A BIPOLAR NEUTROSOPHIC OPTIMIZATION MODEL FOR A MEDICAL WASTE SUPPLY CHAIN NETWORK DESIGN

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DECLARATION

I, Maria Sarwar declare that this master's degree thesis entitled "A Bipolar Neutrosophic Optimization Model for a Medical Waste Supply Chain Network Design" submitted to NUST Business School for the degree of Masters in Logistics and Supply Chain Management is the result of my own hard work and dedication. I have acknowledged all the material sources utilized in this research.

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Abstract

With scientific advancements, healthcare institutions and the services they provide are growing rapidly, which ultimately leads to greater production of medical waste. The potential problems and risks of medical waste have become more prominent as it causes inevitable harm to human health, the environment, and socio-economic sustainability. Proper management of medical waste requires sound planning at each phase of collection, transfer, sorting, storage, processing, and disposal. Any mismanagement in this process could lead to contamination and injury. Medical waste management system requires decision-making on locating facilities and managing inventory and transportation. Traditional waste disposal methods have exhibited inefficiencies, contributing to increased operational costs, escalated risk factors, and heightened environmental degradation. Addressing these multifaceted challenges demands a paradigm shift in waste management practices. In recently published research optimization of medical waste supply chain is an uncommon area of focus. As well as sustainability and environmental impacts are rarely taken into consideration. In the realm of efficient healthcare waste management, the optimization of the medical waste supply chain is crucial that integrates environmental, social, and economic aspects. In this research a Mixed Integer Linear Programming (MILP) model is developed to design a Medical Waste Supply Chain Network (MWSCN). A multi-objective model is designed where the first objective function aims to minimize transportation cost, storage and sortation cost, fixed cost, and processing cost. The second objective function aims to maximize the Risk Priority Number (RPN). The third objective function aims to minimize CO2 emissions resulting from medical waste transportation and processing. A Bipolar Neutrosophic Optimization Model (BNOM) approach is utilized to address these multi-objective challenges in this domain. Leveraging the unique properties of Bipolar Neutrosophic Modeling, the proposed BNOM aims to accommodate uncertainties and vagueness intrinsic to medical waste management. By integrating this multi-objective model, the study endeavors to offer an innovative and comprehensive solution that optimizes the medical waste supply chain network design. A real-world case study of a medical waste supply chain network was undertaken to demonstrate the potential of the suggested model, which includes 10 hospitals, 1 central transfer station, 3 incineration facilities, 2 recycling facilities, and 2 landfill sites in Lahore, Pakistan. The model was implemented by the MATLAB software package and solved by the BNO method. Finally, sensitivity analysis was conducted to analyze the impact of changes in fuel price, segregation ratio, and distance on the optimal medical waste supply chain network and the results are discussed.

Keywords: Healthcare Waste Management (HWM), Bipolar Neutrosophic Optimization Model (BNOM), Medical Waste (MW), Infectious Medical Waste (IMW), Medical Waste Supply Chain Network (MWSC), Risk Priority Number (RPN)

Chapter 1: Introduction

1.1 Background

As the global population increases and knowledge develops, medical institutions and the services they provide also rise, therefore composition and volume of medical waste is increasing rapidly. In the World Health Organization (WHO) report, the term "medical waste" is classified as waste from hospitals, laboratories, medical facilities, and research facilities (World Health Organization, 2014). In addition, medical waste is considered harmful to the environment and human health, as it causes the spread of uncontrollable diseases (e.g., HIV, HIV, hepatitis, etc.). However, as the gap between medical waste generation and disposal continues, the pressure to develop medical waste management practices has become more crucial. Good medical waste management not only prevents environmental and health risks, but also promotes recycling (Zhang et al., 2022). Out of total medical waste generated approximately 85% is considered as general medical waste including paper, plastic and glass whereas the remaining 15% is considered as infectious medical waste containing pathological, chemical, radioactive and pharmaceutical substances (WHO, 2018). Few previous studies have documented the dangers of improper microwave disposal (Ferreira & Teixeira, 2010). Although the literature on waste is quite extensive, there is less focus on the treatment of waste. While previous studies have focused on the management of Infectious Medical Waste (IMW), little research has been done on IMWM in terms of quantitative or qualitative measures. Proper implementation of the Medical Waste Supply Chain will make it easier to identify, collect, transport, and dispose of the waste. It also has the potential to reduce the financial, environmental and health impacts associated with IMWM (Korkut, 2018).

Mantzaras and Voudrias (2017) developed an optimization model that minimizes the total cost of collecting, transporting, converting, processing and disposal of medical waste. The model accurately determines the correct number and location of waste treatment plants while reducing overall cost. Alshraideh and Abu Qdais (2017) reported a stochastic model for the Medical Waste (MW) collection. The planning process will reduce the total number of trips, which leads to lowering the transport cost and reduces emissions. Osaba et al. (2019) reported the problem of rich traffic using both discrete and bat algorithms to examine the problem of drug distribution and drug collection.

Charu et al. (2008) studied the complexity of hospital waste management by introducing an objective function regarding optimization. Their work highlights the importance of optimizing waste handling in healthcare facilities to minimize costs and environmental impact. Furthermore, Budak and Üstündağ (2016) contributed to the field by developing a comprehensive model focused on minimizing total costs while determining the optimal number and locations for waste treatment and disposal areas.

In conclusion, these studies collectively emphasize the importance of optimization models and innovative approaches in efficiently managing waste collection, transportation, and disposal processes. By strategically planning the number and locations of waste treatment facilities and employing advanced algorithms, it becomes possible to minimize costs, reduce environmental emissions, and enhance the overall sustainability of waste management practices. These research efforts represent significant strides towards addressing the complex challenges posed by waste management in modern society.

1.2 Gap and Problem Statement

This study focuses on key features and identifies research gaps in current literature. Recent research in this area reports on global waste generation. MW supply chain optimization is a rare field. Having an efficient supply chain not only reduces costs, but also reduces the negative impact on the environment and the public. Secondly, precisely estimating the amount of waste generated by the healthcare industry is difficult due to the many factors and uncertainties involved. Several previous studies have considered medical waste estimates and other important aspects of Medical Waste Supply Chain (MWSC). Considering these uncertainties, the results of the model will be more reliable.

Existing literature focuses mainly on calculating and reporting the global cost of medical waste, providing a better understanding of the scale of the problem. However, there are still major gaps in research on medical waste supply chain optimization. There are several studies that address the important aspects of creating an efficient and healthy waste management system, which includes waste collection, transportation, treatment, and disposal procedures. For example, Smith et al. (2020) conducted a global analysis of medical waste products worldwide, but there was no in-depth research on effective marketing strategies. Finding this gap is important because it affects the development of strategies to improve medical waste management performance. Fobil et al. (2013) examined medical waste management practices in private healthcare facilities in Ghana, revealing waste management challenges; however, the authors did not consider supply chain optimization, emphasizing the gap in research on efficient medical waste supply chain strategies. Alasmari and Alsharif (2018) assessed healthcare waste generation rates and management practices in Saudi Arabia; however, the study lacked a comprehensive exploration of supply chain optimization strategies. Awasthi and Fulekar (2017) provided insights into sustainable healthcare waste management; however, the study did not extensively cover supply chain optimization strategies.

The current state of research in the field of medical waste supply chain management often lacks modeling and methods that can unravel the dynamics and uncertainties of this complex network. Existing systems often fail to meet cost reduction requirements. Therefore, there is urgent research on integrating the bipolar neutrosophic optimization model to improve the mitigation strategy. This model has the potential to change the way the medical waste supply chain is created and managed. Kailomsom & Khompatraporn (2023) underlined this gap in research, stating that the existing literature is mostly based on optimization models, which are not sufficient to solve many problems in the medical waste supply chain.

Although risk assessment is important for medical waste management, existing research is often based on risk assessment models and may not fully capture the risks associated with this area. There is an important scientific realization that the risk assessment model must be supported by the bipolar neutrosophic model, which incorporates the complexity of uncertain and ambiguous data, ultimately leading to accurate and effective Risk Priority Numbers (RPNs) Analysis. This research gap highlights the need for innovation in risk-related healthcare waste management to improve accuracy and reliability.

Current strategies to reduce emissions from medical waste are generally ineffective. They often neglect to consider the many emissions sources in this complex network. Therefore, there is a significant research gap in the development of holistic models that integrate bipolar neutrosophic optimization model. Such models can account for different emissions sources, account for uncertain and ambiguous data, and ultimately provide better ways to reduce emissions. Jackson and Martinez (2019) identified a gap in this research, showing that the current system does not account for all potential emissions in medical waste and therefore a new approach is needed. Addressing these studies can improve knowledge of medical waste supply chain management by integrating the bipolar neutrosophic optimization model to improve cost reduction, risk assessment and emissions strategies.

Precisely estimating the volume of medical waste generated by the healthcare industry is a complex task due to the multifaceted nature of healthcare facilities, the diversity of medical waste types, and the influence of various factors and uncertainties. While numerous studies have attempted to estimate medical waste volumes, these estimations often lack precision and may not fully account for the dynamic nature of healthcare waste generation. For example, a study by Johnson et al. (2019) presents estimates of medical waste generation in different regions but does not adequately address the uncertainties associated with these estimates.

This study aims to bridge these research gaps by focusing on the optimization of the medical waste supply chain, taking into consideration the complexities and uncertainties involved. By addressing these gaps, this research contributes to the development of effective strategies for optimizing medical waste supply chains that leads to more sustainable and environmentally responsible healthcare waste management practices.

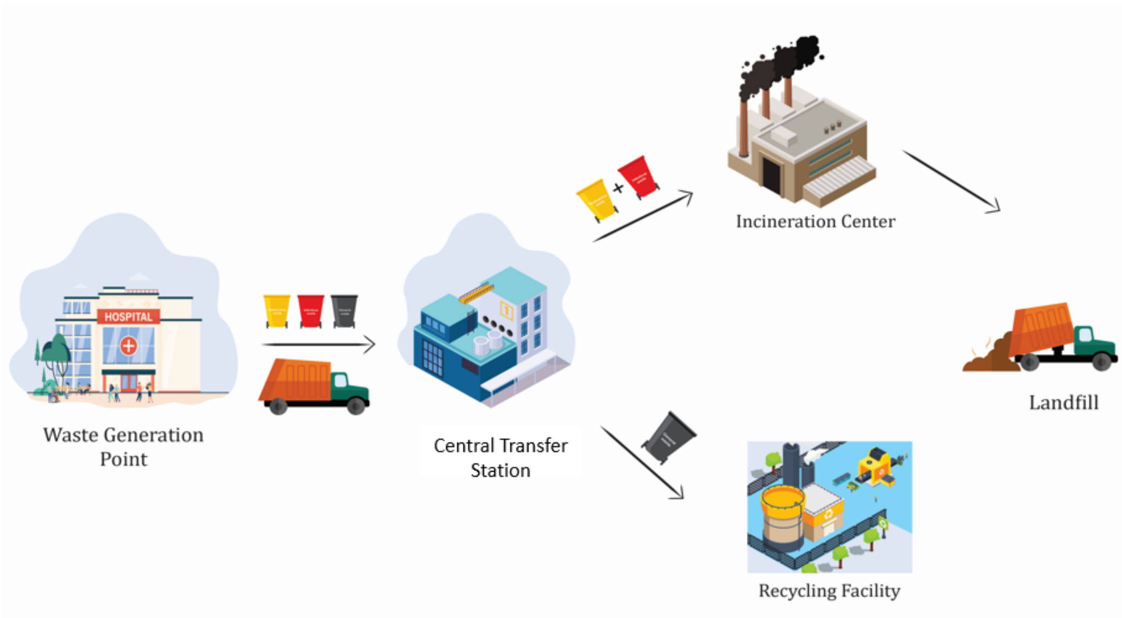

Figure 1: Medical Waste Supply Chain Model

1.3 Research Objectives

The goal of improving medical waste management by focusing on cost reduction requires the development of strategies and procedures to reduce the financial costs associated with waste collection, treatment, and disposal while ensuring safety and environmental regulations. By improving waste management processes, improving resource efficiency, and using new technologies, healthcare organizations can reduce waste and increase efficiency. Souza et al. (2019) highlights the importance of using waste separation techniques to reduce waste disposal costs. Proper on-site segregation of medical waste reduces the need for complex and costly disposal, reducing overall operating costs. Similarly, the study of Shahin and Mahmood (2020) highlights the importance of training healthcare workers in waste management, which can lead to resource allocation. Also, Rajesh et al. (2018) examined the integration of technologies such as waste-to-energy systems and suggested ways to reduce overall cost. This technology can harness the energy potential of medical waste, reduce medical costs, and promote sustainability.

