on minimizing human suffering and saving lives. On the other hand, commercial supply chains aim to optimize the flow of goods and services to meet customer demands and maximize profits (Beamon 2004).

Uncertainty is the prevailing characteristic of humanitarian logistics. Table 3 compares critical humanitarian logistics and commercial supply chain attributes (Beamon 2004; Pujawan et al. 2009; Vega and Roussat 2019).

Table 3: Commercial Supply Chain vs Humanitarian Logistics

| | **Commercial Supply Chain** | **Humanitarian Logistics** |
|---|---|---|
| **Objectives** | Meeting customer demands<br>Maximizing profits | Saving lives<br>Providing relief and assistance to affected populations<br>Minimizing human suffering |
| **Priorities** | Cost-effectiveness and efficiency<br>Customer satisfaction | Delivering aid quickly and efficiently to those in need |
| **Challenges** | Optimizing supply chain operations<br>Reducing costs<br>Meeting customer expectations | Limited access to the affected areas<br>Lack of infrastructure<br>Rapidly changing situations |
| **Demand** | Relatively stable<br>Predictable from historical data | Unknown in time, place, type, and amount<br>Should be evaluated right away |
| **Supply** | Predetermined sources of supply<br>Supply and demand are interdependent. | Various suppliers, regardless of their certification status<br>Insufficiency of crucial resources and an excessive amount of unsolicited donations |
| **Lead Time** | Almost planned | Short lead time for unexpected massive demand and diverse items |
| **Stakeholders** | Businesses<br>Suppliers<br>Customers | Governments<br>Non-Governmental Organizations (NGOs)<br>Donors<br>Affected communities |
| **Social Costs** | Economic costs and benefits | Human suffering |
| **Performance Measurement Method** | According to standardized indexes | Based on response time, saving lives, and meeting needs |

## 1.7- Conditions and Challenges After a Disaster Onset

Following the occurrence of a disaster, the response phase is initiated. The current phase of the humanitarian operation is of utmost importance and requires immediate action, ideally within a matter of days or even hours following the commencement of the disaster. Obtaining accurate information regarding the extent of damages and the level of demand poses a challenging task. Furthermore, essential provisions such as food and medical supplies are frequently inadequate. In the aftermath of a disaster, ensuring access to uncontaminated water, adequate sanitation facilities, proper nutrition, suitable shelter, prevention of communicable diseases, and related matters emerge as imperative considerations for public health. Infrastructures like roads might be severely damaged or blocked by debris. For instance, in 2016, Hurricane Matthew caused catastrophic flooding in North Carolina (NC), closing over 600 roadways for over ten days. Traditional airports may become inoperable; storage facilities may also face destruction; Hospitals or local clinics might be fully or partially destroyed.

Meanwhile, the surge in the count of individuals affected by disasters and sustaining injuries has escalated significantly, potentially surpassing the capacity of local clinics or hospitals to accommodate and treat them adequately. Hence, it may be imperative to establish temporary medical facilities close to the affected areas, equipped with surgical and other complex medical apparatus, as well as adequately trained personnel (Coppola 2015).

In the present scenario, the provision of transportation for diverse environmental health endeavours, including the relocation of assessment and operational teams and affected individuals in the aftermath of a disaster, as well as the transportation of equipment and supplies, poses a significant challenge, if not an impossible one. Additionally, the high demand for transportation during a disaster can lead to traffic congestion, further slowing down relief efforts. Also, The capacity to effectively allocate appropriate relief supplies to the right individuals in vulnerable populations, ensuring timeliness and adequacy (Yadav and Barve 2018), and salvage wounded people (Costa et al. 2012) is crucial to addressing the disaster effectively. In the given scenario, the absence of timely and effective provision of assistance to individuals impacted by the disaster could result in loss of life. So, efficiency in humanitarian logistics is a crucial determinant of success, as it ensures the smooth and effective movement of goods and services within the supply chain (Costa et al. 2012).

## 1.8- Dissertation Organization

The current dissertation is structured into six comprehensive chapters, each serving a distinct purpose. A brief overview of each chapter is provided below:

Chapter 1 lays the foundation by delving into the fundamental definition of a disaster and exploring its related concepts. This chapter also encompasses a discussion about the various phases of disaster management. Furthermore, it highlights the significance of humanitarian logistics in the context of disaster response and examines the prevailing conditions and challenges encountered in the aftermath of a disaster onset.

Chapter 2 delves into the categorization of research works on humanitarian logistics. It provides a literature overview from three perspectives: mathematical models and objective functions, optimization algorithms, and Vehicle Routing Problem (VRP). The present state of each facet will be evaluated and addressed, as will relevant studies in the humanitarian context. Finally, the current study's contribution to the literature is examined.

Chapter 3 starts with defining the problem we are going to address in this investigation. Afterwards, we discuss our three objective functions in-depth, encompassing two innovative objective functions to design a resilient last-mile distribution system. Finally, the related mathematical model will be constructed.

Chapter 4 begins by examining the architecture of Fuzzy Inference Systems (FISs) and their components and establishing two FISs to evaluate two novel objective functions introduced in Chapter 3. The exploration then extends to two robust evolutionary algorithms from the literature suitable for addressing high-dimensional optimization problems with conflicting objectives: the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Non-dominated Ranked Genetic Algorithm (NRGA). Also, we discuss how we can deal effectively with inherent uncertainties and conflicting goals encountered in the last-mile distribution process in humanitarian logistics, benefiting from the synergistic combination of FISs and evolutionary algorithms.

In Chapter 5, we examine and compare the performance of the employed algorithms in addressing both small-scale and large-scale problems, employing some critical criteria. Appropriate statistical tests are conducted, and the results are analyzed in detail.

Chapter 6 concludes the dissertation and provides an overview of the study. It provides a concise summary of this research's main steps and contributions. The identified limitations and future research recommendations in this field are also discussed.

# 2- Literature Review

Within the field of humanitarian logistics, the majority of scholarly articles can typically be classified into three general categories (Habib et al. 2016; Hezam and Nayeem 2021):

1. *Facility location*: Involves determining the optimal locations for facilities such as warehouses, distribution centres, and hospitals to ensure reliable delivery of relief supplies during emergencies. Concerning the timeline of the disaster, facility location problems encompass the decisions made prior to and in the aftermath of a disaster. This category of HL problems aims to position these facilities such that the demand of the disaster-stricken area is met with the least delivery cost and the highest degree of service.
2. *Network design and relief distribution*: This category deals with optimizing the distribution of humanitarian supplies from the facilities to the impacted people. It consists of relief distribution planning models, vehicle routing models, assessment routing models, transportation of causalities models, global relief distribution models, and location routing models. The primary topic of objective functions in this area is to improve responsiveness and cost efficiency. Nevertheless, the principal objective is to preserve human life.
3. *Mass Evacuation*: This category involves optimizing the evacuation process in disaster situations. It includes determining evacuation routes, managing the flow of evacuees, traffic control planning, designing mass evacuation models, and optimizing evacuee pickup point depots. This category aims to ensure the safety of evacuated people and efficient evacuation.

Distribution occurs at multiple levels (Anaya-Arenas et al. 2014): At the outset, expansive Distribution Centres (DCs) are situated in secure locations beyond the hot zone, serving as reception and consolidation points for relief goods procured from external suppliers. These DCs are vital in supplying various reliefs, including water, food, shelter, blood, and medicines, to distribution centres in the affected area, commonly called Humanitarian Aid Distribution Centres (HADCs). The primary function of HADCs is to ensure the timely supply of essential provisions to hospitals or medical centres that directly cater to the healthcare needs of the affected population. These healthcare service centres are often called Points of Demand (PODs) in the existing literature.

After the onset of a disaster, the primary focus is on making crucial decisions regarding selecting appropriate DCs and HADCs. These sites are chosen from a predetermined list of identified and strategically positioned locations during the preparedness phase. The second category of decisions within the logistic deployment involves allocating available resources to the HADCs while considering the specific requirements of the affected individuals these centres aim to assist. The third type of decision pertains to the transportation process between HADCs and PODs and the allocation of relief goods to these PODs. This complex phase involves careful planning and coordination to ensure the essential relief items reach the intended destinations efficiently and on time.

The effective implementation of a well-functioning relief distribution system is paramount in safeguarding human lives during disasters. Figure 3 illustrates the distribution network. The primary objective of this study is to focus on achieving the optimal allocation of relief goods to

PODs while also determining the most efficient routes for distributing these essential goods from HADCs to the respective PODs.

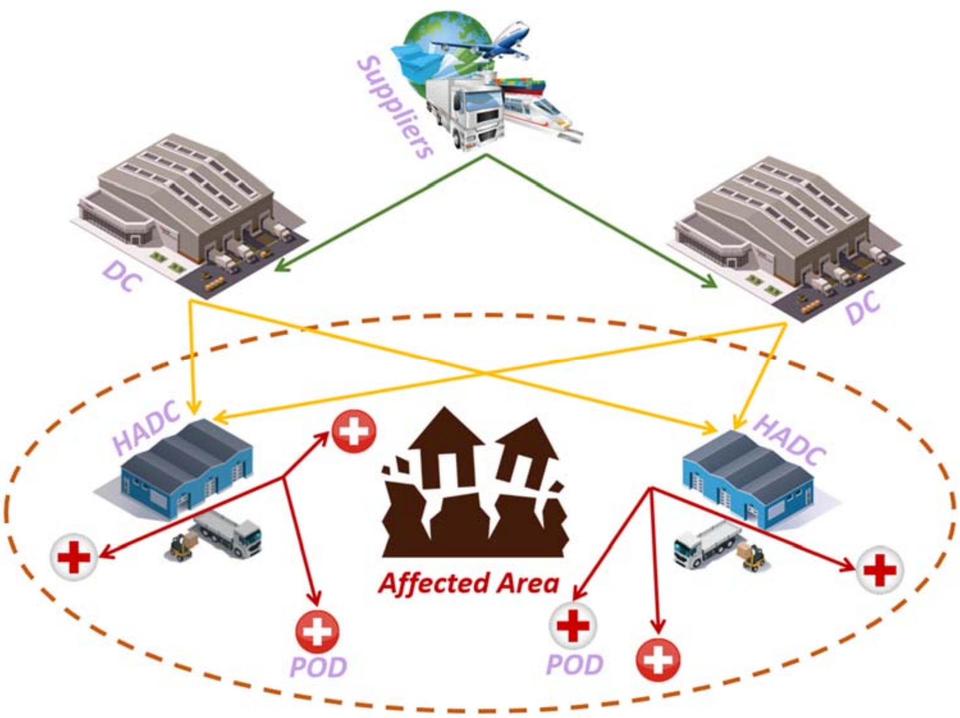



Figure 3: Distribution Network

One of the worst disasters ever was the Torrey Canyon oil leak. An estimated 25–36 million gallons of crude oil were spilt when the supertanker SS Torrey Canyon went aground on rocks off the southwest coast of the United Kingdom in 1967. The oil impacted several hundred miles of shoreline in Spain, Guernsey, France, and Britain.

In January of 1969, another incident involved an oil leak in Santa Barbara. It is important to note that three million gallons of oil were released when an offshore oil rig experienced a blowout off the coast of California. Regrettably, this resulted in the loss of seabirds, dolphins, and other marine creatures as the oil spill spread across 800 square miles. Furthermore, the tourism industry in Santa Barbara suffered setbacks due to the pollution caused by this event on its beaches.

These two environmental disasters, along with other similar catastrophes that occurred in the 1960s, garnered significant global attention. Extensive research efforts were undertaken to prevent similar disasters and preserve the marine ecosystem. The optimization models proposed by Charnes et al. (1976) and Charnes et al. (1979) are considered pioneering initiatives in humanitarian logistics.

Charnes et al. (1976) developed a multidimensional "goal programming" to help allocate resources in the United States Coast Guard's MEP program. The model extends to a "goal interval programming" type, using ranges for goals. Piecewise linear functions accommodate deviations. The model applies to person-hour allocation and MEP program planning.

Charnes et al. (1979) introduced a model to aid Coast Guard management in planning for equipment to handle pollution incidents. The model covers offloading, containment, and removal stages. A deterministic equivalent is derived using the zero-order rule of chance-constrained programming, replaced later with goal programming. Numerical examples illustrate the model’s potential uses, especially for budgetary planning and risk and equipment efficiency coefficient evaluation. Since then, optimization models have progressed in structure and the methods they put into practice.

The primary objective of the current research is to establish a multi-objective relief distribution system during the disaster response phase. This framework aims to establish optimal routes for a fleet of vehicles to efficiently deliver relief supplies to affected regions while ensuring the effective distribution of these supplies among PODs. In pursuit of this goal, the literature will be reviewed from three distinct perspectives:

- Mathematical Models and Objective Functions;
- Optimization Algorithms;
- Vehicle Routing Problems.

## 2.1- Mathematical Models and Objective Functions

Within the literature, mathematical models are typically categorized into two primary groupings: deterministic models and non-deterministic models. Furthermore, two distinct clusters emerge in the realm of objective functions: single-objective and multi-objective models. In the subsequent sections, we will embark on a more comprehensive exploration of these topics.

### 2.1.1- Deterministic Models and Non-deterministic Models

Two mathematical approaches are used to address problems in the humanitarian context (Hezam and Nayeem 2021): the Deterministic approach and the Non-deterministic approach. In the deterministic approach, in the model, it is assumed that all inputs are predetermined and known. This approach disregards any uncertainty or variation in the data. However, the ambiguous nature of HL issues makes the problems in this context challenging to solve.

To tackle this complexity, researchers employ Non-deterministic models that account for the uncertainty in parameters and strive to identify the best solution under various circumstances. Non-deterministic Models can be broadly categorized into two types: stochastic models and robust models. In stochastic models, uncertain parameters are represented by probability distributions. These parameters are represented using a set of scenarios with specified probability. On the other hand, robust models handle uncertainty through two approaches: robust models incorporating discrete scenarios and robust models incorporating interval uncertainty. Other approaches, like fuzzy set theory, safeguard against the model's probabilistic nature.

Generally speaking, deterministic models are more straightforward to solve and put into practice. Moreover, they tend to be faster and demand less resources than non-deterministic models. However, it is crucial to exercise caution when employing models in real-world situations where uncertainties often arise since these models do not account for parameter uncertainty.

In general, choosing deterministic or non-deterministic models relies on the nature of the current problem and the accessible data. Deterministic models work well for clearly defined problems, whereas non-deterministic models may be proper for complex and unpredictable problems.

### 2.1.2- Single-Objective Models and Multi-Objective Models

In the aftermath of a disaster, uncertainty, limited resources, and time constraints necessitate establishing a reliable and efficient relief distribution system. Contrary to commercial distribution systems prioritizing profit and cost considerations, relief distribution systems are primarily designed to prioritize responsiveness. In the present context, responsiveness is defined by concerning its capacity to preserve human lives. Within the existing body of literature, researchers attempted to achieve a suitable balance between cost and responsiveness to construct relief distribution systems that are both efficient and effective. Also, a range of objective functions have been introduced to serve this goal. Some objective functions that are highly significant and relevant can be identified as follows (Gutjahr and Nolz 2016; Luo et al. 2023):

- *Cost*: Considering the restricted availability of resources, minimizing the operating expenses, both fixed and variable, is a prevalent objective when it comes to transportation and relief equipment;
- *Response time*: refers to the capacity to distribute humanitarian relief on time that is crucial for impacted individuals and should be reduced to a minimum;
- *Shortest distance*: the shortest route to the points of demand for delivering relief products;
- *Coverage*: the quantity of relief goods delivered to impacted people. The goal is to maximize demand satisfaction or minimize unfulfilled demand;
- *Equity*: refers to the extent to which humanitarian help is given in a just and impartial manner among individuals and communities in need.

Other objective functions studied in the literature include untreated injured people, supply chain reliability, humanitarian operation security, route reliability, transportation risk, and social costs such as the lack of essential reliefs or psychological cost (Gutjahr and Nolz 2016; Vahdani et al. 2018; Ghasemi et al. 2020; Hezam and Nayeem 2021).

### 2.1.3- Review of Studies Regarding Mathematical Models and Objective Functions

When addressing relief distribution challenges after a disaster onset, the literature features the utilization of deterministic models (Balcik et al. 2008; Afshar and Haghani 2012; Pérez-Rodríguez and Holguín-Veras 2016). Nonetheless, many researchers choose non-deterministic models to confront the inherent uncertainties within this context (Najafi et al. 2013; Fereiduni et al. 2016; Haghi et al. 2017; Paydar et al. 2018; Eshghi et al. 2022). Furthermore, while some scholars employ single objective functions (Afshar and Haghani 2012; Pérez-Rodríguez and Holguín-Veras 2016; Fereiduni et al. 2016) to formulate efficient and effective methods of distributing aid, a prevailing trend in most studies involves the definition of multi-objective functions (Balcik et al. 2008; Najafi et al. 2013; Haghi et al. 2017; Paydar et al. 2018; Eshghi et al. 2022).

An overview of the research conducted in the literature concerning relief distribution, mainly focusing on applied mathematical models and the utilized objective functions, is presented in Table 4. In the following, we will investigate these studies in more detail: Balcik et al. (2008) were among the pioneers in developing the last-mile distribution model in the realm of humanitarian logistics. Their focus lay on a vehicle-based last-mile distribution system, wherein a local distribution centre served as the hub for storing and distributing emergency relief supplies to multiple demand locations. To achieve optimal allocation of these emergency supplies among the various demand points and to determine efficient delivery schedules for each vehicle, their model had two fundamental objective functions: minimizing transportation costs and maximizing benefits to aid recipients. Their approach to this optimization challenge was deterministic. Moving on to Afshar and Haghani (2012), their work aimed to present a single-objective mathematical model that thoroughly represents the integrated logistical activities carried out in the aftermath of natural disasters. This model controls the movement of various relief commodities across the supply chain, from their sources to their ultimate delivery to recipients. The objective function of their model was to minimize the total amount of weighted unsatisfied demand. Similar to Balcik et al. (2008), Afshar and Haghani (2012) also employed a deterministic approach to optimize the flow of relief commodities and resource utilization throughout the supply chain. The model's efficacy was demonstrated through a series of numerical experiments. Najafi et al. (2013) embarked on constructing a comprehensive logistics planning model during the earthquake response phase, focusing on the efficient employment of limited resources to deliver emergency relief efficiently. Their study proposed a model featuring three distinct objective functions: minimizing the total number of untreated wounded persons, minimizing the total unmet demands over the planning horizon, and minimizing the total deployment of vehicles in the response efforts. Notably, they introduced a robust approach to ensure the distribution plan's effectiveness across diverse post-earthquake scenarios. Pérez-Rodríguez and Holguín-Veras (2016) contributed to the literature by developing a single-objective inventory-allocation-routing model to facilitate the optimal allocation of critical supplies in post-disaster humanitarian logistics. The core objective function of their mathematical model was to minimize social costs linked to the distribution of these critical supplies, encompassing logistical costs incurred by the relief group and the deprivation costs borne by the beneficiaries. The deprivation costs encapsulated the economic value of human suffering resulting from the unavailability of essential goods or services. It is important to note that the authors' approach was deterministic, not accounting for system uncertainty in their optimization efforts.

