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OPTIMIZING HUMANITARIAN RELOCATION OF CONTAGIOUS AND NON-CONTAGIOUS POPULATIONS DURING THE RECOVERY PHASE: A MODEL FOR MINIMIZING COST AND TIME UNDER UNCERTAINTY

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In recent years, there has been a growing significance of research on humanitarian logistics for both researchers and practitioners. This research is crucial for aiding relief operations. While there has been extensive study of mathematical models for disaster operations management in the preparedness and response phases, the recovery phase models still need more attention. One of the significant challenges during the recovery phase is the spread of contagious diseases in the affected area, which necessitates the timely and cost-effective transportation of both contagious and non-contagious populations while preventing further casualties and disease spread. The paper proposes a multi-objective solid transportation model with different conveyance types for the relocation process to address these challenges. The proposed multi-objective model seeks to minimize two essential objectives: the cost and time required for relocation, and includes factors such as transportation, penalties, accommodations, medical expenses, halts, refueling, and maintenance. To account for the unpredictability and vagueness of input data in post-disaster scenarios, the proposed model incorporates fuzzy inputs and introduces a novel defuzzification technique that is validated by comparing it with an existing methodology. The research employs optimization techniques using the LINGO optimizing solver and presents a case study and particular cases that provide valuable management insights for improving decision support systems. Among the optimization techniques, namely the Neutrosophic compromise approach, Goal programming, Fuzzy goal programming, and Global criterion method, the optimal solution is obtained using the Neutrosophic compromise approach. The cost and time objective values obtained using the Neutrosophic compromise approach are 2034725 and 3923, respectively.

Keywords: Post-disaster Relocation; Multi-Objective Transportation Problem; Single-Valued Hexagonal Neutrosophic Number; Multi-Objective Compromise Techniques; LINGO.

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1. INTRODUCTION

Catastrophic events like natural disasters or those caused by human activities can strike any region, often without warning. A wide range of disasters such as earthquakes, floods, storms, droughts, landslides, volcanic activities, fires, floods, avalanches, extreme cold and heat waves, and cyclones have caused extensive damage, loss of life, devastating living conditions and caused loss of millions of dollars in property. In 2017, Hurricane Maria struck Puerto Rico and resulted in the deaths of over 3000 people and the displacement of over 130000 people (British broadcasting corporation, 2018). A seismic event and subsequent tsunami struck Indonesia's Sulawesi region in 2018, causing more than 4300 fatalities and displacing more than 170000 individuals (Australian government, 2018). Another natural disaster in the form of severe flooding due to monsoon rains impacted Kerala state in southern India during the same year, leading to the displacement of over 1.4 million individuals and the loss of more than 400 lives (Business standard, 2018). In 2019, Cyclone Idai hit Mozambique, Zimbabwe, and Malawi, resulting in over 1000 deaths and the displacement of over 146000 people (United nations children's fund, 2020). The year 2020 witnessed a devastating flood in Assam, resulting in the loss of 123 lives and 26 additional fatalities due to landslides (Assam government report 1, 2020). The impact of the flood was widespread, with 5474 villages affected by the disaster. Compounding the problem was the presence of over 24000 active cases of COVID-19 in the state at the time of the flood, making it even more challenging to relocate both contagious and non-contagious populations to RCs (Indian express, 2020). These factors created a complex logistical challenge that required a well-coordinated and efficient approach to post-disaster relief operations.

Disaster management (DM) has emerged as an essential research area, focusing on mitigating the impact of disasters on vulnerable communities. DM entails a four-pronged approach consisting of mitigation, preparation, response, and recovery, necessitating a multifaceted and multidimensional strategy to reduce the likelihood and severity of disasters. The objective of mitigation is to reduce the frequency and severity of disasters, whereas the objective of preparation is to plan activities that improve survival prospects and mitigate losses. Efforts are made to mitigate the effects of disasters during and after their occurrence during the response phase. Finally, recovery efforts aim to reestablish the afflicted area to its pre-disaster condition. In the context of DM, humanitarian logistics is pivotal in alleviating the distress of susceptible communities. It entails effectively evacuating people from disaster-affected areas and efficiently managing and disseminating crucial commodities and resources at a reduced cost. This can include emergency medical and sanitary supplies, food, water, personal protective, and temporary shelter equipment. The practical implementation of humanitarian logistics can significantly impact the success of DM efforts by ensuring that relief reaches those who need it most quickly and effectively.

Following a disaster, the priority is addressing the immediate fatalities and relieving the surviving victims. This necessitates a robust humanitarian logistics response, which has garnered increasing attention in recent years. The physical and psychological toll on survivors can be significant, and it is essential to alleviate their suffering by providing necessary relief. However, staying near the disaster-affected area can result in significant economic and social losses, as well as lead to various psychological afflictions such as emotional volatility, disrupted sleep, apprehension, post-traumatic stress disorder, and despondency. As Tatham and Kovacs (Klumpp *et al.*, 2015) pointed out, disaster relief logistics should address survivors' needs and support their emotional well-being by providing access to health services, counseling, and other psychological support mechanisms through the relocation process. The significance of efficient relocation approaches in controlling the transmission of contagious diseases is emphasized in a study conducted by (Arima *et al*., 2011) (Majumder and Saha, 2019). The research emphasizes that disaster-stricken regions with inadequate access to fundamental necessities, including safe drinking water, healthcare, and sanitation, are especially prone to disease outbreaks. It further argues that implementing effective relocation models can significantly reduce the risk of disease outbreaks (cholera, typhoid fever, malaria, dengue fever, tetanus, measles) and improve the overall health outcomes of affected populations. While there are a limited number of humanitarian relocation models that consider both contagious and non-contagious populations simultaneously (Bhakuni *et al*., 2023), past relocation models, have not placed sufficient emphasis on the type of conveyance used during the relocation process and the total time required to relocate affected populations. This research addresses these limitations by proposing a new model considering these critical factors.

This research paper aims to present a mathematical model for addressing the solid transportation problem (STP) in the context of disaster relief efforts. While the transportation problem (TP) was initially conceptualized by F. L. Hitchcock in 1941, Haley introduced the STP as an extension of the TP in 1962, considering additional conveyance constraints. In instances where STP involves multiple objectives, it is known as the multi-objective solid transportation problem (MOSTP). STP and MOSTP have garnered increasing attention over the years, particularly in emergency scenarios that demand a swift response and an effective management system. The research paper also examines various obstacles in humanitarian logistics that may impede disaster operations and explores the implementation of several compromise optimization techniques. The decision-maker must make optimal decisions while considering the total infrastructure damage and casualties during the relocation process. A transportation model is essential to ensure the timely allocation of disaster-affected populations to the resettlement area. The proposed model for multi-objective TPs considers two conflicting objectives. It is worth noting that the scholarly work on mathematical modeling for MOSTP in DM has seen a surge in attention over the years, and this research paper adds to the growing reservoir of expertise in this field.

The multi-objective solid transportation model (MOSTM) is commonly employed to optimize objective functions and constraints in crisp environments. However, applying MOSTM to real-world TP's can lead to inaccuracies in problem parameter representation, mainly due to the uncertainty and conflicts inherent in the system (Chakraborty *et al*., 2019). To address these issues, researchers introduced the fuzzy set theory to account for imprecise problem parameters. L.A. Zadeh introduced the fuzzy concept in 1965 (Zadeh, 1965), while intuitionistic fuzzy (Atanassov, 1986) was developed in 1986 by K.T. Atanassov to address the degree of non-membership function. However, intuitionistic fuzzy has limitations in handling indeterminacy. On the other hand, F. Smarandache neutrosophic fuzzy, introduced in 1999, offered a more robust approach by utilizing three membership functions - truth membership function (TMF), indeterminacy membership function (IMF), and falsity membership function (FMF) - to represent objective functions and constraints. Abdel-Basset expounded on using neutrosophic fuzzy sets for approaching TP with improved accuracy and reliability, as discussed in (Abdel-Basset *et al*., 2018) (Majumder *et al*., 2023). In 2010, Wang *et al*. proposed the concept of a single-valued neutrosophic number (SVNN), which consists of a single component with three membership values. In 2014, Deli and Subas expanded on the concept of SVNN by introducing the single-value triangular neutrosophic number (SVTNN) and single-value trapezoidal neutrosophic number (SVTPNN). SVTNN comprises nine components with three membership values, whereas SVTPNN consists of twelve components with three membership functions. In 2019, Chakraborty *et al*. expanded the notion of SVTPNN to include a single-valued pentagonal neutrosophic number (SVPNN) comprising fifteen components and three corresponding membership values. More recently, in 2022, Framila and Sandhiya introduced the idea of single-valued hexagonal neutrosophic numbers (SVHNN), extending the SVPNN concept. The SVHNN includes eighteen components and three corresponding membership values.

In the present work, the inputs of the proposed model have been represented as SVHNN. Contrasting hexagonal fuzzy numbers with traditional triangular or trapezoidal fuzzy numbers makes it apparent how the former poses specific obstacles in its formulation and definition (Chakraborty et al., 2021). Nonetheless, it provides an extra means of articulating indeterminate information, which helps apply novel strategies to various practical challenges. The hexagonal methodology conveys general information exhaustively while allowing for the practical depiction of ambiguity. It offers decision-makers a more realistic means of computation and manipulation than previous fuzzy representation methods. Using triangular or trapezoidal fuzzy numbers may be challenging in particular circumstances, such as assignment issues with six variables. To resolve these problems, it is essential to use hexagonal fuzzy numbers.

The existing MOSTM in the literature has been executed on a case study that examines the 2020 Assam flood. The case study employs SVHNN as its input format. Our rationale for incorporating SVHNN into the model is based on several factors. During the post-disaster phase, the number of casualties and affected populations vary as time progresses; hence, we have considered the number of people to be relocated as SVHNN for a more realistic approach. The disaster-affected areas are more vulnerable to contagious diseases, which makes it challenging for transport agencies to reach the relocation centers. The alteration of travel distance, traffic congestion, and various routes impassable caused by the damage to roads, highways, tunnels, and bridges results in a change in the cost and time of transportation along with the expected arrival time at each relief center, therefore, are considered as SVHNN. With the expected transportation time alteration, the penalty cost is also considered SVHNN. The number of available rooms at the relief centers during the relocation process alters depending upon their cleaning and maintenance; the number of working staff available for laundry, meals, and healthcare services can vary based on the availability, which results in a change in their working wages, the availability of fresh food and medical equipment's, prescribed medicines, medical consultants can alter based on the transportation accessibility of the relief center. Thus, the accommodation cost, time, the capacity of relief centers, and medical costs are considered SVHNN. The queue at gas stations because of panic buying and the changes in the number of working gas stations results in an alteration of refueling time; the age group of the population sitting at each type of conveyance has a particular requirement to halt the conveyance in the mid of the relocation process—further, the lifespan and durability of each type of conveyance result in an alteration in maintenance time. Thus, the halt, refueling, maintenance, and working time of conveyance is taken as SVHNN. The proposed revised removal area method (RRAM) converts the inputs represented as SVHNN into a crisp number. A compromise solution is obtained using goal programming (GP), fuzzy goal programming (FGP), global criterion method (GCM), and neutrosophic compromise approach (NCA).

This study aims to reduce delays in the relocation process, offering a relocation model applicable to contagious and non-contagious situations. It prioritizes safety by providing separate conveyance for both populations. To address data uncertainty following disasters, the study employs the SVHNN methodology. Additionally, it introduces a novel defuzzification technique, outlining its advantages over existing methods in detail. The model is tested in a real-life case study of the 2020 Assam flood, utilizing various compromise techniques to achieve optimal results.

Furthermore, a thorough sensitivity analysis is conducted for the cost-objective components of MOSTM. These analyses provide numerous key managerial insights that are very beneficial considering the cost-efficient relocation of the affected population. The particular cases associated with the MOSTM provide valuable insights to the decision-maker in addressing the multi-objective relocation problems.

The current study delves into the following pivotal research queries concerning disaster relief operations:

1. In the context of post-disaster relocation, how can the organization and management of transportation be optimized to efficiently facilitate the simultaneous movement of contagious and non-contagious populations?
2. One of the main challenges encountered during the post-disaster phase is the alteration of input data. How is this uncertainty managed and addressed within the relocation model?
3. How does conveyance play a crucial role in the relocation process, and what happens when we limit each conveyance's working time?
4. In what ways does the existing literature need to be revised to provide adequate relocation models for both contagious and non-contagious populations? What is the pressing need to address the requirements of these specific population groups in the post-disaster relocation process?

The queries mentioned above are thoroughly discussed within the existing literature. Queries 1 and 3 are addressed using the MOSTM in section 5.2 Modelling. In contrast, query 2 is addressed by incorporating SVHNN as the data input. A detailed explanation is presented in section 3, Mathematical preliminaries, section 4, Proposed revised removal area method for converting SVHNN to crisp number, and section 7.1, Input data for the real-life model. Finally, query 4 is addressed through sections 2.2: Impact of contagious diseases on affected population in post-disaster phase, 2.3 Causes of Assam disaster and relocation models, and 2.4 Multi-objective solid transportation models for post-disaster phase operating under fuzzy environment. The current manuscript is structured subsequently.

Section 2 presents an extensive and meticulous analysis of pertinent literature to scrutinize the previous studies in the corresponding field. Section 3 provides the fundamental mathematical principles associated with the proposed method. Section 4 proposes a defuzzification method designed to transform SVHNN to crisp numbers, and the method's efficacy is established through a comparative analysis with existing approaches. Section 5 presents a case study centered on the Assam flood involving the development of MOSTM for the affected population of Assam. Section 6 elucidates the various compromise methods employed to obtain the solution of the proposed MOSTM. Section 7 comprises an in-depth examination of the numerical experiments and results obtained, incorporating a sensitivity analysis and a study of some particular cases. This analysis aims to comprehensively understand the optimal solution obtained using numerous compromise techniques. The sensitivity analysis investigates how varying input parameters affect the solution obtained while examining specific cases, providing an opportunity to evaluate the method's effectiveness in practical scenarios. Section 8 provides managerial insights derived from the solution of MOSTM, sensitivity analysis, and particular cases. Finally, Section 9 concludes the paper, summarizing the proposed approach and outlining future research directions.

2. LITERATURE REVIEW

This section presents a detailed survey of existing literature, specifically highlighting different aspects of the post-disaster relocation process for affected populations. Specifically, the study covers the significance of RC during the relocation process, the impact of contagious diseases on affected populations after a disaster, the underlying reasons for the Assam catastrophe, relocation strategies, and MOSTM's for the post-disaster phase that operates under a fuzzy environment. This literature review aims to identify the research gaps and highlight new findings that could contribute to developing the proposed model. To facilitate a thorough examination of the literature, this section is subdivided into five subsections, each providing insights into a different aspect of the subject matter. A literature review table 1 portrays a detailed review of the literature associated with humanitarian logistics. Overall, this literature review provides a comprehensive understanding of the existing research in this field, informing the proposed model's development and outlining potential avenues for future research.

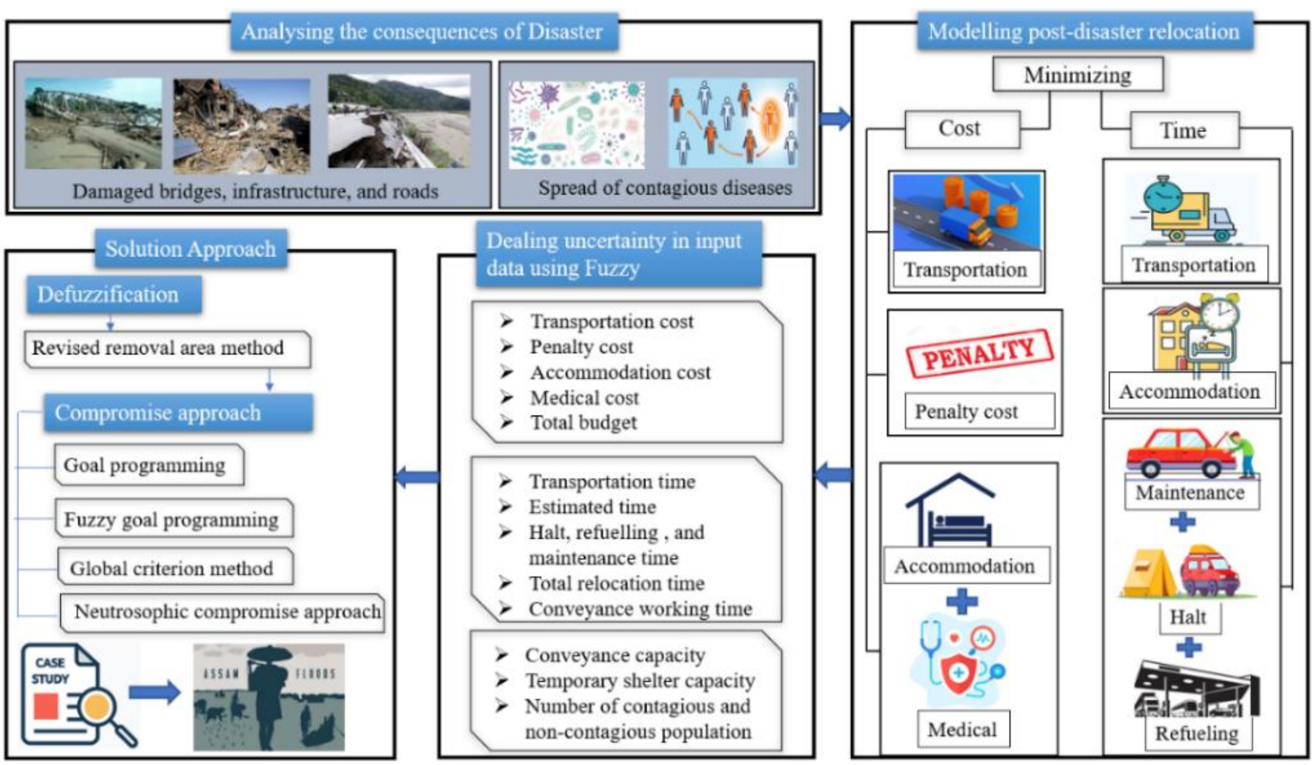

Figure 1. The Figure presents the proposed framework for post-disaster relocation, which includes analyzing consequences, implementing modeling under fuzzy inputs, and obtaining compromise solutions through a case study

Figure 1 provides a concise summary of the research conducted in the literature. Analyzing the Figure in a clockwise direction reveals a thorough examination of the consequences of disasters, encompassing the damage to bridges, infrastructure, and roads and the potential spread of contagious diseases. In light of these challenges, post-disaster relocation is modeled to minimize cost and time. The cost objective components include transportation, penalties, accommodation, and medical expenses, while the time objective components encompass transportation, accommodation, maintenance, halts, and refueling. The fuzzy set theory addresses uncertainties in the data associated with cost and time objectives and the constraints within the MOSTM. The solution methodology involves the defuzzification of MOSTM from fuzzy to equivalent crisp models and implementing a compromise approach to attain the optimal result.