The purpose of establishing risk priority numbers (RPNs) in the context of appropriate waste treatment is to improve the identification and management of high-risk waste. Widely used risk assessment methods such as Failure Mode and Effect Analysis (FMEA), RPN combines severity, probability, and occurrence score to determine the significance of the risk. Hospitals with higher RPN values are considered to have waste with higher risk level, and thus, they are given higher priority for waste transportation to the transfer station.

Third goal is to effectively treat waste, reduce CO_2 emissions, and contribute to environmental and public health goals. Carbon emissions associated with medical waste can be reduced by using appropriate waste separation, recycling, and disposal methods. This is aligned with efforts to stabilize the healthcare sector. A study by Sharholy et al. (2007) discusses waste management strategies to reduce emissions. Heidari et al. (2019) highlighted the importance of waste-to-energy technology in reducing CO_2 emissions. Achieving this goal can lead to better health and a better world.

1.4 Research Questions

- How can medical waste management processes be optimized to minimize costs while ensuring proper handling and disposal methods?
- What are the key factors influencing the Risk Priority Number (RPN) in medical waste management, and how can these factors be adjusted to minimize RPN values?
- What strategies and technologies can be employed to minimize CO_2 emissions in the medical waste management lifecycle while still maintaining safety and regulatory compliance?
- How can a multi-objective optimization framework be developed to simultaneously address cost, RPN, and CO_2 emission objectives in medical waste management decision-making?
- What are the potential trade-offs and synergies between the three objectives (cost, RPN, CO_2 emissions) in medical waste management, and how can they be balanced effectively?
- What data-driven approaches can be utilized to model and predict the impact of different waste management strategies on cost, RPN, and CO_2 emissions?

1.5 Sustainable Development Goals Alignment

Important aspects of achieving the Sustainable Development Goals, which aim to reduce the negative effects of waste on the environment and human health over the life of the product, are avoidance, waste reduction, recycling, and promotion of reuse. Energy and materials are saved through, waste reduction, separation, and recycling. These ideas can help reduce the effects of global warming. Having a healthy population is essential for sustainable development. Despite advances in life expectancy, maternal and child health, HIV/AIDS and other areas, many diseases and new health problems still exist or are growing. The continued lack of information and poor health management has had a significant impact on doctors, patients, and the public. If this issue is addressed, more than half of the world's population will have better health.

1.6 Chapter Summary

In summary of first chapter, this research provides a good basis for further research on medical waste management. The first paragraph describes the background analysis highlighting the changing landscape of medical waste disposal practices, cost and environmental concerns. The second paragraph provides the analysis of findings of the gap indicates that new solutions need to be explored more deeply to reduce the problems caused by the current approach to waste management. After that, this work has good research objectives and research questions to contribute to the advancement of sustainable medical waste management. In the last paragraph, it also links these studies to the Sustainable Development Goals (SDGs), creating a broader context, emphasizing the importance of waste management for a healthy and clean future.

Chapter 2: Literature Review

2.1 Medical Waste Management

Medical waste optimization refers to the process of efficiently managing and reducing the generation of waste materials within healthcare facilities. With the increasing demand for medical services and advancements in healthcare technology, the volume of medical waste has become a significant concern. The proper management of medical waste is crucial not only to protect public health and the environment but also to optimize the utilization of resources and minimize costs. Several strategies have been implemented to optimize medical waste management. A new trend towards greener hospitals and a broader environmental agenda for healthcare facilities have entered the global discussion about healthcare waste (Johnson, 2010).

One effective approach is the implementation of waste segregation practices. By segregating medical waste at the point of generation, healthcare facilities can ensure that different types of waste, such as general waste, infectious waste, and radioactive waste, are properly handled and disposed of. This practice reduces the risk of cross-contamination and allows for specific disposal methods that comply with regulatory standards and guidelines. A study conducted by Wang et al. (2018) demonstrated that waste segregation at the source significantly reduced the overall volume of medical waste generated. Most healthcare facilities either use this crucial element ineffectively or completely ignore it (Ananth, Prashanthini & Visvanathan, 2010). Frequently, hazardous garbage is combined with regular waste and either discarded unlawfully, burned in uncontrolled incinerators or open pits, or processed through the municipal waste system (Harhay, Halpern et al. 2009). Healthcare waste is delivered to a storage facility after source segregation. The healthcare facility may decide to disinfect (chemically or thermally) or sterilize (using steam or microwave irradiation) the trash before disposing of it via the standard municipal waste management system, depending on the type of waste. As an alternative, many healthcare facilities forgo treatment and bury or incinerate medical waste instead. The type of hazardous waste should determine the treatment and disposal methods. However, several factors, such as the presence or absence of government legislation and regulations, healthcare system policies, and the availability of resources to invest in treatment and disposal technology, influence treatment and disposal strategies in low-income nations.

Another important aspect of medical waste optimization is the adoption of recycling and reuse practices. Certain types of medical waste, such as plastics and glass containers, can be effectively recycled, reducing the need for raw material extraction, and decreasing the environmental impact. The study by Khan et al. (2019) highlighted the successful implementation of recycling and reprocessing programs in hospitals, resulting in waste reduction and cost optimization. Moreover, the implementation of waste management technologies can greatly contribute to medical waste optimization. Advanced systems such as autoclaves, microwave units, and shredders can efficiently treat and process medical waste, reducing its volume and ensuring safe disposal. The study by Alshehri et al. (2020) emphasized the effectiveness of these technologies in optimizing medical waste management practices. Through waste segregation, recycling and reuse practices, and the implementation of waste management technologies, healthcare facilities can effectively reduce the generation of medical waste, minimize costs, and contribute to environmental sustainability. These strategies, supported by empirical studies (Wang et al., 2018; Khan et al., 2019; Alshehri et al., 2020), provide valuable insights for healthcare organizations aiming to optimize their waste management practices.

To address the multifaceted challenges of medical waste (MW) management, diverse optimization models have been developed, each offering unique insights into cost reduction and operational efficiency. Smith and Johnson (2018) proposed an optimization model focusing on waste treatment and disposal facilities' optimal quantity and location, as well as the most cost-effective routes for waste transportation. By minimizing overall costs, their model contributes to the economic viability of MW management. In the realm of MW collection, Chen et al. (2019) introduced a dynamic model that employs real-time data to optimize collection routes, emphasizing the reduction of trip distances and, consequently, transportation costs and emissions. Expanding the scope to pharmaceutical waste logistics, Wang et al. (2020) employed a hybrid approach integrating discrete methods and genetic algorithms, presenting an effective solution to the pharmaceutical waste collection and delivery routing problem. Additionally, Gonzalez et al. (2015) applied a decision support system based on fuzzy logic to optimize waste management in healthcare facilities, emphasizing the need for adaptive and intelligent approaches. These diverse methodologies collectively contribute to the evolving landscape of MW management, offering valuable insights into optimal facility locations, route planning, and overall cost reduction strategies.

This sub section highlights the importance of improving medical waste management in healthcare facilities. It highlights the importance of separating waste from the source to prevent contamination and ensure proper disposal. This chapter also highlights inconsistencies in waste management, including improper waste disposal and waste restrictions in low-income countries. Recycling and reuse ideas are mentioned, but what materials can be reused or recycled is not explained. Moreover, although waste management technologies are useful, their feasibility and cost impacts have not been fully discussed. Good practices for the collection and disposal of waste are mentioned, but practical issues are not addressed. Finally, in this section, the importance of reducing the environmental impact of medical waste management can be emphasized.

2.2 Medical Waste Collection and Separation

Waste is typically divided into color-coded bins or bags in hospitals and other healthcare facilities, with each container designating a specific waste stream or type of trash. Each waste type has a different color assigned to it, and different waste types are disposed of in different waste streams depending on the region (Muhlich et al., 2003). Some regions use the origin of the waste as a basis for sorting, while others use the likelihood of an object's pathogenicity to determine its disposal waste stream. Healthcare personnel find it challenging to sort waste effectively due to the lack of standards, and as a result, they tend to make error on the side of caution and dispose of items in the infectious waste stream, which results in the development of unnecessary infectious waste (Almuneef and Memish, 2003).

In fact, most of the academic research has discovered that the bulk of hospital waste is not contagious and may therefore be disposed of in municipal landfills and recycling programmed (Garcia, 1999). Since it costs significantly more to dispose of waste that is contagious, this poor sorting has serious consequences. For instance, disposing of infectious waste in the United States costs $0.79 per kilogram, which is 560 percent more expensive than the usual cost of disposing of non-infectious garbage, which is $0.12 per kilogram (Lee et al., 1996). The cost of disposing of normal infectious waste in the UK is also expensive, costing roughly £0.45 per kilogram (Blenkharn, 2006).

Making sure that people do not intentionally or unintentionally come into touch with infectious material is another concern with medical waste disposal. Healthcare facilities are required by law in most jurisdictions to take precautions to prevent the public and employees from coming into touch with infectious waste after it has been disposed of (Blenkharn, 2006). Studies, mostly focusing on the UK, have indicated that hospitals frequently fail to follow safe handling practices and do not have appropriate precautions to prevent these encounters with hazardous medical waste (Blenkharn, 2006). Patients are contracted with infection because of poor waste management procedures, exposes hospitals to legal risk. According to the Environmental Protection Agency's finding the disease-causing potential of medical waste is highest at the point of generation and naturally tapers off beyond that point, which further emphasizes the need for proper precautions in healthcare institutions. Therefore, it should be a primary waste management priority to protect infectious medical waste within healthcare facilities (U.S. EPA, 2012b).