Fereiduni et al. (2016) focused on optimizing decision-making about the distribution and evacuation of aid resources following an earthquake. Their single-objective model targeted minimizing total costs, encompassing transportation, operational, and inventory costs associated with distribution and evacuation. To tackle uncertainty effectively, they introduced a robust bi-level approach. To illustrate the practicality of their proposed model, the study presented a case study based on the hypothetical Tehran earthquake scenario in Region 1. In contrast, Haghi et al. (2017) introduced a multi-objective programming paradigm for strategically positioning healthcare facilities and humanitarian commodities distribution centres, distributing relief supplies effectively, and moving victims to health centres. Within the relief distribution domain, they considered two objective functions: minimizing response costs (encompassing transportation, shortage, and inventory holding costs) and maximizing satisfaction levels at demand points (achieved by minimizing the sum of maximum shortages). Notably, this model considered uncertainties in demand, supply, and cost parameters and facility vulnerabilities to earthquakes. Consequently, they employed a robust optimization approach to navigate these uncertainties. Shifting the focus to Paydar et al. (2018), their contribution encompassed a multi-objective model tailored for the supply and distribution of relief commodities in disaster-stricken regions, especially under environmental uncertainty. This optimization model aimed to determine the strategic placement of distribution and evacuation centres and the equitable allocation of relief commodities to areas affected by earthquakes, categorized according to their structural integrity. This model considered three objective functions: cost minimization, responsiveness maximization, and demand coverage maximization. A robust optimization approach was integrated to address uncertainties, and the model's validation was carried out through a case study conducted in Amol, Iran. Lastly, Eshghi et al. (2022) presented a robust multi-objective model for location-allocation planning in emergency relief operations during disasters. Their model embraced three objective functions: the maximization of service fairness to damaged areas, the maximization of fair commodity disaster management, and the minimization of overall logistical expenses. The authors conducted a case study analysis within an area characterized by high seismic activity and historical earthquake records in northern Iran, demonstrating the efficiency and applicability of their approach.

Table 4: Relief Distribution Review (Mathematical Models and Objective Functions)

| Author(s) | Deterministic / Non-Deterministic | Single-Objective / Multi-Objective | Objective Function(s) |
|---|---|---|---|
| (Balcik et al. 2008) | Deterministic | Multi-Objective | Minimizing transportation costs<br>Maximizing benefits to aid recipients |
| (Afshar and Haghani 2012) | Deterministic | Single-Objective | Minimizing the overall quantity of weighted unmet demand |
| (Najafi et al. 2013) | Non-Deterministic | Multi-Objective | Minimizing the total number of untreated wounded persons<br>Minimizing the total unmet demands over the planning horizon<br>Minimizing the total deployment of vehicles in the response efforts. |
| (Pérez-Rodríguez and Holguín-Veras 2016) | Deterministic | Single-Objective | Minimizing social costs |
| (Fereiduni et al. 2016) | Non-Deterministic | Single-Objective | Minimizing total costs |
| (Haghi et al. 2017) | Non-Deterministic | Multi-Objective | Minimizing response costs (encompassing transportation, shortage, and inventory holding costs)<br>Maximizing satisfaction levels at demand points (achieved by minimizing the sum of maximum shortages). |
| (Paydar et al. 2018) | Non-Deterministic | Multi-Objective | Minimizing costs<br>Maximizing responsiveness<br>Maximizing demand coverage |
| (Eshghi et al. 2022) | Non-Deterministic | Multi-Objective | Maximizing service fairness to damaged areas<br>Maximizing fair commodity disaster management<br>Minimizing overall logistical expenses |

## 2.2- Optimization Algorithms

There are two specific optimization algorithms in the literature: exact and approximate (Akwafuo). Exact algorithms are designed to provide precise solutions to problems, as their name implies. However, approximate algorithms solve problems approximately. The approximate algorithms may be further classified into two main categories: heuristic algorithms and meta-heuristic algorithms. Figure 4 shows the classifications of optimization algorithms.

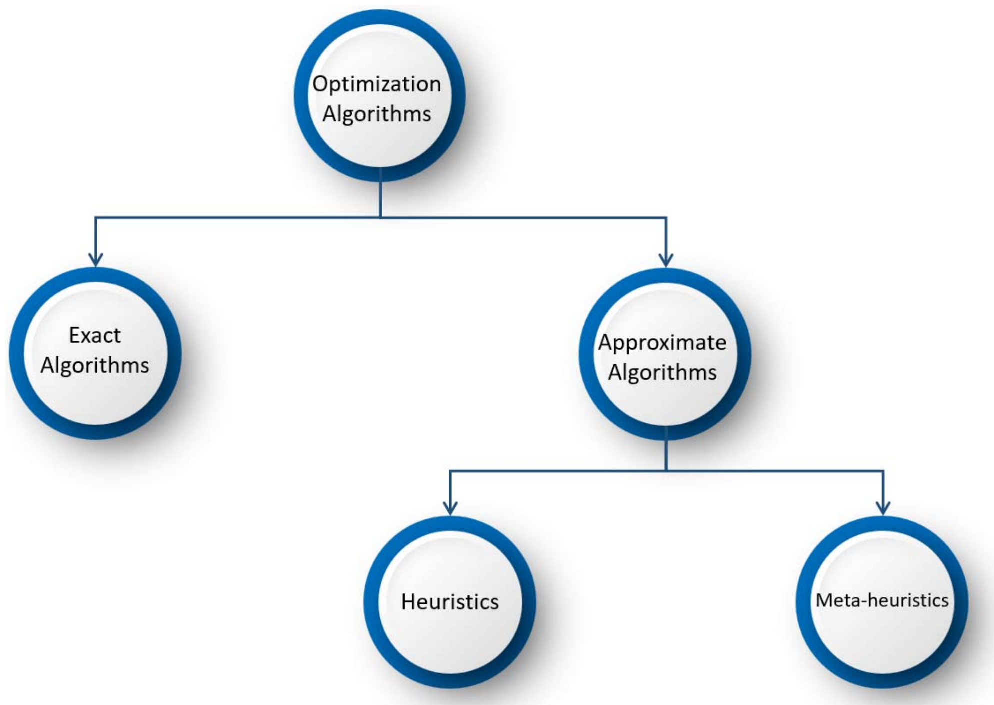



Figure 4: Classification of Optimization Algorithms

### 2.2.1- Exact Algorithms

Exact algorithms are limited to specific instances, determined by their complexity concerning restrictions and objectives. If an optimization problem can be solved, the exact algorithms will produce the optimal solution by exploring every possible solution thoroughly. Exact algorithms invariably yield identical solutions when confronted with identical input. This characteristic guarantees the capacity to replicate and dependability in achieving the optimal solution. Nevertheless, it is essential to note that exact algorithms cannot provide answers for all situations. Specifically, generating feasible solutions for large instances is a significant challenge regarding their time efficiency. The evaluation of an exact algorithm's complexity is commonly quantified with its time and space requirements. Exact algorithms may exhibit exponential time complexity, wherein the computational time grows exponentially with the problem's scale. Consequently, since relief distribution problems are considered large-scale problems, the use of exact algorithms for addressing such problems is relatively limited in the literature (Luo et al. 2023). Dynamic programming and integer linear programming are among the exact algorithms.

### 2.2.2- Approximate Algorithms

As previously stated, the approximate algorithms may be categorized into two distinct groups: heuristic algorithms and meta-heuristic algorithms.

#### 2.2.2.1- Heuristic Algorithms

A heuristic refers to experience-derived methods to address problems, acquire knowledge, and make discoveries. It represents an approach specifically designed to solve problems quickly when traditional methods are excessively time-consuming or to identify an approximate solution in cases where conventional methods fail to pinpoint precise ones. It is important to note that heuristics do not provide a guarantee of discovering the optimal solution; as such, they are generally characterized as approximate rather than exact algorithms. Typically, these algorithms are adept at swiftly producing solutions that closely approximate the best possible outcome. While these algorithms may occasionally yield precise results, they are still classified as heuristics until rigorous proof establishes their result as the definitive best solution (Desale et al. 2015).

#### 2.2.2.2- Meta-Heuristic Algorithms

Meta-heuristic is a computational approach that aims to optimize a problem by iteratively enhancing a candidate solution based on a predetermined quality measure. Meta-heuristics have the characteristic of making little or no assumptions on the issue under optimization, hence enabling them to explore extensive search spaces encompassing several potential solutions. Nevertheless, it should be noted that metaheuristics do not provide a guarantee of discovering an optimal solution. The majority of metaheuristics have the following characteristics (Desale et al. 2015):

- Guiding tactics for the search process. The goal is to explore the search space for near-optimal solutions efficiently;
- Covering a wide range of strategies, from simple local search procedures to complicated learning processes;
- Often characterized by their approximate nature and inherent non-determinism;
- Having a characteristic of generality, not problem-specific.

Evolutionary Algorithms (EAs) constitute a subset of meta-heuristics that get inspiration from natural evolution and adaptation principles. EAs are highly suitable for addressing diverse computationally challenging problems because of their inherent simplicity, considerable flexibility, and broad application. It is imperative to quickly create solutions for operational challenges related to emergency aid during emergencies. Therefore, conventional exact methods are frequently costly regarding computational resources and have a restricted range of applicability. When considering EAs in contrast, they offer distinct advantages such as their exceptional efficiency when it comes to exploring extensive solution spaces, their innate capability to effectively address uncertainty and randomness, their resilience and resistance to noise, and their ability to scale seamlessly to high-dimensional problems. Consequently, EAs prove highly suitable for tackling emergency problems (Zheng et al. 2015). Within the realm of EAs, Genetic Algorithm (GA) (Holland 1992) and Ant Colony Optimization (ACO) (Dorigo and Di Caro 1999) are among the prominent variants commonly encountered in the literature.

### 2.2.3- Review of Studies Regarding Optimization Algorithms

Certain researchers use exact algorithms in the existing literature (Rivera et al. 2016; Safaei et al. 2020) to optimize objective functions within relief distribution and routing. Nonetheless, it is noteworthy that a significant portion of studies lean toward the use of approximate algorithms (Zhang et al. 2011; Li et al. 2014; Hu et al. 2016; Cao et al. 2018; Huo and Wang 2022; Beheshtinia et al. 2023) to seek optimal solutions, primarily due to the inherent complexity, especially when dealing with large-scale problems.

Table 5 provides an overview of the research conducted in the literature about the distribution of relief supplies following disasters, with a specific focus on optimization algorithms. In the following, we will delve into a more detailed examination of these studies. Zhang et al. (2011) focused on enhancing the efficiency of relief efforts by optimizing emergency logistics distribution routing. They developed a mathematical model to minimize delivery times for relief supplies to demand points. To tackle this challenge, they implemented an advanced ant colony algorithm called Fish-Swarm Ant Colony Optimization (FSACO). Simulation results consistently validated the algorithm's effectiveness, demonstrating that FSACO consistently produces superior solutions compared to the standard ant colony algorithm. Li et al. (2014) addressed optimizing resource distribution to demand points in emergency scenarios to minimize total travel time. They employed an improved Simulated Annealing (SA) algorithm for this purpose. A series of computational experiments were conducted to validate their approach, affirming the robustness of their proposed model and the algorithm's effectiveness. Moving forward, Rivera et al. (2016) researched the multi-trip Cumulative

Capacitated Single-Vehicle Routing Problem (mt-CCSVRP) within disaster logistics. They investigated scenarios where a single vehicle made successive trips to serve the affected area, aiming to minimize the sum of arrival times. An exact algorithm, the extended Bellman-Ford algorithm, was devised to achieve optimal solutions. Results indicated the algorithm's superior performance, outperforming a commercial Mixed Integer Programming (MIP) solver, particularly for small instances. Hu et al. (2016) introduced the Bi-Objective Robust Emergency Resource Allocation (BRERA) framework, designed to optimize the allocation of emergency resources considering efficiency and equity across uncertainties. The Particle Swarm Optimization (PSO) algorithm was applied to solve the BRERA model efficiently. Comparative analysis against MIP in a real-case scenario showcased the effectiveness of PSO as a heuristic algorithm.

Continuing the exploration of sustainable disaster supply chain relief distribution strategies, Cao et al. (2018) addressed the challenge of formulating sustainable disaster supply chain relief distribution strategies with a multi-objective mixed-integer nonlinear programming model. This model aimed to maximize the minimum level of perceived satisfaction among victims while minimizing the maximum variation in perceived satisfaction. To solve this complex problem, a Genetic Algorithm was introduced. Validation through the Wenchuan earthquake as a case study confirmed that the Genetic Algorithm effectively balances solution quality and computation time, addressing sustainability concerns in relief distribution. Safaei et al. (2020) aimed to create an integrated relief logistics framework for disaster contexts. They presented a bi-objective, bi-level optimization model to minimize total operational costs and unmet demand. This nonlinear model was reformulated into a single-level linear problem, utilizing Goal Programming (GP) to minimize deviations from objectives. The model's performance was validated through an emergency planning case study for an earthquake disaster. Huo and Wang (2022) introduced a comprehensive three-level network allocation model for post-disaster material scheduling and distribution. This model focused on minimizing the total dispatch time for emergency medical rescue supplies and enhancing fairness by reducing the maximum waiting time for delivery to all rescue points. An enhanced version of the Nondominated Sorting Genetic Algorithm II (NSGA-II) addressed this challenge. Comparative analysis against NSGA and PSO algorithms demonstrated NSGA-II's superior performance in this context. Beheshtinia et al. (2023) tackled efficiently distributing relief goods in disaster-affected areas to minimize delivery time. They formulated a Mixed-Integer Linear Programming (MILP) model for this purpose. Additionally, they utilized the Multiple League Championship Algorithm (MLCA), along with its novel adaptations, the League Base Multiple League Championship Algorithm (L-MLCA) and the Playoff Multiple League Championship Algorithm (P-MLCA). The experimental findings indicate that P-MLCA consistently performs better than the other two algorithms.

Table 5: Relief Distribution and Routing Review (Optimization Algorithms)

| Author(s) | Objective Function(s) | Exact / Approximate | Optimization Algorithm(s) |
|---|---|---|---|
| (Zhang et al. 2011) | Minimizing delivery times to demand points | Approximate | Fish-Swarm Ant Colony Optimization (FSACO) |
| (Li et al. 2014) | Minimizing total travel time | Approximate | Improved Simulated Annealing (SA) |
| (Rivera et al. 2016) | Minimizing the sum of arrival times | Exact | Bellman-Ford Algorithm |
| (Hu et al. 2016) | Maximizing the overall utility of relief resources (efficiency)<br>Maximizing the minimal satisfaction rate (fairness) | Approximate | Particle Swarm Optimization (PSO) |
| (Cao et al. 2018) | Maximizing the minimum level of perceived satisfaction among victims<br>Minimizing the maximum variation in perceived satisfaction | Approximate | Genetic Algorithm (GA) |
| (Safaei et al. 2020) | Minimizing total operational costs<br>Minimizing total unmet demand | Exact | Goal Programming (GP) |
| (Huo and Wang 2022) | Minimizing the total dispatch time for emergency medical rescue supplies<br>Minimizing the maximum waiting time for delivery to all rescue points (fairness) | Approximate | Improved Nondominated Sorting Genetic Algorithm II (NSGA-II) |
| (Beheshtinia et al. 2023) | Minimizing delivery time | Approximate | Multiple League Championship Algorithm (MLCA)<br>League Base Multiple League Championship Algorithm (L-MLCA)<br>Playoff Multiple League Championship Algorithm (P-MLCA) |

## 2.3- Vehicle Routing Problem

The Vehicle Routing Problem (VRP) is a well-known combinatorial optimization problem that involves calculating the most effective delivery routes for a fleet of vehicles assigned to visit specific destinations. The primary aim is to identify the optimal routes and the sequence in which vehicles should visit these locations to minimize the total cost or the distance travelled. This optimization process must also adhere to various constraints, including vehicle capacity, delivery time windows, and customer demands (Akwafuo). Scholars have delved into the context of vehicle routing and delivery scheduling since as far back as 1959 when Dantzig and Ramser (1959) first presented the Truck Dispatching Problem.

### 2.3.1- VRP Variants

In addition to the basic VRP, the literature encompasses a multitude of VRP variants aimed at addressing various vehicle routing optimization problems. Han and Wang (2018) classifies VRP into six main categories:

1. *Capacitated Vehicle Routing Problem (CVRP)*: multiple vehicles are dispatched from a single warehouse, ensuring that the total demand on each route remains within the vehicle's capacity limit;
2. *Heterogeneous Vehicle Routing Problem (HVRP)*: considers the utilization of vehicles with different capacities for optimizing the delivery routes, particularly relevant in spare parts supply optimization;
3. *Multi-Depot Vehicle Routing Problem (MDVRP)*: introduces the concept of multiple depots, enabling vehicles to initiate their routes from various starting points;
4. *Vehicle Routing Problem with Time Window (VRPTW)*: incorporates time constraints, necessitating that customers be served within specified time windows;

5. *Multi Depot Vehicle Routing Problem with Time Windows (MDVRPTW)*: involves multiple depots, each with its fleet of vehicles and a set of customers with distinct time windows for service;
6. *Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows (MDHVRPTW)*: accommodates a heterogeneous fleet of vehicles originating from multiple depots, all of which must adhere to customers' time windows.

Other researchers may introduce additional VRP variations, such as the 16 variants considered by Konstantakopoulos et al. (2022). In summary, across all VRP types, the overarching objective remains consistent: to identify optimal delivery routes for the distribution of items while accounting for the specific characteristics inherent to the particular problem at hand.

In emergency logistics planning, a distinct variation of VRP, known as Emergency VRP, deals with considerable uncertainty. It involves coordinating a limited fleet of heterogeneous vehicles for critical deliveries under strict time constraints and challenging environmental conditions where infrastructure, including road networks and communication systems, is often unreliable and unpredictable. Moreover, coordinating efforts among various organizations engaged in relief operations poses significant complexity. Additionally, the conditions of the affected population and the relief requirements can swiftly evolve (Akwafuo).

Emergency VRP prioritizes timeliness and risk management over transportation costs. Given the intricate nature of delivery and logistics operations in emergencies, it is evident that emergency VRP presents more significant challenges compared to the traditional VRP and its typical variations (Luo et al. 2023).

### 2.3.2- Review of Emergency VRP Studies

In the realm of Emergency VRP research, primary constraints often revolve around the limited capacity of vehicles and the time windows associated with demand points (Hamedi et al. 2012; Wen et al. 2016; Qin et al. 2017; Yi et al. 2019; Wu and Xiang 2021; Mishra et al. 2022; Tan et al. 2023). Additionally, some scholars have explored supplementary constraints, including factors like road safety and the availability of vehicles (Gai et al. 2015; Wen et al. 2016; Qin et al. 2017; Mishra et al. 2022).

Table 6 offers an overview of the research endeavours within the relief distribution literature, specifically focusing on Emergency VRP in the aftermath of disasters. In the following, we will delve deeper into examining these studies: In humanitarian disaster response planning, various studies have delved into the critical aspect of selecting dependable routes. In the work by Hamedi et al. (2012), the authors introduced a model for routing and scheduling supply transportation while incorporating time window constraints for each node. Their objective function revolved around minimizing a weighted total cost, encompassing four cost functions: travel distance, travel time, risk exposure, and risk accumulation cost. Gai et al. (2015) introduced a multi-objective model for post-disaster route planning in a related study. They focused on two objective functions: minimizing total travel time and maximizing route safety. Additionally, they accounted for three significant constraints in vehicle routing: road safety, arc conditions, and congestion. The efficient delivery of blood supplies in emergency scenarios via Unmanned Aerial Vehicles (UAVs) was addressed by Wen et al. (2016). Their approach involved a multi-objective algorithm to minimize total mileage and the number of UAVs required for blood supply. This optimization considered the limited capacity of each UAV and the available quantity of UAVs. Efficiently routing emergency vehicles to meet uncertain demand sustainably in post-disaster situations was the concern of Qin et al. (2017). They structured their study around minimizing the total expected cost, encompassing factors such as total expected shortage penalty, total expected surplus penalty, total transportation costs, and total vehicle operating costs. Their model adhered to constraints like vehicle load capacity, maximum available vehicles at service centres, and time constraints for vehicle arrival and service windows at demand points.