2.1 Relocation Center Significance During The Post-Disaster Relocation Process for The Affected Population

After a calamity, the affected population frequently experiences a state of shock, trauma, and apprehension concerning their future as they have lost their loved ones and belongings. Losing one's abode is a significant cause of tension (Macit *et al*., 2022), as the rebuilding process may be prolonged. To aid these individuals during this transition phase, RC is made available to fulfill their essential requirements, such as safety, seclusion, and minimal comfort conditions (Gao *et al*., 2017). This center serves to avert subsequent disasters and assists in re-establishing a sense of normality. In addition, it is vital to the success of the relocation effort as it provides a safe place for people to recover and enables proper planning and execution of relocation activities. The specifications and objectives of provisional centers vary depending on the process phase, with the temporary stage typically offering more intricate and proficient solutions. Félix *et al*. (2015) demonstrate the crucial role of RC in providing the population with proper basic amenities so that they can stay with dignity, privacy, and protection. Recent studies have focused on the advantages of developing temporary RC based on the generative design method (Afonso *et al*., 2021). At the same time, Chen *et al*. (2021) discussed building Lego architecture for RC for the post-disaster emergency. Abe *et al*. (2018) further discuss the participatory method for post-disaster construction of RC.

Numerous kinds of literature are considering the identification and establishment of RCs. They primarily focus on finding the best-suited location based on social, ecological, and economic factors (Nappi *et al*., 2015), (Nappi *et al*., 2019). While other developed models to transport the surplus resources within RCs, (Haq Amir *et al*., 2019) and (Zhou *et al*., 2020) discuss the selection of transportation network for route identification, traveling time, and the number of paths between source and RCs. However, there needs to be more research on the transportation of displaced populations to RC, considering the cost and time of transportation.

2.2 Impact of Contagious Diseases on Affected Population in The Post-Disaster Phase

Numerous natural calamities, such as tsunamis, landslides, earthquakes, cyclones, and tornadoes, have been linked to the proliferation of contagious diseases. These ailments comprise a diverse array of illnesses, including but not limited to diarrhea, Japanese encephalitis, measles, influenza, tuberculosis, malaria, chickenpox, dengue, and typhoid fever. These outbreaks can cause significant morbidity and mortality among affected populations and pose a major public health challenge.

By the definition given by the World Health Organization, an outbreak of a contagious disease is characterized by its occurrence in a population at a higher rate than what is usually anticipated. The number of casualties may significantly increase without proper precautionary measures. This highlights the critical need for timely and effective responses to prevent the spread of contagious diseases and mitigate their impact on affected communities. The frequency and severity of natural disasters have intensified in the past few years, leading to massive financial losses and causing the demise of millions of individuals. Cyclone Ldai in Zimbabwe (2019) led to a cholera outbreak resulting in 54 deaths and 6000 cases; a flood in Bangladesh (2020) resulted in the outbreak of waterborne disease impacting 16000 cases; and in Nigeria (2022), a flood resulted in an outbreak of cholera causing 40 deaths and 3000 cases (Greenpeace, 2022).

Following floods, the potential for infection transmission is notably higher and is a significant concern. The risk of infection is predominantly posed by the survivors rather than the deceased (Wilson *et al*., 2000). Sewage overflow resulting from flooding can contaminate freshwater sources often used for drinking and personal hygiene, posing a significant risk of infection (Mengel *et al*., 2014). Pit toilets can further contribute to the pollution of freshwater sources with fecal matter. The floodwaters are loaded with pathogens, which can lead to a sharp rise in the number of infections in the affected area, making it difficult to carry out the relocation process effectively (Tutu *et al*., 2019). The situation is exacerbated when contagious individuals are relocated alongside non-contagious individuals without adequate attention to appropriate measures and prompt relocation. To address these challenges, there is a need for a mathematical model that considers the simultaneous relocation of both contagious and non-contagious populations. This model will help optimize these populations' transportation to RCs, reducing the risk of further casualties and ensuring everyone is relocated efficiently and safely.

2.3 Causes Of Assam Disaster And Relocation Models

The Assam floods of 2020 resulted from a confluence of factors, including heavy rainfall, the release of water from upstream dams, and human-induced changes to the river system. The state received 30% more rainfall than usual during the monsoon season in 2020, which led to an unexpected surge in the water level of the Brahmaputra and its associated tributaries, causing flooding in major state districts. The situation was exacerbated due to a surge in COVID-19 cases and waterborne diseases in the impacted regions. During the post-disaster phase, government and private agencies faced challenges in relocating affected populations and the risk of disease transmission to unaffected populations (Simonovic *et al*., 2021).

Table 1. Literature review

								Objectives					
References	TP	STP	UNC	Population		SLT	CS	Cost			Time		
				NCT	CT			TC	PC	AMC	TT	HRMT	AT
Xie *et al.* (2015)	∗	−	PR	∗	−	LR	∗	∗	∗	−	−	−	−
Jin *et al.* (2015)	∗	−	PR	∗	∗	SSA	∗	−	−	−	∗	−	−
Ahmadi *et al.* (2015)	∗	−	ST	∗	−	NSA	∗	−	∗	−	∗	−	−
Mohamadi *et al.* (2016)	∗	−	FZ	∗	−	HA	∗	∗	−	−	∗	−	−
Xu *et al.* (2016)	∗	−	FZ	∗	−	GA	∗	∗	−	−	∗	−	−
Galarce *et al.* (2017)	∗	−	−	∗	−	MILP	∗	∗	−	−	−	−	−
Trivedi *et al.* (2017)	∗	−	FZ	∗	−	GP	∗	∗	−	−	−	−	−
Mohamadi *et al.* (2017)	∗	−	PR	∗	−	ECM	∗	∗	∗	−	∗	−	−
Liu *et al.* (2018)	−	∗	ST	∗	−	RO	∗	∗	−	∗	∗	−	−
Tlili *et al.* (2018)	∗	−	−	−	∗	GA	∗	−	−	∗	−	−	−
Nikoo *et al.* (2018)	∗	−	−	∗	−	BBA	∗	∗	−	−	∗	−	−
Sarma *et al.* (2018)	∗	−	−	∗	−	LO	∗	∗	∗	−	−	−	−
Noham *et al.* (2018)	∗	−	PR	∗	−	TSA	∗	∗	−	−	∗	−	−
Yahyaei *et al.* (2019)	∗	−	ST	∗	−	MILP	∗	∗	∗	∗	−	−	−
Ghasemi *et al.* (2020)	−	∗	ST	∗	−	ECM	∗	∗	∗	∗	−	−	−
Mansoori *et al.* (2020)	−	∗	PR	∗	−	LWT	∗	∗	−	∗	∗	−	−
Mohammadi *et al.* (2021)	−	∗	FZ	−	∗	THM	−	∗	−	−	−	−	−
Jamali *et al.* (2021)	−	∗	FZ	−	∗	GP	∗	∗	−	∗	−	−	−
Ghasemi *et al.* (2022)	∗	−	ST	∗	−	ECM	∗	∗	∗	−	∗	−	−
Eshghi *et al.* (2022)	−	∗	ST	−	∗	ECM	∗	∗	−	∗	−	−	−
Sun *et al.* (2022)	∗	−	ST	∗	−	ECM	∗	∗	−	∗	−	−	−
Bhakuni *et al.* (2023)	−	∗	FZ	−	∗	GCM, FGP	∗	∗	−	∗	∗	−	−
This paper	−	∗	FZ	∗	∗	GP, FGP, GCM, NCA	∗	∗	∗	∗	∗	∗	∗

Note: UNC=Uncertainty, PR=Probability, ST=Stochastic, FZ=Fuzzy, NCT=Non-contagious, SLT=Solution technique, CT=Contagious, CS=Case study, TC=Transportation Cost, PC=Penalty Cost, AMC=Accommodation and medical cost, TT=Transportation time, HRMT= Halt, refueling, and maintenance time, AT=Accommodation time, LR=Lagrange relaxation, SSA=Solution search algorithm, NSA=Neighborhood search algorithm, HA=Heuristic algorithm, GA=Genetic algorithm, RO=Robust optimization, MILP=Mixed-integer linear programming, GP=Goal programming, BBA=branch and bound algorithm, LO=Lingo optimization, TSM=Tabu-search method, ECM=Epsilon-constraint method, FGP=Fuzzy goal programming, GCM=Global criterion method, NCA=Neutrosophic compromise approach, THM= Torabi and Hassini method, LWT=Lexicographic Weighted Tchebycheff. The star "∗" symbol indicates the presence of the corresponding element in the author's work, while the "−" signifies the absence of the specified element in the respective paper.

Most of the regions of Assam are wracked by at least one to two waves of flooding almost every year. The primary cause is climate change, heavy rainfall, deforestation, and the construction of dams and embankments in the Brahmaputra basins. The current studies on Assam focus on mitigating waterlog in urban areas, prediction of a flood using hybrid machine learning (Sahoo *et al*., 2021), assessment of riverbank erosion, and factors influencing crop productivity in flood susceptible regions (Das *et al*., 2020), satellite-based monitoring of recent heavy flooding (Mishra *et al*., 2019) and many more. However, as per our current research and literature surveys, we found that there needs to be more research on the humanitarian relocation model. The recent relocation literature on Assam focuses on theoretical aspects of women's resilience and adaptability in times of migration and the effect of climate-related disasters on human mobilities (Krishnan *et al*., 2022) (Majumder and Saha, 2019); this research broadly focuses on theoretical view on the relocation process but lack mathematical modeling. As per our current literature survey, a single mathematical model with a case study based on the Assam flood exists to consider the distribution of emergency supplies in the disaster-impacted region (Sarma *et al*., 2023). Given the severity and recurrence of floods in Assam and the need to decrease the number of human casualties, it is imperative to address the research gap by formulating relocation models that account for the relocation of the affected populations.

2.4 Multi-Objective Solid Transportation Models for Post-Disaster Phase Operating Under Fuzzy Environment

In 1941, Hitchcock (Hitchcock, 1941) posited that the Transportation Problem (TP) can be categorized as a specific type of Linear Programming Problem (LPP) that is governed by a particular set of constraints and objectives. The primary goal of the problem is to identify the optimal transportation policy that minimizes overall transportation expenses. The conventional models of TP typically involve multiple input parameters, including unit transportation cost, accessibility of commodities at the source, and demand for goods at the destination. Additionally, the concept of TP is extended to a more comprehensive framework known as STP (Haley, 1962), incorporating the conveyance capacities as an additional constraint.

In contemporary times, there has been a discernible surge in researchers' focus on leveraging STP models for both h crisp and uncertain environments. Although the data linked with an STP (Majumder *et al*., 2023) can be crisp on occasion, it cannot always be considered as such due to factors like data aggregation from various sources, incomplete information, instability in financial markets, and imperfect statistical analysis (Majumder *et al*., 2023). When dealing with uncertain situations, fuzzy set theory is deemed suitable for managing the vagueness, leading to a fuzzy solid transportation problem. Several studies, such as Kundu *et al*. (2013), Bit *et al*. (1993), and Das *et al. (*2016), have provided various mathematical models of solid transportation problems under a fuzzy environment. Rabiei *et al*. (2023) introduced a novel multi-objective model for volunteer assignment in the post-disaster phase based on the fuzzy inference system. Gharib *et al*. (2022), using the neuro-fuzzy inference system, developed a model for the distribution of shelters in the post-disaster. Almais *et al*. (2019) fuzzy concept for the reconstruction and rehabilitation in the post-disaster phase.

The humanitarian relocation model is an emerging approach that uses fuzzy logic to support post-disaster relocation planning for vulnerable populations. Studies have proposed fuzzy-based models to consider multiple factors, such as demographic characteristics, the number of affected people, infrastructure, and environmental factors, in post-disaster relocation of vulnerable populations (Najafi *et al*., 2013). The outcomes of these studies suggest that fuzzy-based models can provide more accurate and reliable results than traditional models that do not consider the complex and dynamic nature of the relocation process (Trivedi *et al*., 2017). Using fuzzy-based models can facilitate stakeholder engagement and collaboration in decision-making and ensure that the relocation process is equitable, sustainable, and culturally appropriate. Moreover, fuzzy-based models can incorporate multiple criteria and scenarios to support uncertainty-free decision-making and enable policymakers to identify optimal relocation plans that minimize the negative impacts on vulnerable populations. Overall, the humanitarian relocation model can contribute to building more resilient communities and reducing the adverse effects of disasters on vulnerable populations.

2.5 Research Gaps, Motivation, and Contributions

The study's key aspects encompass identified gaps in current literature, the driving force behind the research, and the unique contributions it seeks to make in post-disaster humanitarian relocation. These points illuminate the study's direction and emphasize its objectives in advancing comprehensive and efficient relocation models.

1. The existing post-disaster relocation literature emphasizes non-contagious populations, leaving a gap in concurrently addressing both contagious and non-contagious groups. This omission is critical, given the specialized care required for contagious individuals and the potential for disease transmission, leading to increased mortality rates.
2. Our study aims to bridge this gap by developing a relocation model that effectively accommodates contagious and non-contagious populations, prioritizing safety during relocation.
3. Previous humanitarian relocation research emphasizes timely movement but overlooks conveyance types, especially for contagious and non-contagious populations. Our research addresses this by aiming to create a comprehensive humanitarian relocation model that accounts for distinct conveyance types for each population group.
4. New constraints are introduced to make the model more practical, reflecting real-life scenarios, such as restrictions on conveyance working types and different time aspects of the conveyance, such as halt, refueling, and maintenance. This ensures the model is theoretical and applicable in practical, dynamic post-disaster.
5. By incorporating fuzzy concepts, such as uncertainty and imprecision, into the model, decision-makers can account for the complexity and unpredictability of post-disaster situations. This approach leads to a more flexible and adaptable model applicable in various disaster scenarios, including those involving contagious populations.

3. MATHEMATICAL PRELIMINARIES

In this section, SVHNN is presented along with initial definitions. The benefits of employing SVHNN over a traditional fuzzy set are emphasized, particularly in handling uncertainties and vagueness in practical situations. Fuzzy set theory, introduced in 1965, has opened avenues for applying it to various optimization problems faced in real-world scenarios. This theory has demonstrated remarkable efficacy in resolving intricate optimization problems with indefinite and uncertain information. It has provided a means of representing the data's ambiguity and making well-informed decisions. The proposed defuzzification approach for SVHNN builds on this concept and offers further enhancements in addressing these challenges.