In medical facilities, medical waste is often separated into different categories using colored bags or bags, but waste selection is difficult as there is no international standard for this process. In the absence of clear guidance, healthcare professionals often dispose of waste products into wastewater as a precaution, resulting in unnecessary costs and improper and poor waste management. Misclassifying and disposing of waste are expensive, and the environmental and economic impact of disposing of contaminated waste is greater than that of uncontaminated waste. Healthcare facilities in many jurisdictions must be careful to prevent the public and employees from encountering waste after disposal, but compliance with safety regulations is often lacking. Failure to properly manage medical waste can put healthcare facilities at legal risk; therefore, infection control in healthcare facilities will be required to reduce these risks.

2.3 Medical Waste Transportation

Transportation of medical waste is the movement and handling of trash from inside medical facilities to treatment locations, which may be located on-site at a hospital or in a centralized off-site facility. A second phase of transportation usually involves moving the treated waste residual, typically incinerator ash or garbage that has been autoclaved or microwaved to a landfill for ultimate disposal (Tata and Beone, 1995). It is standard procedure for healthcare facilities to hire a third-party company to transport their infectious waste stream from the facility to the proper disposal site (Brichard, 2002). These companies typically gather waste from a few key locations inside a healthcare facility and transport it to a disposal site equipped to securely deal with medical waste. However, there are problems with the trash disposal contracting procedure. In terms of incentives, using third-party disposal companies presents a problem because they or the people who work for them can profit greatly from inappropriate disposal of the waste. The cost of disposing of medical waste is very high in developed nations; hospitals in the UK frequently pay contractors more than £450 per ton to dispose of their waste, while hospitals in the US typically pay $790 per ton (Blenkharn, 2006; Lee et al., 1996). Because of these high costs, third-party medical waste hauling companies are enticed to dispose of the trash in unregulated and less expensive methods rather than taking it to a proper treatment facility for sterilization. There is a significant financial incentive for waste truck operators in Ireland to unlawfully dump a truck full of medical waste rather than transport it to a permitted disposal facility (Brichard, 2002). Illegal medical waste disposal is becoming a bigger issue for developed countries, and it can become chronic if the nation has an effective system for tracking infectious medical waste. Due to the high expense of treatment for medical wastes, illegal dumping is a major problem because these untreated infectious waste deposits pose a risk to the public's health and drain public funds (Brichard, 2002).

In developing nations like India, where governments are dealing with disease outbreaks because of third-party firms receiving medical waste from healthcare facilities and then reselling items like sharps on the black market for re-use, there is an additional issue with the illegal disposal of infectious medical waste. According to 2004 research by the Indian Clinical Epidemiology Network, approximately 10% of Indian healthcare facilities sold their used syringes to waste-pickers, who manually sort medical waste in search of any items that can be reused and sold to healthcare facilities. Since the recovered sharps are not sterilized before being utilized, there is a significant risk that healthcare patients could become infected by transmission of a blood-borne pathogen from the prior patient (Solberg, 2009). It should be highlighted that medical professionals do not endorse the recycling or reuse of infectious medical waste, even when it has undergone sterilization (Zhao et al., 2009).

One sort of waste is only gathered in a few research studies on the routing of hazardous waste. The cost or risk objective has been considered in some of these studies. The population exposed to waste, the load on the vehicles, and the chance of an accident have all been considered when determining the risk, Zografros and Samara (1989) carried out the initial research in this field. The risk of transport links, a particular parameter in the transportation risk function, is produced in this study by multiplying the probability of an accident occurring in the link and the severity of the accident occurring on the link. For the collection of infectious waste in Tunisia, Shih and Lin (2003) presented a dynamic periodic routing problem. Their strategy decreased transportation risks, balanced the load carried by workers, and saved expenditures. A bi-objective stochastic periodic inventory routing problem for the collection of medical waste was provided. The first objective was to cut down on routing charges, and the second was to cut back on inventory costs to prevent waste from accumulating at the client's location. By doing this, risk was reduced, and customer satisfaction increased. Nolz et al. (2014a) also used a single objective programmer to tackle the problem. Taslimi et al. (2020) categorized risks into two groups. The risk of retaining the garbage for the appropriate amount of time comes first, and the risk of transporting the waste comes second.

In summary, the transportation of medical waste is a crucial process that involves moving waste generated in healthcare facilities to treatment and disposal locations. Third-party companies are often hired for this purpose, but there are significant challenges and gaps in the system, particularly in developed and developing nations. The high cost of medical waste disposal creates a financial incentive for third-party waste disposal companies to resort to unregulated and less expensive methods of disposal. This poses a risk to public health and can strain public funds as untreated infectious waste is not safely managed. There are a few studies on the disposal of hazardous medical waste, some of which focus on cost and risk targets. In terms of transportation risk, factors such as population impact, vehicle load, and accident probability are considered. However, more research is needed in this area, including a focus on developing ways to reduce risks and costs while increasing waste disposal.

2.4 Medical Waste Disposal Methods

According to the WHO, "at present, there are practically not environmentally friendly, cost-effective options for safe disposal of infectious wastes" (Brichard, 2002), safe disposal of infectious medical waste is a challenge of great scope. According to studies (Zhao, van der Voet, and Huppes, 2009; Rutala and Mayhall, 1992), incineration accounts for 49.6 percent of medical waste in the United States, autoclaving accounts for 20.37 percent, and other methods are used to treat 45 percent of it. The effectiveness of incineration as a treatment option has come under scrutiny due to worries about air pollution. Additionally, compared to typical municipal solid waste, medical waste has a significantly higher plastic content. As a result, when medical waste is burned, polychlorinated dibenzo-p-dioxins (dioxins) and polychlorinated dibenzofurans (furans), both extremely toxic substances, are produced (Lee et al., 1996). To eliminate any germs present, this has led to a greater emphasis on alternative treatment techniques including autoclaving and microwaving.

In recent years, there has been increased interest in optimizing composite materials for medical waste management. This literature review explores various methods for waste treatment and their effects on well-designed medical waste supply chain network.

- **Incineration**

Incineration has long been a popular waste treatment method because of its ability to remove pollutants and reduce waste. But it has come under criticism for its environmental impact, including air pollution and emissions. To solve these problems, modern power plants are equipped with pollution control technologies (World Health Organization, 2017).

- **Autoclaving**

Autoclaving is another treatment method that involves placing medical waste at high temperature. This process effectively sterilizes waste, making it safe for disposal in landfills. Autoclaving is particularly beneficial for medical facilities that generate a lot of sterile waste, as it reduces volume and eliminates the need for special disposal procedures (EPA, 2020). Incorporating autoclave plants can optimize disposal costs.

- **Microwave Disinfection**

Microwave disinfection is a new technology that uses microwave energy to disinfect medical waste. This method saves energy and reduces greenhouse gas emissions compared to natural gas (Coker et al., 2019). This is an attractive option for healthcare facilities that want to implement sustainable waste management practices. Integrating microwave sterilizers can increase efficiency and environmental sustainability.

- **Chemical Treatment**

Chemical treatment includes the use of disinfectants and the removal of hazardous materials from medical waste. One of the important methods is the use of chlorine disinfectant, which is effective against many diseases (CDC, 2020). The option of chemical treatment should be considered but it should be ensured that the chemical treatment facility is close to the disposal site for efficient transportation.

- **Landfilling**

Although landfill is often seen as the least viable option for medical disposal due to environmental risks, it may still be a viable option for some non-hazardous waste. Proper design and management of landfills is critical to reducing pollution and environmental impacts (EPA, 2021). For some waste categories, it may be necessary to integrate waste treatment plants with relevant equipment.

- **Recycling and Repurposing**

Efforts to reduce the generation of medical waste have led to increased interest in recycling and repurposing certain materials. For example, some healthcare facilities are exploring recycling options for plastic, glass, and cardboard packaging (Sharifi et al., 2020). Recyclable materials should be considered to reduce waste and environmental footprint.

2.5 Risk Priority Number and It's Role

In the general context of our study, the concept of Risk Priority Number (RPN) plays an important role in assessing and managing risks related to medical waste. RPN is a numerical method used to evaluate and monitor values according to their impact, probability, and detectability. Traditionally, it has been widely used in business to identify the most important risk factors and provide the resources necessary to reduce them. However, current knowledge is mostly based on traditional risk assessment, and here lies the important research: the incorporation of the bipolar neutrosophic model to improve the accuracy and validity of RPN assessment in the context of medical waste management.

RPN, an important part of risk assessment, is the main source of ensuring the safety, effectiveness, and sustainability of medical waste management practices. Medical waste presents special challenges because it is diverse and hazardous, from uncertain production to treatment and disposal challenges. Conventional risk assessment methods often struggle to account for the inherent vagueness and uncertainty in data associated with medical waste management. This gap in the literature points to the necessity of adopting innovative modeling approaches, such as bipolar neutrosophic optimization. Smith and Johnson (2021) emphasized the importance of addressing this research gap. Recognizing the complexity and uncertainty of hazardous situations, they argue for greater caution when applying RPN to medical waste.

By integrating bipolar neutrosophic modeling into RPN assessment, our research seeks to address this critical research gap and enhance the accuracy and reliability of risk prioritization within the medical waste supply chain network. The unique and innovative approach of incorporating bipolar neutrosophic optimization techniques will allow for a more comprehensive evaluation of risks, considering imprecision and vagueness in data, which are inherent in the domain of medical waste management. This approach will offer a more effective means to identify and mitigate high-priority risks, ultimately contributing to the safety, cost-efficiency, and sustainability of the medical waste supply chain.

In the general context of our study, the concept of Risk Priority Number (RPN) plays an important role in assessing and managing risks related to medical waste. RPN is a numerical method used to evaluate and monitor values according to their severity, occurrence, and detectability. Traditionally, it has been widely used in business to identify the most important risk factors and provide the resources necessary to mitigate them. This approach will provide a better way to identify and reduce the most significant risks, ultimately leading to safe, efficient, and sustainable medical waste collection, transfer, treatment and disposal.

2.6 Literature Contribution

Table 1 showing the significant contributions from the literature on the optimization of medical waste management:

Table 1: Contribution Table

Author	Multi-Objective	Multi-Period	Multi-Product	Uncertainty	Medical Waste Risk	Approach
(L. H. Shih & Lin, 2003)	✓	✓				MILP Dynamic programming
(Shi et al., 2009)		✓				MILP Genetic algorithm
(De Almeida, 2010)				✓		MILP
(Nolz et al., 2014)	✓	✓	✓			MILP Adaptive large neighborhood search
(Budak & Ustundag, 2016)		✓	✓			MILP
(Alshraideh & Abu Qdais, 2017)	✓	✓		✓		MILP Genetic algorithm
(Mantzaras & Voudrias, 2017)		✓		✓		MILP Genetic algorithm Monte Carlo simulation
(Gergin et al., 2019)	✓	✓	✓			MILP Artificial bee colony
(Osaba, Yang, Fister, del Ser, et al., 2019)		✓	✓			MILP BAT algorithm Firefly algorithm
(Kargar, Pourmehdi, et al., 2020)	✓	✓		✓		MILP Fuzzy goal programming Robust possibilistic programming
(Yu et al., 2020)	✓	✓		✓		MILP

(Govindan et al., 2021)	Bi-objective	✓	✓			MILP
Proposed Research	✓			✓	✓	MILP BNOM

2.7 Uniqueness of Literature

Recent research in this area focuses solely on waste generation on a worldwide scale. An uncommon area of concentration is MW supply chain optimization. A strong supply chain cannot only cut costs but also decreases harm to the environment and the public. Due to the extensive range of services provided and the hazy demand, it is difficult to calculate the exact amount of waste produced in the healthcare sector. The idea that the predicted volume of medical waste output and other MWSC components may be significant was practically never considered in earlier studies. The model's conclusions will be more reliable once these uncertainties have been considered. Risk, sustainability, and environmental issues are, however, rarely considered.