Addressing the emergency VRP in sudden disasters involving relief materials, Yi et al. (2019) tried to optimize vehicle assignments for transporting these materials from storage areas to disaster sites. Their model aimed to minimize travel and delivery time while accommodating vehicle capacity constraints. By starting the widespread COVID-19 outbreak, Wu and Xiang (2021) conducted a study on the CVRP. They focused on strategically distributing emergency resources and optimizing vehicle routing to enhance emergency response efficiency. Their study centred on Wuhan city in China, acting as a distribution hub for 30 cities to minimize total transportation costs, accounting for vehicle capacity constraints. Mishra et al. (2022) concentrated on devising distribution schedules for relief items at supply points during humanitarian crises. They drew inspiration from the ChiChi earthquake in Taiwan, devising their case study with an analogous scenario. Their approach accounted for multiple supply points with vehicles of varying capacity, cost, and time constraints. Their proposal introduced a model to establish efficient distribution schedules, emphasizing optimizing distribution time and vehicle operational cost. Furthermore, their optimization framework also prioritized minimizing unmet demand for relief items in disaster-affected regions. Lastly, Tan et al. (2023) addressed the challenges of emergency logistics distribution in major epidemic scenarios, such as the early stages of the COVID-19 pandemic. Their emergency VRP optimization model aimed to minimize total cost, considering factors like the fixed cost of departure, time cost, early/late penalty cost, vehicle delivery cost, and vehicle capacity constraints, all while adhering to demand point time windows.

Table 6: Emergency VRP Review

| Author(s) | Objective Function(s) | Constraint(s) | Optimization Algorithm(s) |
|---|---|---|---|
| (Hamedi et al. 2012) | Minimizing weighted total cost (including Travel distance, Travel time, Risk exposure, and Risk accumulation cost) | Time Window | A Heuristic-based Genetic Algorithm |
| (Gai et al. 2015) | Minimizing total travel time<br>Maximizing the safety of the route | Road Safety<br>Arc Conditions<br>Congestion | A Heuristic Algorithm based on A* and D* Algorithm |
| (Wen et al. 2016) | Minimizing the total mileage<br>Minimize the number of required Unmanned Aerial Vehicles (UAVs) | UAV Capacity<br>Available UAVs | An extended Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) |
| (Qin et al. 2017) | Minimizing the total expected cost ( including the Total expected shortage penalty, the Total expected surplus penalty, the Total transportation costs, and the Total operating costs of vehicles) | Vehicle Capacity<br>Available Vehicles<br>Time Windows | A Heuristic-based Genetic Algorithm |
| (Yi et al. 2019) | Minimizing the total travel and delivery time | Vehicle Capacity | Enhanced Monarch Butterfly Optimization (EMBO) |
| (Wu and Xiang 2021) | Minimizing the total transportation cost | Vehicle Capacity | Simulated Annealing - Genetic Algorithm (SA-GA) |
| (Mishra et al. 2022) | Minimizing the distribution time<br>Minimizing vehicles' operational cost.<br>Minimizing unmet relief items demand | Available Vehicles<br>Vehicle Capacity, Cost, and Time | A multi-objective evolutionary optimization algorithm with the greedy heuristic search |
| (Tan et al. 2023) | Minimizing total cost (including Fixed cost of departure, Time cost, Early/Late penalty cost, and Vehicle delivery cost) | Vehicle Capacity<br>Time Windows | Improved PSO |

## 2.4- Contributions

In conclusion, building an efficient and effective system for allocating relief resources is difficult due to its unique qualities. Disasters are unpredictable, leading to uncertainties and dynamic changes in the demand for relief items and the supply itself. The demand for relief supplies can vary depending on the scale and impact of the disaster, often requiring time-sensitive action. On the other hand, various factors, such as resource availability or transportation issues, can affect the supply.

Furthermore, various factors affect how the relief distribution system may function: The time window for delivering relief supplies can be extremely narrow, while natural disasters may disrupt transportation infrastructure. If so, reaching areas and distributing resources will be challenging. Balancing these constraints to optimize relief supply distribution poses a real challenge. Additionally, it is crucial to prioritize resource allocation based on need, which often involves complex decisions and delicate trade-offs between efficiency and fairness. It increases the complexity of system design. Besides all the mentioned challenges, the time constraints for planning and executing a relief distribution system are also significant.

In this chapter, we reviewed the numerous investigations by scholars who have directed their attention to optimizing relief distribution, particularly emphasizing classical measurable objective functions. Nevertheless, researchers have given limited attention to subjective indexes and approaches based on human reasoning processes for addressing the optimization of relief distribution. In addition, it is worth noting that while a significant body of research on routing in the context of location problems exists, there is a scarcity of studies that specifically address routing for last-mile distribution.

This research is motivated by the need for efficient and effective vehicle routing in a humanitarian context and allocating limited available medical relief supplies to the PODs in the response phase of a natural sudden disaster.

To be more specific, in the vehicle routing phase, this process encompasses selecting among a heterogeneous fleet of vehicles for serving the PODs and determining the visiting order of PODs by each vehicle in a way that operational cost is minimized and PODs receive the reliefs regarding their time window. Also, in the allocation phase, limited relief supplies are distributed among PODs to minimize the importance of unmet demands in PODs.

To solve it optimally, we provide a multi-objective model and compare two robust evolutionary algorithms, NSGA-II and NRGA. To address the inherent ambiguity and uncertainty inside the system, FISs are utilized. Our research makes a dual contribution to the existing body of literature:

1. In addition to operational costs, our study proposes the inclusion of subjective indices, namely the importance of unmet demands and the importance of late-satisfied demands, as alternatives to traditional metrics such as unmet demands and late-satisfied demands;
2. FISs are utilized to encapsulate decision-makers' expertise and simulate the cognitive process of human thinking to evaluate defined subjective indexes effectively. The flexibility of the suggested model allows for its adaptation to various contexts, drawing upon expert knowledge.

As far as we know, it is the first time in the literature that FISs have been integrated into Genetic Algorithms to assess the solutions.

# 3- Model Formulation

In this chapter, our focus centres on establishing our mathematical model to build a robust relief distribution system in the humanitarian context. The subsequent sections will delineate the problem statement, introduce the objective functions pertinent to the study's characteristics, and construct the model.

## 3.1- Problem Definition

After the occurrence of a sudden-onset disaster, humanitarian aid agencies are confronted with crucial decisions regarding how to respond and assist those affected. One of the pivotal steps preceding these response decisions is the Rapid Needs Assessment (RNA) (IFRC 2008), where humanitarian organizations swiftly evaluate the needs of the affected population. Simultaneously, assessing the damage to critical infrastructures, including transportation networks, healthcare facilities, and communication systems and determining the scale of those impacted is imperative. The RNA starts immediately after a disaster strikes and has to be completed as soon as possible to evaluate the disaster's impact and population needs quickly.

The Distribution Centres (DCs) are responsible for collecting and dispatching relief supplies to the affected region, including water, food, tents, hygiene products, and more, to the Humanitarian Aid Distribution Centres (HADCs) situated within the affected region. Subsequently, these HADCs oversee the coordination and management of the allocation of relief commodities to Points of Demand (PODs). This final phase in the relief supply chain, which pertains to delivering relief supplies from HADCs to PODs, is known as last-mile distribution.

More precisely, the last-mile distribution problem revolves around devising an optimal distribution plan, encompassing delivery schedules, vehicle routes, and the quantities of emergency supplies dispatched to PODs throughout disaster relief endeavours. Given the substantial costs associated with unmet demand, the paramount objective is to maximize the benefits to aid recipients while minimizing the logistical costs (Balcik et al. 2008).

Last-mile distribution frequently poses the most formidable and time-consuming challenge in the delivery process. Limitations tied to transportation resources and emergency supplies, difficulties arising from damaged transportation infrastructure, and issues related to coordination among humanitarian actors are among the primary hurdles encountered in last-mile distribution. A schematic depiction of the last-mile distribution system is presented in Figure 5.

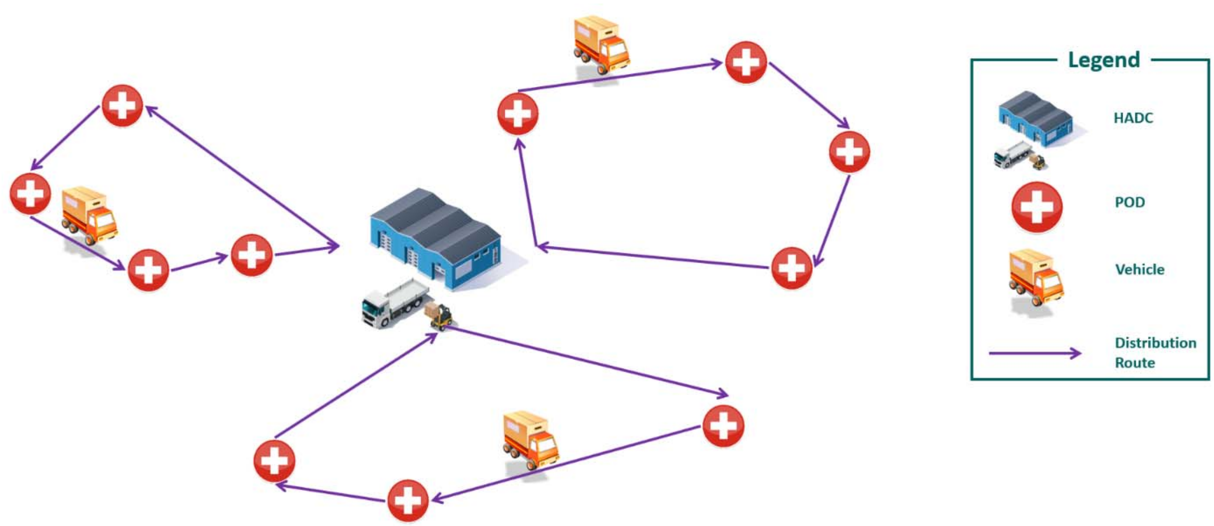



Figure 5: A Last-Mile Distribution System Schematic Diagram

Furthermore, the post-disaster environment is often characterized by overcrowded and unsanitary conditions, which can foster the spread of diseases. Hygiene products play a vital role in curbing disease transmission, and medical supplies are indispensable for treating and preventing illnesses and injuries. Hence, providing such relief items is critical to averting epidemics and saving lives within disaster-affected communities.

Consequently, the focal problem examined in this investigation revolves around the development of an efficient, effective, and fair last-mile distribution system for disbursing emergency aid supplies from a single HADC to multiple PODs within the impacted area, operating under specific assumptions:

1. A singular HADC exists that provides service to all PODs via roadways;
2. The geographic locations of the HADC and PODs have been identified, along with their respective distances from one another;
3. In the distribution operation, each POD is served once;
4. Each POD's time window and demand level are known;
5. The number of individuals impacted and served by each POD is determined;
6. The determination of the emergency level of PODs is conducted by experts using a numerical scale ranging from 0 to 100;
7. Given the involvement of many players, such as relief organizations and NGOs, in delivering disaster aid, a heterogeneous fleet of vehicles will be utilized in the operation;
8. The speed, capacity, and operating costs of vehicles vary;
9. Each vehicle commences its journey from the HADC and, upon completing the delivery of relief goods, returns to the HADC;
10. A uniform category of medical units, such as a bundle of essential medical supplies, will be allocated to PODs. The capacity of vehicles will be assessed in terms of the quantity of units they can transport;
11. Following the occurrence of a disaster, critical infrastructure such as highways and roads may sustain severe damage. Consequently, the transportation capacity will

be significantly restricted. In order to evaluate the distance between two points, it is necessary to consider the physical distance and the feasibility of utilizing the existing road infrastructure. This consideration involves assigning an integer value within the range of 1 to 3, denoting the levels of transportation accessibility as standard, limited, and very limited, respectively.

One of the significant challenges in post-disaster distribution systems is the limited availability of relief items. The demand often far exceeds the available inventory, and the unavailability of relief items can lead to the loss of human lives. Therefore, a primary objective in designing distribution systems is always to effectively address the challenge of relief item scarcity. Strategies are formulated to ensure that relief items reach those in greatest need in a timely, efficient, and equitable manner. As observed in the literature review in Chapter 2, many researchers have considered minimizing unmet demand as a critical objective function in the design of distribution systems.

Assume a scenario where two PODs exhibit identical levels of demand. A common approach is to allocate an equal amount of relief to each one. However, let us introduce a more complex scenario. Consider that POD 1 experiences higher demand than POD 2. It might appear logical to allocate more relief to POD 1 to minimize unmet demand. While this allocation strategy can be efficient, it does not necessarily translate to effectiveness.

In an effective relief distribution system, other critical factors come into play. These factors include the number of patients in each POD and the emergency level of the PODs. To illustrate this, let us examine the scenario presented in Figure 6. There are two PODs that exhibit similar amounts of demand and an equal proportion of unfulfilled demand. Both PODs also serve an equal number of patients. Nonetheless, the emergency level of POD 2 surpasses that of POD 1. Consequently, it becomes evident that POD 2 requires a larger share of relief, and an equal allocation of relief is not a suitable decision. In essence, the POD with a higher emergency

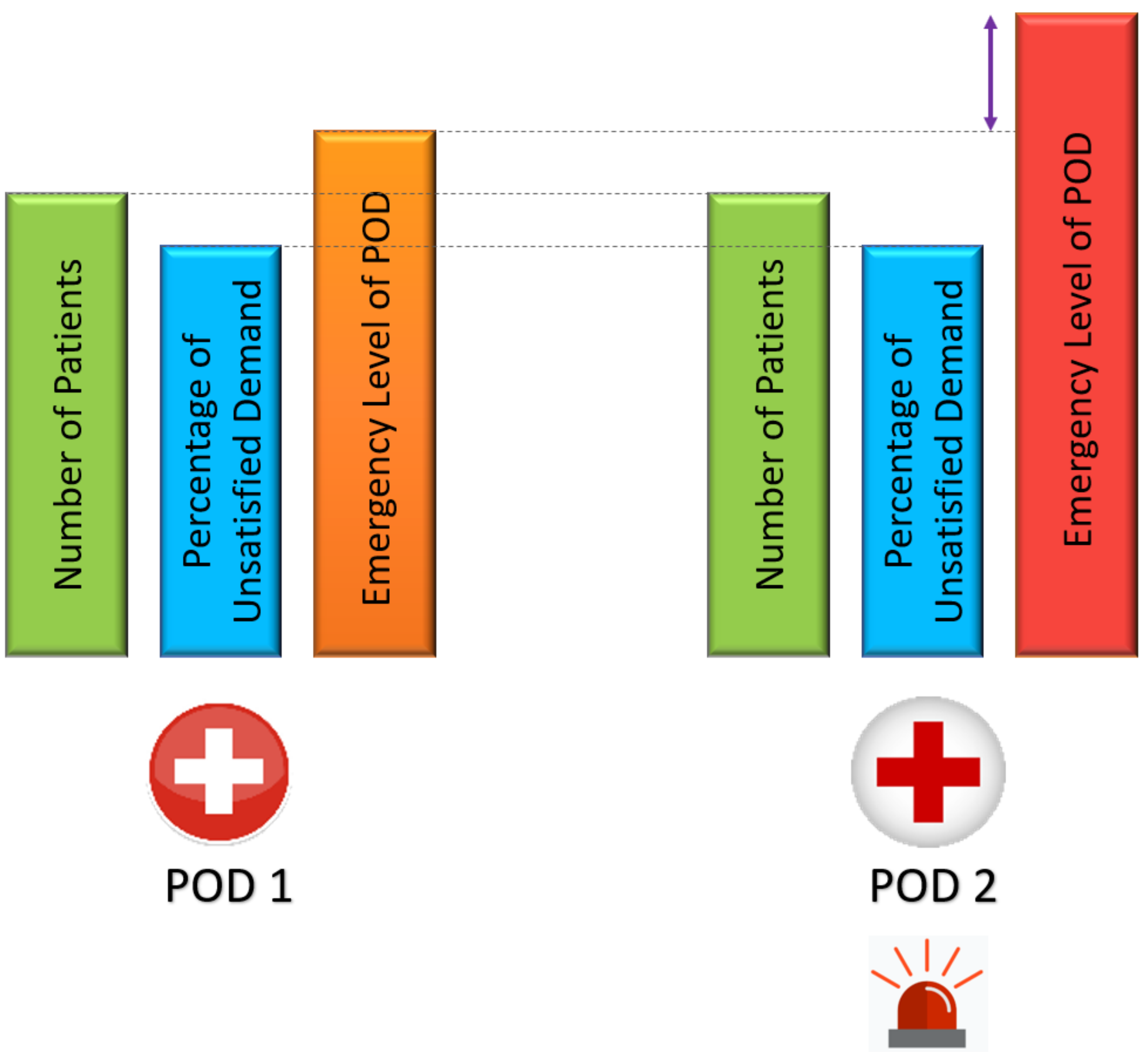



Figure 6: Critical Factors in Determining the Importance of Unmet Demand

level should have a smaller proportion of unmet demand when both PODs serve the same number of patients.

Consequently, we introduce the "Importance of unmet demand" index instead of merely "unmet demand" index. We aim to minimize the "Importance of unmet demand", which represents a more accurate and appropriate metric. By employing a Fuzzy Inference System (FIS), we can calculate the importance of unmet demand by considering influential variables: the number of patients, the percentage of unsatisfied demand, and the emergency level of the PODs. This approach encapsulates expert knowledge to make appropriate relief allocation decisions.

The same rationale applies to the time objective. As elaborated in Chapter 2, researchers have traditionally adopted delivery times or total response time as their primary objective functions when addressing time window constraints in humanitarian operations. However, placing sole reliance on minimizing delivery time or delivery delays without considering other pertinent factors can potentially undermine the overall effectiveness of the relief distribution system.

Consider a scenario in which two PODs share identical time window constraints. An effective relief distribution system does not necessarily mean that serving these PODs has the same priority regarding the time objective. Prioritizing adherence to the time window for a POD serving a higher number of patients or one experiencing a more critical emergency level takes precedence in determining the sequence of POD visits. As illustrated in Figure 7, let us assume two PODs exhibit equivalent levels of emergency and tardiness in delivering relief supplies.

However, POD 2 caters to a larger patient population. Therefore, the importance of late-satisfied demand in POD 2 is higher, and the system should serve this POD more quickly than POD 1.