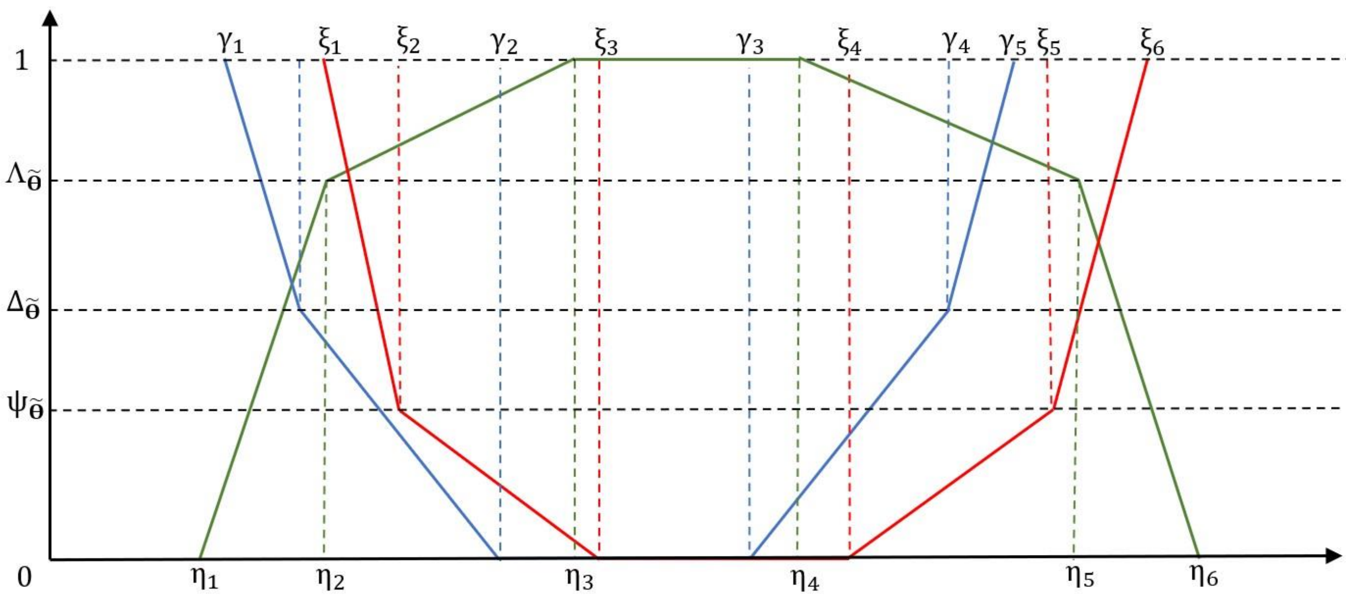

Figure 2. The Membership functions of the hexagonal neutrosophic number

3.1 Fuzzy Set

Let X be a crisp set and let $\varphi_{\tilde{S}}$ be a membership function that takes values in the interval $[0,1]$. The fuzzy set $\tilde{S}$ in X is defined as a collection of ordered pairs $\tilde{S}$ (Zadeh, 1985) in X is a set of ordered pair $\tilde{s} = \{(x, \varphi_{\tilde{S}}): x \in X, \varphi_{\tilde{S}} \in [0,1]\}$, where x represents an element of X, and $\varphi_{\tilde{S}}$ denotes the degree of membership of x in the fuzzy set $\tilde{S}$. Usually, this set is represented by the pair $(x, \varphi_{\tilde{S}})$.

3.2 Single-Valued Neutrosophic Set

A single-valued neutrosophic set: As defined (Wang *et al.*, 2010), is denoted by $\tilde{T}$ and is represented by the ordered triple $\langle x; [\alpha_{\tilde{T}}, \beta_{\tilde{T}}, \gamma_{\tilde{T}}]\rangle$, where $x \in X$ is a single-valued independent variable, and $\alpha_{\tilde{T}}$, $\beta_{\tilde{T}}$, and $\gamma_{\tilde{T}}$ refer to the TMF, IMF, and FMF, respectively.

3.3 Single-Valued Hexagonal Neutrosophic Set

A Single-valued hexagonal neutrosophic number (SVHNN) is characterized as $\tilde{\Theta} = (\eta_1, \eta_2, \eta_3, \eta_4, \eta_5, \eta_6)(\xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6)(\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6); \Lambda_{\tilde{\Theta}}, \Psi_{\tilde{\Theta}}, \Delta_{\tilde{\Theta}}\}$ where $\eta_1, \eta_2, \eta_3, \eta_4, \eta_5, \eta_6, \xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \in R$ and are components of SVHNN $\tilde{\Theta}$. $\Lambda_{\tilde{\Theta}}$ is the degree of TMF, $\Psi_{\tilde{\Theta}}$ is the degree of IMF, $\Delta_{\tilde{\Theta}}$ is the degree of FMF. The $T_{\tilde{\Theta}}$ is TMF, $I_{\tilde{\Theta}}$ is IMF, $F_{\tilde{\Theta}}$ is FMF (Framila *et al.*, 2022). The graphical representation of $\tilde{\Theta}$ is shown in Figure 2. The membership functions are described as follows:

$$\mathrm{T}_{\tilde{\Theta}} = \begin{cases} \Lambda_{\tilde{\Theta}}\left(\dfrac{x-\eta_1}{\eta_2-\eta_1}\right) \ if\ \eta_1 \le x \le \eta_2 \\ \Lambda_{\tilde{\Theta}} + \dfrac{(1-\Lambda_{\tilde{\Theta}})(x-\eta_2)}{\eta_3-\eta_2} \ if\ \eta_2 \le x \le \eta_3 \\ 1 \ if\ \eta_3 \le x \le \eta_4 \\ \Lambda_{\tilde{\Theta}} + \dfrac{(1-\Lambda_{\tilde{\Theta}})(\eta_5-x)}{\eta_5-\eta_4} \ if\ \eta_4 \le x \le \eta_5 \\ \Lambda_{\tilde{\Theta}}\left(\dfrac{\eta_6-x}{\eta_6-\eta_5}\right) \ if\ \eta_5 \le x \le \eta_6 \\ 0 \ otherwise \end{cases} \quad \mathrm{I}_{\tilde{\Theta}}$$

$$(x) = \begin{cases} \Psi_{\tilde{\Theta}} + \frac{(\Psi_{\tilde{\Theta}}-1)(x-\xi_1)}{\xi_2-\xi_1} \ if\ \xi_1 \le x \le \xi_2 \\ \Psi_{\tilde{\Theta}}\left(\frac{\xi_3-\mathrm{x}}{\xi_3-\xi_2}\right) \ if\ \xi_2 \le x \le \xi_3 \\ 0 \ if\ \xi_3 \le x \le \xi_4 \\ \Psi_{\tilde{\Theta}}\left(\frac{\mathrm{x}-\xi_4}{\xi_5-\xi_4}\right) \ if\ \xi_4 \le x \le \xi_5 \\ \Psi_{\tilde{\Theta}} + \frac{(1-\Psi_{\tilde{\Theta}})(x-\xi_5)}{\xi_6-\xi_5} \ if\ \xi_5 \le x \le \xi_6 \\ 1 \ otherwise \end{cases}$$

$$\mathrm{F}_{\tilde{\Theta}} = \begin{cases} \Delta_{\tilde{\Theta}} + \dfrac{(\Delta_{\tilde{\Theta}}-1)(x-\gamma_1)}{\gamma_2-\gamma_1} \ if\ \gamma_1 \le x \le \gamma_2 \\ \Delta_{\tilde{\Theta}}\left(\dfrac{\gamma_3-\mathrm{x}}{\gamma_3-\gamma_2}\right) \ if\ \gamma_2 \le x \le \gamma_3 \\ 0 \ if\ \gamma_3 \le x \le \gamma_4 \\ \Delta_{\tilde{\Theta}}\left(\dfrac{\mathrm{x}-\gamma_4}{\gamma_5-\gamma_4}\right) \ if\ \gamma_4 \le x \le \gamma_5 \\ \Delta_{\tilde{\Theta}} + \dfrac{(1-\Delta_{\tilde{\Theta}})(x-\gamma_5)}{\gamma_6-\gamma_5} \ if\ \gamma_5 \le x \le \gamma_6 \\ 1 \ otherwise \end{cases}$$

4. PROPOSED REVISED REMOVAL AREA METHOD FOR CONVERTING SINGLE-VALUED HEXAGONAL NEUTROSOPHIC NUMBER TO CRISP NUMBER

In this section, we have introduced the RRAM and the methodology to derive the defuzzification function for SVHNN. The effectiveness of this proposed method has been demonstrated through a comparative analysis with existing literature.

In 2018, Chakraborty *et al*. proposed the removal area method (RAM), which introduced a defuzzification function to transform triangular neutrosophic numbers into equivalent crisp numbers. Subsequently, in 2019, Chakraborty (Chakraborty *et al.*, 2019) applied the same approach to convert linear pentagonal fuzzy numbers to equivalent crisp numbers. RAM's fundamental principle is to remove different regions of the fuzzy number and calculate the area of each removed region. The average of these areas is then computed, and the resulting function is designated as the defuzzification function for the corresponding fuzzy number. Our proposed RRAM is also based on the partial removal of different regions of a fuzzy number. However, we additionally consider that the chosen area in each step of RRAM should encompass the previously selected region. We have provided a detailed step-by-step procedure for obtaining the defuzzification function.

Step 1. The decision-maker input their SVHNN as follows:

$$\tilde{\Theta} = \{(\eta_1, \eta_2, \eta_3, \eta_4, \eta_5, \eta_6)(\xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6)(\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6); \Lambda_{\tilde{\Theta}}, \Psi_{\tilde{\Theta}}, \Delta_{\tilde{\Theta}}\}$$

Step 2. The SVHNN exhibits TMF, IMF, and FMF, and the defuzzification function for each membership function is computed individually. Subsequently, the average of all the memberships is determined to achieve the required defuzzification function for SVHNN. Figure 3 illustrates the various regions of TMF, and the area of each region is evaluated as follows:

- AR(a) = area of an enclosed region from the first step in Figure 3 = $\eta_1 \Lambda_{\tilde{\Theta}}$

- AR(b) = area of an enclosed region from the second step in Figure 3 = $\eta_2 \Lambda_{\tilde{\Theta}}$
- AR(c) = area of an enclosed region from the third step in Figure 3 = η_3
- AR(d) = area of an enclosed region from the fourth step in Figure 3 = η_4
- AR(e) = area of an enclosed region from the fifth step in Figure 3 = $\eta_5 \Lambda_{\tilde{\Theta}} + \frac{(\eta_4+\eta_5)(1-\Lambda_{\tilde{\Theta}})}{2}$
- AR(f) = area of an enclosed region from the sixth step in Figure 3 = $\frac{(\eta_5+\eta_6)\Lambda_{\tilde{\Theta}}}{2} + \frac{(\eta_4+\eta_5)(1-\Lambda_{\tilde{\Theta}})}{2}$
- DT = defuzzification function of TMF =$\frac{AR(a)+AR(b)+AR(c)+AR(d)+AR(e)+AR(f)}{6}$
- DT =$\frac{\eta_1\Lambda_{\tilde{\Theta}}+\eta_2\Lambda_{\tilde{\Theta}}+\eta_3+\eta_4+\eta_5\Lambda_{\tilde{\Theta}}+\frac{(\eta_4+\eta_5)(1-\Lambda_{\tilde{\Theta}})}{2}+\frac{(\eta_5+\eta_6)\Lambda_{\tilde{\Theta}}}{2}+\frac{(\eta_4+\eta_5)(1-\Lambda_{\tilde{\Theta}})}{2}}{6}$
  $= \frac{2\eta_3+4\eta_4+2\eta_5+2\eta_1\Lambda_{\tilde{\Theta}}+2\eta_2\Lambda_{\tilde{\Theta}}-2\eta_4\Lambda_{\tilde{\Theta}}+\eta_5\Lambda_{\tilde{\Theta}}+\eta_6\Lambda_{\tilde{\Theta}}}{12}$

Step 3. The different region of IMF is delineated through Figure 4. The area of each region is calculated as follows:

- AR(g) = area of an enclosed region from the first step in Figure 4 = $\xi_1(1-\Psi_{\tilde{\Theta}})$
- AR(h) = area of an enclosed region from the second step in Figure 4 = $\xi_2(1-\Psi_{\tilde{\Theta}})$
- AR(i) = area of an enclosed region from the third step in Figure 4 = ξ_3
- AR(j) = area of an enclosed region from the fourth step in Figure 4 = ξ_4
- AR(k) = area of an enclosed region from the fifth step in Figure 4 = $\xi_5(1-\Psi_{\tilde{\Theta}}) + \frac{(\xi_4+\xi_5)\Psi_{\tilde{\Theta}}}{2}$
- AR(l) = area of an enclosed region from the sixth step in Figure 4 = $\frac{(\xi_5+\xi_6)(1-\Psi_{\tilde{\Theta}})}{2} + \frac{(\xi_4+\xi_5)\Psi_{\tilde{\Theta}}}{2}$
- DI = defuzzification function of IMF =$\frac{AR(g)+AR(h)+AR(i)+AR(j)+AR(k)+AR(l)}{6}$
- DI =$\frac{\xi_1(1-\Psi_{\tilde{\Theta}})+\xi_2(1-\Psi_{\tilde{\Theta}})+\xi_3+\xi_4+\xi_5(1-\Psi_{\tilde{\Theta}})+\frac{(\xi_4+\xi_5)\Psi_{\tilde{\Theta}}}{2}++\frac{(\xi_5+\xi_6)(1-\Psi_{\tilde{\Theta}})}{2}+\frac{(\xi_4+\xi_5)\Psi_{\tilde{\Theta}}}{2}}{6}$
- DI =$\frac{2\xi_1+2\xi_2+2\xi_3+2\xi_4+3\xi_5+\xi_6-2\xi_1\Psi_{\tilde{\Theta}}-2\xi_2\Psi_{\tilde{\Theta}}+2\xi_4\Psi_{\tilde{\Theta}}-\xi_5\Psi_{\tilde{\Theta}}-\xi_6\Psi_{\tilde{\Theta}}}{12}$

Step 4. The different region of FMF is delineated through Figure 5. The area of each region is calculated as follows:

- AR(g) = area of an enclosed region from the first step in Figure 5 = $\gamma_1(1-\Delta_{\tilde{\Theta}})$
- AR(h) = area of an enclosed region from the second step in Figure 5 = $\gamma_2(1-\Delta_{\tilde{\Theta}})$
- AR(i) = area of an enclosed region from the third step in Figure 5 = γ_3
- AR(j) = area of an enclosed region from the fourth step in Figure 5 = γ_4
- AR(k) = area of an enclosed region from the fifth step in Figure 5 = $\gamma_5(1-\Delta_{\tilde{\Theta}}) + \frac{(\gamma_4+\gamma_5)\Delta_{\tilde{\Theta}}}{2}$
- AR(l) = area of an enclosed region from the sixth step in Figure 5 = $\frac{(\gamma_5+\gamma_6)(1-\Delta_{\tilde{\Theta}})}{2} + \frac{(\gamma_4+\gamma_5)\Delta_{\tilde{\Theta}}}{2}$
- DF = defuzzification function of FMF =$\frac{AR(g)+AR(h)+AR(i)+AR(j)+AR(k)+AR(l)}{6}$
- DF = $\frac{\gamma_1(1-\Delta_{\tilde{\Theta}})+\gamma_2(1-\Delta_{\tilde{\Theta}})+\gamma_3+\gamma_4+\gamma_5(1-\Delta_{\tilde{\Theta}})+\frac{(\gamma_4+\gamma_5)\Delta_{\tilde{\Theta}}}{2}++\frac{(\gamma_5+\gamma_6)(1-\Delta_{\tilde{\Theta}})}{2}+\frac{(\gamma_4+\gamma_5)\Delta_{\tilde{\Theta}}}{2}}{6}$
- DF = $\frac{2\gamma_1+2\gamma_2+2\gamma_3+2\gamma_4+3\gamma_5+\gamma_6-2\gamma_1\Delta_{\tilde{\Theta}}-2\gamma_2\Delta_{\tilde{\Theta}}+2\gamma_4\Delta_{\tilde{\Theta}}-\gamma_5\Delta_{\tilde{\Theta}}-\gamma_6\Delta_{\tilde{\Theta}}}{12}$

Step 5. The defuzzification function of SVHNN is acquired by taking the average of the values of DT, DI and DF. Therefore, the resultant function is:

$$D(SVHNN) = \frac{DT+DI+DF}{3}$$
$$= \frac{2\eta_3+4\eta_4+2\eta_5+2\eta_1\Lambda_{\tilde{\Theta}}+2\eta_2\Lambda_{\tilde{\Theta}}-2\eta_4\Lambda_{\tilde{\Theta}}+\eta_5\Lambda_{\tilde{\Theta}}+\eta_6\Lambda_{\tilde{\Theta}}}{12} + \frac{2\xi_1+2\xi_2+2\xi_3+2\xi_4+3\xi_5+\xi_6-2\xi_1\Psi_{\tilde{\Theta}}-2\xi_2\Psi_{\tilde{\Theta}}+2\xi_4\Psi_{\tilde{\Theta}}-\xi_5\Psi_{\tilde{\Theta}}-\xi_6\Psi_{\tilde{\Theta}}}{12} + \frac{2\gamma_1+2\gamma_2+2\gamma_3+2\gamma_4+3\gamma_5+\gamma_6-2\gamma_1\Delta_{\tilde{\Theta}}-2\gamma_2\Delta_{\tilde{\Theta}}+2\gamma_4\Delta_{\tilde{\Theta}}-\gamma_5\Delta_{\tilde{\Theta}}-\gamma_6\Delta_{\tilde{\Theta}}}{12}$$