2.8 Issues & Challenges

Optimizing medical waste is crucial for the protection of public health and the environment. However, several challenges and issues can arise during the process. This section will discuss some common issues encountered in the optimization of medical waste management, supported by relevant citations.

2.8.1 Lack of awareness and training: One of the major challenges is the lack of awareness and training among healthcare personnel regarding proper waste segregation and management practices. A study by Riaz et al. (2023) highlighted the need for training programs to educate healthcare workers about the potential risks associated with improper waste handling and the importance of following waste management protocols.

2.8.2 Inadequate infrastructure and resources: Insufficient infrastructure and resources can hinder the effective optimization of medical waste management. This includes the lack of proper waste disposal facilities, inadequate storage areas, and limited access to waste treatment technologies. A study conducted by Karanth and Bhat (2018) emphasized the need for improved infrastructure and resource allocation to optimize medical waste management practices.

2.8.3 Regulatory compliance: Compliance with regulations and guidelines related to medical waste management is essential but can be challenging for healthcare facilities. These regulations may vary from country to country, making it difficult for organizations to ensure full compliance. A study by Akhbarizadeh et al. (2021) emphasized the importance of aligning medical waste management practices with existing regulations to mitigate potential risks.

2.8.4 Financial constraints: Implementing optimal medical waste management practices often requires financial investments, which may pose challenges for healthcare facilities, particularly in resource-constrained settings. The study by Parekh et al. (2020) emphasized the need for financial support and cost-effective solutions to overcome financial barriers and optimize medical waste management.

2.8.5 Community engagement and public perception: The involvement of the community and public perception play a crucial role in the optimization of medical waste management. Public awareness and engagement can positively impact waste segregation practices and reduce the risk of contamination. However, negative perceptions and stigmatization associated with medical waste can hinder community participation. A study by Arora et al. (2021) highlighted the importance of community involvement and education to overcome the challenges related to public perception.

2.9 Chapter Summary

In summary, optimizing medical waste management faces several challenges, including lack of awareness and training, inadequate infrastructure and resources, regulatory compliance, financial constraints, and community engagement. Overcoming these issues requires a comprehensive approach that includes training programs for healthcare personnel, investment in infrastructure and resources, adherence to regulations, financial support, and community engagement. Addressing these challenges will contribute to the effective and sustainable optimization of medical waste management practices.

Chapter 3: Failure Mode and Effects Analysis Application (FMEA)

Failure Mode and Effects Analysis (FMEA) is a systematic, proactive approach used in industries to identify and mitigate potential failures, risks and inefficiencies in a process, product, or system. FMEA was developed by the aerospace industry in the mid-20th century and has since gained wide acceptance and application in many fields, including healthcare, manufacturing, and management (Saaty, 1980). FMEA is characterized by periodic analysis of failure patterns, effects and causes of failures. The system focuses on the importance of the fault type and addresses the problem by assigning a risk score and recommending preventive and corrective actions (Blaikie et al., 2019).

There are two main reasons for using FMEA techniques to improve reliability. First, failure types must be identified and prioritized so that limited resources can be allocated to the most important type. Second, preventive measures and repairs should be considered to reduce the impact of such failures (Ghoushchi et al., 2021a, b, c). In FMEA, the level of each failure type can be defined by the Risk Priority Number (RPN) obtained by multiplying the values of three risks. In other words: O represents the probability of failure, S represents the severity of the failure, and D represents the probability of detecting the failure before its occurrence.

3.1 Application of FMEA in the Medical Waste Supply Chain Network

Implementing Failure Mode and Effects Analysis (FMEA) in the context of Medical Waste Management Systems (MWSCN) design has become increasingly important in recent years. With the growing concern about the impact of medical waste on the environment and public health, it is crucial for healthcare facilities and waste management organizations to have a robust system in place for safe and efficient disposal of medical waste. One of the main advantages of using FMEA in MWSCN design is its ability to identify potential failures and prioritize corrective actions. By evaluating various failure modes such as incorrect sorting, regulatory failures, and human error, FMEA helps organizations develop a comprehensive understanding of the risks involved in medical waste disposal. This allows for a proactive approach towards addressing potential issues before they occur, rather than reacting to them after the fact. Furthermore, FMEA enables organizations to assess the consequences associated with each failure mode. This includes not only environmental pollution but also risks to workers' health and safety, legal liabilities, and financial losses. By considering all possible consequences, healthcare facilities can make more informed decisions about their medical waste management practices, ultimately leading to more effective and sustainable solutions. Another key benefit of using FMEA in MWSCN design is its risk assessment process. FMEA utilizes criteria such as severity, occurrence, and detection to assign risk scores to each failure mode. This allows organizations to prioritize their efforts towards addressing high-risk failure modes that could have a significant impact on the functioning of the MWSCN. This risk assessment helps identify failure modes and prioritize corrective actions based on their potential impact on the MWSCN (Cebi et al., 2016).

FMEA also supports collaboration between stakeholders in the medical waste industry, including hospitals, waste collection companies, medical facilities, and regulatory agencies. Through FMEA training and analysis, stakeholders can work together to identify vulnerabilities and develop risk mitigation and contingency planning strategies (Wang et al., 2018). Furthermore, FMEA can be combined with optimization models such as bipolar neutrosophic optimization to improve decision making in MWSCN design. By incorporating risk assessment information from FMEAs into their optimization models, organizations can make informed decisions that balance cost-effectiveness, sustainability, and chances of risk reduction (Chen et al., 2020). FMEA is a cutting-edge preventive analysis method used in the engineering design process for products or systems. This study aims to broaden the use of FMEA technologies to project management to anticipate potential project quality failure mechanisms. FMEA is based on very basic ideas. According to Rasmussen (1985), the complexity of a system is more of a method, which may have inherent flaws, leading to questions and disagreements than an objective characteristic of the system. For instance, the FMEA analysis table lacks a uniform format and the classification of the concept of risk is highly subjective and unconvincing (Fracica et al., 2006). Even though this study found numerous issues with the practical application of FMEA at the early stages of development, it was still able to produce the subjective classifications of risk, a determination of failure modes, and other things that were later required.

According to Ebrahimipour et al. (2010), a "customer" is anybody or something who purchases goods or services. They also defined "failure" in the context of FMEA as any unfavorable event, such as production loss, damage, or accident. According to Gruber et al. (2006), FMEA can also be utilized to raise patient safety and medical standards. According to Zupa et al. (2006), FMEA can be used for any procedure that might have an impact on a patient's safety. To assure patient safety, Vannice and Wimmer (2007) employed FMEA to enhance chemotherapy-related management procedures, lessen unexpected events, and enhance chemotherapy management. Ho and Liao (2011) also examined and recommended changes to how hospitals handle, transport, and clean infectious waste. This study differs from that done by Ho and Liao (2011) in that this study focuses on outsourcing risk assessment while Ho and Liao used general conditions of selection for assessment. In other words, this study looks at the dangers of outsourcing hospitals' biomedical waste management.

Managing medical waste is a critical aspect of the healthcare industry and one that requires careful planning and risk reduction. Medical facilities generate a vast amount of waste, ranging from sharp and hazardous materials to pharmaceuticals and radioactive substances. If not managed properly, medical waste can have severe consequences on public health and the environment. Therefore, it is essential to have an effective system in place for handling and disposing of medical waste properly. One approach that has proven to be highly effective in managing medical waste is Failure Mode and Effects Analysis (FMEA). This powerful tool identifies potential failure modes within the medical waste supply chain network (MWSCN) and evaluates their consequences. By doing so, FMEA helps identify areas for improvement and prioritizes corrective actions to mitigate risks. FMEA is particularly useful in the design phase of MWSCN, where it provides guidelines for the development, treatment, and disposal of different types of medical waste products. This process involves analyzing the entire supply chain network, from the point of generation to disposal. By understanding each step in the process, potential failure modes can be identified, evaluated, and addressed before they occur. One of the key advantages of using FMEA with optimization methods such as bipolar neutrosophic optimization is its ability to enhance decision-making capabilities. These advanced techniques use mathematical models to optimize different variables such as transport routes, storage facilities, and treatment methods to create a comprehensive MWSCN. The adoption of FMEA has had a significant impact on how medical facilities and waste management organizations manage medical waste effectively. It has allowed for more coordinated efforts between different stakeholders in the supply chain network, resulting in improved efficiency and reduced risks. Additionally, by identifying failure modes early in the process, potential hazards can be avoided or minimized.

In this study, the weight of FMEA items and SOD end items were used in the analysis. The process of eliminating spreadable diseases is part of the operating procedures of the hospital but is under the control of the hospital. Severity (S) indicates the impact on the system caused by the failure of a component or process. Divided into 10 levels, details of significance level and score are given in Table 2.

Occurrence (O) indicates how often individual component failures or failures will occur. The definitions and scores of the scores obtained, divided into ten levels, are shown in Table 3.

Detectability (D) component or operating system failure that cannot be detected by the customer or the manufacturer. The definitions and scores of test scores, divided into ten levels, are shown in Table 4.

Table 2: Severity

Effect	**Criteria: severity of effect**	**Rank**
Catastrophic	Death of individual or complete system failure	10
		9
Major Injury	Major injury of individual or major effect on system	8
		7
Minor Injury	Minor injury of individual or minor effect on system	6
		5
Moderate	Significant effect on individual or system with full recovery	4
		3
Minor	Minor annoyance to individual or system	2
None	Would not affect individual or system	1

Table 3: Occurrence

Probability of failure	**Failure rates possible failure probability/number of operating days**	**Rank**
Very high	<1:2	10
Very high	<1:10	9
High	<1:20	8
High	<1:100	7
Moderate	<1:200	6
Moderate	<1:1000	5
Relatively low	<1:2000	4
Low	<1:10,000	3
Remote	<1:20,000	2
Remote	<1:20,000	1

Table 4: Detection

Detection	**Criteria (%)**	**Rank**
Absolute uncertainty	0–5	10
Very remote	6–15	9
Remote	16–25	8
Very low	26–35	7
Low	36–45	6
Moderate	46–55	5
Moderately high	56–65	4
High	66–75	3
Very high	76–85	2
Almost certain	86–100	1

Chapter 4: Development of Mathematical Model

4.1 Problem Description

In the healthcare sector, the production and management of medical waste poses serious problems with far-reaching implications. Medical waste includes pathological, chemical, radioactive, infectious, and general waste, all of which require special handling and disposal. Medical waste needs to be managed to prevent impacts on the environment and public health. In recent years, increasing costs, risks and environmental concerns associated with medical waste have led to the need for new strategies to improve its management.