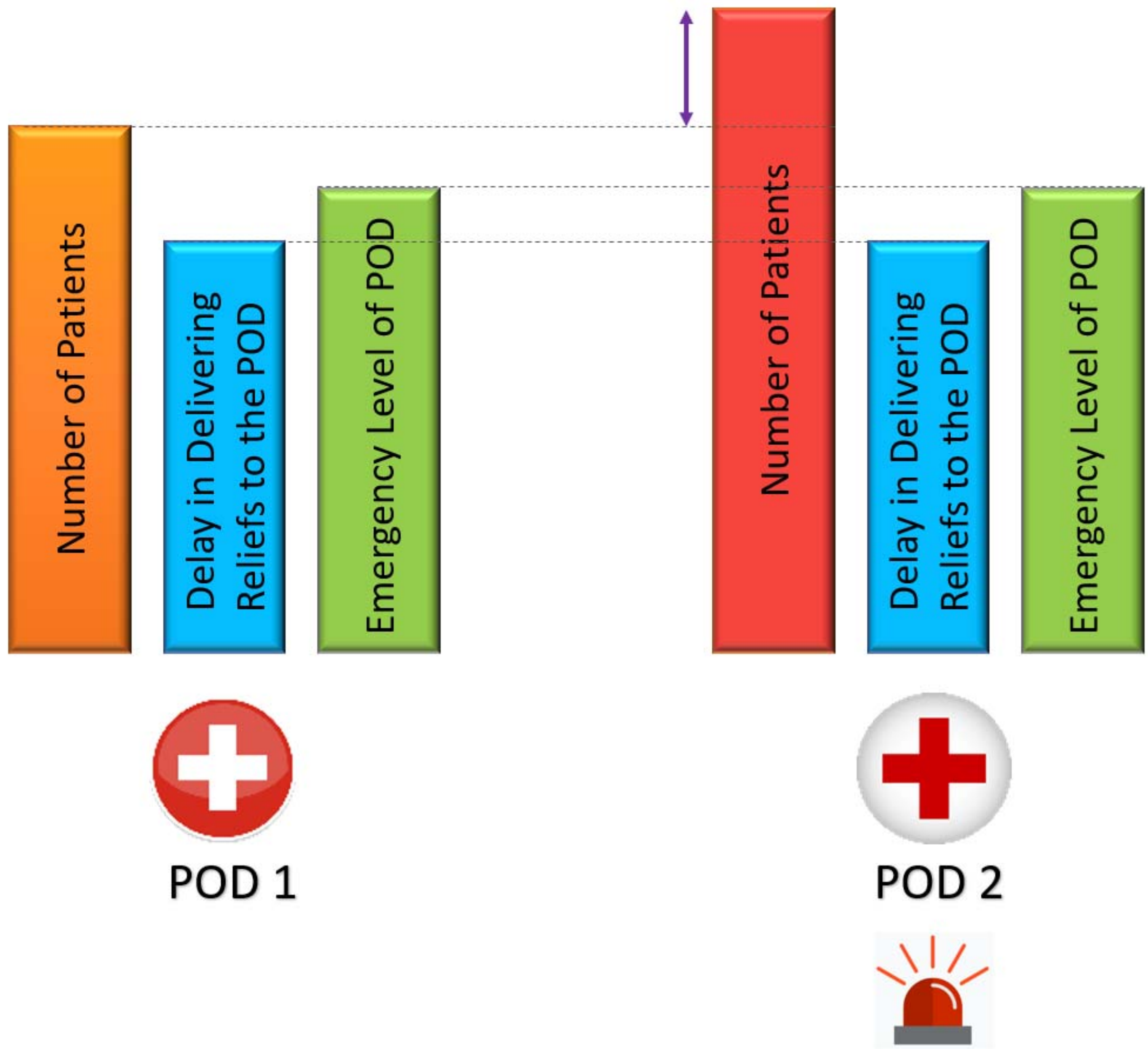



Figure 7: Critical Factors in Determining the Importance of Late-Satisfied Demand

In this study, we introduce the "Importance of late-satisfied demand" index and aim to minimize this index instead of solely fixating on minimizing delivery times. The computation of this newly introduced index is based on crucial influencing factors, including the number of patients covered in the POD, the emergency level of the POD, and the extent of delay in delivering relief supplies. This process is inherently subjective, considering decision-makers' expertise and priorities, as well as the specific characteristics of the prevailing situation. Developing a FIS provides a suitable mean to capture the inherent uncertainty and encapsulate decision-makers' insights in a mathematical framework.

This study delves into the intricacies of last-mile distribution within the humanitarian context. Our primary objective is to establish effective and efficient strategies for determining delivery schedules, vehicle routes, and the quantities of emergency supplies allocated to PODs. Using appropriate objective functions tailored to the humanitarian context is paramount in creating a resilient relief distribution system.

This chapter is dedicated to an in-depth examination of the three objective functions employed in this study. Notably, two of these objective functions are novel contributions to the literature tailored to the unique characteristics of relief distribution within the humanitarian context: the importance of unmet demand and the importance of late-satisfied demand. Additionally, we employ two FISs to measure these two objective functions. Furthermore, this chapter provides an in-depth discussion of the mathematical model utilized in our research. In Chapter 4, we will introduce the specific FISs used in his study and explain two evolutionary algorithms applied to tackle the problem. Also, we discuss combining the power of FISs with the evolutionary algorithms used in this research to design an efficient and effective relief distribution system in a humanitarian context.

## 3.2- Notations for Sets, Parameters, Indices, and Variables

Notations for sets, parameters, indices, and variables that will be used throughout the study are provided in this section. Table 7 presents a list of the notations and their corresponding meanings.

Table 7: Notations for Sets, Parameters, Indices, and Variables

| Notation | Definition |
|---|---|
| $P_0$ | Depot (HADC) |
| P | Set of n PODs $P = \{1,2,\dots,n\}$ |
| i, i′ | Indices to refer PODs $i, i' \in P$ |
| A | Set of arcs $\{(i,i'),\ \ i \neq i'\}$ |
| $Dist_{i,i'}$ | Length of arc (i,i′) ∈A (distance between $P_i$, $P_{i'}$ in Kilometer) |
| $Arc\_cond_{i,i'}$ | The feasibility of transportation for the arc (i,i′), $Arc\_cond_{i,i'} \in \{1,2,3\}$ |
| Sup_Global | Total number of humanitarian supplies available in HADC |
| V | Set of distribution vehicles |
| j | Index for referring to vehicles $j \in V$ |
| $Cap_j$ | Capacity of vehicle j in units of loads |
| $Vel_j$ | Velocity of vehicle j (Km/h) |
| $Cf_j$ | The fixed cost associated with the employment of vehicle j |
| $Cv_j$ | The cost associated with the utilization of vehicle j per kilometre |
| $Tour_j$ | The ordered group of PODs that vehicle j services, $Tour_j \subset P,\quad Tour_j \cap Tour_{j'} = \emptyset\ \ \forall\, j,j' \in V\ ,\quad \bigcup_{j \in V} Tour_j = P$ |
| $L_{w,j}$ | The $w^{th}$ node that gets service from vehicle j |
| $Em_i$ | Emergency level of node $P_i$, $Em_i \in [0\ 100]$ |
| $nPatient_i$ | The number of patients in node $P_i$ |
| $Dem_i$ | Demand of node $P_i$ (in units) |
| $Sup_i$ | Allocated supply to node $P_i$ (in units) |
| $Unmetd\_perc_i$ | The percentage of unsatisfied demand in node $P_i$ $\left(\frac{Dem_i - Sup_i}{Dem_i}\right)$ |
| $Imp\_unmetd_i$ | Importance of unmet demand in node $P_i$, $Imp\_unmetd_i \in [0\ 100]$ |
| Imp_unmetd_total | The sum of the importance of unmet demand across all nodes |
| $Tmax_i$ | Latest allowed time to receive relief supply in node $P_i$ (in units of time) |

| Notation | Definition |
|---|---|
| $Tdelivery_i$ | The time it takes to deliver relief supplies to node $P_i$ (in units of time) |
| $Delay_i$ | Delay in the delivery of relief supplies to node $P_i$ (in time units) |
| $Imp\_late\_satisd_i$ | Importance of late-satisfied demand in node $P_i$, $Imp\_late\_satisd_i \in [0\ 100]$ |
| Imp_late_satisd_total | The sum of the importance of late-satisfied demand across all nodes |
| $x_{i,j}$ | A binary value, $x_{i,j}=1$, means that vehicle j is providing service to node $P_i$, otherwise $x_{i,j}=0$ |
| $Path_{i,i',j}$ | A binary value, $Path_{i,i',j}=1$ means that Vehicle j goes to node i′ right after going to node i, otherwise $Path_{i,i',j}=0$ |

## 3.3- Objective Functions

Our model comprises three primary objective functions: operational cost, the importance of unmet demand, and the importance of late-satisfied demand. Notably, the latter two objective functions are innovative subjective indices quantified using FISs. In the subsequent sections, we shall provide an in-depth elucidation of these objective functions.

### 3.3.1- Operational Cost

Given the finite nature of resources, a frequently employed objective function is the minimization of operational cost associated with a fleet of vehicles. The concept encompasses both fixed and variable costs. The current study examines the fixed cost associated with vehicle employment and the variable cost associated with vehicle usage, which is contingent upon the distance travelled by each vehicle type. The operational cost is formulated as follows:

$$Operational\ Cost = \sum_{i \in P} \sum_{j \in V} Path_{P_0,i,j} \times Cf_j + \sum_{i \in (P_0 \cup P)} \sum_{i\prime \in (P_0 \cup P)} \sum_{j \in V} Path_{i,i',j} \times dist_{i,i'} \times Cv_j \quad (1)$$

Eq. (1) shows the sum of fixed and variable costs of using the vehicle fleet in the relief operations.

### 3.3.2- The Importance of Unmet Demand Index

This study aims to shift the focus from the conventional analysis of the unmet demand index to the exploration of the importance of the unmet demand index within a POD. This new index is assessed considering three key factors: the number of patients covered within the POD, the emergency level of the POD, and the percentage of unsatisfied demand in the POD. The importance of unmet demand is assessed based on these indicators, drawing on the knowledge and experience of decision-makers and considering the current circumstances.

Notably, this evaluation is a qualitative process inherently involving uncertainty. Here is where FISs play a pivotal role. FISs serve as a mapping tool, employing fuzzy logic to translate input parameters, which, in this context, encompass the three indices mentioned above, into an output value representing the importance of unmet demand. For a comprehensive exploration of our FIS structure, we provide further details in Chapter 4. By employing FISs to model the qualitative knowledge and reasoning of domain experts, we effectively address the inherent uncertainty and ambiguity within the system. The FIS developed for evaluating the importance of unmet demand is as follows:

$$FIS_1: (nPatient, Em, Unmetd\_perc) \rightarrow Imp\_unmetd \qquad (2)$$

$$Imp\_unmetd_i = \begin{cases} 0 & if\ \ Sup_i = dem_i \\ FIS_1\left(nPatient_i, Em_i, \dfrac{dem_i - sup_i}{dem_i}\right) & if\ \ Sup_i < dem_i \end{cases} \quad \forall i \qquad (3)$$

$$Imp\_unmetd\_total = \sum_{i \in P} Imp\_unmetd_i \qquad (4)$$

Expression (2) demonstrates that $FIS_1$ assesses the importance of unmet demand by considering three indexes: the number of patients covered in the POD, the emergency level of POD, and its percentage of unsatisfied demand. Eq. (3) outlines how the importance of unmet demand for each individual POD is computed. If the relief supply allocated to a POD is less than its demand level, the importance of unmet demand of this POD will be evaluated by the introduced FIS. Lastly, Eq. (4) aggregates the values of the importance of unmet demand across all PODs to determine the overall importance of unmet demand.

### 3.3.3- The Importance of Late-Satisfied Demand Index

Like the importance of the unmet demand index in the previous section, again, we want to shift our attention to a fresh metric: the importance of late-satisfied demand. This shift is aimed at departing from conventional metrics such as delivery time delays or total response time, which have been extensively utilized in prior research. We also evaluate this new index based on three primary factors: the number of patients covered in the POD, the emergency level of POD, and the delay in delivering relief to the POD. A FIS is deployed to assess this index based on the expertise and experience of decision-makers and the prevailing circumstances. For a comprehensive understanding of our employed FIS, detailed information can be found in Chapter 4. The equations necessary for calculating the importance of the late-satisfied demand index are presented below:

$$FIS_2: (nPatient, Em, Delay) \rightarrow Imp\_late\_satisd \qquad (5)$$

$$Tdelivery_i = \begin{cases} \dfrac{dist_{P_0,L_{1,j}} \times Arc\_cond_{P_0,L_{1,j}}}{vel_j} & if\ L_{1,j} = i \\ \dfrac{dist_{P_0,L_{1,j}} \times Arc\_cond_{P_0,L_{1,j}}}{vel_j} + \displaystyle\sum_{w=1}^{L_{w+1,j}=i} \dfrac{dist_{L_{w,j},L_{w+1,j}} \times Arc\_cond_{L_{w,j},L_{w+1,j}}}{vel_j} & if\ L_{1,j} \neq i \end{cases} \quad \forall i\ ,j\!:\ i \in Tour_j \quad (6)$$

$$Delay_i = \begin{cases} 0 & if\ Tdelivery_i \leq Tmax_i \\ Tdelivery_i - Tmax_i & if\ Tdelivery_i > Tmax_i \end{cases} \quad \forall i \qquad (7)$$

$$Imp\_late\_satisd_i = \begin{cases} 0 & if\ \ Delay_i = 0 \\ FIS_2(nPatient_i, Em_i, Delay_i) & if\ \ Delay_i > 0 \end{cases} \quad \forall i \qquad (8)$$

$$Imp\_late\_satisd\_total = \sum_{i \in P} Imp\_late\_satisd_i \qquad (9)$$

Expression (5) outlines that $FIS_2$ assesses the importance of late-satisfied demand by considering the number of patients covered in the POD, the emergency level of POD, and the delay in delivering relief to the POD. The delivery time of relief supplies to a POD is evaluated using Eq. (6), while in Eq. (7), the delays in delivering these supplies are calculated. Eq. (8) indicates how the importance of late-satisfied demands for each individual POD is evaluated. If the delivery time of relief supplies exceeds the time window of a POD, the importance of late-satisfied demand of this POD will be assessed by the introduced $FIS_2$. Lastly, Eq. (9) summarizes the importance of late-satisfied demand across all PODs to determine the overall importance of late-satisfied demand.

## 3.4- Model Settings

This model seeks to minimize three objective functions: operational cost, the total importance of unmet demand and the total importance of late-satisfied demand. Drawing upon the analysis of the objective functions presented in the preceding section, the model is structured as follows:

$$\boldsymbol{Min}\ Cost = \sum_{i\in P}\sum_{j\in V} Path_{P_0,i,j} \times Cf_j$$

$$+ \sum_{i\in(P_0\cup P)}\ \sum_{i\prime\in(P_0\cup P)}\ \sum_{j\in V} Path_{i,i',j} \times dist_{i,i\prime} \times Cv_j \qquad (10)$$

$$\boldsymbol{Min}\ Imp\_unmetd\_total = \sum_{i\in P} Imp\_unmetd_i \qquad (11)$$

$$\boldsymbol{Min}\ Imp\_late\_satisd\_total = \sum_{i\in P} Imp\_late\_satisd_i \qquad (12)$$

*Subject to:*

$$Sup\_Global < \sum_{i\in P} Dem_i \qquad (13)$$

$$Sup_i \leq Dem_i \quad \forall i \in P \qquad (14)$$

$$\sum_{i \in P} Sup_i . x_{i,j} \leq Cap_j \quad \forall j \in V \qquad (15)$$

$$\sum_{j \in V} x_{i,j} = 1 \quad \forall i \in P \qquad (16)$$

$$\sum_{i \in P} Path_{P_0,i,j} = 1 \quad \forall j \in V \qquad (17)$$

$$\sum_{i \in P} Path_{i,P_0,j} = 1 \quad \forall j \in V \qquad (18)$$

$$Dem_i > 0, \quad Sup_i \geq 0, \quad Cap_j > 0, \quad Vel_j > 0 \qquad \forall i \in P, j \in V \qquad (19)$$

Our study encompasses three distinct objective functions, denoted as equations (10), (11), and (12). Eq. (10) aims to minimize the operational costs of using the fleet of vehicles to distribute relief items. Eq. (11) is focused on minimizing the total importance of unmet demands across all PODs. Finally, Eq. (12) seeks to minimize the total importance of late-satisfied demand, again across all PODs.

The model is also subjected to some constraints. Constraint (13) denotes that the aggregate quantity of relief supplies accessible at the HADC falls below the total sum of the demands of all PODs. Constraint (14) places an upper limit on the relief supplies a POD can receive, ensuring they do not exceed their demand levels. Constraint (15) requires that the capacity of each distribution vehicle should be sufficient to cover the cumulative allocation of relief supplies to PODs designated to be visited by that particular vehicle.

Constraint (16) stipulates that each POD receives relief items once during the distribution operation. Constraints (17) and (18) mandate that each distribution vehicle commences its route from the HADC and ultimately returns to the same centre. Finally, Constraint (19) maintains the feasibility of the model by ensuring that the values of parameters and decision variables remain within an acceptable range.

# 4- Algorithm Design

This chapter comprises two sections: The first introduces the specific FISs employed in this study, providing an extensive examination of their structure. In the subsequent section, we explore two robust evolutionary algorithms in the literature: NSGA-II and NRGA. Also, we discuss integrating FISs with evolutionary algorithms to deal effectively with inherent uncertainties and conflicting goals encountered in humanitarian logistics.

## 4.1- The Architecture of Employed Fuzzy Inference Systems

Fuzzy Inference System (FIS) is a widely embraced computational framework rooted in fuzzy set theory, employing fuzzy if-then rules and fuzzy reasoning. The main strength of FIS lies in its ability to manage scenarios characterized by significant uncertainty and incomplete data. FIS functions by mapping information from the input space, represented by variable values, to the output space, where decisions are made. It accomplishes this by emulating human reasoning and decision-making processes (Jang et al. 1997). There are three main types of FISs in the literature:

1. Mamdani Fuzzy Inference System;
2. Sugeno Fuzzy System (Also known as Takagi–Sugeno–Kang fuzzy system);
3. Tsukamoto Fuzzy System.

The distinction among these three FISs lies in formulating their fuzzy rule consequences (Jang et al. 1997). Among these, the first two FIS variants have obtained greater prominence in the academic literature. Mamdani systems, recognized for their proficiency, excel in managing complex systems by mimicking human-like reasoning processes. In contrast, Sugeno systems find their niche in modelling and controlling systems that mathematical functions or algorithms can describe.

Within this investigation, we utilize the Mamdani FIS (Mamdani and Assilian 1975) to assess the Importance of unmet demand and the Importance of late-satisfied demand at PODs, relying on input variables. The configuration of the proposed FISs is visually depicted in Figure 8.