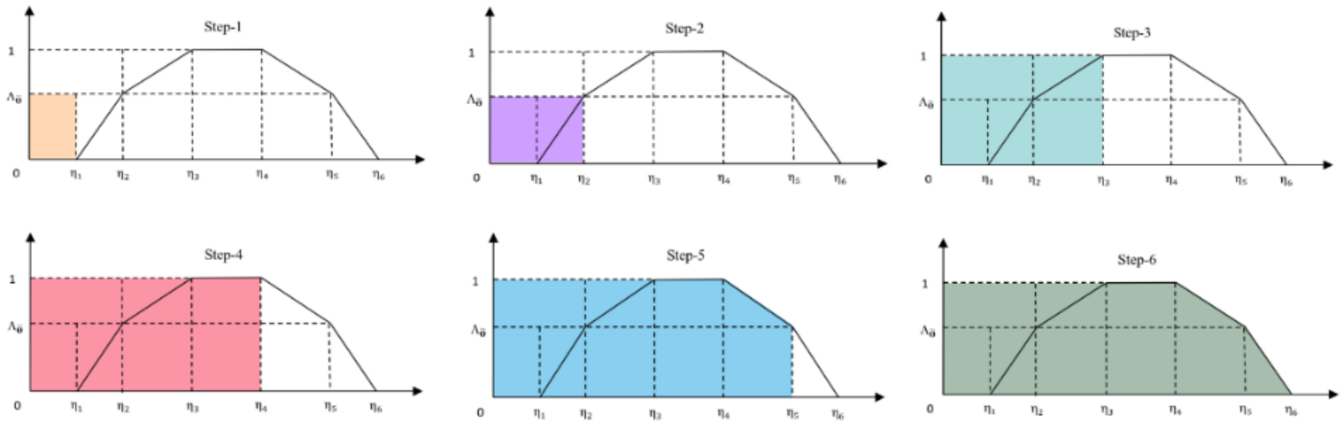

Figure 3. Differently shaded regions of truth membership function

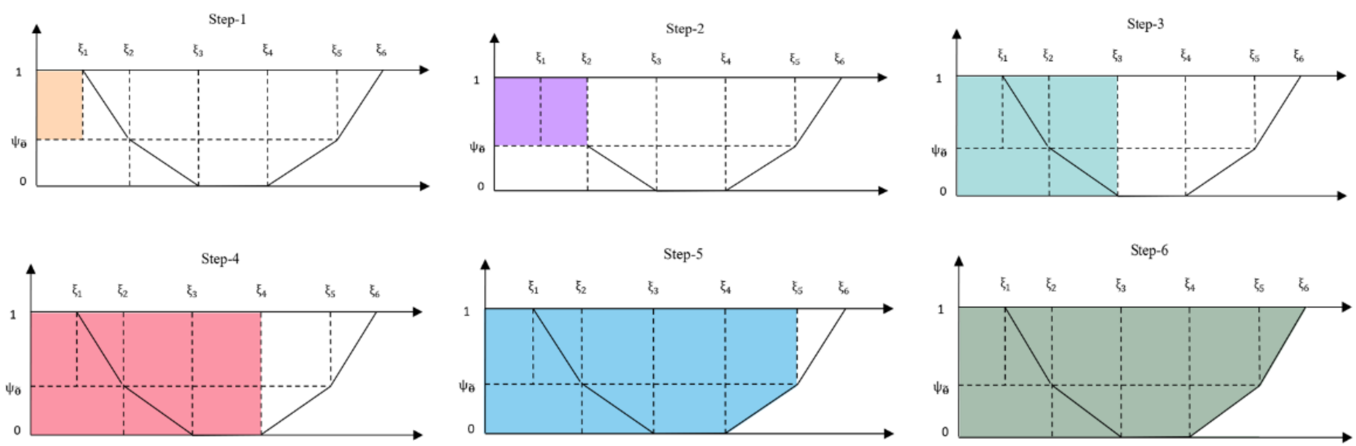

Figure 4. Different shaded regions of indeterminacy membership function

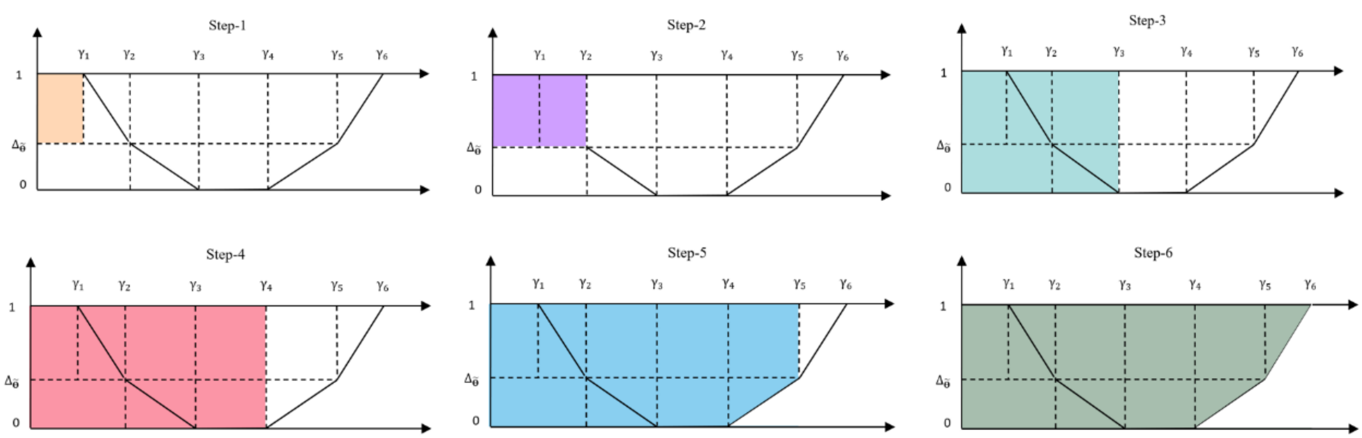

Figure 5. Different shaded regions of falsity membership function

Following the defuzzification function D(SVHNN) obtained from Step 5, the MOSTM in section 5 is converted to an equivalent crisp number. The obtained model can be solved using standard methods.

4.1 Verification of The Proposed Defuzzification Method with Previously Published Research

We investigated various methods from the existing literature to validate the performance of our proposed defuzzification method. The comprehensive examination is as follows:

4.1.1 Comparison with The Assignment Problem from (Chakraborty *et al.*, 2018)

The work presented (Chakraborty *et al*., 2018) illustrates a problem on page 20 that deals with route selection, in which the RAM approach was employed to convert fuzzy parameters into equivalent crisp numbers. However, in our study, we have opted to employ the RRAM method for the same problem and achieved superior outcomes. Specifically, the problem involves three distinct types of trucks located at a terminal station that must transport goods to three factories while minimizing travel costs. To better convey the essence of the problem, a graphical depiction is presented in Figure 6. Using the defuzzification technique outlined in section 4, as proposed in this paper, we have transformed the transportation costs from Table 7 on page 21 of (Chakraborty *et al*., 2018) into equivalent crisp numbers, as shown in Table 1. This approach has been pivotal in our research and yielded superior results in solving this problem.

We have employed the same approach described to ensure an impartial solution to the assignment problem (Chakraborty *et al*., 2018). The methodology involves two steps. First, we select the minimum value from each row in Table 1 and then subtract that value from every element in the corresponding row. The resulting values are presented in Table 2. Second, we select the minimum value from each column in Table 2 and subtract that value from every element in the corresponding column. This process yields the results shown in Table 3.

It can be observed that three minimum lines are necessary to cover all the zeroes in the matrix shown in Table 4. Consequently, truck-1 will go to factory-3, truck-2 will go to factory-2, and truck-3 will go to factory-1. The cost of transportation is minimized to 2.72+1.83+3.72=8.27. In contrast, the minimum transportation cost obtained by (Chakraborty et al., 2018) is 8.55, more significant than the proposed RRAM's result of 8.27. Table 5 compares the final optimal solutions obtained using our proposed RRAM and the existing method (Chakraborty et al., 2018). Since the problem aims to be minimized, we can conclude that the proposed RRAM provides better results than RAM.

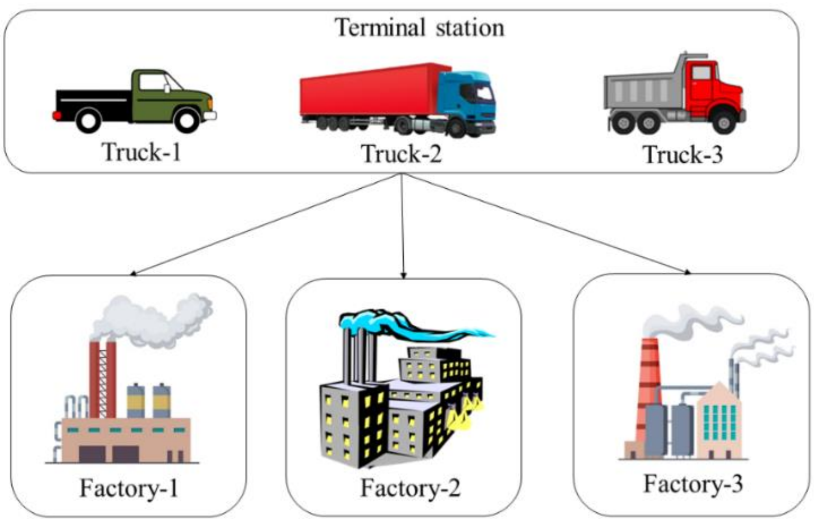

Figure 6. Diagrammatic representation of the assignment problem stated in (Chakraborty, 2018)

Table 2. Transportation cost in equivalent crisp environment

	Factory-1	Factory-2	Factory-3
Truck-1	4.1	2.53	2.72
Truck-2	1.92	1.83	2.29
Truck-3	3.72	5.04	4.76

Table 3. Select the minimum from each row and subtract each row element from that minimum element

	Factory-1	Factory-2	Factory-3
Truck-1	1.57	0	0.19
Truck-2	0.09	0	0.46
Truck-3	0	1.32	1.04

Table 4. Select the minimum from each column and subtract elements of the column from that minimum element

	Factory-1	Factory-2	Factory-3
Truck-1	1.57	0	0
Truck-2	0.09	0	0.27
Truck-3	0	1.32	0.85

Table 5. The comparison of optimal solution (minimizing) of assignment problem obtained using proposed and existing method

	Transportation cost
Proposed method	8.27
Existing method (Chakraborty *et al.*, 2018)	8.55

4.1.2 Comparison with The Assignment Problem from (Das *et al.*, 2020)

The TP stated in (Das *et al*., 2020) consists of the transportation of dress from three plants to three different warehouses in Odisha. The objective is to minimize the overall cost of transportation. The problem stated on page 9 of (Das *et al*., 2020) exists in a fuzzy environment. Using the proposed RRAM from section 4, the problem is defuzzified, converted to an equivalent crisp problem, and delineated using Table 6.

Table 6. Unit transportation cost along with supply and demand

	Warehouse-1	Warehouse-2	Warehouse-3	Supply
Factory-1	12	3	8	22
Factory-2	5	6	6	49
Factory-3	9	6	1	48
Demand	44	57	50	

Table 7. The allocation of supply and demand constraint

	Warehouse-1	Warehouse-2	Warehouse-3	Supply
Factory-1	12	3(22)	8	22
Factory-2	5(12)	6(35)	6(2)	49
Factory-3	9	6	1(48)	48
Demand	44	57	50	

Table 8. The comparison of optimal solution (minimizing) obtained using the proposed and existing method

	Transportation cost
Proposed method	396
Existing method (Das *et al.*, 2020)	418

The solution of Table 6 is obtained using the same technique adopted by the author (Das *et al*., 2020). The reason for considering the same technique is that other methods may provide superior or inferior results. Still, using the same techniques, we can compare the solutions based on the same ground and thus Figure out which defuzzification technique is better. The final solution obtained after solving Table 6 is represented in Table 7. The minimum cost of transportation $=3\times22+5\times12+6\times35+6\times2+1\times48=396$. Table 8 compares the final optimal solution obtained using our proposed RRAM and the existing method from (Das *et al*., 2020). Since the problem is minimized, the proposed method solution provides superior results.

4.1.3 Comparison of Proposed Revised Removal Area Method with (Nafei *et al.*, 2019) and (Das *et al.*, 2020)

In the preceding sections, 4.1.1 and 4.1.2, we compared different defuzzification methods based on a minimization problem. To broaden the scope of comparison and make it more comprehensive, we are now including a maximization problem in this section. Specifically, we will examine the problem described on pages 8 of (Nafei *et al*., 2019) and 89 of (Das *et al*., 2020).

Maximize $Z = \tilde{4}x_1 + \tilde{3}x_2$
subject to,
$\tilde{4}x_1 + \tilde{2}x_2 \leq \widetilde{12}$
$\tilde{3}x_1 + \tilde{6}x_2 \leq \tilde{5}$
$x_1, x_2 \geq 0,$

The optimization mentioned above problem exists in the fuzzy environment, which is converted to equivalent crisp form using the proposed RRAM from section 4. After applying the defuzzification technique, the obtained crisp problem as:

Maximize $Z = 3.81x_1 + 3.01x_2$
subject to,
$4.44x_1 + 1.94x_2 \leq 12.44$
$3.16x_1 + 6.81x_2 \leq 4.66$
$x_1, x_2 \geq 0,$

Solving the above crisp optimization problem, we obtained the optimal value of the objective function as Z=5.6. Table 9 compares the final optimal solution obtained using our proposed RRAM and the existing method from (Nafei *et al*., 2019) and (Das *et al*., 2020). Since the problem is maximizing, the solution obtained using the proposed method provides better results when compared with (Nafei *et al*., 2019) and (Das *et al*., 2020).

Table 9. The comparison of optimal solution(maximizing) obtained using the proposed and existing method

	Objective function value
Proposed method	5.6
Existing method (Nafei *et al*., 2019)	2.4
Existing method (Das *et al*., 2020)	4.2

5. PROBLEM STATEMENT AND MODEL FORMATION

This section thoroughly examines the 2020 Assam flood, employing a case study approach that incorporates mathematical modeling to facilitate the relocation of both contagious and non-contagious populations affected by the disaster. The pictorial representation of damage caused by the disaster is illustrated in Figure 7. The discourse delves into the fundamental causes of the calamity, with particular emphasis on the impact of water-borne diseases, and provides an in-depth analysis of post-disaster data. Furthermore, this study brings to the fore the scarcity of essential amenities in the afflicted area. By leveraging mathematical modeling, this study presents a novel strategy for DM, which enhances the systematic and efficient relocation of affected populations. This study contributes valuable insights into the field of DM and highlights the importance of mathematical modeling for an effective relocation process.

5.1 Case Study

The case study is conducted in Assam, a state in India. Assam accounts for about 9.40% of India's total flood-prone area and 39.58% of its area. It signifies that the flood-prone area of Assam is four times the national mark of the flood-prone area of the country. Assam possesses a vast network of rivers, with Brahmaputra and Barak being its two major rivers. Due to climate change and the increase in global temperature, there has been a significant increase in the annual monsoon rainfall in different regions of Assam, further resulting in the rise in water levels of major rivers like Brahmaputra and Barak. With the increase in water level, most districts of Assam witness flooding and landslides every year. The significant floods that shocked Assam were in 1954, 1962, 1972, 1977, 1984, 1988, 1998, 2002, 2004, 2012, 2019, and 2020. As per the government of Assam, floods account for an average yearly loss of approximately Rs. 200 crores (Assam government report 1, 2020).

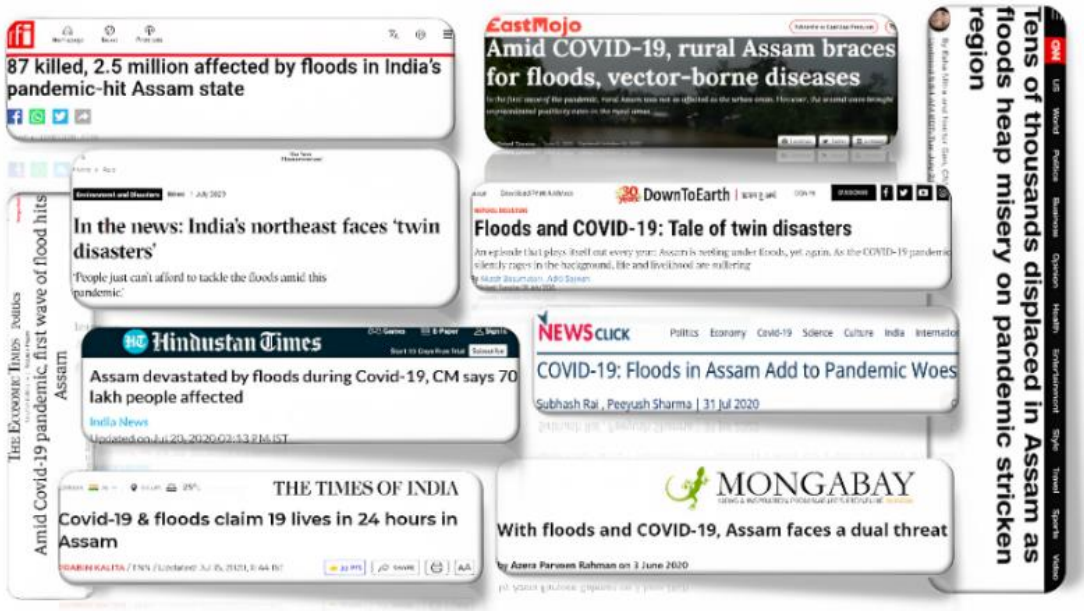

Figure 7. The news related to the spread of COVID-19 and vector-borne diseases during a flood in Assam, 2020. (Deccan herald, 2020), (Radio France international, 2020), (Economic times, 2020), and (Times of India, 2020)

In 2020, during monsoon season, Assam received 1164 mm of rainfall, 30% more than usual. The nearby states, Sikkim and Arunachal Pradesh, also received excess rainfall of around 16% and 45%, respectively (India meteorological department, 2020). This resulted in heavy floods across many districts of Assam. According to Assam's Revenue and Disaster Management, flood directly and indirectly affected over 7 million people and 5,474 villages, damaging 10,204 permanent and 47,847 temporary houses, 10,204 embankments, and 174 bridges. A total of 0,2 million hectares of crop area was destroyed. It is estimated that 123 people lost their lives, and thousands lost their homes (Assam government report 2, 2020). The families stuck in the flooded zone have to face numerous health challenges.