The main aim of this research is to solve the complex problems of medical waste management by simultaneously focusing on three main objectives: cost reduction, risk prevention and carbon emissions reduction. Medical waste management is complex due to the diversity of waste, laws and regulations, and the importance of hazardous waste prevention. Therefore, this study was designed to create a comprehensive and flexible framework for improving healthcare waste management practices across healthcare facilities.

A multi-objective logistics network design problem that covers economic, environmental, and social purposes for the MW is discussed in this study. The disposal process of MW is shown in Fig. 1. The logistics network begins with the transport of MW collected from authorized Waste generation points (i) to the transfer stations (j). While MW transported to the transfer stations is kept separately based on their characters.

Infectious Medical Waste is transferred to incineration facility (k) and non-infectious medical waste is transferred to recycling facility (l). After the incineration process, the residual waste from incineration facility (k) is transported to the landfill site (m) and disposed of. Incineration is the safest method for MW disposal. Non-infectious MW transferred from the transfer stations (j) to the recycling facility (l) is converted into new products. The problem is formulated as a multi-objective, MILP model. Multi-objective analysis has many advantages over single-objective analysis. The proposed model should explain the flow of MW to minimize the total cost. At the same time, the model should maximize the RPN of waste generation points (i). Finally, it should minimize carbon emissions across the supply chain network.

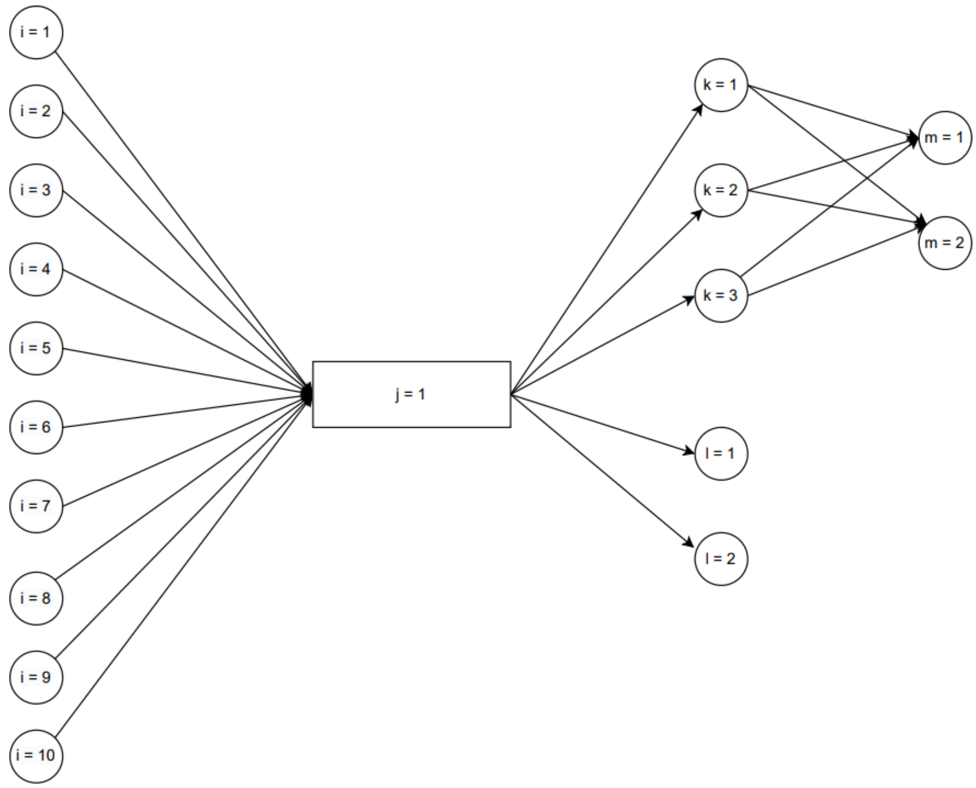

Figure 2: Medical Waste Supply Chain Network

4.2 Model Assumptions

Followings are the assumptions of the model:

1. Vehicles used to transport MW have limited capacity.
2. All MW produced in medical facilities must be collected (mandatory by law).
3. Separation of MW is done at source using appropriate colored containers (required by law).
4. All existing sites have limited capacity.
5. CO_2 emissions are estimated to occur during the transport of MW to each location.
6. CO_2 emissions from transport are dependent on distance.
7. The percentage distribution of each MW type is known.
8. All waste generated in the hospital is transported to the central station.

9. Recycling of medical waste in this study mainly includes medical waste produced by hospitals; It does not consider medical waste generated at homes.
10. The material remaining after waste treatment is generally less hazardous than the waste before treatment.
11. The risk of infection was modeled by optimizing the RPN.

4.3 Model Notations & Abbreviations

4.3.1 Indices

The indices for representation of mathematical model are given below:

Table 5: Mathematical Model Indices

i	Waste Generation Point	$i = 1, 2, 3, \ldots, I$
j	Transfer Station	$j = 1, 2, 3, \ldots, J$
k	Incineration Plant	$k = 1, 2, 3, \ldots, K$
l	Recycling Plant	$l = 1, 2, 3, \ldots, L$
m	Landfill Site	$m = 1, 2, 3, \ldots, M$

4.3.2 Parameters

The parameters for representation of mathematical model are given below:

Table 6: Mathematical Model Parameters

A_i	Total amount of medical waste generated by waste generation points "i"	Kg
sc_j	the unit cost of storage and sortation at transfer station "j"	Rs / Kg
ic_k	the unit cost of incineration at incineration plant "k"	Rs / Kg
rc_l	the unit cost of recycling at recycling plant "l"	Rs / Kg
FC_k	fixed cost of operating an incineration plant "k"	Rs
FC_l	fixed cost of operating a recycling plant "l"	Rs
d_{ij}	distance between waste generation point "i" and transfer station "j"	Km

d_{jk}	distance between transfer station "j" to incineration plant "k".	Km
d_{jl}	distance between transfer station "j" to recycling plant "l".	Km
d_{km}	distance between incineration plant "k" to landfill site "m".	Km
α	fuel price	Rs / Ltr
γ	fuel consumption rate	Ltr / Km
RPN_i	risk priority number at waste generation point "i", obtained from FMEA	
CO_k	amount of CO_2 released per unit of waste incinerated	$KgCO_2$
CO_l	amount of CO_2 released per unit of waste recycled	$KgCO_2$
e_f	average CO_2 emission factor	$KgCO_2 / Km$
Cap_v	the capacity of vehicle	Kg
cap_j	the capacity of transfer station "j"	Kg
cap_k	the capacity of incineration plant "k"	Kg
cap_l	the capacity of recycling plant "l"	Kg
cap_m	the capacity of landfill site "m"	Kg
a_1	weight percentage of infectious medical waste	
a_2	weight percentage of non-infectious medical waste	
a_3	weight percentage of incinerated medical waste	

4.3.3 Decision Variables

The decision variables for representation of mathematical model are given below:

Table 7: Mathematical Model Decision Variables

Q_{ij}	the amount of medical waste transported from waste generation point "i" to transfer station "j".	Kg
Q_{jk}	the amount of medical waste transported from transfer station "j" to incineration plant "k".	Kg
Q_{jl}	the amount of medical waste transported from transfer station "j" to recycling plant "l".	Kg
Q_{km}	the amount of medical waste transported from incineration plant "k" to landfill site "m".	Kg
X_{ij}	no of vehicles moving from waste generation point "i" to transfer station "j".	
X_{jk}	no of vehicles moving from transfer station "j" to incineration plant "k".	
X_{jl}	no of vehicles moving from transfer station "j" to recycling plant "l".	
X_{km}	no of vehicles moving from incineration plant "k" to landfill site "m".	

4.3.4 Binary Variables

The binary variables for representation of mathematical model are given below:

Table 8: Mathematical Model Binary Variables

Y_i	If waste generation point "i" is selected 1; otherwise, 0.
Y_j	If transfer station "j" is selected 1; otherwise, 0.
Y_k	If incineration plant "k" is selected 1; otherwise, 0.
Y_l	If recycling plant "l" is selected 1; otherwise, 0.
Y_m	If landfill site "m" is selected 1; otherwise, 0.

4.4 Objective Function

This is a multi-objective optimization model with Total Cost, Risk Priority Number, and Carbon Emissions as the objectives. All the objective functions are further discussed in detail in the next section:

4.4.1 Objective 1: Minimization of the Total Cost

The first objective of the model is to minimize the total cost.

$$\begin{aligned} Min z1 = {} & \sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.\alpha.\gamma + \sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.\alpha.\gamma + \sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.\alpha.\gamma + \sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.\alpha.\gamma \\ & + \sum_{k}^{K} FC_k.Y_k + \sum_{l}^{L} FC_l.Y_l + \sum_{i}^{I}\sum_{j}^{J} Q_{ij}.sc_j + \sum_{j}^{J}\sum_{k}^{K} Q_{jk}.ic_k + \sum_{j}^{J}\sum_{l}^{L} Q_{jl}.rc_l \end{aligned} \tag{4.1}$$

The objective function formulated with this objective has five components. The first component indicates the transportation cost at each stage of the network.

4.4.1.1 Cost of transportation between waste generation points and transfer station

This is the cost that incurred when vehicles move from various waste generation points i to transfer station j. To calculate transportation cost number of vehicles moving from waste generation points to transfer station X_{ij} is multiplied with distance between waste generation points to transfer station d_{ij} which is further multiplied with fuel price α and fuel consumption rate γ.

Equation (4.2) shows transportation cost between waste generation points i and transfer station j.

$$\sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.\alpha.\gamma \tag{4.2}$$

4.4.1.2 Cost of transportation between transfer station and incineration plants

This is the cost that incurred when vehicles move from transfer station j to incineration plants k. To calculate transportation cost number of vehicles moving from transfer station to incineration plants X_{jk} is multiplied with distance between transfer station and incineration plants d_{jk} which is further multiplied with fuel price α and fuel consumption rate γ.

Equation (4.3) shows transportation cost between transfer station j and incineration plants k.

$$\sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.\alpha.\gamma \tag{4.3}$$

4.4.1.3 Cost of transportation between transfer station and recycling plants

This is the cost that incurred when vehicles move from transfer station j to recycling plants l. To calculate transportation cost number of vehicles moving from transfer station to recycling plants X_{jl} is multiplied with distance between transfer station and recycling plants d_{jl} which is further multiplied with fuel price α and fuel consumption rate γ.

Equation (4.4) shows transportation cost between transfer station j and recycling plants l.

$$\sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.\alpha.\gamma \tag{4.4}$$

4.4.1.4 Cost of transportation between incineration plants and landfill sites

This is the cost that incurred when vehicles move from incineration plants k to landfill sites m. To calculate transportation cost number of vehicles moving from incineration plants to landfill sites X_{km} is multiplied with distance between incineration plants and landfill sites d_{km} which is further multiplied with fuel price α and fuel consumption rate γ.