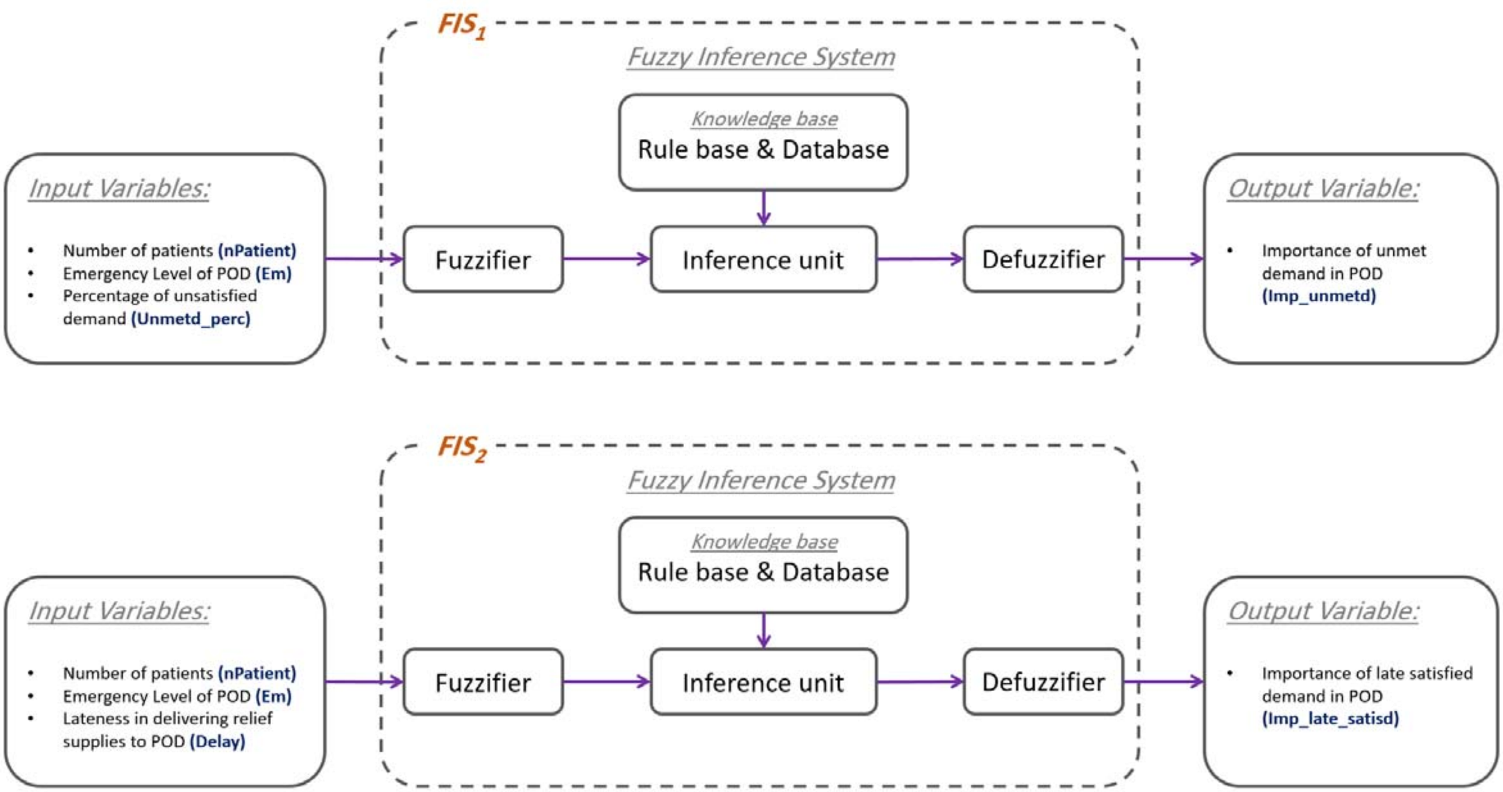



Figure 8: The Proposed FISs' Structure

As illustrated in Figure 8, $FIS_1$ is responsible for assessing the Importance of unmet demand at each POD, while $FIS_2$ evaluates the Importance of late-satisfied demand in each POD. Each FIS employs its input variables to determine its corresponding output variable.

For $FIS_1$, the input variables encompass the Number of patients, the Emergency level of the POD, and the Percentage of unsatisfied demand. $FIS_1$ utilizes these input variables to evaluate the Importance of unmet demand at the POD.

In contrast, $FIS_2$ operates with a distinct set of input variables, including the Number of patients, the Emergency level of the POD, and the Lateness of delivering relief supplies to the POD. $FIS_2$ evaluates the Importance of late-satisfied demand at the POD, drawing upon the specified input variables.

In the realm of mathematics, variables typically assume numerical values. However, in fuzzy logic applications, using non-numeric linguistic variables to enhance the representation of rules and facts is a common practice (Ying 2000). Specifically, linguistic variables are characterized by values expressed as words or sentences from natural language. This approach is highly advantageous in addressing challenging situations that are either inadequately specified or too complex to be represented by standard quantitative expressions (Zimmermann 2011). Within the framework of our proposed FISs, both input and output variables undergo evaluation in an imprecise and inherently subjective manner facilitated by incorporating linguistic variables. Input and output linguistic variables of two proposed FISs are available in Table 8.

Linguistic variables are connected to membership functions, which measure the inherent uncertainty within a set, indicating an element's membership level within that set. In simpler terms, membership functions serve as a visual representation illustrating the extent of involvement of each input. Experts within the domain where fuzzy sets are defined have the flexibility to shape or determine the type of membership functions. In other words, the membership functions for fuzzy sets can take on various forms, guided by the expertise of domain specialists (Sabri et al. 2013).

Table 8: Input and Output Linguistic Variables

| Fuzzy Inference System | Variable Type | Variable Name | Notation |
|---|---|---|---|
| **$FIS_1$** | Input | Number of patients | nPatient |
| | | Emergency Level of POD | Em |
| | | Percentage of unsatisfied demand | Unmetd_perc |
| | Output | Importance of unmet demand in POD | Imp_unmetd |
| **$FIS_2$** | Input | Number of patients | nPatient |
| | | Emergency Level of POD | Em |
| | | Lateness in delivering relief supplies to POD | Delay |
| | Output | Importance of late-satisfied demand in POD | Imp_late_satisd |

In a FIS structure, the fuzzy set membership functions are defined in the Database. In the current study, we employ two known membership functions: triangular and trapezoidal membership functions. The linguistic values associated with linguistic variables and their related fuzzy numbers in this study are presented in Table 9.

Table 9: Linguistic Values and Fuzzy Numbers

| Linguistic Variable | Linguistic Value | Fuzzy Number |
|---|---|---|
| Number of patients | Low | [0 0 25 50] |
| | Medium | [25 50 75] |
| | High | [50 75 100 100] |
| Emergency Level of POD | Low | [0 0 25 50] |
| | Medium | [25 50 75] |
| | High | [50 75 100 100] |
| Percentage of unsatisfied demand | Low | [0 0 25 50] |
| | Medium | [25 50 75] |

| Linguistic Variable | Linguistic Value | Fuzzy Number |
| --- | --- | --- |
| | High | [50 75 100 100] |
| Lateness in delivering relief supplies to POD | Low | [0 0 30 60] |
| | Medium | [30 60 90] |
| | High | [60 90 180 180] |
| Importance of unmet demand in POD | Very low | [0 0 10 30] |
| | Low | [10 30 50] |
| | Medium | [30 50 70] |
| | High | [50 70 90] |
| | Very high | [70 90 100 100] |
| Importance of late-satisfied demand in POD | Very low | [0 0 10 30] |
| | Low | [10 30 50] |
| | Medium | [30 50 70] |
| | High | [50 70 90] |
| | Very high | [70 90 100 100] |

As illustrated in Figure 8, each FIS comprises four primary components (Sabri et al. 2013):

1. *Fuzzifier*: This element converts precise input values into their respective degrees of membership within the associated linguistic values.
2. *Knowledge base*: Is composed of rule base and Database:

   a) The rule base encompasses all fuzzy if-then rules. These rules are linguistic statements detailing how the FIS should make decisions. By utilizing linguistic variables, fuzzy rules create a link between input and output variables. In the current study, each FIS includes three input variables, each characterized by three membership functions: Low, Medium, and High. This results in the formulation of 27 rules for each FIS, attained through combining these input variables and their associated membership functions. It allows easy modification based on expert knowledge to suit specific circumstances. Tables 10 and 11 display the rule bases for $FIS_1$ and $FIS_2$, respectively. For instance, rule 8 in Table 10 is formulated as follows: If the Number of patients in POD is Low AND the Emergency level of POD is High AND the Percentage of unsatisfied demand in POD is Medium, THEN the Importance of unmet demand in POD is Medium.

b) The Database includes the membership functions of fuzzy sets utilized in formulating fuzzy if-then rules.

3. *Inference unit*: This component serves as a mapping process, taking the fuzzified inputs from the Fuzzifier to the rule base and generating a fuzzified output for each rule. Subsequently, these outputs are merged to produce an integrated fuzzy result.
4. *Defuzzifier*: Converts the fuzzy result generated by the inference unit into a real number, representing the ultimate output of the FIS.

The specifications of the devised FISs are outlined as follows:

- FIS type: 'Mamdani';
- And method: 'Min';
- Or method: 'MAX';
- Implication method: 'Min';
- Aggregation method: 'MAX';
- Defuzzification: 'Centroid'.

Table 10: Rule Base of FIS1

| | IF (Input variables) | | | Then (Output variable) |
|---|---|---|---|---|
| **Rule No.** | **nPatient** | **Em** | **Unmetd_perc** | **Imp_unmetd** |
| **1** | Low | Low | Low | Very Low |
| **2** | Low | Low | Medium | Very Low |
| **3** | Low | Low | High | Very Low |
| **4** | Low | Medium | Low | Low |
| **5** | Low | Medium | Medium | Low |
| **6** | Low | Medium | High | Low |
| **7** | Low | High | Low | Low |
| **8** | Low | High | Medium | Medium |
| **9** | Low | High | High | Medium |
| **10** | Medium | Low | Low | Low |
| **11** | Medium | Low | Medium | Low |
| **12** | Medium | Low | High | Medium |
| **13** | Medium | Medium | Low | Medium |
| **14** | Medium | Medium | Medium | Medium |
| **15** | Medium | Medium | High | High |
| **16** | Medium | High | Low | Medium |
| **17** | Medium | High | Medium | High |
| **18** | Medium | High | High | High |
| **19** | High | Low | Low | Medium |
| **20** | High | Low | Medium | Medium |
| **21** | High | Low | High | Medium |
| **22** | High | Medium | Low | High |
| **23** | High | Medium | Medium | High |
| **24** | High | Medium | High | Very High |
| **25** | High | High | Low | High |
| **26** | High | High | Medium | Very High |
| **27** | High | High | High | Very High |

Table 11: Rule Base of $FIS_2$

| | IF (Input variables) | | | Then (Output variable) |
|---|---|---|---|---|
| **Rule No.** | **nPatient** | **Em** | **Delay** | **Imp_late_satisd** |
| **1** | Low | Low | Low | Very Low |
| **2** | Low | Low | Medium | Very Low |
| **3** | Low | Low | High | Very Low |
| **4** | Low | Medium | Low | Low |
| **5** | Low | Medium | Medium | Low |
| **6** | Low | Medium | High | Low |
| **7** | Low | High | Low | Low |
| **8** | Low | High | Medium | Medium |
| **9** | Low | High | High | Medium |
| **10** | Medium | Low | Low | Low |
| **11** | Medium | Low | Medium | Low |
| **12** | Medium | Low | High | Medium |
| **13** | Medium | Medium | Low | Medium |
| **14** | Medium | Medium | Medium | Medium |
| **15** | Medium | Medium | High | High |
| **16** | Medium | High | Low | Medium |
| **17** | Medium | High | Medium | High |
| **18** | Medium | High | High | High |
| **19** | High | Low | Low | Medium |
| **20** | High | Low | Medium | Medium |
| **21** | High | Low | High | Medium |
| **22** | High | Medium | Low | High |
| **23** | High | Medium | Medium | High |
| **24** | High | Medium | High | Very High |
| **25** | High | High | Low | High |
| **26** | High | High | Medium | Very High |
| **27** | High | High | High | Very High |

## 4.2- Implementing Evolutionary Algorithms: NSGA-II and NRGA

Deb et al. (2002) introduced the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a prominent Multi-Objective Evolutionary Algorithm (MOEA). Subsequently, Al Jadaan et al. (2008) proposed a similar algorithm, the Non-dominated Ranked Genetic Algorithm (NRGA). Acknowledged for their efficacy in multi-objective optimization, both NSGA-II and NRGA hold significant standing in the literature (Ghasemi et al. 2019).

Categorized under Evolutionary Algorithms, a subset of meta-heuristics, NSGA-II and NRGA exhibit a non-problem-specific nature, making them adaptable for various problem domains. Their efficiency extends to addressing high-dimensional problems and navigating extensive solution spaces.

In real-world optimization problems, specifically in humanitarian contexts, objectives are often conflicting, and it is vital to balance competing goals. NSGA-II and NRGA, rather than pinpointing a singular solution, can identify a set of Pareto-optimal solutions. This set of solutions depicts the trade-offs among conflicting objectives.

While both NSGA-II and NRGA share a common structural foundation, they differ primarily in their selection strategies. NSGA-II utilizes a binary tournament selection for choosing candidates in crossover and mutation, whereas NRGA adopts a roulette wheel selection operator.

Leveraging their adaptability and proficiency in managing multiple conflicting objectives, NSGA-II and NRGA prove well-suited for optimizing the objective functions pertinent to our investigation. Therefore, both NSGA-II and NRGA are utilised in the present study, and their results are subject to a comparative analysis. Figure 9 illustrates a visual depiction of the NSGA-II and NRGA.

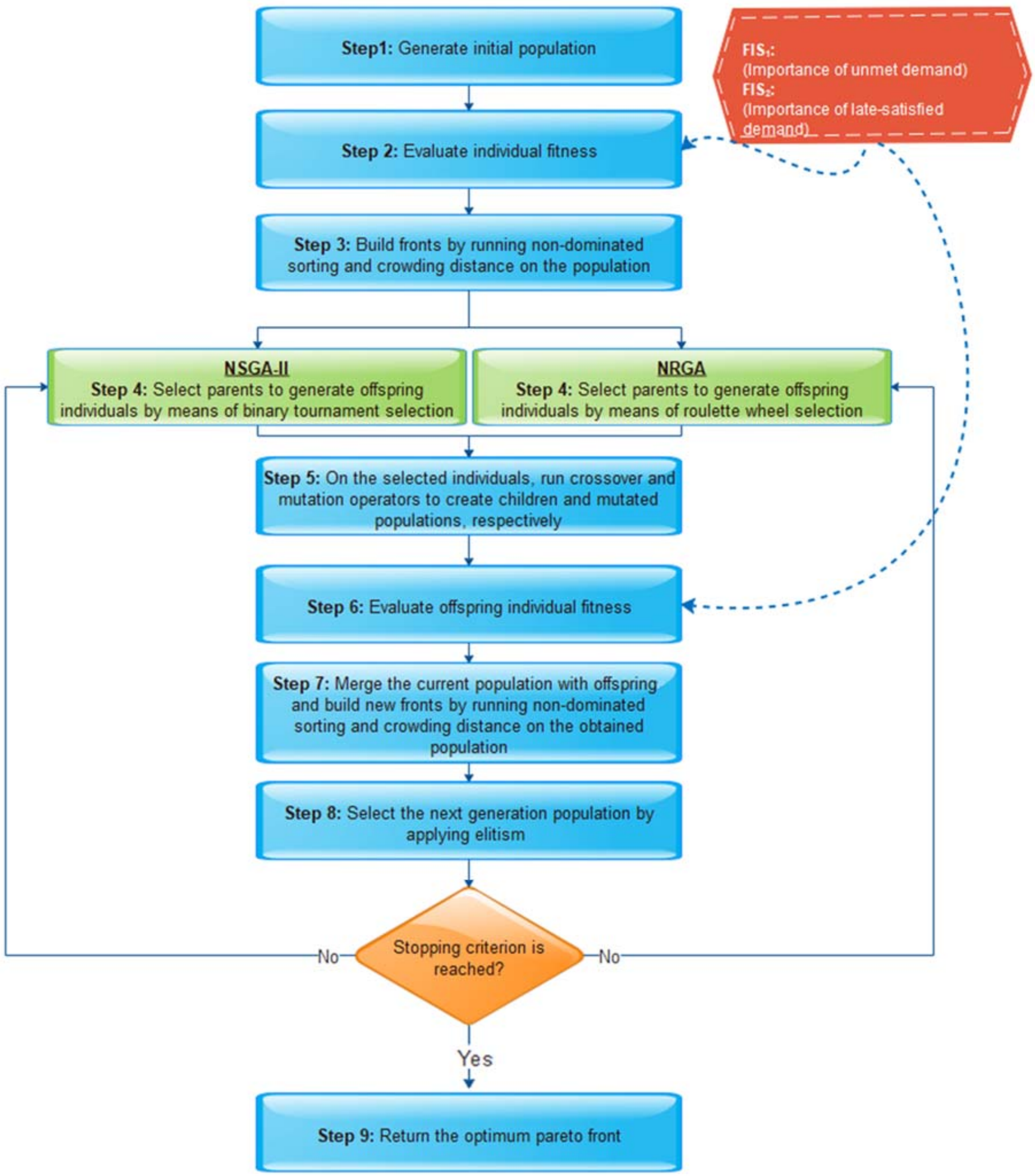



Figure 9: Visual Depiction of the NSGA-II and NRGA

The following concisely explains the steps involved in the algorithms mentioned above (Deb et al. 2002; Al Jadaan et al. 2008):

**Step 1: Initialization and Chromosome Encoding**

A specified quantity of potential solutions is randomly generated in the initial phase. Each proposed solution is alternatively referred to as an individual or a chromosome. Each solution in this study determines the following:

4. The vehicles assigned to service the PODs;
5. The specific sequence of PODs that each vehicle should serve;
6. The quantity of relief supply allocated to each POD.

In this study, we utilize a chromosome structure represented by a two-dimensional matrix, as depicted schematically in Figure 10.

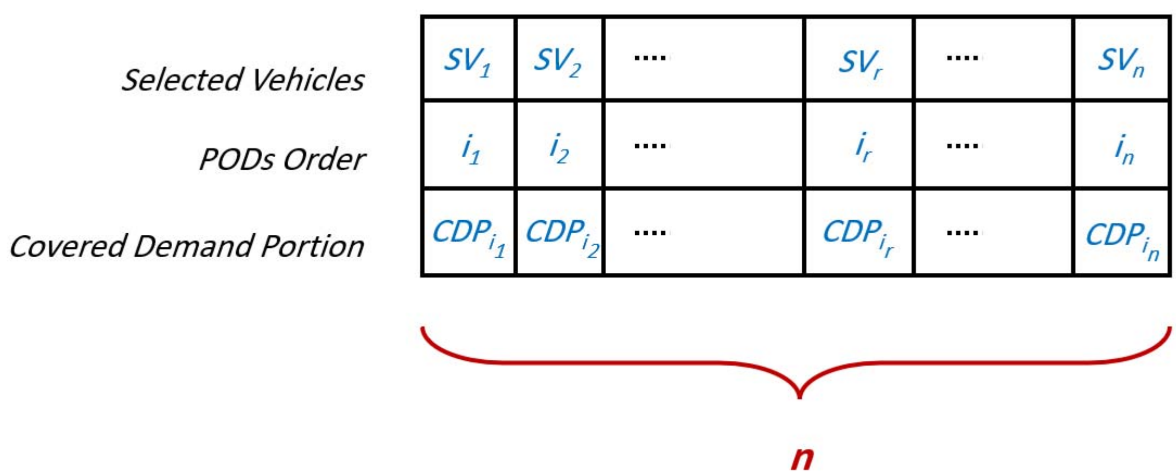



Figure 10: Structure of a Chromosome

The number of columns (n) in the chromosome structure equals the number of PODs in the affected area. In the initial row, all designated vehicles for POD service are outlined. The genes (alleles) take on real values ranging between 0 and 1, to be subsequently correlated with vehicle numbers through Expression (20):

$$\lfloor SV_r \times m \rfloor + 1 \qquad (20)$$

$SV_r$ is a real number ($0 \leq SVr < 1$), and $m$ represents the total number of available vehicles.

The second row encompasses a permutation of POD numbers ($i_r \in P$).

Finally, the genes within the third row are filled with real numbers ranging from 0 to 1. Considering the vehicle responsible for servicing $POD_{i_r}$, it will be interpreted as the proportion of the vehicle load allocated to $POD_{i_r}$, as outlined in Expression 21:

$$\frac{CDP_{i_r}}{\sum_{i_r=i_1}^{i_n} CDP_{i_r} \times x_{i_r,j}} \quad \forall j \qquad (21)$$

The chosen encoding method ensures the feasibility of each generated solution within the chromosome structure.

To see how a solution is encoded in a chromosome, we examine a numerical example: consider a scenario with ten PODs and three vehicles tasked with distributing relief supplies to these PODs. We construct a chromosome with ten genes in each row in this case. Figure 11 (A) depicts a raw random solution. The genes in the first row (Selected Vehicles) and the third row (Covered Demand Portion) are filled with random real numbers ranging between 0 and 1, while the second row (PODs Order) represents the permutation of POD numbers.