There were reports of Dengue, Malaria, and Japanese Encephalitis caused by the stagnant water due to floods. The fear of COVID-19 stymied the diagnosis of the patients, and restrictions further impeded the attempts to eliminate mosquito breeding grounds and create awareness among all the populations at high risk of getting contagious. As a result of infrastructure failure, the supply of resources could have been better, making it difficult for healthcare personnel to reach the affected population. Numerous articles focused on the population's hazardous conditions in the flood-affected areas and the difficulty in the relocation process due to the COVID-19 outbreak (Indian express, 2020). The news articles delineating the spread of COVID-19 and flooding in different regions of Assam and the hardships faced during relocation are represented in Figure 8.

- Contemplating the availability of budget and the need for prompt population relocation, the model objectives are designed to minimize the relocation cost and time. The biggest challenges persisting in the flood-affected areas were the scarcity of food and fresh drinking water, unavailability of medical supplies, and damage to water, sanitation, and electricity facilities. Thus, to counter this dire need for relocation, we have introduced a penalty function in our proposed model.
- A thorough study was conducted on the data available on the Assam DM authority website from 03.07.2020 to 14.10.2020, and using that, five districts were selected as source points for relocation. These selections were based entirely on the intensity of damage and unavailability of essential amenities to the population staying in these districts. Based on the same data, we found that three districts were the least affected and were selected as RCs locations. The pictorial representation of source points and RCs is represented in Figure 9.
- In the post-disaster phase, the data associated with the number of the affected population available for relocation fluctuated daily. The number of damaged roads and bridges increased, resulting in alteration of path, time, and cost of transportation between source and RCs. To counter this challenge, we have used fuzzy as the input data for the proposed model.

Figure 8. The submerged houses, damaged crops, roads, and NDRF rescue operation carried out during the Assam flood in 2020 (clockwise). (Daily news and analysis, 2020), (Grain mart, 2020), and (Zee news, 2020)

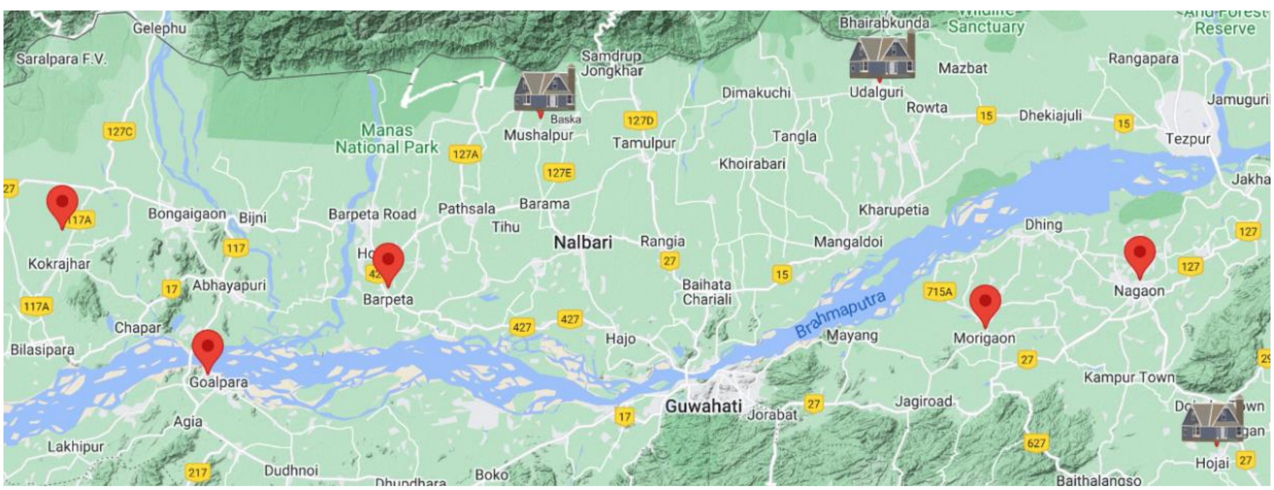

Figure 9. An illustrative visualization of the source and relocation centers established for the relocation of affected populations during the Assam flood of 2020

5.2 Modelling

In this section, we introduce the MOSTM for the relocation of the affected population of Assam, and a brief interpretation of the proposed model is highlighted.

5.2.1 Indices

- G Set of tentative sources, indexed by g
- S Set of RCs, indexed by s
- Q Set of conveyance for non-contagious population, indexed by q
- M Set of conveyance for contagious population, indexed by m

5.2.2 Parameter

- $\widetilde{CN}_{gsq}$ fuzzy cost of transportation of non-contagious individual from source g to RC s using *qth* type conveyance
- $\widetilde{CI}_{gsm}$ fuzzy cost of transportation of contagious individual from source g to RC s using mth type conveyance
- $\widetilde{PN}_{gsq}$ fuzzy penalty cost, which is imposed if a non-contagious population traveling from source through *qth* type conveyance does not reach RC s within the expected time
- $\widetilde{PI}_{gsm}$ fuzzy penalty cost, which is imposed if contagious population traveling from source g through *mth* type conveyance does not reach RC s within the expected time
- $\widetilde{AMN}_s$ fuzzy accommodation and medical cost of the non-contagious individual staying at RC s
- $\widetilde{AMI}_s$ fuzzy accommodation and medical cost of the contagious individual staying at RC s
- $\widetilde{TN}_{gsq}$ fuzzy time taken to transport non-contagious population from source g to RC s using *qth* type conveyance
- $\widetilde{TI}_{gsm}$ fuzzy time taken to transport contagious population from source g to RC s using mth type conveyance
- $\widetilde{EN}_{gsq}$ fuzzy expected time within which non-contagious population traveling from source g using qth type Conveyance must reach RC s
- $\widetilde{EI}_{gsm}$ fuzzy expected time within which contagious population traveling from source g using mth type the conveyance must reach RC s
- $\widetilde{HRMTN}_{gsq}$ fuzzy halt, refueling, and maintenance time taken by qth type conveyance transporting non-contagious population traveling from source g to RC s
- $\widetilde{HRMTI}_{gsm}$ fuzzy halt, refueling, and maintenance time taken by mth type conveyance transporting contagious population traveling from source g to RC s
- $\widetilde{ACN}_s$ fuzzy time taken to accommodate non-contagious population at sth RC
- $\widetilde{ACI}_s$ fuzzy time taken to accommodate contagious population at sth RC
- $\widetilde{NN}_q$ fuzzy number of the non-contagious population that *qth* type conveyance can carry
- $\widetilde{NI}_m$ fuzzy number of the contagious populations *mth* type conveyance can carry
- $\widetilde{CPN}_s$ fuzzy capacity of sth RC for non-contagious population
- $\widetilde{CPI}_s$ fuzzy capacity of sth RC for contagious population
- $\widetilde{PPN}_g$ fuzzy number of the non-contagious population that must be transported from source g to relocation centers.
- $\widetilde{PPI}_g$ fuzzy number of the contagious populations that must be transported from source g to relocation centers.
- $\widetilde{TP}$ fuzzy total number of contagious and non-contagious population that needs to be transported to relocation centers
- $\widetilde{LWN}_q$ fuzzy limited working time of qth type conveyance carrying non-contagious population
- $\widetilde{LWI}_m$ fuzzy limited working time of mth type conveyance carrying contagious population
- $\widetilde{TT}$ fuzzy total time within which relocation of both contagious and non-contagious populations must be completed
- $\widetilde{TB}$ fuzzy total budget allocated for transportation of population

5.2.3 Decision Variables

- x_{gsq} unknown number of non-contagious individuals transported from source g to RC s using qth type conveyance
- y_{gsm} unknown number of contagious individuals transported from source g to RC s using mth type conveyance
- $\rho_{gsq} = \begin{cases} 1 \; if \; x_{gsq} > 0 \\ 0 \; otherwise \end{cases}$
- $\gamma_{gsm} = \begin{cases} 1 \; if \; y_{gsm} > 0 \\ 0 \; otherwise \end{cases}$

5.2.4 Mathematical Model

$$
\begin{aligned}
MinZ_1 = & \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{CN}_{gsq}\,x_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{CI}_{gsm}\,y_{gsm} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{PN}_{gsq}\,\rho_{gsq} \\
& + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{PI}_{gsm}\,\gamma_{gsm} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{AMN}_{s}\,x_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{AMI}_{s}\,y_{gsm}
\end{aligned} \tag{1}
$$

$$
MinZ_2 = \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\left(\widetilde{TN}_{gsq} + H\widetilde{RMT}N_{gsq} + \widetilde{ACN}_{s}\right)\rho_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\left(\widetilde{TI}_{gsm} + H\widetilde{RMT}I_{gsm} + \widetilde{ACI}_{s}\right)\gamma_{gsm} \tag{2}
$$

$Subject\ to$

$$
\widetilde{PN}_{gsq} = \begin{cases}\widetilde{PN}\ if\ \widetilde{TN}_{gsq} > \widetilde{EN}_{gsq} \\ 0\ otherwise\end{cases} \quad g = 1,2,\ldots,G, s = 1,2,\ldots,S, q = 1,2,\ldots,Q, \tag{3}
$$

$$
\widetilde{PI}_{gsm} = \begin{cases}\widetilde{PI}\ if\ \widetilde{TI}_{gsm} > \widetilde{EI}_{gsm} \\ 0\ otherwise\end{cases} \quad g = 1,2,\ldots,G, s = 1,2,\ldots,S, m = 1,2,\ldots,M, \tag{4}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S} x_{gsq} \le \widetilde{NN}_{q}\ q = 1,2,\ldots,Q, \tag{5}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S} y_{gsm} \le \widetilde{NI}_{m}\ m = 1,2,\ldots,M, \tag{6}
$$

$$
\sum_{g=1}^{G}\sum_{q=1}^{Q} x_{gsq} \le \widetilde{CPN}_{s}\ s = 1,2,\ldots,S, \tag{7}
$$

$$
\sum_{g=1}^{G}\sum_{m=1}^{M} y_{gsm} \le \widetilde{CPI}_{s}\ s = 1,2,\ldots,S, \tag{8}
$$

$$
\sum_{s=1}^{S}\sum_{q=1}^{Q} x_{gsq} \le \widetilde{PPN}_{g}\ g = 1,2,\ldots,G, \tag{9}
$$

$$
\sum_{s=1}^{S}\sum_{m=1}^{M} y_{gsm} \le \widetilde{PPI}_{g}\ g = 1,2,\ldots,G, \tag{10}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q} x_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M} y_{gsm} \le \widetilde{TP} \tag{11}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S}(\widetilde{TN}_{gsq} + H\widetilde{RMT}N_{gsq})\rho_{gsq} \le \widetilde{LWN}_{q}\ q = 1,2,\ldots,Q, \tag{12}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S}(\widetilde{TI}_{gsm} + H\widetilde{RMT}I_{gsm})\gamma_{gsm} \le \widetilde{LWI}_{m}\ m = 1,2,\ldots,M, \tag{13}
$$

$$
\sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\left(\widetilde{TN}_{gsq} + H\widetilde{RMT}N_{gsq} + \widetilde{ACN}_{s}\right)\rho_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\left(\widetilde{TI}_{gsm} + H\widetilde{RMT}I_{gsm} + \widetilde{ACI}_{s}\right)\gamma_{gsm} \le \widetilde{TT} \tag{14}
$$

$$
\begin{aligned}
& \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{CN}_{gsq}\,x_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{CI}_{gsm}\,y_{gsm} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{PN}_{gsq}\,\rho_{gsq} \\
& + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{PI}_{gsm}\,\gamma_{gsm} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{q=1}^{Q}\widetilde{AMN}_{s}\,x_{gsq} + \sum_{g=1}^{G}\sum_{s=1}^{S}\sum_{m=1}^{M}\widetilde{AMI}_{s}\,y_{gsm} \le \widetilde{TB}
\end{aligned} \tag{15}
$$

$$
0 \le x_{gsq}, 0 \le y_{gsm}\ g = 1,2,\ldots,G, s = 1,2,\ldots,S, q = 1,2,\ldots,Q, m = 1,2,\ldots,M, \tag{16}
$$

5.2.5 Model Interpretation

The objective function (1) is the cost minimization function, comprising six costs. The first two costs are the total cost of transportation of non-contagious ($\widetilde{CN}_{gsq}$) and contagious population ($\widetilde{CI}_{gsm}$). Since the transportation of a contagious population, as compared with a non-contagious population, requires more safety and precautions, the cost associated with the transportation is kept different. Moreover, the conveyance choice for the population is also different, which results in different costs. The subsequent two costs are penalty costs, which are levied when non-contagious ($\widetilde{PN}_{gsq}$) and contagious population ($\widetilde{PI}_{gsm}$) do not reach RCs within the expected time. These penalties are imposed in cases where disruptions in the transport process, whether from logistical snags or unforeseen issues, impede the rapid and efficient transfer of individuals to their designated RCs. In such situations, these penalties incentivize and ensure the smooth execution of the transportation process, fostering a greater sense of urgency and accountability in mitigating delays in the relocation process. The final two cost elements encompass accommodation and medical expenses ($\widetilde{AMN}_s$ and $\widetilde{AMI}_s$). The former pertains to providing shelter, temporary housing, or other accommodations for the affected individuals, ensuring their safety and well-being during the crisis. The latter involves the healthcare and medical treatment required to address the needs of the non-contagious and contagious populations, including diagnosis, treatment, and any medical interventions necessitated by the situation.

The objective function (2) is the time minimization function, comprising six crucial times. The transportation time, halt, refueling, maintenance time, and accommodation time for non-contagious ($\widetilde{TN}_{gsq}, \widetilde{HRMTN}_{gsq},$ and $\widetilde{ACN}_s$) and contagious population ($\widetilde{TI}_{gsm}, \widetilde{HRMTI}_{gsm},$ and $\widetilde{ACI}_s$). This function intricately manages time during operational processes, considering multiple time-related aspects. It includes transportation time, which focuses on the efficiency and punctuality of travel. Halt time denotes planned stops for activities like passenger or cargo handling. Refueling time is dedicated to necessary breaks for replenishing fuel or energy resources. Maintenance time addresses unforeseen operational disruptions that may necessitate repairs or upkeep.

Furthermore, the function incorporates accommodation time for non-contagious and contagious populations, ensuring their well-being and comfort throughout the journey. Equations 3 and 4 describe the criteria for implementing penalty cost associated with the objective function (1). Restrictions 5 and 6 limit the number of non-contagious and contagious populations in *qth* and *mth* type conveyance, respectively. Constraints 7 and 8 ensure that the population allocation to each RC is less than its capacity, while constraints 9 and 10 state the number of populations that need to be relocated from different sources. The constraint ensures that every affected population is relocated to the relief center. They serve as a fundamental assurance that every impacted population, regardless of their source, is effectively and comprehensively transferred to the designated relief center, underscoring the commitment to safeguarding the well-being of all individuals during the relocation process, while constraints 11 state the total number of populations that need to be relocated. Constraints 12 and 13 restrict the working time for each type of conveyance. Constraints 14 and 15 set the time and budget limit for the relocation process. Constraint 16 designates that decision variables are non-negative integers.