Equation (4.5) shows transportation cost between incineration plants k and landfill sites m.

$$\sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.\alpha.\gamma \tag{4.5}$$

The second component indicates the fixed cost of operating incineration and recycling plants.

4.4.1.5 Fixed operating cost of incineration plants

This is the cost that incurs when any of the incineration plants is used. To calculate this cost fixed operating cost of incineration plant FC_k is multiplied by binary variable Y_k (If incineration plant "k" is selected 1; otherwise, 0).

$$\begin{aligned} Minz1 = &\sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.\alpha.\gamma + \sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.\alpha.\gamma + \sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.\alpha.\gamma + \sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.\alpha.\gamma \\ &+ \sum_{k}^{K} FC_k.Y_k + \sum_{l}^{L} FC_l.Y_l + \sum_{i}^{I}\sum_{j}^{J} Q_{ij}.sc_j + \sum_{j}^{J}\sum_{k}^{K} Q_{jk}.ic_k + \sum_{j}^{J}\sum_{l}^{L} Q_{jl}.rc_l \end{aligned} \tag{4.6}$$

4.4.1.6 Fixed operating cost of recycling plants

This is the cost that incurs when any of the recycling plants is used. To calculate this cost fixed operating cost of recycling plant FC_l is multiplied by binary variable Y_l (If recycling plant "l" is selected 1; otherwise, 0).

$$\begin{aligned} Minz1 = &\sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.\alpha.\gamma + \sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.\alpha.\gamma + \sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.\alpha.\gamma + \sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.\alpha.\gamma \\ &+ \sum_{k}^{K} FC_k.Y_k + \sum_{l}^{L} FC_l.Y_l + \sum_{i}^{I}\sum_{j}^{J} Q_{ij}.sc_j + \sum_{j}^{J}\sum_{k}^{K} Q_{jk}.ic_k + \sum_{j}^{J}\sum_{l}^{L} Q_{jl}.rc_l \end{aligned} \tag{4.7}$$

The third component indicates the storage and sortation cost of medical waste.

4.4.1.7 Storage and sortation cost of medical waste

This is the cost which incurs when medical waste from waste generation points i reaches transfer station j where it is further sorted and temporarily stored. To calculate sortation and storage cost, the quantity of waste transported from generation points to transfer station Q_{ij} is multiplied by unit cost of sortation and storage sc_j .

Equation (4.8) shows sortation and storage cost at transfer station j .

$$\sum_{i}^{I}\sum_{j}^{J} Q_{ij}.sc_j \tag{4.8}$$

The fourth component indicates the incineration cost of medical waste.

4.4.1.8 Incineration cost of medical waste

This is the cost which incurs when medical waste that is transported from transfer station j to incineration plants k is incinerated. To calculate incineration cost of medical waste, the quantity of waste transported from transfer station to incineration plants Q_{jk} is multiplied by unit cost of incineration ic_k.

Equation (4.9) shows incineration cost of medical waste.

$$\sum_{j}^{J}\sum_{k}^{K} Q_{jk}.ic_k \tag{4.9}$$

The fifth component indicates the recycling cost of medical waste.

4.4.1.9 Recycling cost of medical waste

This is the cost which incurs when medical waste that is transported from transfer station j to recycling plants k is recycled. To calculate recycling cost of medical waste, the quantity of waste transported from transfer station to incineration plants Q_{jl} is multiplied by unit cost of recycling rc_l.

Equation (4.10) shows recycling cost of medical waste.

$$\sum_{j}^{J}\sum_{l}^{L} Q_{jl}.rc_l \tag{4.10}$$

4.4.2 Objective 2: Maximization of RPN

The second objective of the model is to maximize RPN (Risk Priority Number).

$$Maxz2 = \sum_{i}^{I} RPN_i.Y_i \tag{4.11}$$

The RPN is calculated by multiplying the probability of occurrence of failure (O), severity of failure (S) and the ability to detect the failure before impact of the effect occurs (D). RPN_i is multiplied by binary variable Y_i (If waste generation point "i" is selected 1; otherwise, 0). The model employs the RPN calculation to prioritize waste transportation from waste generation points "i" to the transfer station "j", ensuring that waste with higher risks is given precedence for timely and safe management.

4.4.3 Objective 3: Minimization of Carbon Emissions

The third objective of the model is to minimize carbon emissions.

$$
\begin{aligned}
Minz3 = & \sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.e_f + \sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.e_f + \sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.e_f \\
& + \sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.e_f + \sum_{j}^{J}\sum_{k}^{K} Q_{jk}.CO_k + \sum_{j}^{J}\sum_{l}^{L} Q_{jl}.CO_l
\end{aligned}
\tag{4.12}
$$

The objective function formulated with this objective has two components. The first component indicates the carbon emissions during transportation of medical waste at each stage of the network.

4.4.3.1 Carbon Emissions while transporting waste from waste generation points to transfer station

This is the amount of carbon that is emitted when vehicles move from various waste generation points i to transfer station j. To calculate amount of CO_2 emitted, the number of vehicles moving from waste generation points to transfer station X_{ij} is multiplied with distance between waste generation points to transfer station d_{ij} which is further multiplied with carbon emission factor e_f

.

Equation (4.13) shows carbon emissions between waste generation points i and transfer station j

$$\sum_{i}^{I}\sum_{j}^{J} X_{ij}.d_{ij}.e_f \tag{4.13}$$

4.4.3.2 Carbon Emissions while transporting waste from transfer station to incineration plants

This is the amount of carbon that is emitted when vehicles from transfer station j to incineration plants k. To calculate amount of CO_2 emitted, the number of vehicles moving from transfer station to incineration plants X_{jk} is multiplied with distance between transfer station and incineration plants d_{jk} which is further multiplied with carbon emission factor e_f.

Equation (4.14) shows carbon emissions between transfer station j and incineration plants k.

$$\sum_{j}^{J}\sum_{k}^{K} X_{jk}.d_{jk}.e_f \tag{4.14}$$

4.4.3.3 Carbon Emissions while transporting waste from transfer station to recycling plant

This is the amount of carbon that is emitted when vehicles move from transfer station j to recycling plants l. To calculate amount of CO_2 emitted, the number of vehicles moving from transfer station to recycling plants X_{jl} is multiplied with distance between transfer station and recycling plants d_{jl} which is further multiplied with carbon emission factor e_f.

Equation (4.15) carbon emissions between transfer station j and recycling plants l.

$$\sum_{j}^{J}\sum_{l}^{L} X_{jl}.d_{jl}.e_f \tag{4.15}$$

4.4.3.4 Carbon Emissions while transporting waste from incineration plants to landfill sites

This is the amount of carbon that is emitted when vehicles from incineration plants k to landfill sites m. To calculate amount of CO_2 emitted, the number of vehicles moving from incineration plants to landfill sites X_{km} is multiplied with distance between incineration plants and landfill sites d_{km} which is further multiplied with carbon emission factor e_f.

Equation (4.16) shows carbon emissions between incineration plants k and landfill sites m.

$$\sum_{k}^{K}\sum_{m}^{M} X_{km}.d_{km}.e_f \tag{4.16}$$

The second component of the equation indicated the carbon emissions resulting from the use of incineration and recycling plants.

4.4.3.5 Carbon emissions at incineration plants

This is the amount of carbon that is emitted when waste is incinerated. To calculate the emissions the amount of CO_2 released per unit of waste incinerated CO_k is multiplied by quantity of waste incinerated Q_{jk}.

Equation (4.17) shows carbon emissions at incineration plants k.

$$\sum_{j}^{J}\sum_{k}^{K} Q_{jk}.CO_k \tag{4.17}$$

4.4.3.6 Carbon emissions at recycling plants

This is the amount of carbon that is emitted when waste is recycled. To calculate the emissions the amount of CO_2 released per unit of waste recycled CO_l is multiplied by quantity of waste recycled Q_{jl}.

Equation (4.18) shows carbon emissions at recycling plants l.

$$\sum_{j}^{J}\sum_{l}^{L} Q_{jl}.CO_l \tag{4.18}$$

4.4.4 Types of Variables

$$Y_i, Y_j, Y_k, Y_l, Y_m \in \{0,1\} \tag{4.19}$$

This equation represents that Y_i, Y_j, Y_k, Y_l, Y_m are binary variables. They represent selection of waste generation points "i", transfer station "j", incineration plants "k", recycling plants "l" and landfill sites "m".

$$X_{ij}, X_{jk}, X_{jl}, X_{km}, Q_{ij}, Q_{jk}, Q_{jl}, Q_{km} \geq 0 \tag{4.20}$$

This equation represents that all other decision variables must be non-negative.

4.5 Constraints

The constraints of the mathematical model are listed below with explanation:

4.5.1 Supply Constraint

$$\sum_{j}^{J} Q_{ij} = A_i \qquad \forall i \tag{4.21}$$

This equation represents that the total quantity of medical waste flowing from waste generation points "i" to transfer station "j" would always be equal to total amount of medical waste generated by various waste generation points "i".

4.5.2 Transshipment Constraint

$$\sum_{i}^{I} Q_{ij} = \sum_{k}^{K} Q_{jk} + \sum_{l}^{L} Q_{jl} \qquad \forall j \tag{4.22}$$

$$\sum_{j}^{J} Q_{jk} = a1.\sum_{i}^{I} Q_{ij} \qquad \forall k \tag{4.23}$$

$$\sum_{j}^{J} Q_{jl} = a2.\sum_{i}^{I} Q_{ij} \qquad \forall l \tag{4.24}$$

This equation represents that the quantity of medical waste flowing from waste generation points "i" to transfer station "j" must be equal to the sum of quantity of medical waste flowing from transfer station "j" to incineration plants "k" and quantity of medical waste flowing from transfer station "j" to recycling plants "l".

$$\sum_{m}^{M} Q_{km} = a3.\sum_{k}^{K} Q_{jk} \qquad \forall m \tag{4.25}$$

This equation represents that the quantity of ashes transported to landfill sites "m" must be equal to the quantity of ashes generated from the incineration of infectious medical waste at incineration plants "k".

4.5.3 Capacity Constraints

$$\sum_{i}^{I} Q_{ij} \leq cap_j \qquad \forall j \tag{4.26}$$

This equation represents that the capacity of transfer station "j" must be less than or equal to the quantity of waste transferred from waste generation points "i" to the transfer station "j".

$$\sum_{j}^{J} Q_{jk} \leq cap_k.Y_k \qquad \forall k \tag{4.27}$$

This equation represents that the capacity of the incineration plants "k" must be less than or equal to the quantity of waste transferred from transfer station "j" to the incineration plants "k".

$$\sum_{j}^{J} Q_{jl} \leq cap_l . Y_l \qquad \forall l \tag{4.28}$$

This equation represents that the capacity of the recycling plants "l" must be less than or equal to the quantity of waste transferred from transfer station "j" to the recycling plants "l".

$$\sum_{k}^{K} Q_{km} \leq cap_m . Y_m \qquad \forall m \tag{4.29}$$

This equation represents that the capacity of the landfill sites "m" must be less than or equal to the quantity of waste transferred from the incineration plants "k" to the landfill sites "m".