The values in two rows—the Selected Vehicle row and the Covered Demand Portion row—must be parsed to interpret this random solution. Using Expression (20), the values in the Selected Vehicle row are interpreted as vehicle numbers, resulting in the parsed chromosome shown in Figure 11 (B). It is evident from the parsing that vehicle number 1 will distribute relief items to PODs 4, 5, and 3 in sequential order. Likewise, vehicle number 2 serves PODs 10, 8, and 9, respectively, and vehicle number 3 serves PODs 1, 6, 2, and 7, respectively.

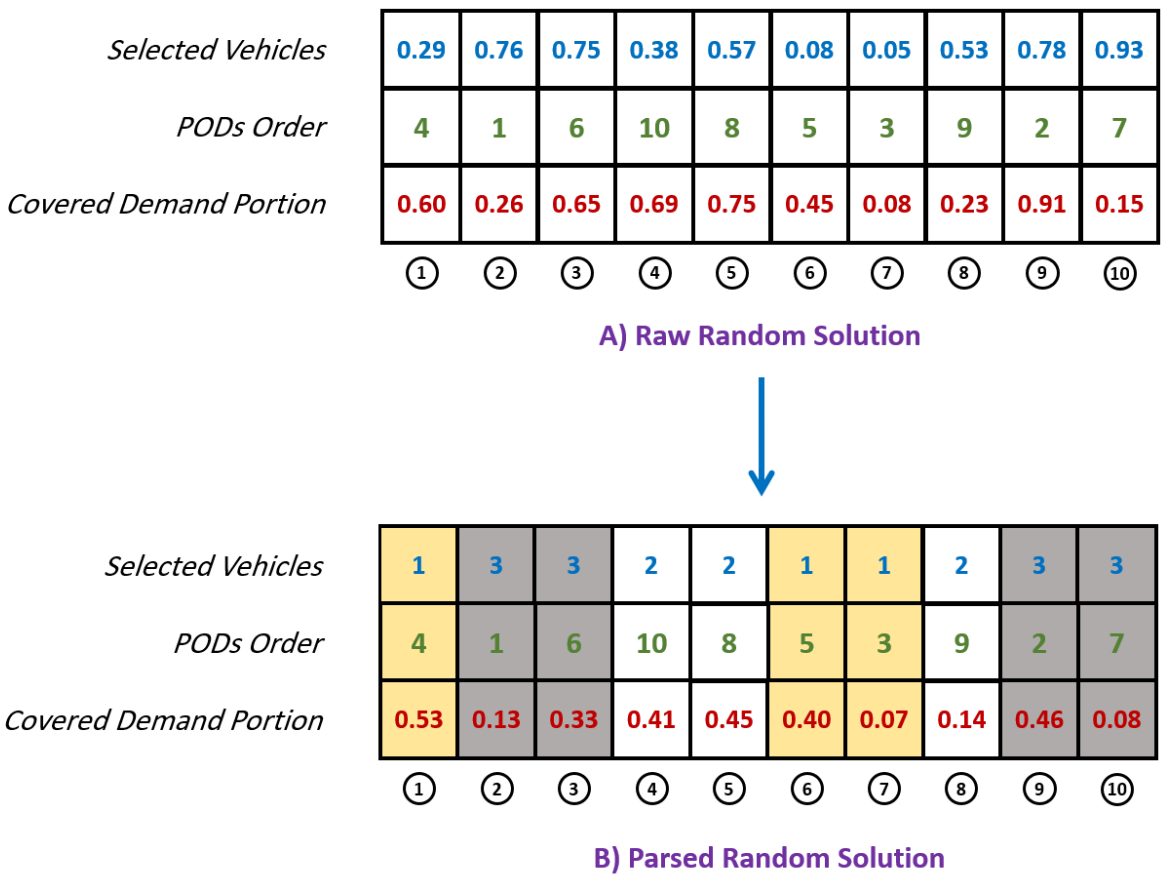



Figure 11: A Random Solution

Similarly, the proportion allocated to each POD is calculated by applying Expression (21) to the Covered Demand Portion row. For instance, POD 4 will receive 53% of the relief supplies available in vehicle number 1, and POD 1 will receive 13% of the relief supplies available in vehicle number 3.

**Step 2: Individual Evaluation**

Each individual undergoes assessment based on three distinct objective functions: Operational cost, Importance of unmet demand, and Importance of late-satisfied demand. Two latter objective functions are evaluated using predefined FISs.

In fact, in this investigation, we leverage the adaptability of FISs for decision-making in uncertain scenarios and the robust optimization capabilities of NSGA-II and NRGA in managing multiple conflicting objectives within a high-dimensional humanitarian context. Integrating FISs with evolutionary algorithms presents a synergistic approach, offering a flexible and resilient tool for designing an effective last-mile distribution system in humanitarian operations. This combination addresses the inherent uncertainties and conflicting goals encountered in humanitarian logistics, providing a comprehensive solution for optimizing the complexities of relief supply distribution.

**Step 3: Building Fronts**

A non-dominated sorting procedure is executed on the population, considering individuals' fitness concerning the three defined objective functions. Dominance between individuals is established such that an individual, A, dominates another, B when A is as proficient as B in all objectives and superior to B in at least one objective. Consequently, individuals are categorized into various non-dominated fronts. Subsequently, the crowding distance, a metric indicating an individual's proximity to its neighbours, is employed to arrange individuals within each non-dominated front. Larger crowding distances signify increased diversity, affording enhanced coverage of the Pareto front.

**Step 4: Selection Strategy**

NSGA-II employs binary tournament selection to determine parents for generating offspring individuals. Two individuals are randomly chosen and compared, with the one holding a superior front rank being selected. When rankings are equal, the winner is selected based on the individual's higher crowding distance.

Conversely, NRGA employs the roulette wheel selection strategy. Initially, a front is randomly selected, with better-ranked fronts more likely to be chosen. Following that, an individual from the selected front is randomly chosen using the same technique, with individuals possessing higher crowding distances being more likely to be chosen.

**Step 5: Crossover and Mutation**

Crossover and mutation are robust genetic operators facilitating the exploration and exploitation of the search space. Crossover enables genetic inheritance, while mutation preserves genetic diversity across generations. By applying these operators to selected parents from Step 4, offspring are generated, constituting a new population for the subsequent generation.

**Step 6: Offspring Evaluation**

The generated offspring are evaluated based on the three defined objective functions, mirroring the evaluation process in Step 2.

**Step 7: Population Merging**

Combining the existing population with children and mutated populations results in a merged population. This mixed population is sorted using non-dominated sorting and crowding distance to yield new fronts.

**Step 8: Generation Formation**

The next generation is formed by selecting the best individuals from the combined and sorted population, adhering to the elitism strategy and maintaining the original population's size. The elitism approach allows the algorithm to have a better convergence towards the Pareto-optimal front.

Upon concluding this step, the output is returned (Step 9) if the stopping criterion, such as reaching a certain number of repetitions, is met. Otherwise, the algorithm proceeds to Step 4 for the next iteration.

**Step 9: Return the Output**

The algorithm returns the first-rank Pareto in the population, recognized as Pareto-optimal. This set of solutions stands out as no other individual surpasses these solutions within the Pareto. All the solutions in the Pareto-optimal set are optimum, illustrating the inherent trade-offs among the defined objective functions.

# 5- Performance Analysis of Evolutionary Algorithms

To address the last-mile distribution problem utilizing evolutionary algorithms, this chapter introduces two distinct problem sets:

1. *Small-size problem*: In this scenario, the affected area comprises 10 PODs, with three vehicles tasked with distributing relief supplies among these PODs.
2. *Large-size problem*: Expanding the scope, this scenario involves 20 PODs within the affected area, and a fleet of six vehicles manages the distribution of relief supplies.

For each of these scenarios, a set of 30 random problems is generated and subsequently tackled utilizing both NSGA-II and NRGA. The Pareto fronts obtained by applying NSGA-II and NRGA for the first large-size problem are illustrated in Figure 12.

To assess and compare the performance of NSGA-II and NRGA, aligned with earlier investigations conducted by Haghi et al. (2017), Rabbani et al. (2010), and Zitzler and Thiele (1998), this study employs five key criteria to evaluate the effectiveness of evolutionary algorithms:

1. *CPU Time*. The computational efficiency of algorithms is represented by their CPU run-time. In particular, the algorithm's scalability is strongly tied to its computing efficiency as the problem size increases.
2. *Number of Non-dominated Solutions (NNS)*. The set of non-dominated solutions represents the Pareto front. It is a collection of solutions where no solution is better than others in all objective functions. Finding non-dominated diverse solutions is

crucial for appropriate trade-offs among conflicting objectives functions. Higher NNS means more diversity and more efficient exploration within the decision space.

3. *Mean Ideal Distance (MID)*. The best solution, which is ideal regarding all objective functions, is called the ideal solution. In this study which is a minimization problem with three objective functions, (0, 0, 0) is the ideal solution. MID is the average distance of Pareto solutions from the ideal solution (Eq. 22):

$$MID = \sum_{i=1}^{n} \frac{C_i}{n} \qquad (22)$$

$C_i$ represents the distance between non-dominated solution $i$ and the ideal solution, whereas $n$ represents the total number of non-dominated solutions.

MID is a metric indicating the algorithm's robustness in converging toward the ideal solution across all objective functions. Lower MID signifies more efficiency in exploring the entire solution space globally and convergence of the solutions in the Pareto front.

4. *Spacing Metric (SM)*. This metric indicates how well the solutions in the Pareto front are distributed across the solution space (Eq. 23):

$$SM = \frac{\sum_{i=1}^{n-1} \left| \bar{d} - d_i \right|}{(n-1)\bar{d}} \qquad (23)$$

The Euclidean distance between two neighbouring solutions is represented by $d_i$, whereas the average of these $d_i$ values is denoted as $\bar{d}$. A zero value in this metric signifies a perfectly uniform distribution.

Well-distributed solutions represent the algorithm's robustness in efficiently exploring the solution space and avoiding getting stuck in local optima. As a result, it provides the decision-makers with a variety of high-quality trade-off options.

5. *Hypervolume (HV)*. The Pareto front solutions encompass a volume or region relative to a specified reference point (Eq. 24):

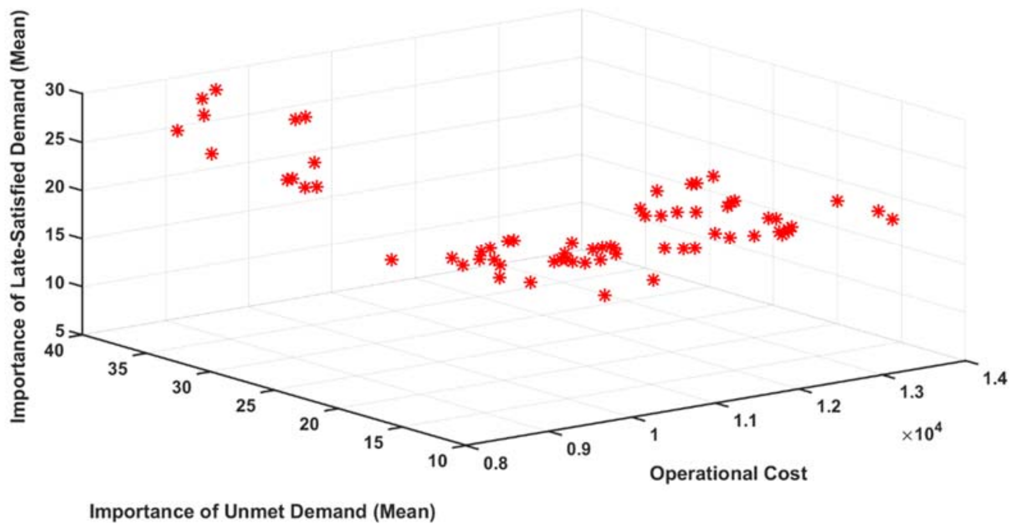
$$HV = volume\left(\bigcup_{i=1}^{n} v_i\right) \quad (24)$$

Where $v_i$ represents the volume or area filled by the solution *i* relative to the reference point in the solution space. The reference point for this study is determined by selecting the worst values obtained for each of the three objective functions from the Pareto front of all problems solved by both NSGA-II and NRGA.

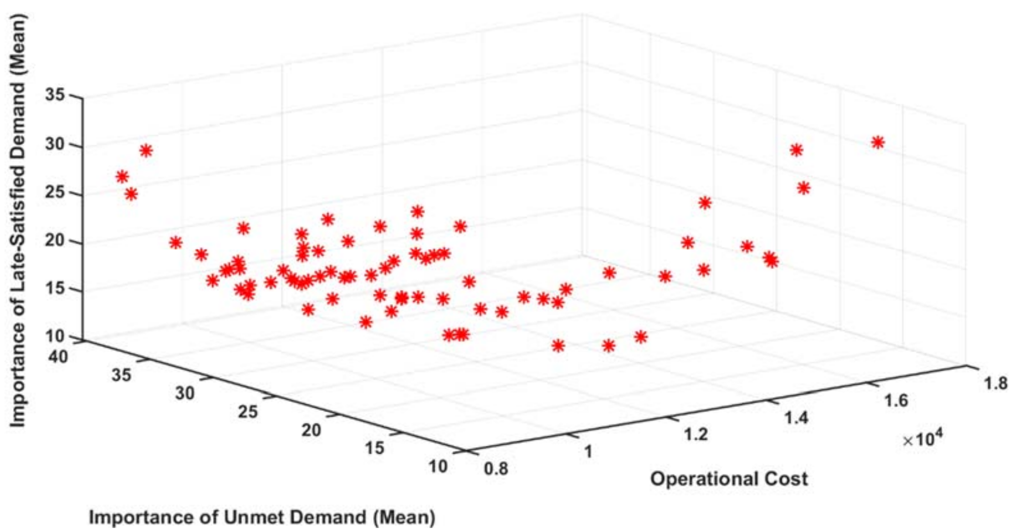
Hypervolume serves as a measure for both the diversity and convergence aspects. Higher Hypervolume means higher efficiency in finding a diverse set of non-dominated solutions alongside high-quality solutions.

The NSGA-II and NRGA algorithms are implemented using MATLAB R2021b on a computer equipped with an Intel(R) Core ™ i5-3230M CPU running at a clock speed of

2.60GHz and 6GB of DDR3 memory. Additionally, to facilitate a comparative analysis of NSGA-II and NRGA performance, IBM SPSS Statistics version 26 is utilized.




a) Pareto Front of NSGA-II for the First Large-Size Problem




b) Pareto Front of NRGA for the First Large-Size Problem

Figure 12: Pareto Front of NSGA-II and NRGA

### 5.1- Performance Analysis of Algorithms in Small-Size Problems

To evaluate the performance of NSGA-II and NRGA in addressing small-size problems, we generated 30 random problem instances, each encompassing 10 PODs, with three vehicles designated for distributing relief supplies among these PODs. Subsequently, both algorithms were applied to solve all generated problems, and data related to five pre-defined criteria were collected for subsequent analysis.

In order to conduct appropriate statistical tests to evaluate the performance of employed evolutionary algorithms in this study, first, we should test the normality of the obtained data distributions. For this purpose, we utilized Kolmogorov-Smirnov and Shapiro-Wilk tests. The results are presented in Table 12.

Table 12: Normality Test for Small-Size Problems (CPU Time, NNS, MID, SM, and HV)

**Tests of Normality**

| | Type | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|---|
| | | Statistic | df | Sig. | Statistic | df | Sig. |
| **CPU Time** | NSGA-II | .119 | 30 | .200* | .948 | 30 | .151 |
| | NRGA | .121 | 30 | .200* | .955 | 30 | .235 |
| **NNS** | NSGA-II | .318 | 30 | .000 | .677 | 30 | .000 |
| | NRGA | .250 | 30 | .000 | .804 | 30 | .000 |
| **MID** | NSGA-II | .096 | 30 | .200* | .980 | 30 | .813 |
| | NRGA | .096 | 30 | .200* | .986 | 30 | .950 |
| **SM** | NSGA-II | .113 | 30 | .200* | .967 | 30 | .449 |
| | NRGA | .089 | 30 | .200* | .969 | 30 | .509 |
| **HV** | NSGA-II | .070 | 30 | .200* | .967 | 30 | .470 |
| | NRGA | .128 | 30 | .200* | .935 | 30 | .067 |

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

The outcomes of the Kolmogorov-Smirnov and Shapiro-Wilk tests conducted on CPU Time, MID, SM, and HV across both NSGA-II and NRGA algorithms reveal that the null hypothesis of normal distribution is accepted for these variables. However, in the case of NNS, the results indicate a rejection of the null hypothesis of normal distribution for both applied evolutionary algorithms.

Therefore, to compare the performance of NSGA-II and NRGA concerning variables with a normal distribution (CPU Time, MID, SM, and HV), we employed the parametric Independent-samples T Test with a 95% confidence interval (CI) for the mean difference (Tables 13, 14). Conversely, for the non-normally distributed variable NNS, the non-parametric Mann-Whitney U Test was applied (see Table 15).

Table 13: Group Statistics for Small-Size Problems (Criteria: CPU Time, MID, SM, and HV)

**Group Statistics**

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **CPU Time** | NSGA-II | 30 | 73.6660 | 2.73734 | .49977 |
| | NRGA | 30 | 74.0486 | 3.08294 | .56287 |
| **MID** | NSGA-II | 30 | 1.1259 | .08322 | .01519 |
| | NRGA | 30 | 1.1217 | .09544 | .01743 |
| **SM** | NSGA-II | 30 | 1.4441 | .17415 | .03180 |
| | NRGA | 30 | 1.3781 | .16738 | .03056 |
| **HV** | NSGA-II | 30 | 46185.79 | 25243.707 | 4608.849 |
| | NRGA | 30 | 43668.84 | 27300.422 | 4984.352 |

Table 14: Independent-samples T Test in Small-Size Problems (Criteria: CPU Time, MID, SM, and HV)

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | | Lower | Upper |
| **CPU Time** | Equal variances assumed | .198 | .658 | -.508 | 58 | .613 | -.38256 | .75272 | -1.88929 | 1.12417 |
| | Equal variances not assumed | | | -.508 | 57.199 | .613 | -.38256 | .75272 | -1.88974 | 1.12462 |
| **MID** | Equal variances assumed | .881 | .352 | .179 | 58 | .858 | .00415 | .02312 | -.04213 | .05043 |
| | Equal variances not assumed | | | .179 | 56.945 | .858 | .00415 | .02312 | -.04215 | .05045 |
| **SM** | Equal variances assumed | .000 | .991 | 1.497 | 58 | .140 | .06602 | .04410 | -.02225 | .15430 |
| | Equal variances not assumed | | | 1.497 | 57.909 | .140 | .06602 | .04410 | -.02226 | .15430 |
| **HV** | Equal variances assumed | 1.374 | .246 | .371 | 58 | .712 | 2516.945 | 6788.613 | -11071.940 | 16105.829 |
| | Equal variances not assumed | | | .371 | 57.648 | .712 | 2516.945 | 6788.613 | -11073.708 | 16107.597 |

Table 15: Mann-Whitney U Test in Small-Size Problems (Criteria: NNS)

| Test Statistics[a] | |
|---|---|
| | NNS |
| **Mann-Whitney U** | 400.000 |
| **Wilcoxon W** | 865.000 |
| **Z** | -.790 |
| **Asymp. Sig. (2-tailed)** | .429 |

a. Grouping Variable: Algorithm (NSGA-II and NRGA).