6. METHODS FOR SOLVING MULTI-OBJECTIVE OPTIMIZATION PROBLEMS

The proposed MOSTM for relocating the non-contagious and contagious population in section 5.2 consists of two objective functions. Objective function 1 minimizes the overall cost of relocation, and objective function 2 minimizes the overall relocation time. Because of the conflicting nature of the objective functions, we have employed the compromise solution technique to obtain the optimal solution for the proposed MOSTM. The optimal solution is obtained using GP, FGP, NCA, and GCM. The detailed description of the compromise techniques is mentioned below:

6.1 Goal Programming

The GP was developed by Charnes and Cooper (Johnsen *et al.*, 1961). The GP assigns goals $\overline{\Lambda}_q$ to each objective function Λ_q. These goals are obtained by solving each objective function independently. The objective is to minimize the overall deviation from these goals, acquired by defining positive (D_q^+) and negative deviations (D_q^+) for each objective function. The MOSTM is converted into a single objective function and is formulated below:

$$min \sum_{q=1}^{Q} \left(D_q^+ + D_q^-\right)$$

$subject\ to,$
$\Lambda_q + D_q^+ + D_q^- = \overline{\Lambda}_q \quad q = 1,2,\cdots,Q,$
$D_q^+ D_q^- = 0\ q = 1,2,\ldots,Q,$
$constraints\ (3) - (16)$
$0 \le D_q^+ D_q^-\ q = 1,2,\ldots,Q,$

6.2 Fuzzy Goal Programming

In 1972, Zimmermann (Zimmermann, 1972) introduced the concept of fuzzy linear programming as an extension of linear programming. He defined objective functions and constraints as fuzzy parameters; in 1997 (Mohamed, 1997), Mohamed drew attention to the relationship between GP and FGP and how one could lead to another. He also proposed the linear membership function for the goal and constraints of the multi-objective problem. Further, Zangiabadi and Malek 2007 enhanced the concept of FGP by introducing the hyperbolic membership function to define goals and constraints. In this literature, we have used the FGP approach proposed by Zangiabadi and Malek, and the methodology to solve the proposed MOSTM is defined below: The positive deviation (V_q^+) and negative deviation (V_q^-) variables for the objective functions (ξ_q) as follows:

$$V_q^+ = \max\left(0, \xi_q - \bar{\xi}_q\right) = \frac{1}{2}\left\{\left(\xi_q - \bar{\xi}_q\right) + \left|\xi_q - \bar{\xi}_q\right|\right\}, \quad q = 1,2,\ldots,Q,$$

and

$$V_q^- = max\left(0, \bar{\xi}_q - \xi_q\right) = \frac{1}{2}\left\{\left(\bar{\xi}_q - \xi_q\right) + \left|\bar{\xi}_q - \xi_q\right|\right\}, \quad q = 1,2,\ldots,Q,$$

In a minimizing problem, if we require $\xi_q(x) \le \overline{\xi}_q(x)$, then minimizing the distance between $\xi_q(x)$ and $\overline{\xi}_q(x)$ results in the minimization of V_q^+ and considering D_q and M_q as the desired and maximum acceptable level of achievement for the q-th objective function, respectively. Below are the steps to obtain the solution using FGP for the MOSTM, as described in section 5.2.

- Each objective function of MOSTM is solved independently, i.e., considering only a single objective function at one time and ignoring the remaining. Considering $l_1, l_2, \ldots, l_n$ are the unknown variables' values obtained after solving each objective function independently.
- Each objective function value is calculated using the unknown variables obtained from step 1. We obtained $\xi_1(l_1)$, $\xi_1(l_2)$, ..., $\xi_1(l_n)$, $\xi_2(l_1)$, $\xi_2(l_2)$, ..., $\xi_2(l_n)$, ..., $\xi_Q(l_1)$, $\xi_Q(l_2)$, ..., $\xi_Q(l_n)$.
- Using the value of each objective function obtained from step 2, we find the best $\left(D_q\right)$ and the worst $\left(M_q\right)$ value for the respective objective function.
  $D_q = \min_{\forall s \in N} \xi_q(l_s)$ *and* $M_q = \max_{\forall s \in N} \xi_q(l_s)$ *where* $N = 1,\ 2,\ \ldots, n, q = 1,2,\ldots,Q,$

- Considering the hyperbolic membership function, the following single objective model emerges:

  $Min\ \Omega$
  subject to,

  $$\frac{1}{2} + \frac{1}{2}\frac{e^{\left\{\frac{(D_q+M_q)}{2}-\xi_q\right\}\varphi_q} - e^{-\left\{\frac{(D_q+M_q)}{2}-\xi_q\right\}\varphi_q}}{e^{\left\{\frac{(D_q+M_q)}{2}-\xi_q\right\}\varphi_q} - e^{-\left\{\frac{(D_q+M_q)}{2}-\xi_g\right\}\varphi_q}} - V_q^+ + V_q^- = 1$$

  $\Omega \ge V_q^-$, q= 1, 2, …, Q,
  $V_q^+ V_q^- = 0$
  constraints (3)-(16)
  0$\le \Upsilon \le$*1,*

  $$\varphi_q = \frac{6}{M_q - D_q}$$

6.3 Global Criterion Method

The GCM (Hwang *et al*., 1979) is a compromise technique to obtain the solution for MOSTM. The principal advantage of this approach above other multi-objective optimization approaches is that it does not require the Pareto ranking mechanism (Chiandussi *et al.*, 2012). The solution of MOSTM is obtained by minimizing the ratio of the difference between each objective function and its respective ideal solution. Below are the steps to obtain the compromise solution using GCM for the MOSTM, as described in section 5.2.

- Each objective function ($\Gamma_1, \Gamma_2, \ldots, \Gamma_Q$) is solved independently, ignoring all others.
- Using the solution obtained using step 1, the ideal objective vectors are termed as $\Gamma_1{}^{min}, \Gamma_2{}^{min}, \ldots, \Gamma_q{}^{min}$ and $\Gamma_1{}^{max}, \Gamma_2{}^{max}, \ldots, \Gamma_Q{}^{max}$,.
- The MOSTM is converted to a single objective, as shown below:

$$\min\left\{\sum_{q=1}^{Q}\left(\frac{\Gamma_q - \Phi_q^{min}}{\Phi_q^{min}}\right)^r\right\}^{\frac{1}{r}}$$

subject to,
constraints (3)-(16)
$1 \leq r \leq \infty$

6.4 Neutrosophic Compromise Approach

The Neutrosophic compromise approach (NCA) deals with optimization problems by introducing truth, falsity, and IMF (Rizk *et al*., 2018). The NCA maximizes the degree of TMF and IMF and minimizes the degree of FMF. Below are the steps to obtain the compromise solution using NCA for the MOSTM, as described in section 5.2.

- The objective functions $\Phi_1, \Phi_2, \ldots$, and Φ_q are solved individually
- For the solution obtained using Step 1, we calculate the bounds for each objective function's minimum (μ_q) and maximum (ν_q) values. The obtained values are shown below:

$$\mu_q = \min_{\forall s \in N}\{\Phi_q\}_{q=1}^{Q} \text{ and } \nu_q = \max_{\forall s \in N}\{\Phi_q\}_{q=1}^{Q}$$

- The derived value of μ_q and ν_q from step 2 calculates the truth, falsity, and indeterminacy membership bounds.

$\nu_q^T = \nu_q, \mu_q^T = \mu_q$ truth membership,
$\nu_q^F = \nu_q^T, \mu_q^F = \mu_q^T + \kappa_q(\nu_q^T - \mu_q^T)$ falsity membership,
$\mu_q^G = \mu_q^T + \epsilon_q(\nu_q^T - \mu_q^T), \mu_q^G = \mu_q^T$ indeterminacy membership
where $0 \leq \epsilon_q \leq 1$ and $0 \leq \kappa_q \leq 1$

- The MOSTM is converted to a single objective and is stated as follows:

Max $\varrho - \chi + \epsilon$
subject to,
constraints (3)-(16)
$\Phi_q + (\nu_q^T - \mu_q^T)\varrho \leq \nu_q^T$
$\Phi_q + (\nu_q^G - \mu_q^G)\chi \leq \nu_q^G$
$\Phi_q + (\nu_q^F - \mu_q^F)\epsilon \leq \mu_q^F$
$\varrho \geq \epsilon, \varrho \geq \chi, \varrho + \chi + \epsilon \leq 3$
$\varrho, \epsilon, \varrho \in [0,1], q = 1, 2, \ldots, Q$

7. NUMERICAL EXPERIMENTS AND DISCUSSIONS

This section implements the proposed MOSTM in the case study conducted on the Assam flood in 2020. Based on the post-disaster damage information provided by the Assam state DM authority official website (Assam government report 1, 2020), we have considered five source points and three destination points. These source points are the worst affected districts of

Assam from where the population will be relocated to destination points, i.e., RC. The location of the RCs is chosen based on the least affected districts during the flood. The source points are in Assam's Kokrajhar, Barpeta, Goalpara, Morigaon, and Nagaon districts. The RC is in Assam's Baksa, Udalguri, and Hojai districts. The causes of calamity are climate change, intense rainfall, deforestation, and the construction of dams and barriers within the Brahmaputra basins. Due to the sudden and extreme rain, there needed to be more time for flood preparedness among the population residing in locations designated as source points for the mathematical model. The overwhelming flood subsequently led to an electricity shortage and disrupted food supply in the affected region. The confluence of the peak of the COVID-19 pandemic and stagnant water significantly increased the likelihood of spreading contagious diseases. The decision-maker encounters dual challenges in the post-disaster phase: firstly, the risk of disease transmission to non-affected populations and, secondly, the deterioration of the health of the already affected population. Given the lack of essential amenities in the affected regions, the proposed relocation model is tailored to transfer the population to relief centers efficiently. The model meticulously ensures the segregation of contagious and non-contagious populations during transportation, mitigating the risk of further spreading disease. The cost and time objectives underpinning the model guarantee both cost-effectiveness and expeditious relocation to relief centers, prioritizing the prompt delivery of aid to the affected populace.

LINGO is an optimization modeling software developed by LINDO Systems Inc. This software is used for modeling, solving, and analyzing linear, nonlinear, integer, quadratic, and stochastic models in an efficient, more straightforward, and more effective way. The mathematical model is coded in LINGO optimization software and is executed on a mobile workstation with the configuration of 11th Gen Intel(R) Core (TM) i9 @ 3.20 GZ processor with 64.00 GB RAM. LINGO executes multiple CPU cores to execute models, thereby reducing processing time. It enables us to construct an optimization model rapidly in a format that is easily accessible and can extract inputs directly from databases and spreadsheets. A significant advantage of LINGO is that decision-makers can work on prototyping problems with small-scale datasets and quickly shift to big data to study multiple scenarios. In addition, LINGO can solve mathematical models with up to 32,000 variables and 16,000 constraints (Optimization software, 2023).

7.1 Input Data for The Real-Life Model

The inputs for the proposed MOSTM in section 5.2 are in Table 11-19 in the appendix. The appendix for all the data associated with Table 11-19 is available at https://github.com/bhakunimayank6/appendix-inputs-for-case-study-conducted-on-assam-flood. Tables 11, 12, 13, 14, 15, and 16 represent the cost of transportation, transportation time, and estimated time for contagious and non-contagious populations. Tables 17 and 18 delineate the halt, refueling, and maintenance time the conveyance takes. Table 19 depicts input for accommodation time, accommodation and medical cost, capacity of conveyance and RC, number of contagious and non-contagious population that needs to be relocated, time restriction of conveyance, penalty cost, and restriction in overall cost and time.

7.2 Result Analysis

The MOSTM proposed in section 5.2 consists of two objective functions, and in order to obtain the optimal solution of the MOSTM, we used the compromise techniques discussed in section 6. The inputs of MOSTM are based on the actual case study conducted on the Assam flood in 2020 and are mentioned in Tables 11-19. The inputs for the model are considered SVHNN, which are converted to crisp numbers using the proposed defuzzification method from section 4.

The solutions obtained using GP, FGP, GCM, and NCA using LINGO optimization software are exhibited in Table 10. The solution obtained using NCA and GCM is illustrated in Figure 10, and using GP and FGP is demonstrated in Figure 11. Using GP, the cost and time objective function values are $Z_1 = 2244360$ and $Z_2 = 3931$, respectively. 1495 non-contagious and 1144 contagious populations, 1934 non-contagious and 1015 contagious populations, and 1106 non-contagious and 1561 contagious populations were transported from sources to RC $s = 1$, $s = 2$, and $s = 3$, respectively. Among the *qth* type conveyance for the non-contagious population, 2139 were transported using conveyance one while 1743 and 653 were transported through conveyance 2 and 3, respectively. Whereas for the contagious population using *mth* type conveyance, 1436 were transported using conveyance one while 1535 and 749 were transported through conveyance 2 and 3, respectively.

Table 10. Optimum results were obtained using compromise techniques after defuzzification using the proposed method

GP	FGP	GCM	NCA
Objective function value			
$Z_1 = 2244360$	$Z_1 = 2056758$	$Z_1 = 2057063$	$Z_1 = 2034725$
$Z_2 = 3931$	$Z_2 = 4500$	$Z_2 = 3956$	$Z_2 = 3923$
Allocations			

GP	FGP	GCM	NCA
$x_{131} = 416, x_{211} = 889$ $x_{223} = 347, x_{321} = 228$ $x_{332} = 384, x_{422} = 1359$ $x_{511} = 606, x_{533} = 306$ $y_{122} = 810, y_{211} = 470$ $y_{222} = 205, y_{233} = 365$ $y_{311} = 674, y_{432} = 520$ $y_{433} = 292, y_{531} = 292$ $y_{533} = 92$ and all other $x_{gsq} = 0$ and $y_{gsm} = 0.$	$x_{122} = 316, x_{211} = 747$ $x_{311} = 113, x_{312} = 875$ $x_{321} = 24, x_{422} = 304$ $x_{431} = 1055, x_{533} = 1101$ $y_{112} = 220, y_{122} = 590$ $y_{211} = 340, y_{222} = 424$ $y_{231} = 276, y_{311} = 674$ $y_{422} = 1, y_{431} = 147$ $y_{433} = 664, y_{531} = 2$ $y_{533} = 381, y_{532} = 1$ and all other $x_{gsq} = 0$ and $y_{gsm} = 0$	$x_{122} = 416, x_{211} = 1120$ $x_{312} = 615, x_{321} = 113$ $x_{422} = 115, x_{431} = 806$ $x_{432} = 438, x_{533} = 912$ $y_{122} = 810, y_{211} = 560$ $y_{222} = 205, y_{231} = 57$ $y_{232} = 218, y_{311} = 674$ $y_{431} = 148, y_{433} = 664$ $y_{533} = 384$ and all other $x_{gsq} = 0$ and $y_{gsm} = 0$	$x_{122} = 416, x_{211} = 1236$ $x_{312} = 499, x_{321} = 113$ $x_{422} = 115, x_{431} = 790$ $x_{432} = 454, x_{533} = 912$ $y_{112} = 218, y_{122} = 592$ $y_{211} = 342, y_{222} = 423$ $y_{231} = 275, y_{311} = 674$ $y_{431} = 148, y_{433} = 664$ $y_{533} = 384$ and all other $x_{gsq} = 0$ and $y_{gsm} = 0$

Using FGP, the value of the cost objective is $Z_1 = 2056758$, which is fewer when compared with GP. At the same time, the value of the time objective is $Z_2 = 4500$, which is more when compared with GP. Therefore, there is no dominant solution between GP and FGP. FGP allocates 1735, 644, and 2156 non-contagious and 1234, 1015, and 1471 contagious populations to RC $s = 1$, $s = 2$, and $s = 3$ respectively. Utilizing GCM, the value of cost and time objectives are $Z_1 = 2057063$ and $Z_2 = 3956$, respectively. While comparing the results with GCM, GP, and FGP, the GCM provides a lower Z_1 value when compared with GP while the higher when compared with FGP. Meanwhile, for objective Z_2, the GCM provides an intermediate value between the solution obtained using GP and FGP. Hence, there is no dominant solution comparing GP, FGP, and GCM. The GCM allocates 1735, 644, and 2156 non-contagious and 1234, 1015, and 1471 contagious populations to RC $= 1$, $s = 2$, and $s = 3$, respectively. Employing NCA, the cost objective function value is Z_1=2034725, and the time objective is Z_1=3923. While comparing the objective functions' value with GP, FGP, and GCM, we found that NCA provides the minimum value. The NCA allocates 1735, 644, and 2156 non-contagious and 1234, 1015, and 1471 contagious populations to RC $= 1$, $s = 2$, and $s = 3$, respectively.

Figure 10. The allocations made by NCA and GCM

If we analyze the total number of allocations of the contagious and non-contagious population on each RCs $s = 1,2,3$ made by FGP, GCM, and NCA, we find that all the allocations are the same. However, NCA still provides better results when compared with FGP and GCM. This is because the total number of populations allocated to each RC $s = 1,2,3$ is the same, but the number of people traveling from different sources and conveyance varies. Referring to Table 9, we find that fewer allocations are present in x_{312}, x_{422}, x_{431}, x_{533}, y_{112}, y_{222}, y_{231} and more allocations are there in x_{211}, x_{122}, x_{321}, y_{211}, y_{122}, y_{431}, and x_{533} using NCA rather than FGP. Similarly, if we compare NCA with GCM, we find fewer allocations in x_{312}, x_{422}, x_{431}, x_{533}, y_{112}, y_{222}, y_{231}, and more in y_{222} and y_{231}. In general, the NCA allocates in such a way that less cost and time is utilized to relocate the population from sources Kokrajhar ($g = 1$), Barpeta ($g = 2$), Goalpara ($g = 3$), Morigaon ($g = 4$), and Nagaon ($g = 5$) to the RC at Baksa ($s = 1$), Udalguri ($s = 2$), and Hojai ($s = 3$) using $k = 1,2,3$ type of conveyance.