4.5.4 Demand Constraints

$$X_{ij} \geq \frac{A_i}{Cap_v} \tag{4.30}$$

This equation represents the number of vehicles required to move from waste generation points "i" to transfer station "j".

$$X_{jk} \geq \frac{Q_{jk}}{Cap_v} \tag{4.31}$$

This equation represents the number of vehicles required to move from transfer station "j" to incineration plants "k".

$$X_{jl} \geq \frac{Q_{jl}}{Cap_v} \tag{4.32}$$

This equation represents the number of vehicles required to move from transfer station "j" to recycling plants "l".

$$X_{km} \geq \frac{Q_{km}}{Cap_v} \tag{4.33}$$

This equation represents the number of vehicles required to move from incineration plants "k" to landfill sites "m".

4.6 Chapter Summary

This chapter is divided into three main sections. In the first section, problem description has been discussed. In second section model assumptions are discussed and in the last section, A multi-objective mathematical model of infectious medical waste has been designed and discussed in detail. The multi-objective model is discussed in detail with all the parameters, decision variables, objective functions, and constraints.

The three objective functions of the model have been discussed which include total cost, risk prioritization number, and carbon emissions. The first objective is minimization of cost which includes transportation cost, fixed cost of operating facilities, storage plus sortation cost, incineration cost and recycling cost of medical waste. The second objective is the maximization of risk priority numbers ensuring that waste with higher risks is given precedence for timely and safe management. And the third objective is minimization of carbon emissions during the transportation, incineration, and recycling of medical waste. Several constraints that the model takes into consideration are supply constraint, transshipment constraint, capacity constraints, type of variables constraints and demand constraints.

Chapter 5: Case Study

Pakistan is a developing country in the South Asia. The number of medical facilities in Pakistan has increased significantly in recent years. According to the statistics of the Ministry of Health and Medical Education of Pakistan (2021), the total number of beds in hospitals in 2019 was approximately 133,707. Pakistan has a large healthcare system. These include 5,000 primary health units, 600 rural health centers, 7500 other primary health care centers, and more than 100,000 female health workers serving nationwide. These primary health care services are supported by a network of 989 secondary hospitals at the tehsil for referral and district levels. Population growth and increased access to medical services have led to an increase in medical waste.

Environmental organizations and the Ministry of Health and Medical Education supervise the management of waste generated by medical facilities. The eastern part of Pakistan has more population than other parts of the country. Therefore, medical waste management in East Pakistan is more important than other areas. Therefore, the city of Lahore in Punjab province with a population of more than 13 million was chosen as the research area.

This quantitative case study examines the status of medical waste management practices in healthcare facilities across Pakistan. The aim of the study is to optimize the prevailing methods of waste disposal, cost cutting techniques and examine the challenges faced by healthcare institutions in managing medical waste. Data were collected through structured surveys conducted among medical staff, waste management staff and facility managers. The findings highlight the need to improve waste management infrastructure, raise awareness among health care providers, and strengthen law enforcement to address growing medical waste concerns in Pakistan.

Medical waste management is an important aspect of public health and environmental sustainability. Improper disposal of medical waste technique poses a high cost to medical waste companies and the hospital or clinics. This quantitative research paper examines medical waste management practices in healthcare organizations to understand current practices and identify areas for improvement.

The numerical example is developed to evaluate the model with the proposed methodology. The numerical example considers the medical waste supply chain network with fixed cost and variable cost as part of objective function. To solve the presented numerical example, the values of some parameters are taken from the existing literature, while other parameter values are based on real data taken from industry. The model is based on the supply chain network discussed above.

The cost function comprises of most parameters. The cost of transportation across the network is calculated by multiplying the number of vehicles moving between nodes, distance between nodes, fuel price and fuel consumption rate. The number of vehicles moving from one node to another is calculated using the amount of waste generated at the waste generation point and the capacity of the vehicle. Distance between the nodes is calculated using Google Maps. All data for this objective function is taken from the industry.

The second objective function comprises of Risk Priority Number (RPN). RPN is calculated for each hospital based on the considered failure modes in medical waste management. The data for this objective function is taken from the industry.

The emission function is calculated using the transportation related carbon emissions and emissions occurring during the process of incineration and recycling of medical waste. For transportation related carbon emissions, the number of vehicles moving between the nodes is multiplied with the distance and average CO_2 emission factor. The number of vehicles moving from one node to another is calculated using the amount of waste generated at the waste generation point and the capacity of the vehicle by the model, the distance between nodes is calculated using Google Maps, whereas average CO_2 emission factor is ascertained from the literature. The amount of CO_2 emitted during the process of incineration and recycling is calculated using the quantity of medical waste collected and the amount of CO_2 that is emitted per kg of waste incinerated and recycled. Data for quantity of waste is taken from the industry whereas, data for CO_2 emitted per kg of waste incinerated and recycled is ascertained from the literature.

The example of medical waste supply chain has been taken into consideration for calculating total supply chain cost, RPN (Risk Priority Number) and Carbon Emissions. The supply chain network consists of the following members: 10 waste generation points, 1 central transfer station, 3 incineration plants, 2 recycling plants and 2 landfill sites. This is an example of a medical waste supply chain network with hospitals, central transfer station, recycling plants and landfill sites located in Lahore, Pakistan. Whereas incineration plants are in Sialkot, Kasur, and

Gujranwala. The supply chain model developed is a multi-objective optimization problem. The data collected is used in the mathematical model developed on optimization software for calculation purposes. The case study is explained in detail below:

There are ten waste generation points which are being considered in this medical waste supply chain network. The amount of waste generated at each waste generation point is given below and the waste from every waste generated point is transferred to the central transfer station located at Mian Mir Hospital.

Table 9: Quantity of Waste flowing from Waste Generation Points to Central Transfer Station

Waste Generation Point	Waste Generated
Children Hospital	700
General Hospital	900
Cancer Care Hospital	500
IMC Hospital	200
Mian Mir Hospital	280
Maternity Hospital Chohan Road	9
Maternity Hospital Pathi Road	15
Infectious Disease Hospital	4
PRC Hepatitis Lab	41
Shahdara Hospital	12

Table 10: Distance between Waste Generation Point and Central Transfer Station

Waste Generation Point	Central Transfer Station
Children Hospital	11
General Hospital	14
Cancer Care Hospital	11
IMC Hospital	14
Mian Mir Hospital	0
Maternity Hospital Chohan Road	10
Maternity Hospital Pathi Road	6
Infectious Disease Hospital	11
PRC Hepatitis Lab	7
Shahdara Hospital	15

Once the waste from various waste generation points reaches the central transfer station it is temporarily stored and sorted and after sortation the infectious waste is sent to any of the three incineration facilities located in Sialkot, Kasur, or Gujranwala. The distance between the central transfer station and incineration facilities is given below:

Table 11: Distance between Central Transfer Station and Incineration Plants

Central Transfer Station	Incineration Plants		
	Sialkot	Kasur	Gujranwala
Mian Mir Hospital	127	55	91

After sortation the general waste is sent to the recycling plants for treatment. Recycling plants are located at Kala Shah Kaku and Shahdara. The distance between the central transfer station and recycling plants is given below:

Table 12: Distance between Central Transfer Station and Recycling Plants

Central Transfer Station	Recycling Plants	
	Kala Shah Kaku	Shahdara
Mian Mir Hospital	38	13

Once waste is incinerated it is converted into ashes which need to be properly disposed of in landfill. Therefore, once treated the leftover of incinerated waste is transported to landfill sites for proper disposal. Landfill sites are located at Mehmood Booti and Lakhodher. The distance between the incineration facilities and landfill sites is given below:

Table 13: Distance between Incineration Plants and Landfill Sites

Incineration Plants	Landfill Sites	
	Mehmood Booti	Lakhodher
Sialkot	113	114
Kasur	68	69
Gujranwala	79	78

The findings showed moderate compliance with medical waste management policies in Pakistan. However, disposal practices and disposal methods are flawed, and some places use very expensive disposal methods. Lack of knowledge and training of health personnel and insufficient infrastructure are the main problems that need to be addressed.

This quantitative study sheds light on the current state of medical waste management in healthcare facilities in Pakistan. This study highlights the importance of implementing improvements and improvements that can lead to cost savings, increased awareness of healthcare personnel, and improved management. By addressing these issues, Pakistan can move towards a more sustainable and responsible healthcare system that protects public health and the environment. Policymakers and healthcare providers must first develop and implement waste management strategies to reduce the risks and costs associated with health insurance.

The chapter illustrates the numerical example to analyze the developed model through the proposed methodology. The numerical example considers the real-life medical waste supply chain for the analysis of cost, risk priority number, and carbon emissions. Several deterministic parameters used in this research involve the amount of waste generated by waste generation points and the distance between various nodes across the supply chain network.

Chapter 6: Methodology

A multi-objective mathematical model of infectious medical waste has been designed and discussed in detail. The multi-objective model is discussed in detail with all the parameters, decision variables, objective functions, and constraints. The three objective functions of the model have been discussed which include total cost, risk prioritization number, and carbon emissions. Several constraints have been considered while developing the mathematical model and then finally the mathematical model is solved using neutrosophic optimization approach.

One of the main research objectives of this study is to optimize the medical waste supply chain with uncertain and ambiguous data. Optimization methods often fail to resolve the ambiguities in medical data waste due to discretion. The four-value refined neutrosophic methodology can resolve and model ambiguity which is perfect for this research purpose. It can more fully and accurately reflect the complexities of the real world in medical waste management. Brown and Clark (2020) emphasize the importance of choosing a method that can resolve uncertainty and ambiguity in the context of the medical waste supply chain.

In summary, the choice of the Four-Valued Refined Neutrosophic methodology is radical as it resolves the problem of inconsistency, uncertainty and bipolarity, making it a good choice.

6.1 Four-valued Refined Neutrosophic Set

In the suggested linear programming multi-objective problem for an infectious medical waste supply chain, the inconsistent, uncertain, and imprecise parameters have been dealt with using the neutrosophic set technique. The multi-objective linear programming neutrosophic model that is being described can handle uncertain data, preventing unrealistic modeling. A four-valued neutrosophic strategy is used to further refine the same objectives in the multi-objective mathematical model.

The expenses participate in the refinement of T, I, and F (Zadeh 2018). In this thesis, we will just be concerned with the points listed below. Four-valued refined neutrosophic sets are a special kind of neutrosophic set in which multiple sets are possible by partitioning indeterminacy in several ways. In this work, we will just be concerned with the points listed below.