According to the results obtained in Tables 13 and 14, the performance of NSGA-II and NRGA regarding four criteria with normal distribution is as follows:

1. *CPU Time*: The results of Levene's test indicate that the null hypothesis cannot be rejected (F =0.198, p-value = 0.658 > 0.05). Therefore, there is no significant difference in variances between the groups (NSGA-II and NRGA), and the variances are assumed to be equal. Also, the results of the Independent-samples T test indicate that there is not a significant difference in CPU Time between NSGA-II (M = 73.67, SD = 2.74) and NRGA (M = 74.05, SD = 3.08); t (58) = -0.508, p = 0.613.

2. *MID*: Regarding the results of Levene's test (F =0.881, p-value = 0.352), the p-value is greater than the significance level of 0.05. Therefore, the homogeneity assumption of the variances in NSGA-II and NRGA is met. Also, the results of the Independent-samples T test indicate that there is not a significant difference in MID between NSGA-II (M = 1.13, SD = 0.08) and NRGA (M = 1.12, SD = 0.09); t (58) = 0.179, p = 0.858.

3. *SM*: In Levene's test, it can be seen that the null hypothesis cannot be rejected, and thus, there is no significant difference in variances between the groups (F =0.000, p-value = 0.991). Also, the results of the Independent-samples T test indicate that there is not a significant difference in SM between NSGA-II (M = 1.44, SD = 0.17) and NRGA (M = 1.38, SD = 0.17); t (58) = 1.497, p = 0.140.

4. *HV*: According to the results of Levene's test (F =1.374, p-value = 0.246), We fail to reject the null hypothesis, suggesting that the variances are assumed to be equal between groups. Also, the results of the Independent-samples T test indicate that there is not a significant difference in HV between NSGA-II (M = 46185.79, SD = 25243.71) and NRGA (M = 43668.84, SD = 27300.42); t (58) = 0.371, p = 0.712.

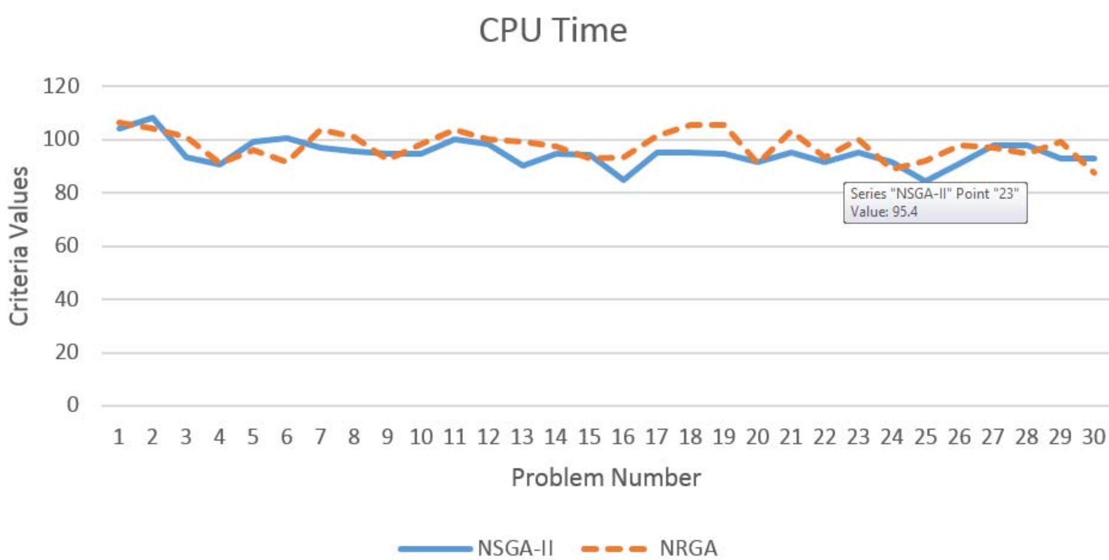
Also, according to the results obtained in Table 15, the performance of NSGA-II and NRGA regarding NNS is as follows:

5. *NNS:* The results of the Mann-Whitney U test indicate a non-significant difference between groups (U = 400.00, p-value = 0.429). In conclusion, we fail to reject the null hypothesis and conclude that there is no difference in the NNS between NSGA-II and NRGA.

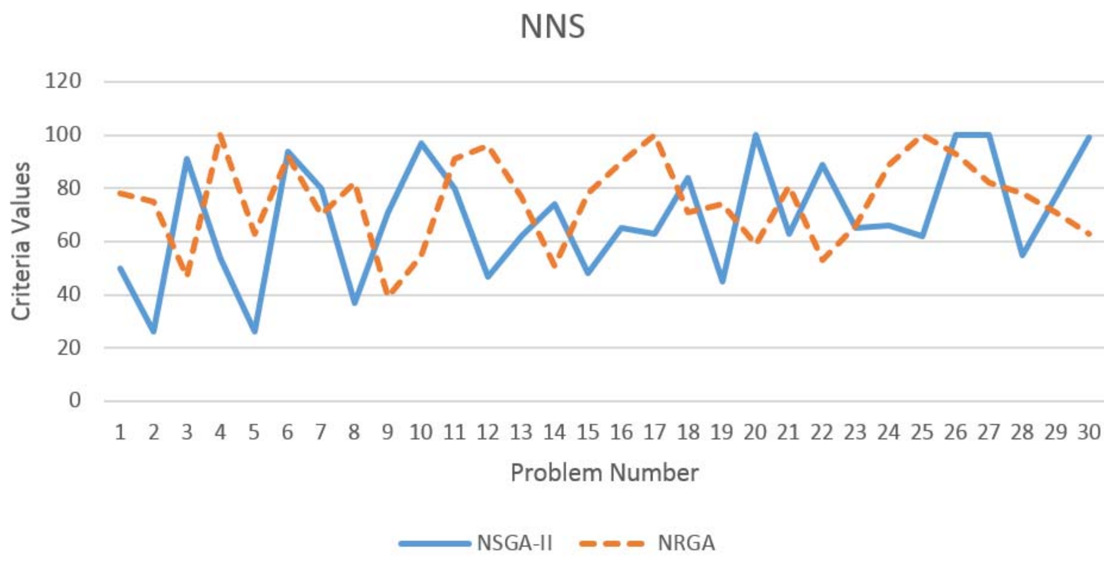
In summary, the results indicate that in small-size problems, there is no significant difference between the performance of NSGA-II and NRGA.

## 5.2- Performance Analysis of Algorithms in Large-Size Problems

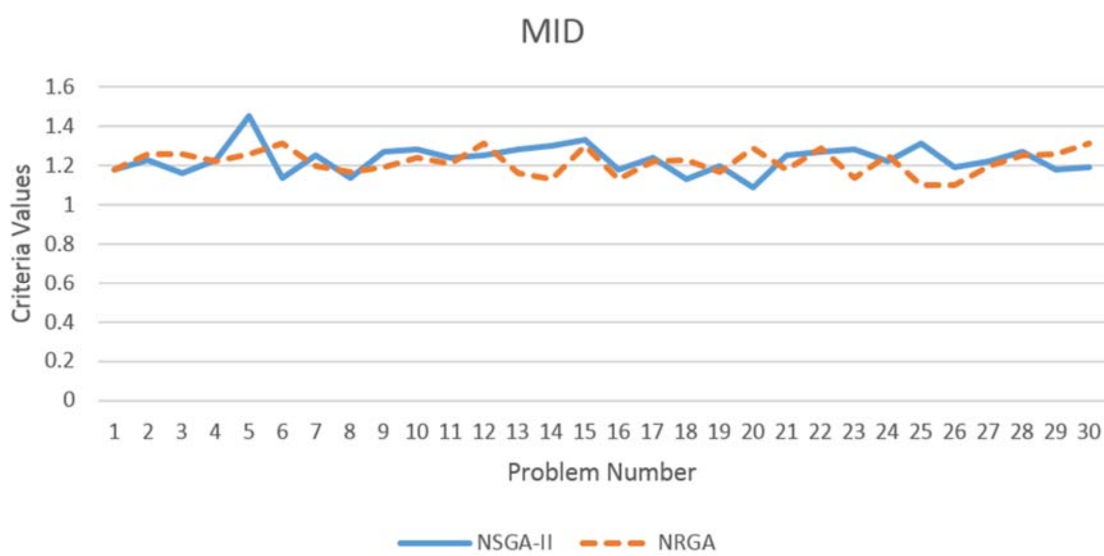
To assess the performance of NSGA-II and NRGA in addressing larger-scale challenges, we adopted the same strategy for evaluating their performance in small-size scenarios. Specifically, 30 random problem instances were generated, each featuring 20 PODs, with six vehicles assigned to distribute relief supplies among these PODs. Subsequently, both algorithms were employed to solve all generated problems, and data associated with five pre-defined criteria were gathered for subsequent analysis. The results in all five criteria regarding large-size problems are shown in Figure 13.



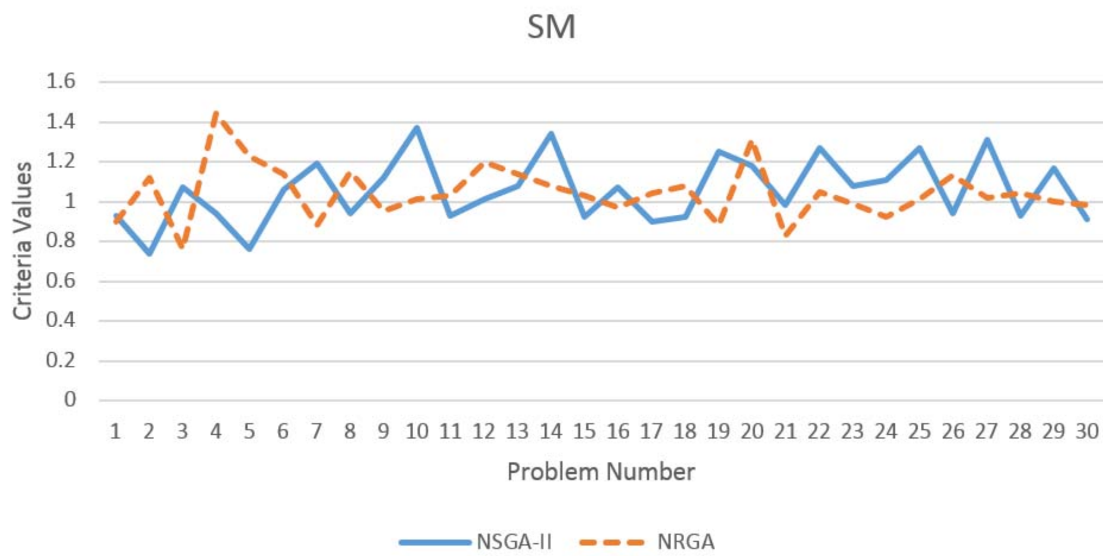

a) Results of NSGA-II and NRGA in CPU Time Criteria



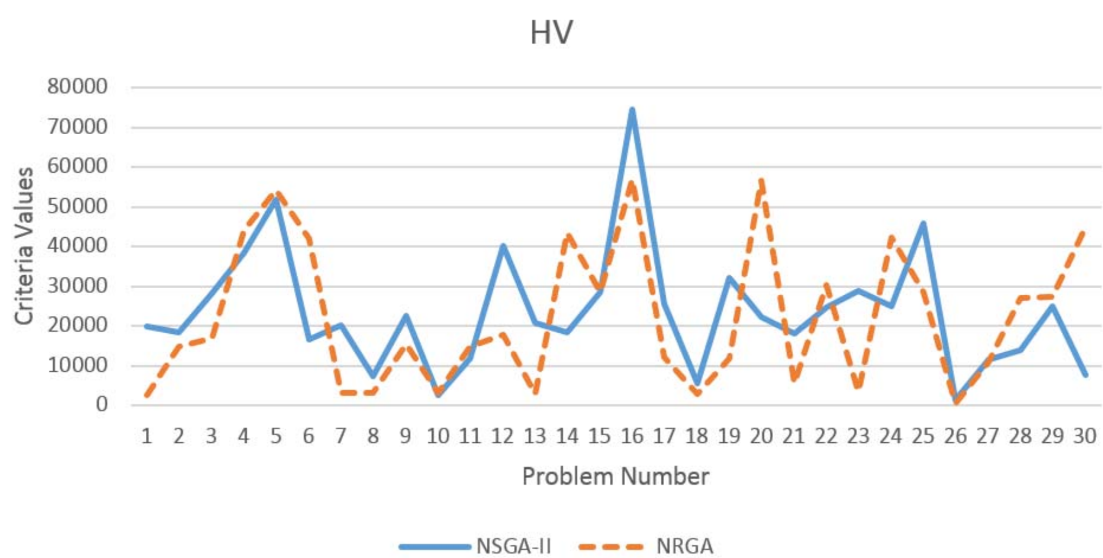

b) Results of NSGA-II and NRGA in NNS Criteria




c) Results of NSGA-II and NRGA in MID Criteria




d) Results of NSGA-II and NRGA in SM Criteria




e) Results of NSGA-II and NRGA in HV Criteria

Figure 13: Obtained Results from NSGA-II and NRGA in Large-Size Problems

Once again, we use Kolmogorov-Smirnov and Shapiro-Wilk tests to assess the normality of the distribution of the obtained data (Table 16). Based on this analysis, we can perform relevant statistical tests to compare the performance of NSGA-II and NRGA in dealing with large-size problems.

Table 16: Normality Test for Large-Size Problems (CPU Time, NNS, MID, SM, and HV)

**Tests of Normality**

| | Type | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|---|
| | | Statistic | df | Sig. | Statistic | df | Sig. |
| **CPU Time** | NSGA-II | .131 | 30 | .200 | .954 | 30 | .214 |
| | NRGA | .123 | 30 | .200* | .962 | 30 | .350 |
| **NNS** | NSGA-II | .088 | 30 | .200* | .953 | 30 | .199 |
| | NRGA | .093 | 30 | .200* | .966 | 30 | .428 |
| **MID** | NSGA-II | .126 | 30 | .200* | .957 | 30 | .255 |
| | NRGA | .088 | 30 | .200* | .958 | 30 | .274 |
| **SM** | NSGA-II | .151 | 30 | .078 | .958 | 30 | .283 |
| | NRGA | .116 | 30 | .200* | .967 | 30 | .464 |
| **HV** | NSGA-II | .169 | 30 | .029 | .905 | 30 | .011 |
| | NRGA | .166 | 30 | .035 | .892 | 30 | .005 |

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

The results from the Kolmogorov-Smirnov and Shapiro-Wilk tests, administered to assess the normality of CPU Time, NNS, MID, and SM across both NSGA-II and NRGA algorithms, affirm the acceptance of the null hypothesis indicating normal distribution for these variables. Nevertheless, in the case of HV, the outcomes show that the null hypothesis of normal distribution is rejected for both implemented evolutionary algorithms.

Hence, to evaluate the performance of NSGA-II and NRGA regarding the variables with a normal distribution (CPU Time, NNS, MID, and SM), we utilized the parametric Independent-samples T Test with a 95% confidence interval (CI) for the mean difference (Tables 17, 18). In contrast, the non-parametric Mann-Whitney U Test was employed for the variable HV, which did not have a normal distribution (Table 19).

Table 17: Group Statistics for Large-Size Problems (CPU Time, NNS, MID, and SM)

**Group Statistics**

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **CPU Time** | NSGA-II | 30 | 94.9972 | 4.82877 | .88161 |
| | NRGA | 30 | 97.7281 | 5.37396 | .98115 |
| **NNS** | NSGA-II | 30 | 69.00 | 21.855 | 3.990 |
| | NRGA | 30 | 75.47 | 16.596 | 3.030 |
| **MID** | NSGA-II | 30 | 1.2315 | .07075 | .01292 |
| | NRGA | 30 | 1.2170 | .06182 | .01129 |
| **SM** | NSGA-II | 30 | 1.0571 | .16707 | .03050 |
| | NRGA | 30 | 1.0438 | .14111 | .02576 |

Table 18: Independent-samples T Test in Large-Size Problems (Criteria: CPU Time, NNS, MID, and SM)

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | | Lower | Upper |
| **CPU Time** | Equal variances assumed | 2.133 | .150 | -2.070 | 58 | .043 | -2.73092 | 1.31905 | -5.37128 | -.09056 |
| | Equal variances not assumed | | | -2.070 | 57.349 | .043 | -2.73092 | 1.31905 | -5.37191 | -.08992 |
| **NNS** | Equal variances assumed | 2.819 | .099 | -1.291 | 58 | .202 | -6.467 | 5.010 | -16.496 | 3.562 |
| | Equal variances not assumed | | | -1.291 | 54.099 | .202 | -6.467 | 5.010 | -16.511 | 3.578 |
| **MID** | Equal variances assumed | .019 | .890 | .845 | 58 | .401 | .01450 | .01715 | -.01983 | .04884 |
| | Equal variances not assumed | | | .845 | 56.975 | .401 | .01450 | .01715 | -.01985 | .04885 |
| **SM** | Equal variances assumed | 2.118 | .151 | .335 | 58 | .739 | .01336 | .03993 | -.06657 | .09328 |
| | Equal variances not assumed | | | .335 | 56.421 | .739 | .01336 | .03993 | -.06662 | .09333 |

Table 19: Mann-Whitney U Test in Large-Size Problems (Criteria: HV)

**Test Statistics[a]**

| | HV |
|---|---|
| **Mann-Whitney U** | 410.000 |
| **Wilcoxon W** | 875.000 |
| **Z** | -.591 |
| **Asymp. Sig. (2-tailed)** | .554 |

a. Grouping Variable: Algorithm (NSGA-II and NRGA).

Based on the findings presented in Tables 17 and 18, the performance of both NSGA-II and NRGA concerning four criteria characterized by a normal distribution is outlined as follows:

1. *CPU Time*: The results of Levene's test indicate that the null hypothesis cannot be rejected (F =2.133, p-value = 0.150 > 0.05). Therefore, there is no significant difference in variances between the groups (NSGA-II and NRGA), and the variances are assumed to be equal. Also, the results of the Independent-samples T test indicate that there was a significant difference in CPU Time between NSGA-II (M = 95.00, SD = 4.83) and NRGA (M = 97.73, SD = 5.37); t(58) = -2.070, p = 0.043.

2. *NNS*: Regarding the results of Levene's test (F =2.819, p-value = 0.099), the p-value is greater than the significance level of 0.05. Therefore, the homogeneity assumption of the variances in NSGA-II and NRGA is met. Also, the results of the Independent-samples T test indicate that there was not a significant difference in

NNS between NSGA-II (M = 95.00, SD = 4.83) and NRGA (M = 97.73, SD = 5.37); t(58) = -1.291, p = 0.202.

3. *MID*: In Levene's test, it can be seen that the null hypothesis cannot be rejected, and thus, there is no significant difference in variances between the groups (F =0.019, p-value = 0.890). Also, the results of the Independent-samples T test indicate that there was not a significant difference in MID between NSGA-II (M = 1.23, SD = 0.07) and NRGA (M = 1.22, SD = 0.06); t(58) = 0.845, p = 0.401.

4. *SM*: According to the results of Levene's test (F =2.118, p-value = 0.151), We fail to reject the null hypothesis, suggesting that the variances are assumed to be equal between groups. Also, the results of the Independent-samples T test indicate that there was not a significant difference in SM between NSGA-II (M = 1.06, SD = 0.17) and NRGA (M = 1.04, SD = 0.14); t(58) = 0.335, p = 0.739.

Additionally, based on the findings from Table 19, the performance of NSGA-II and NRGA concerning HV is outlined as follows:

5. *HV*: The results of the Mann-Whitney U test indicate a non-significant difference between groups (U = 410.00, p-value = 0.554). In conclusion, we fail to reject the null hypothesis and conclude that there is no difference in the HV between NSGA-II and NRGA.