Figure 11. The allocations made by GP and FGP

7.3 Some Particular Cases

This section highlights three distinct cases that were explored in the study. The initial case examines the exclusion of the penalty cost from the objective function, while the second case involves the elimination of the limited working time of the conveyance. Furthermore, the third case compares the existing defuzzification technique RAM and the proposed technique RRAM. The study involved solving the MOSTM using both techniques to achieve this comparison. By analyzing and comparing the results obtained from both techniques, the research aims to provide valuable insights into the effectiveness of these approaches in addressing multi-objective relocation problems.

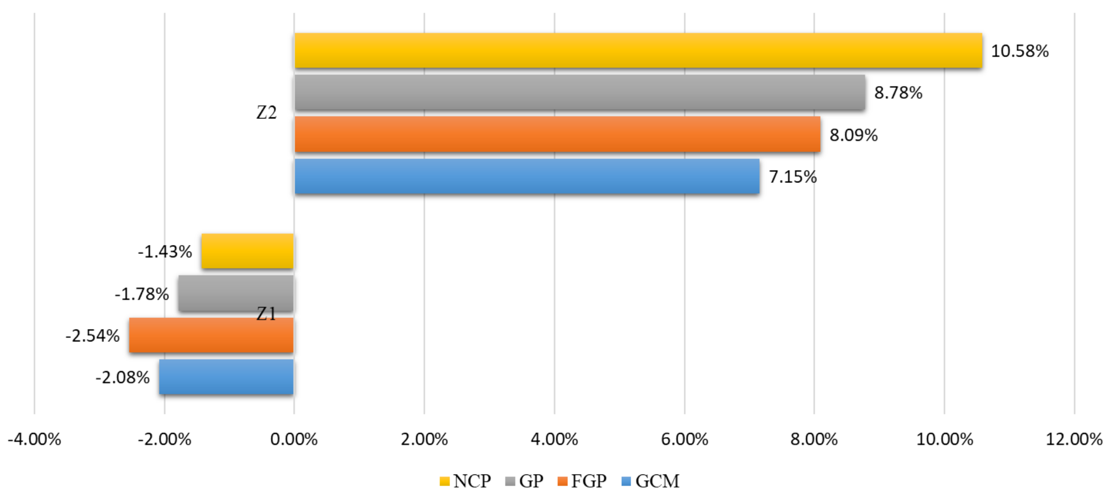

Figure 12. The percentage change in objective functions value with the removal of penalty cost

7.3.1 Removal of Penalty Cost

The objective function (1) comprises penalty costs for contagious and non-contagious populations. It is levied when the population does not reach the RC within the expected time. The reason for considering the penalty cost is that the arrival to each RC must be as quick as possible so that the population can have basic amenities and there is no further increase in casualties. In this section, we have solved the MOSTM stated in section 5.2 by removing penalty costs. From the objective function Z_1, $\widetilde{PN}_{ijk}$ and $\widetilde{PI}_{ijk}$, representing the penalty costs of the non-contagious and contagious population, respectively, are excluded. In contrast, objective function Z_2, which depicts the time, remains unchanged. Constraints 3 and 4 are excluded as they represent the conditions when a penalty is levied. The constraint 15 is further modified based on removing penalty cost. The same inputs mentioned in Tables 10-19 are utilized to obtain the solution using the same compromise solution techniques GP, FGP, GCM, and NCA.

The obtained solution is compared with the previous solution involving the penalty cost. The percentage change obtained in the solution using GP, FGP, GCM, and NCA is demonstrated in Figure 12. With the removal of penalty cost, objective Z_1 is decreased, while objective Z_2 is increased. Using NCA, Z_1 is decreased by 1.43% while Z_2 is increased by at least seven times the decreased percentage of 10.58%. Similarly, employing GP, FGP, and GCM, the Z_2 is decreased by 1.78%, 2.54%, and 2.08%, respectively, whereas Z_2 has increased at least three times the decreased percentage, which is 8.78%, 8.09%, and 7.15%, respectively. The percentage increase in Z_2 is very high compared to the absolute value of the percentage change in Z_1. In the post-disaster phase, time and cost both play a crucial role in allocating the population to RCs. Therefore, there is a need to have a proper balance while minimizing both objectives. Analyzing Figure 12, we can conclude that including penalty cost in the objective function has helped decrease the time objective Z_2 value to a greater extent while having a minor effect on the cost objective Z_1.

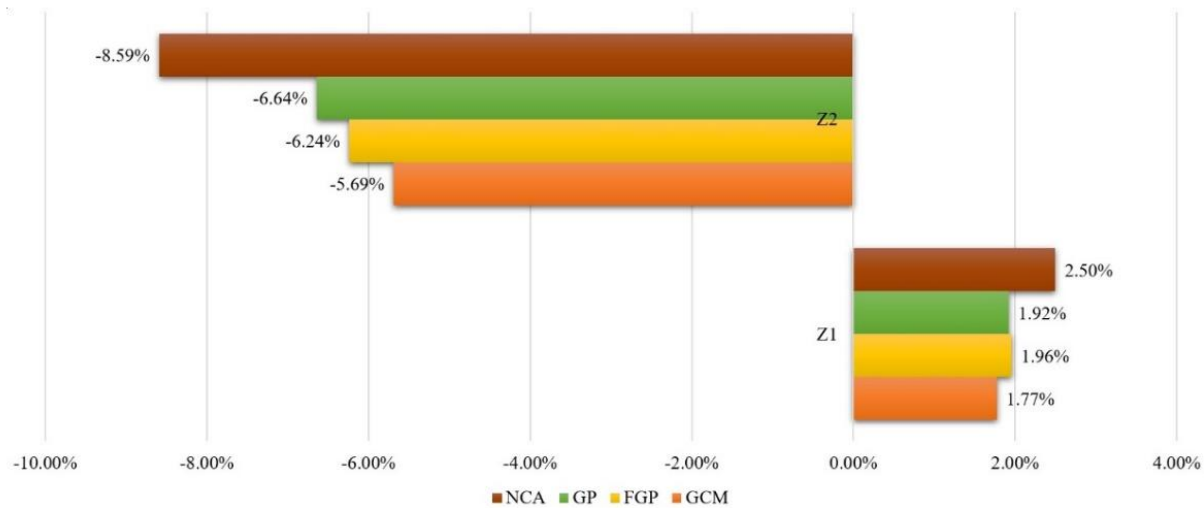

Figure 13. The percentage change in objective functions value with the removal of limited working time

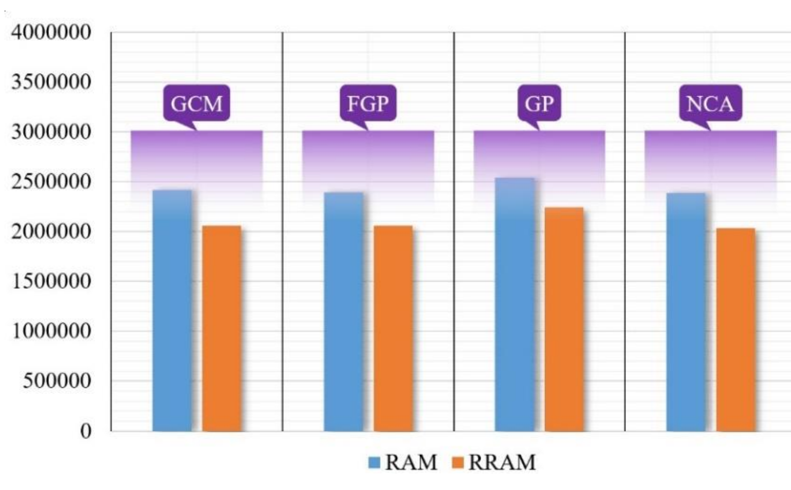

Figure 14. The difference in the value of the cost objective function obtains using RAM and RRAM

7.3.2 Removal of Limited Working Time of Conveyance

The constraints 12 and 13 of MOSTM stated in section 5.2 represent the time restrictions in the working time of each type of conveyance. With the advancement in technology and accurate weather forecasts in the pre-disaster phase, there may be instances where the government and private agencies have an ample number of each type of conveyance. Therefore, there is no regulation on the working time of each conveyance. In this section, we analyzed the result obtained by solving the MOST stated in section 5.2 and removing constraints 12 and 13. We have used the same solution techniques GP, FGP, GCM, and NCA and inputs as in Table 10-19.

The change in the percentage value of the objective function Z_1 and Z_2 when compared with the previous solution constituting the limited working time is shown in Figure 13. The percentage change in objective function Z_1 is positive, delineating the increase in cost; the other way, the percentage change in Z_2 is negative, showing a decrease in time. Using NCA, the percentage change in Z_1 and Z_2 is 2.5% and -8.59%, respectively. Similarly, using GP, FGP, and GCM, the percentage in Z_1 is 1.92%, 1.96%, and 2.24%, respectively, and Z_2 is -6.64%, -6.24%, and -5.69%, respectively. The absolute percentage change in Z_2 is at least three times that in Z_1. The time objective Z_2 is decreased, portraying that if there is no limitation on the working time of conveyance, the relocation process is completed early, whereas the cost objective Z_1 is increased, meaning that more money is utilized in the relocation process. The significant advantage of this analysis is that in the post-disaster phase, if the government and private agencies involved in the relocation process give more importance to the timely relocation of the affected population and can withstand the minor increase in the cost of relocation, then they can prearrange the ample number of conveyances to decrease the relocation time.

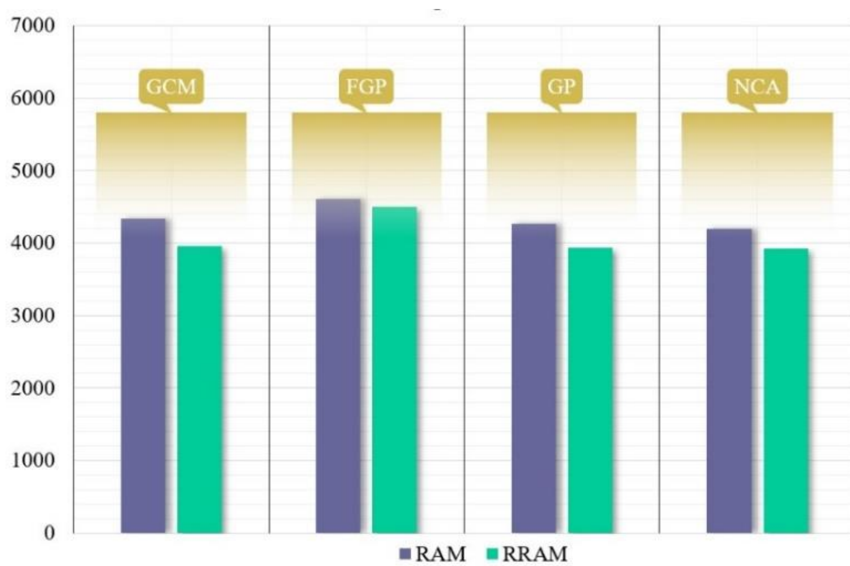

Figure 15. The difference in the value of the time objective function obtained using RAM and RRAM

7.3.3 Comparison between Removal and Revised Removal Area Method Based on Proposed Multi-Objective Solid Transportation Model

In section 4.1, we verify the performance of the proposed RRAM method over existing RAM by comparing its efficiency with the existing literature. This section solved the proposed MOSTM from section 5.2 using RAM and RRAM. The fuzzy MOSTM is first converted to crisp MOSTM using RAM and RRAM, and then we obtain the compromise solution using GCM, FGP, GP, and NCA. The comparison aims to show the proposed RRAM's efficiency over RAM and its perceived advantages while solving real-life problems.

The cost objective values obtained after implementing RAM and incorporating the GCM, FGP, GP, and NCA are 2415135, 2391632, 2538142, and 2384939, respectively. Similarly, using RRAM and compromise techniques GCM, FGP, GP, and NCA, the values are 2057063, 2056758, 2244360, and 2034725, respectively. The values of the time objective function utilizing RAM and GCM, FGP, GP, and NCA are 4340, 4603, 4261, and 4197, respectively. Similarly, employing RRAM and GCM, FGP, GP, and NCA, the values are 3956, 4500, 3931, and 3923, respectively. The detailed comparison of the cost and time objective values is exhibited using Figures 14 and 15, respectively. Analyzing both objective function values, we infer that RRAM provides better results than RAM. Since the MOSTM is based on a real-life relocation process, the proposed defuzzification technique RRAM is suited to be implemented in real-life case studies.

7.4 Sensitivity Analysis

In this section, we examine the change in the cost objective function Z_1 of MOSTM, as stated in section 5.2, with a change in each component. The aim is to analyze the sensitivity of transportation, penalty, accommodation, and medical costs for both non-contagious and contagious populations. The following steps highlight the process of conducting a sensitivity analysis:

We choose one cost at a time, keeping the remaining cost unchanged. For example, we first chose the transportation cost for the non-contagious population, and the five costs remained unaffected. The chosen cost in step 1 is increased by 10%, 20%, 30%, 40%, and 50%, and solutions are obtained using GCM, FGP, GP, and NCA. The results showing percentage change in the overall cost objective are delineated using Figure 16.

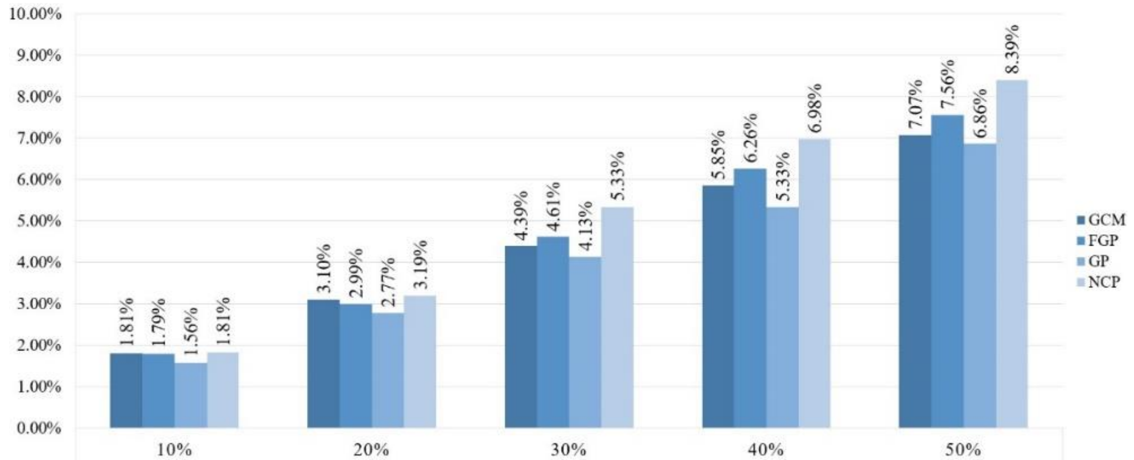

Figure 16. Percentage change in overall cost with the percentage increase in the cost of transportation of non-contagious population

A similar procedure is followed for the remaining costs. Figures 17, 18, 19, 20, and 21 represent the percentage change in overall cost objective with the change in transportation cost of contagious, penalty cost of non-contagious, penalty cost of contagious, accommodation and medical cost of non-contagious, and accommodation and medical cost of contagious population, respectively.

The following insights are obtained based on the sensitivity analysis:

1. On Comparing the cost of transportation of non-contagious (Figure 16) and contagious (Figure 17) populations, the percentage increase in the overall cost objective value is higher for the contagious population. For a 10% increase in the cost of transportation for a non-contagious population, the overall cost objective percentage change obtained using GCM, FGP, GP, and NCP is less when compared with a contagious population. Similar results are obtained for 20%, 30%, 40%, and 50%. From Figures 16 and 17 the increase in overall cost objective value for 10% increase in cost of transportation of non-contagious population is 1.81%, 1.79%, 1.56%, and 1.81%, contagious population is 2.27%, 1.86%, 1.76%, and 2.30% and for 50% increase cost of transportation of non-contagious population is 7.07%, 7.56%, 6.86%, and 8.39%. The contagious population is 10.83%, 12.17%, 10.55%, and 12.37%. Analyzing this value, we can interpret that the increase in the percentage cost of non-contagious and contagious populations sharply increases the difference between the percentage change of overall cost objective value. Thus, we concluded that the cost of transportation for the contagious population is more sensitive than for the non-contagious population.
2. Considering the penalty costs of non-contagious (Figure 18) and contagious (Figure 19) populations, the percentage increase in overall cost objective value for the contagious population is significantly larger. The overall cost objective percentage change acquired using GCM, FGP, GP, and NCP for a 10% increase in penalty cost of the non-contagious population is 1.14%, 1.08%, 1.01%, and 1.31%, respectively, similarly for contagious are 1.56%, 1.68%, 1.40%, and 1.56%, respectively showing a minor difference in the values. The difference becomes more significant with the increase in percentage values 20%, 30%, 40%, and 50%. For a 50% increase in penalty costs of the contagious population, the percentage change in overall cost objective (6.27%, 6.96%, 6.15%, and 6.98%) is much higher compared to non-contagious (4.94%, 5.15%, 5.68%, and 5.95%). Therefore, we concluded that the penalty cost for a contagious population is more sensitive than for a non-contagious population.

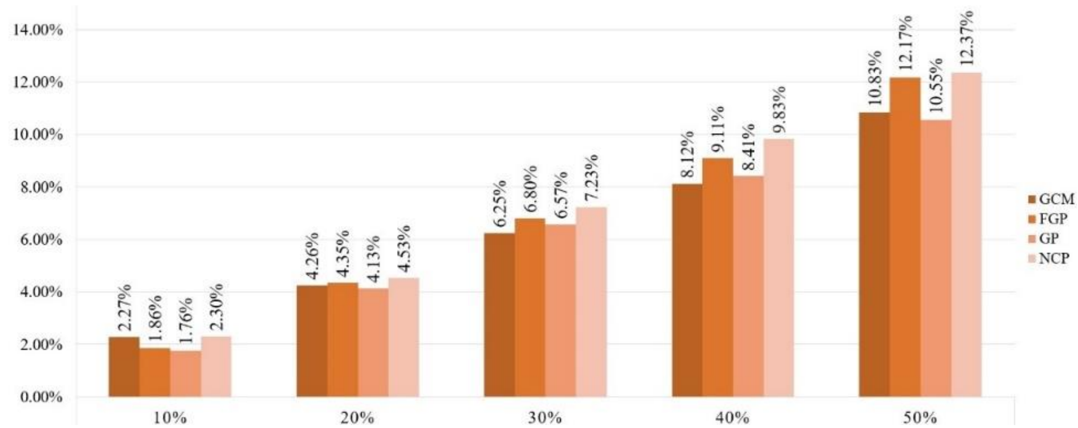

Figure 17. Percentage change in overall cost with the percentage increase in the cost of transportation of contagious population

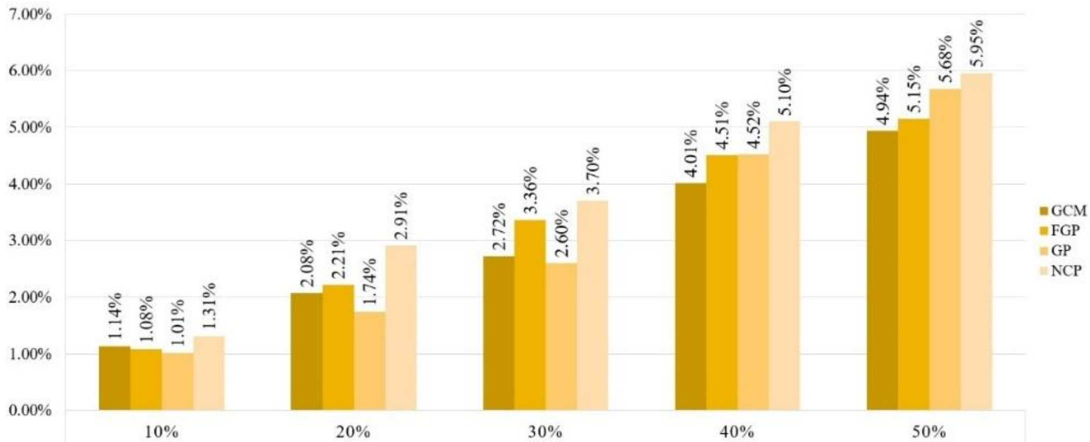

Figure 18. Percentage change in overall cost with the percentage increase in penalty cost of non-contagious population

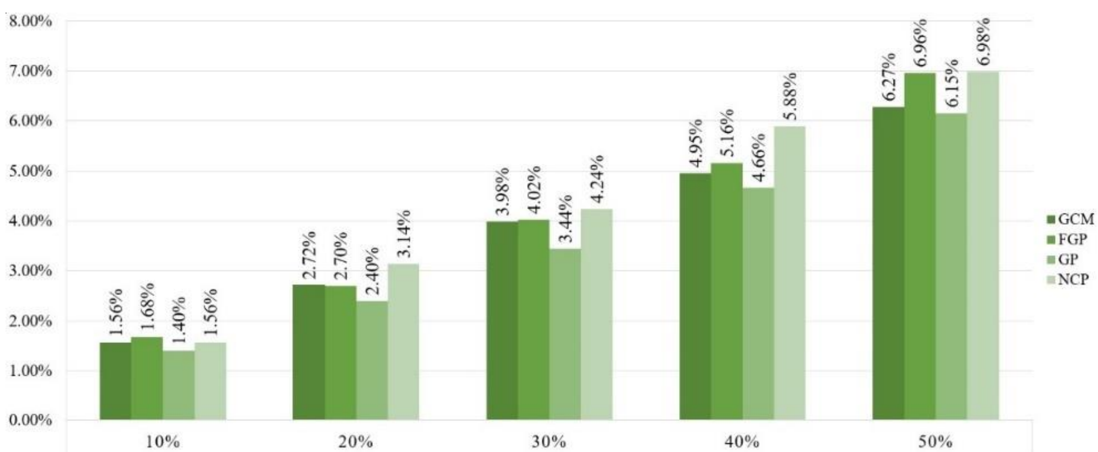

Figure 19. Percentage change in overall cost with the percentage increase in penalty cost of contagious population

3. The 10% increase in accommodation and medical costs for non-contagious populations (Figure 20) resulted in overall cost objective increases of 2.61%, 2.60%, 1.94%, and 2.64% for GCM, FGP, GP, and NCP, respectively. Similarly, a 10% increase for contagious populations (Figure 21) caused overall cost objective increases of 4.46%, 4.47%, 4.00%, and 4.52% for GCM, FGP, GP, and NCP, respectively. Those changes in accommodation and

medical costs of contagious populations impact the overall cost objective value more than non-contagious populations. The same is validated when accommodation and medical costs are further increased by 20%, 30%, 40%, and 50%. In general, the increase in accommodation and medical costs of the contagious population has caused a substantial rise in the value of the overall cost objective, making it more sensitive than the non-contagious population's accommodation and medical costs.

4. The cost of transportation, penalty, accommodation, and medical care is more sensitive for the contagious population than the non-contagious. Of all the six costs associated with the overall cost objective, accommodation and medical costs are the most susceptible, followed by transportation and the penalty.

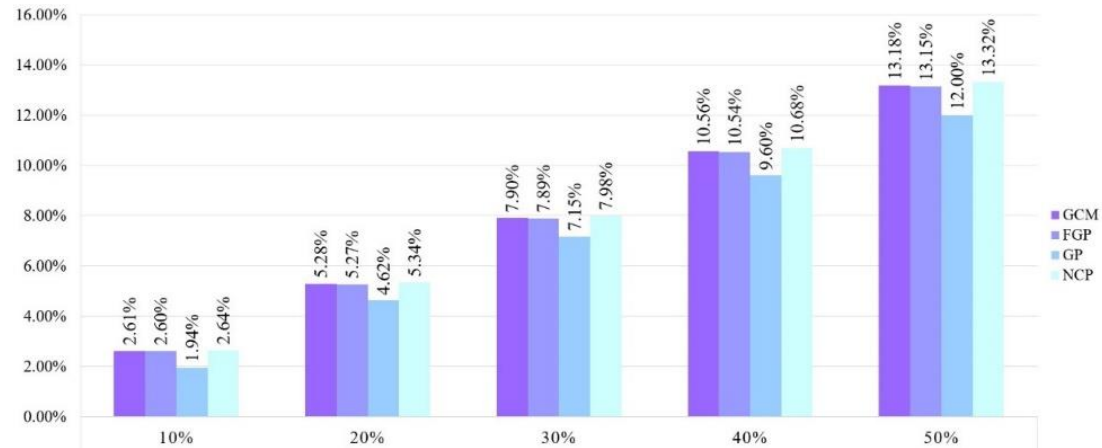

Figure 20. Percentage change in overall cost with the percentage increase in accommodation and medical cost of non-contagious population

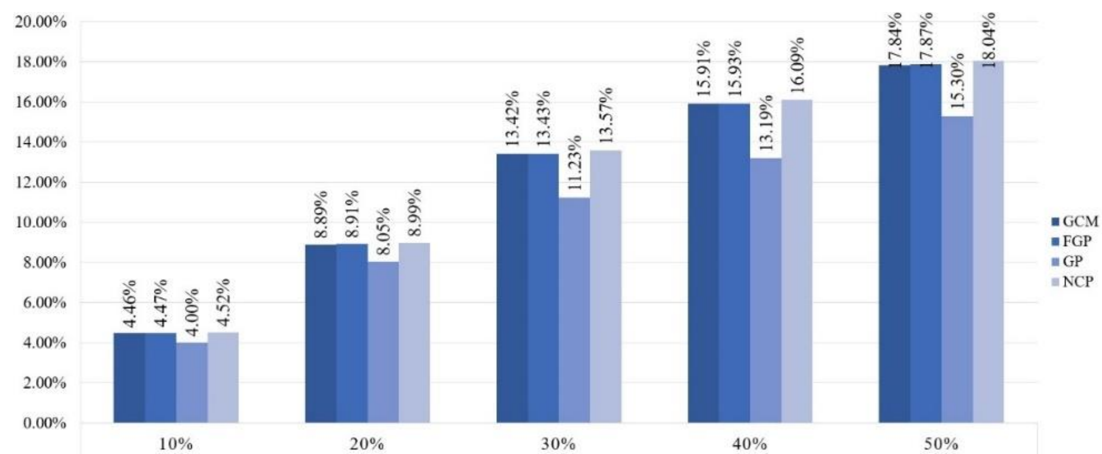

Figure 21. Percentage change in overall cost with percentage increase in accommodation and medical cost of contagious population

Following the above analysis, we concluded that accommodation and medical costs are more sensitive than transportation and penalty. In the pre-disaster phase, while choosing the relocation centers, the decision maker and the center's infrastructure should prioritize that relocation is done where accommodation and medical costs are fewer even though that site has slightly higher transportation or penalty costs. This will eventually decrease the overall cost of relocation. If the accommodation and medical costs are identical for all the RCs, then the decision maker should choose centers with fewer transportation and penalty costs. The cost aligned to the contagious population is more sensitive than non-contagious. Given the choices of RCs and type of conveyance, the decision maker must prioritize the selection based on the cost for contagious than non-contagious (without compromising the safety and comfort of the affected population). Even if some centers or conveyance have a higher cost for contagious and slightly lower costs for non-contagious, those must also be avoided.

The sensitivity analysis is carried out based on the components of the overall cost objective. We have neglected the time objective function in this analysis. However, there may be instances where the cost of accommodation and medical to RCs is low, but the time taken to reach that center is high. So, in that case, the decision maker can choose relocation centers based on their preferences. Suppose more priority is given to minimizing the cost of the relief operation. In that case, the decision maker must prefer centers with the lower cost of accommodation and medical, transport, and penalty, giving less priority to time objective and vice-versa.

8. MANAGERIAL INSIGHTS

The case study has yielded significant managerial insights through its numerical experiments, which offer valuable implications for relocation plans of affected populations. By prioritizing the reduction of total costs and time, this study can enhance the efficiency and effectiveness of disaster response operations, providing decision-makers with the necessary tools for informed decision-making. Based on the numerical outcomes, several key findings have been proposed below:

1. Given the paramount importance of expeditious and secure relocation for contagious and non-contagious populations, selecting a suitable solution method can profoundly impact cost and time. As illustrated in Section 7, NCA provides the optimal solution for MOSTM compared to GP, FGP, and GCM. By choosing NCA as the preferred solution method, managers can minimize the overall cost and time required for relocation, enabling effective resource allocation and ensuring the safety and well-being of affected populations.
2. To minimize casualties and prevent the proliferation of contagious diseases, swiftly relocate affected populations within an expected time frame. As outlined in Section 7.3.1, incorporating a penalty cost function into the relocation process can offer several benefits, including reducing overall relocation time. For managers, integrating a penalty cost function into the objective function can mitigate disease spread, promote social cohesion, and enhance resource access.
3. Although technological advancements and accurate weather forecasting can sometimes aid in predicting the magnitude of damage caused by disasters, there are instances where the intensity of a disaster may be unpredictable, resulting in a deviation from the expected number of casualties. Consequently, there are two possible scenarios depending on the prediction of post-disaster repercussions.
    a. In the first scenario, given this uncertainty, managers can prepare for disasters during the pre-disaster phase by arranging adequate vehicles, assuming that predictions align with post-disaster data. Section 7.3.2 highlights the benefits of arranging ample conveyances, such as reduced relocation time, prompt relocation, and decreased incidence of post-traumatic stress disorder, emotional instability, sleep disturbances, anxiety, and depression.
    b. In the second scenario, where disaster repercussions differ from predicted estimations, a more realistic approach to the relocation model can be achieved by including limited working time. This approach provides authorities waiting at temporary relocation centers with better estimations of affected populations' arrival and settlement time. It enables them to pre-arrange medical aids and basic amenities at the respective centers.
4. In relocating, the influence of cost sensitivity on managerial decision-making holds significant implications. The insights outlined in Section 7.4 highlight two critical considerations for managers:
    a. Accommodation and medical costs are more sensitive than transportation and penalty costs. Hence, to reduce relocation expenses, managers are advised to concentrate on choosing sites or temporary housing with lower Accommodation and medical costs, even if transportation and penalty costs are slightly elevated.
    b. The analysis further underscores that the cost of relocating contagious individuals is more susceptible than that of non-contagious individuals. To minimize relocation costs effectively, managers should prioritize the selection of temporary housing and transportation options tailored to the needs of the contagious population.

9. CONCLUSION AND FUTURE WORK

This research paper presents a MOSTM for relocating both contagious and non-contagious populations in the post-disaster phase. The model's primary objective is to minimize the costs and time required for population relocation, including transportation, penalty, accommodation, and medical expenses. In contrast, the time objective aims to reduce transportation and accommodation time, along with conveyance haul, refueling, and maintenance time. The mathematical model considers separate conveyances to ensure a seamless, contactless relocation process for contagious and non-contagious populations. The proposed solution employs a fuzzy input approach using SVHNN to accommodate the uncertainty present in post-disaster input data. A new defuzzification technique called RRAM is introduced to convert fuzzy inputs into crisp values, and its effectiveness is validated by comparing it to existing literature. The solution is obtained using compromise techniques, such as GP, FGP, GCM, NCA, and the LINGO optimization software. A case study was conducted on the Assam flood in 2020, one of the most flood-prone states in India, to demonstrate the effectiveness of the proposed MOSTM.

The particular cases involving the removal of penalty costs and limited working time are investigated. The removal of penalty cost delineates the significant increase in the relocation time and marginal decrease in the cost objective, thus representing its significant importance in the objective function. The limited working time removal showcases a significant decrease in the relocation time and a minor increase in the relocation cost. It further delineates that if the government and private agencies involved in the relocation process give more importance to the timely relocation of the affected population and can withstand the minor increase in the cost of relocation, then they can prearrange an ample number of conveyances to decrease the relocation time. Further, a particular case involving the solution of proposed MOSTM using the existing RAM and proposed RRAM is done to show the efficiency of the proposed defuzzification technique. A sensitivity analysis of the cost objective divulges that accommodation and medical costs are more sensitive than transportation and penalty costs. Furthermore, it is ascertained that transportation, penalty, accommodation, and medical costs are more sensitive for the contagious population than the non-contagious. Finally, the study provides managerial insights that aid in making better decisions and devising effective measures for potential future disasters.

In response to the escalating occurrence of both natural and man-made disasters, the proposed MOSTM offers an effective solution for the relocation of affected populations. Utilizing the LINGO optimization solver, the MOSTM facilitates swift decision-making by providing optimal solutions, specifying the number of individuals to be relocated from distinct sources to designated relief centers, and outlining the appropriate mode of transportation. The MOSTM addresses many constraints, capturing the complexities of real-life scenarios post-disaster. Given the uncertainties in post-disaster data, the suggested defuzzification technique for SVHNN emerges as a proficient approach to confront this challenge. The combined use of the MOSTM and the defuzzification technique not only aids decision-makers in overcoming the hurdles associated with post-disaster relocation but also effectively addresses the simultaneous transportation of contagious and non-contagious populations to relief centers. The successful real-world implementation of the MOSTM and the defuzzification technique is a significant milestone, paving the way for decision-makers to consider their application in response to various types of disasters.

Considering the research's future perspective, a MOSTM involving a two-stage relocation process can be proposed. Since the initial phase of the disaster, the number of affected populations spread along the affected areas. Thus, the first stage can include the transportation of contagious and non-contagious populations to temporary campsites near the affected areas. The second stage will include relocating campsites to the relocation centers. The model can also incorporate efficient relocation strategies to minimize the carbon footprints in the relation process. We can incorporate the relief distribution to the relocation centers along with humanitarian relocation models. The study can be further extended to other uncertain environments like type-2 fuzzy, stochastic, and probabilistic.

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