In summary, in the comparison of NSGA-II and NRGA across large-size problems, both algorithms exhibited similar performance in NNS, MID, SM, and HV. However, regarding CPU

Time, NSGA-II outperformed NRGA, showing a significant difference. The results suggest that while the two algorithms perform similarly in certain aspects, NSGA-II may be more efficient in computation time.

## 5.3- Comparing the Performance of Algorithms in Small-Size and Large-Size Problems

In the analysis of small-size problems, both NSGA-II and NRGA demonstrated comparable performance across five criteria (CPU Time, NNS, MID, SM, and HV). Statistical tests revealed no significant differences between the algorithms regarding these metrics, suggesting similar effectiveness. For large-size problems, both algorithms again performed similarly in NNS, MID, SM, and HV. However, regarding CPU Time, NSGA-II exhibited a significant advantage over NRGA, indicating superior efficiency. In summary, while both algorithms perform comparably in various aspects, NSGA-II outperforms NRGA regarding computation time for larger-size problems.

# 6- Discussion

In the current investigation, we focused on sudden natural disasters, which have become increasingly pressing in recent years, causing significant human and economic losses. In many cases, they even had a profound historical influence on a global scale.

Sudden natural disasters differ from other kinds of disasters in distinct ways. They start quickly and are erratic in nature. Furthermore, they vary significantly in size and scope, severely destroying critical infrastructure like communication networks, bridges, and roadways and making it more difficult to access the impacted regions. They could also have severe humanitarian repercussions, including death, injury, and relocation.

In this situation, effective humanitarian logistics planning and execution can save lives, alleviate suffering, and support the recovery of communities impacted by disasters. One of the critical activities of humanitarian logistics is last-mile distribution. It involves indicating an optimal distribution plan, encompassing delivery schedules, vehicle routes, and the quantities of emergency supplies dispatched to PODs throughout disaster relief endeavours. Implementing a robust last-mile distribution system optimizes the use of available supplies and enables rapid response to the immediate needs of affected people.

Therefore, our main objective in the current research is to establish a robust last-mile distribution system for allocating limited available medical relief supplies to the PODs, a multi-objective problem during the disaster response phase. As a result, our journey began with reviewing the literature on optimizing relief distribution in a humanitarian context from three distinct perspectives:

1. Mathematical Models (deterministic models and non-deterministic models) and Objective Functions (single-objective and multi-objective models);
2. Optimization Algorithms (exact vs. approximate);
3. Vehicle Routing Problems (especially Emergency VRP).

Nevertheless, researchers have given limited attention to subjective indexes and approaches based on human reasoning processes for optimizing relief distribution. Also, studies specifically addressing routing for last-mile distribution are scarce.

Uncertainties and dynamic changes in the demand for relief items, resource availability, disruption of transportation infrastructure, a narrow time window for delivering relief supplies to PODs, prioritizing resource allocation based on need, making delicate trade-offs between efficiency and fairness, and time constraints for planning and executing a relief distribution system, are among the main challenges that make implementing an efficient and effective last-mile distribution system difficult.

Therefore, we introduced a multi-objective model aiming to minimize three objective functions: 1) operational cost, 2) the importance of unmet demand, and 3) the importance of late-satisfied demand. Our first contribution to the literature is that the latter two objective functions are innovative subjective indices:

1. The importance of unmet demands is assessed considering three key factors: the number of patients covered within the POD, the emergency level of the POD, and the percentage of unsatisfied demand in the POD. It represents a more accurate and appropriate metric than merely an unmet demand index.

2. The importance of late-satisfied demands is evaluated based on three key factors: the number of patients covered in the POD, the emergency level of POD, and the delay in delivering relief to the POD. This index is also a suitable alternative to traditional indices like delivery delays or total response time.

Introducing subjective indices allows us to have more appropriate and accurate objective functions regarding the complex and uncertain situation we face in last-mile distribution.

As our second contribution to the current literature, FISs are employed to encapsulate decision-makers' knowledge and imitate the cognitive process of human thinking to properly assess two introduced subjective indexes. In this way, we effectively address the inherent uncertainty and ambiguity within the system. The flexibility of the suggested model allows for its adaptation to various situations, drawing upon expert knowledge.

We employed two robust evolutionary algorithms (NSGA-II and NRGA) to solve the model, resilient in managing multiple conflicting objectives within a high-dimensional humanitarian context. These algorithms illustrate the inherent trade-offs among the defined objective functions by identifying a set of Pareto optimal solutions.

As far as we know, for the first time in the literature, we integrated FISs with evolutionary algorithms. It presents a synergistic approach, offering a flexible and resilient tool for designing an effective last-mile distribution system in humanitarian operations. This combination addresses the inherent uncertainties and conflicting goals encountered in humanitarian logistics, providing a comprehensive solution for optimizing relief supply distribution.

In dealing with the last-mile distribution system defined in this study, the search space is large, and sometimes the objectives conflict. On the other hand, the ability to find high-quality solutions is of vital importance and can save human lives. Therefore, the robustness of evolutionary algorithms used in this study is crucial in finding such solutions. In the literature, there are several accepted criteria for measuring the performance of algorithms: computational efficiency, number of solutions, convergence toward the ideal solution, effective exploration of the solution space, and diversity of solutions. Therefore, we employed five key criteria to evaluate the effectiveness of evolutionary algorithms:

1. *CPU Time*. Lower CPU run-time means better computational efficiency of algorithms;
2. *Number of Non-dominated Solutions (NNS)*. Higher NNS means more diversity and more efficient exploration within the decision space. It means having appropriate trade-offs among conflicting objective functions;
3. *Mean Ideal Distance (MID)*. Lower MID signifies more efficiency in exploring the entire solution space globally and convergence of the solutions;
4. *Spacing Metric (SM)*. Lower SM values indicate better solution space exploration and avoidance of getting stuck in local optima;
5. *Hypervolume (HV)*. Higher values indicate greater diversity and convergence of solutions.

We tested the algorithms on small-size and large-size problems. In summary, while both algorithms perform comparably in various aspects, NSGA-II outperforms NRGA regarding computation time for larger-size problems.

In fact, our model is adaptable to suit various circumstances. FISs are crucial for achieving this level of adaptability: In addition to incorporating the expertise of experts and the process of human reasoning into FISs to handle uncertainty, decision-makers have the ability to modify the model simply by updating linguistic rules rather than dealing with the intricacies of mathematical computations. This allows them to adapt the model to the changing dynamics of various scenarios.

Also, due to the ability to generate the Pareto front by the employed evolutionary algorithms, decision-makers can select the most suitable optimal solution that best matches the conditions of the problem regarding the situation and according to the existing priorities.

Regarding the limitations of this research, the following can be mentioned:

1. The real-world dynamics of last-mile distribution may involve additional complexities not fully captured in our model. Therefore, despite the flexibility and robustness of the introduced model, its performance in real cases should also be evaluated.
2. Furthermore, our research is restricted to only two qualitative indicators. Other objective functions, like risk assessment, are crucial, and employing FISs to evaluate them will be beneficial.

As a recommendation for future research, the following could be very interesting to study:

1. Considering different modes of transportation, like transportation via air as well as various types of relief supplies, to more accurately simulate actual conditions;
2. Implementing this model in other phases of disasters, including the phases of preparedness and recovery;

3. Utilizing alternative metaheuristic algorithms and evaluating their respective performances;
4. Finally, exploring the hybridization of evolutionary algorithms with machine learning techniques could unlock new avenues for improving distribution efficiency.

In conclusion, our approach to dealing with last-mile distribution in the humanitarian context provides a foundation for further exploration of this field. As the academic community deals with the challenges of last-mile distribution, this study is a meaningful step toward more efficient and effective solutions, ultimately positively impacting disaster response and humanitarian aid efforts.

# Resumen

Esta tesis se centra en los desastres naturales repentinos, que se han vuelto cada vez más acuciantes en los últimos años y han causado importantes pérdidas humanas y económicas. Los desastres naturales repentinos varían significativamente en tamaño y alcance, destruyendo gravemente infraestructuras críticas como redes de comunicación, puentes y carreteras y dificultando el acceso a las regiones afectadas. También pueden tener graves repercusiones humanitarias, incluidas muertes, lesiones y reubicación.

En esta situación, la planificación y ejecución efectiva de la logística humanitaria puede salvar vidas. Una de las actividades críticas de la logística humanitaria es la distribución de última milla. Implica indicar un plan de distribución óptimo, que abarque los cronogramas de entrega, las rutas de los vehículos y las cantidades de suministros de emergencia enviados a los puntos de demanda (POD) durante las tareas de socorro en caso de desastre. La implementación de un sistema sólido de distribución de última milla optimiza el uso de los suministros disponibles y permite una respuesta rápida a las necesidades inmediatas de las personas afectadas.

Por lo tanto, nuestro principal objetivo en esta tesis es establecer un sistema sólido de distribución de última milla para asignar los suministros de socorro médico limitados disponibles a los POD, un problema con múltiples objetivos durante la fase de respuesta al desastre.

Las incertidumbres y los cambios dinámicos en la demanda de artículos de socorro, la disponibilidad de recursos, la interrupción de la infraestructura de transporte, un plazo estrecho para entregar los suministros de socorro a los puntos de entrega, la priorización de la asignación

de recursos en función de las necesidades, la necesidad de hacer concesiones delicadas entre eficiencia y equidad, y las limitaciones de tiempo para planificar y ejecutar un sistema de distribución de socorro, son algunos de los principales desafíos que dificultan la implementación de un sistema de distribución de última milla eficiente y eficaz.

Por lo tanto, introdujimos un modelo multiobjetivo que apunta a minimizar tres funciones objetivas: 1) el coste operativo, 2) la importancia de la demanda insatisfecha y 3) la importancia de la demanda satisfecha tardíamente. Nuestra primera contribución a la literatura es que las dos últimas funciones objetivas son índices subjetivos innovadores:

1. La importancia de las demandas insatisfechas se evalúa considerando tres factores clave: el número de pacientes cubiertos dentro del POD, el nivel de emergencia del POD y el porcentaje de demanda insatisfecha en el POD. Representa una métrica más precisa y apropiada que un mero índice de demanda insatisfecha.
2. La importancia de las demandas satisfechas tardíamente se evalúa en función de tres factores clave: el número de pacientes cubiertos en el POD, el nivel de emergencia del POD y el retraso en la entrega de alivio al POD. Este índice también es una alternativa adecuada a los índices tradicionales como los retrasos en la entrega o el tiempo total de respuesta.

La introducción de índices subjetivos nos permite disponer de funciones objetivas más adecuadas y precisas en relación con la situación compleja e incierta a la que nos enfrentamos en la distribución de última milla.

Como segunda contribución a la literatura actual, se emplean sistemas de inferencia difusa (FIS) para encapsular el conocimiento de los tomadores de decisiones e imitar el proceso cognitivo del pensamiento humano para evaluar adecuadamente dos índices subjetivos introducidos. De esta manera, abordamos de manera efectiva la incertidumbre y ambigüedad inherentes dentro del sistema. La flexibilidad del modelo sugerido permite su adaptación a diversas situaciones, aprovechando el conocimiento de los expertos.

Empleamos dos algoritmos evolutivos robustos (NSGA-II y NRGA) para resolver el modelo, resiliente en la gestión de múltiples objetivos conflictivos dentro de un contexto humanitario de alta dimensión. Estos algoritmos ilustran las compensaciones inherentes entre las funciones objetivo definidas mediante la identificación de un conjunto de soluciones óptimas de Pareto.

Hasta donde sabemos, por primera vez en la literatura, integramos sistemas de información de última milla con algoritmos evolutivos. Presenta un enfoque sinérgico, que ofrece una herramienta flexible y resistente para diseñar un sistema de distribución de última milla eficaz en operaciones humanitarias. Esta combinación aborda las incertidumbres inherentes y los objetivos conflictivos que se encuentran en la logística humanitaria, proporcionando una solución integral para optimizar la distribución de suministros de socorro.

Al tratar con el sistema de distribución de última milla definido en este estudio, el espacio de búsqueda es grande y, a veces, los objetivos entran en conflicto. Por otro lado, la capacidad de encontrar soluciones de alta calidad es de vital importancia y puede salvar vidas humanas. Por lo tanto, la solidez de los algoritmos evolutivos utilizados en este estudio es crucial para encontrar tales soluciones. Empleamos cinco criterios clave para evaluar la eficacia de los algoritmos evolutivos: tiempo de CPU, número de soluciones no dominadas (NNS), distancia ideal media (MID), métrica de espaciado (SM) e hipervolumen (HV).

Probamos los algoritmos en problemas de tamaño pequeño y grande. En resumen, si bien ambos algoritmos funcionan de manera comparable en varios aspectos, NSGA-II supera a NRGA en cuanto a tiempo de cálculo para problemas de mayor tamaño.

De hecho, nuestro modelo es adaptable para adaptarse a diversas circunstancias. Los FIS son cruciales para lograr este nivel de adaptabilidad: además de incorporar la experiencia de los expertos y el proceso de razonamiento humano en los FIS para manejar la incertidumbre, los tomadores de decisiones tienen la capacidad de modificar el modelo simplemente actualizando las reglas lingüísticas en lugar de lidiar con las complejidades de los cálculos matemáticos. Esto les permite adaptar el modelo a la dinámica cambiante de varios escenarios.

Además, debido a la capacidad de generar el frente de Pareto por parte de los algoritmos evolutivos empleados, los tomadores de decisiones pueden seleccionar la solución óptima más adecuada que mejor se adapte a las condiciones del problema con respecto a la situación y de acuerdo con las prioridades existentes.

# Conclusión

Construir un sistema de distribución de última milla eficiente y eficaz es difícil debido a sus características únicas. Los desastres son impredecibles, lo que genera incertidumbres y cambios dinámicos en la demanda de artículos de socorro y en el suministro en sí.

Además, varios factores afectan el funcionamiento del sistema de distribución de socorro: el margen de tiempo para entregar los suministros de socorro puede ser extremadamente estrecho, mientras que los desastres naturales pueden interrumpir la infraestructura de transporte. Si es así, llegar a las zonas y distribuir los recursos será un desafío. Equilibrar estas limitaciones para optimizar la distribución de los suministros de socorro plantea un verdadero desafío. Además, es crucial priorizar la asignación de recursos en función de las necesidades, lo que a menudo implica decisiones complejas y delicadas compensaciones entre eficiencia y equidad. Aumenta la complejidad del diseño del sistema.

Revisamos las numerosas investigaciones realizadas por académicos que han dirigido su atención a la optimización de la distribución de socorro. Sin embargo, los investigadores han prestado una atención limitada a los índices subjetivos y a los enfoques basados en procesos de razonamiento humano para abordar la optimización de la distribución de socorro. Además, cabe señalar que, si bien existe un importante volumen de investigación sobre el enrutamiento en el contexto de los problemas de ubicación, hay una escasez de estudios que aborden específicamente el enrutamiento para la distribución de última milla.

Por lo tanto, esta investigación está motivada por la necesidad de un enrutamiento eficiente y eficaz de los vehículos en un contexto humanitario y la asignación de suministros de socorro médico limitados disponibles a los POD en la fase de respuesta a un desastre natural repentino.

Introdujimos un modelo multiobjetivo con el objetivo de minimizar tres funciones objetivas: 1) el coste operativo, 2) la importancia de la demanda insatisfecha y 3) la importancia de la demanda satisfecha tardíamente. Luego, para resolver el modelo de manera óptima, aplicamos dos algoritmos evolutivos robustos, NSGA-II y NRGA. Para abordar la ambigüedad e incertidumbre inherentes dentro del sistema, se utilizan FIS. Nuestra investigación hace una doble contribución al cuerpo de literatura existente:

1. Dos funciones objetivas que introdujimos son índices subjetivos innovadores: la importancia de la demanda insatisfecha y la importancia de la demanda satisfecha tardíamente. Estos índices representan métricas más precisas y apropiadas que las tradicionales, como el índice de demanda insatisfecha y el tiempo total de respuesta, en relación con la situación compleja e incierta que enfrentamos en la distribución de última milla.

2. Los FIS se utilizan para encapsular la experiencia de los tomadores de decisiones y simular el proceso cognitivo del pensamiento humano para evaluar eficazmente los índices subjetivos definidos. La flexibilidad del modelo sugerido permite su adaptación a diversos contextos, aprovechando el conocimiento de los expertos.

La integración de los FIS con algoritmos evolutivos para evaluar los índices subjetivos presenta un enfoque sinérgico, que ofrece una herramienta flexible y resistente para diseñar un sistema de distribución de última milla eficaz en operaciones humanitarias. Esta combinación aborda las incertidumbres inherentes y los objetivos conflictivos que se encuentran en la logística humanitaria, proporcionando una solución integral para optimizar la distribución de suministros de socorro.

La solidez de los algoritmos evolutivos utilizados en este estudio es crucial para encontrar soluciones de alta calidad. Por lo tanto, empleamos cinco criterios clave para evaluar la eficacia de los algoritmos evolutivos: tiempo de CPU, número de soluciones no dominadas (NNS), distancia ideal media (MID), métrica de espaciado (SM) e hipervolumen (HV).

Probamos los algoritmos en problemas de tamaño pequeño y grande. En resumen, si bien ambos algoritmos funcionan de manera comparable en varios aspectos, NSGA-II supera a NRGA en cuanto a tiempo de cálculo para problemas de mayor tamaño.

De hecho, nuestro modelo es adaptable para adaptarse a diversas circunstancias. Los FIS son cruciales para lograr este nivel de adaptabilidad: además de incorporar la experiencia de los expertos y el proceso de razonamiento humano en los FIS para manejar la incertidumbre, los tomadores de decisiones tienen la capacidad de modificar el modelo simplemente actualizando las reglas lingüísticas en lugar de lidiar con las complejidades de los cálculos matemáticos. Esto les permite adaptar el modelo a la dinámica cambiante de varios escenarios.

Además, debido a la capacidad de generar el frente de Pareto por parte de los algoritmos evolutivos empleados, los tomadores de decisiones pueden seleccionar la solución óptima más adecuada que mejor se adapte a las condiciones del problema con respecto a la situación y de acuerdo con las prioridades existentes.

En cuanto a las limitaciones de esta investigación, se pueden mencionar las siguientes:

1. La dinámica del mundo real de la distribución de última milla puede implicar complejidades adicionales que no se capturan completamente en nuestro modelo. Por lo tanto, a pesar de la flexibilidad y robustez del modelo introducido, también se debe evaluar su desempeño en casos reales.
2. Además, nuestra investigación se limita a solo dos indicadores cualitativos. Otras funciones objetivas, como la evaluación de riesgos, son cruciales y el uso de FIS para evaluarlas será beneficioso.

Como recomendación para futuras investigaciones, lo siguiente podría ser muy interesante de estudiar:

1. Considerar diferentes modos de transporte, como el transporte aéreo, así como varios tipos de suministros de socorro, para simular con mayor precisión las condiciones reales;
2. Implementar este modelo en otras fases de desastres, incluidas las fases de preparación y recuperación;
3. Utilizar algoritmos metaheurísticos alternativos y evaluar sus respectivos desempeños;
4. Finalmente, explorar la hibridación de algoritmos evolutivos con técnicas de aprendizaje automático podría abrir nuevas vías para mejorar la eficiencia de la distribución.

En conclusión, nuestro enfoque para abordar la distribución de última milla en el contexto humanitario proporciona una base para una mayor exploración de este campo. Mientras la comunidad académica se enfrenta a los desafíos de la distribución de última milla, este estudio es un paso significativo hacia soluciones más eficientes y efectivas, que en última instancia impactan positivamente en la respuesta a desastres y en las iniciativas de ayuda humanitaria.

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