Indeterminacy is decomposed into two pieces, uncertainty (UM) and contradiction (CM), where CM=TM^FM. TM, IM, CM, and FM all have values in the range [0, 1], and there is no value for TM that exceeds UM plus CM plus FM that is less than 4. So, we can write FVRNS as

$$\tilde{Z}^{RN} = \left\{ \left(k, TM_{\tilde{Z}^{RN}}(k), UM_{\tilde{Z}^{RN}}(k), CM_{\tilde{Z}^{RN}}(k), FM_{\tilde{Z}^{RN}}(k) : k \in K \right) \right\}$$

When k is continuous, then

$$\tilde{Z}^{RN} = \int_{k} \left\{ k, TM_{\tilde{Z}^{RN}}(k), UM_{\tilde{Z}^{RN}}(k), CM_{\tilde{Z}^{RN}}(k), FM_{\tilde{Z}^{RN}}(k) / dk : k \in K \right\}$$

and when k is discrete, its representation will be

$$\tilde{Z}^{RN} = \sum_{i=1}^{n} \left\{ k, TM_{\tilde{Z}^{RN}}(k), UM_{\tilde{Z}^{RN}}(k), CM_{\tilde{Z}^{RN}}(k), FM_{\tilde{Z}^{RN}}(k_i) / k_i : k_i \in K \right\}$$

The complement of the four-valued refined neutrosophic set is denoted by C_r and is defined as

$$TM_{C_r}(k) = FM_{\tilde{Z}^{RN}}(k),$$

$$UM_{C_r}(k) = 1 - UM_{\tilde{Z}^{RN}}(k),$$

$$CM_{C_r}(k) = 1 - CM_{\tilde{Z}^{RN}}(k),$$

$$FM_{C_r}(k) = TM_{\tilde{Z}^{RN}}(k),$$

6.2 Four-valued Refined Neutrosophic Optimization Technique

Consider a non-linear multi-objective optimization problem,

Minimize $\qquad \{ f_z(k) \} \qquad z = 1, 2, 3, \ldots, n$

such that

$$a_j(k) \leq b_j \qquad j = 1, 2, ..., r$$

where k are decision variables, $f(k)$ represents objective functions $a_j(k)$ represents the constraint functions, and z and r represent the number of objective functions and constraints, respectively. Now the decision set $\tilde{D}$, a conjunction of four-valued neurotrophic objectives and constraints, is defined as

$$\tilde{D} = (\cap_{z=1}^{m} \tilde{O}_m) \cap (\cap_{z=1}^{m} \tilde{L}_j) = \{k, TM_{\tilde{D}}, UM_{\tilde{D}}, CM_{\tilde{D}}, FM_{\tilde{D}}\},$$

$$TM_{\tilde{D}}(k) = \min(TM_{\tilde{O}_1}(k), TM_{\tilde{O}_2}(k), ..., TM_{\tilde{O}_z}(k); TM_{\tilde{L}_1}(k), TM_{\tilde{L}_2}(k), ..., TM_{\tilde{L}_r}(k))$$

$$UM_{\tilde{D}}(k) = \min(UM_{\tilde{O}_1}(k), UM_{\tilde{O}_2}(k), ..., UM_{\tilde{O}_z}(k); UM_{\tilde{L}_1}(k), UM_{\tilde{L}_2}(k), ..., UM_{\tilde{L}_r}(k))$$

$$CM_{\tilde{D}}(k) = \min(CM_{\tilde{O}_1}(k), CM_{\tilde{O}_2}(k), ..., CM_{\tilde{O}_z}(k); CM_{\tilde{L}_1}(k), CM_{\tilde{L}_2}(k), ..., CM_{\tilde{L}_r}(k))$$

$$FM_{\tilde{D}}(k) = \min(FM_{\tilde{O}_1}(k), FM_{\tilde{O}_2}(k), ..., FM_{\tilde{O}_z}(k); FM_{\tilde{L}_1}(k), FM_{\tilde{L}_2}(k), ..., FM_{\tilde{L}_r}(k))$$

for all k ∈ K.

Where $TM_{\tilde{D}}, UM_{\tilde{D}}, CM_{\tilde{D}}$ and $FM_{\tilde{D}}$ represent truth, uncertainty, contradictory and falsity grade of membership of four-valued refined neutrosophic decision set, respectively. Now using the four-valued refined neutrosophic optimization, the above problem is remodeled into a non-linear optimization as

Such that

$$Max\alpha, Max\beta, Max\gamma, Max\delta$$

$$TM_{\tilde{O}_z}(k) \geq \alpha \qquad TM_{\tilde{L}_r}(k) \geq \alpha$$

$$UM_{\tilde{O}_z}(k) \geq \alpha \qquad UM_{\tilde{L}_r}(k) \geq \alpha$$

$$FM_{\tilde{O}_z}(k) \geq \alpha \qquad FM_{\tilde{L}_r}(k) \geq \alpha$$

$$CM_{\tilde{O}_z}(k) \geq \alpha \qquad CM_{\tilde{L}_r}(k) \geq \alpha$$

$$\alpha \geq \beta, \alpha \geq \gamma, \alpha \geq \delta$$

$$\alpha + \beta + \gamma + \delta \leq 4$$

$$\alpha, \beta, \gamma, \delta \in [1, 0]$$

$$a_j(k) \leq b_j \qquad j = 1, 2, \ldots, r$$

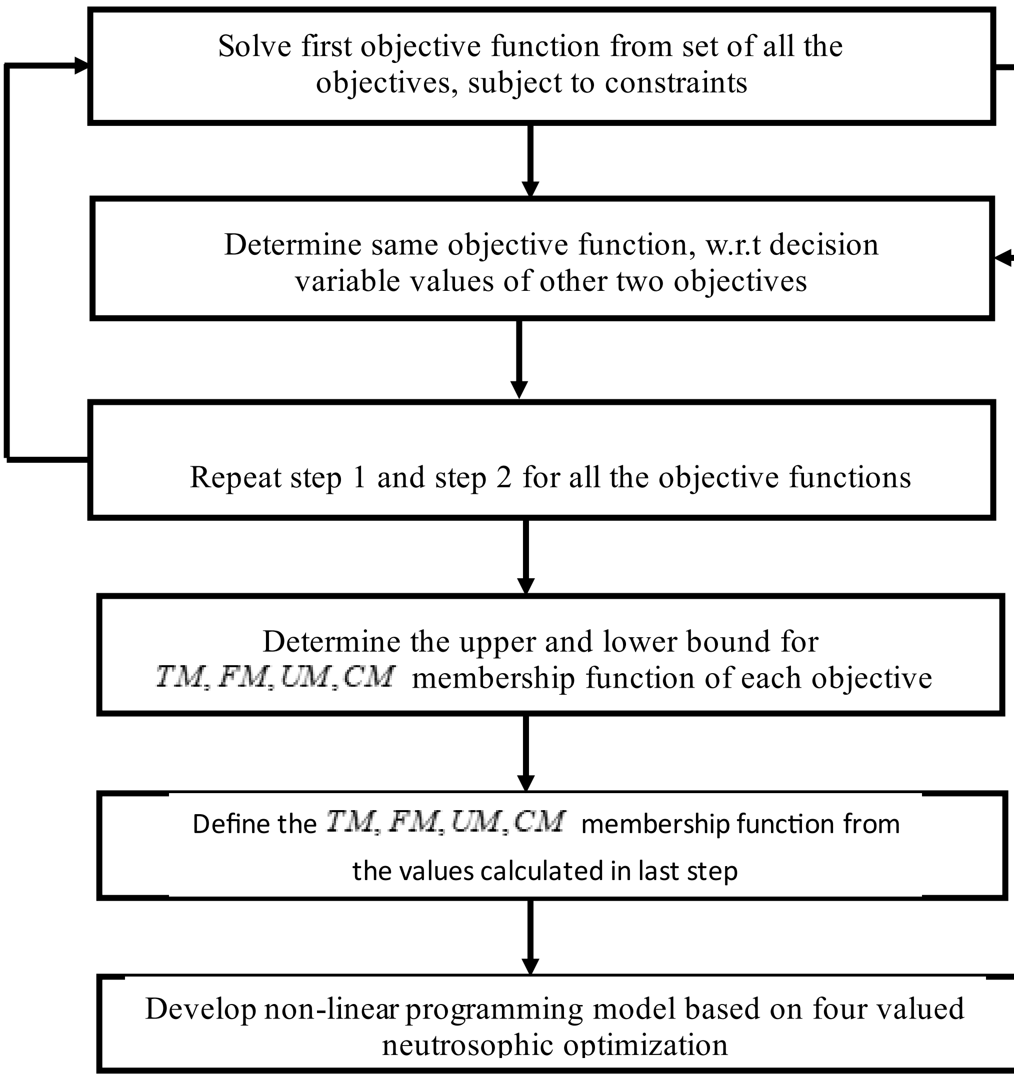

Figure 3: Flowchart for Four-valued Neutrosophic Optimization

6.3 Computational Algorithm

Step 1: Solve the first objective function as a single objective function taken from set of Z objectives. The values of decision variables and objective functions will be computed subject to the given constraints.

Step 2: Now compute the values of the unresolved objective, i.e., (z − 1) using the decision variables from step 1.

Step 3: Continue to the remaining (z − 1) objective function by going through step 1 and step 2.

$$\begin{bmatrix} f_1(k^1) & f_2(k^1) & \cdots & f_p(k^1) \\ f_1(k^2) & f_2(k^2) & \cdots & f_p(k^2) \\ \vdots & \vdots & \ddots & \vdots \\ f_1(k^r) & f_2(k^r) & \cdots & f_p(k^r) \end{bmatrix}$$

Step 4: Find the lower bound $\hat{L}_z^{TM}$ and the upper bound $\hat{U}_z^{TM}$ corresponding to each objective f (k). The lower and upper bounds for truth membership of objectives are

$$\hat{U}_z^{TM} = max\{f_z(k^r)\} \text{ and } \hat{L}_z^{TM} = \min\{f_z(k^r)\}$$

where r = 1, 2,…,z.

The upper $\hat{U}_z^{FM}$ and lower $\hat{L}_z^{FM}$ bounds for falsity membership of objectives are

$$\hat{U}_z^{FM} = \hat{U}_z^{TM} \quad \text{and} \quad \hat{L}_z^{FM} = \hat{L}_z^{TM} + t(\hat{U}_z^{TM} - \hat{L}_z^{TM})$$

Upper $\hat{U}_z^{UM}$ and lower $\hat{L}_z^{UM}$ bounds for uncertainty membership of objectives are

$$\hat{L}_z^{UM} = \hat{L}_z^{TM} \quad \text{and} \quad \hat{U}_z^{UM} = \hat{L}_z^{TM} + s(\hat{U}_z^{TM} - \hat{L}_z^{TM})$$

and the upper and lower bounds for contradictory membership of objectives are

$$\hat{L}_z^{CM} = \hat{L}_z^{TM} \wedge \hat{L}_z^{FM} \quad \text{and} \quad \hat{U}_z^{CM} = \hat{L}_z^{TM} \wedge \hat{L}_z^{FM} + l(\hat{U}_z^{TM} \wedge \hat{U}_z^{FM} - \hat{L}_z^{TM} \wedge \hat{L}_z^{FM})$$

where t, s, l ∈ (0, 1).

Step 5: In this step, we will define truth, uncertainty, falsity, and contradictory membership functions as follows:

$$TM_z(f_z(k)) = \begin{cases} 1 & f_z(k) \le \hat{L}_z^{TM} \\ \dfrac{\hat{U}_z^{TM} - f_z(k)}{\hat{U}_z^{TM} - \hat{L}_z^{TM}} & \hat{L}_z^{TM} \le f_z(k) \le \hat{U}_z^{TM} \\ 0 & f_z(k) \ge \hat{U}_z^{TM} \end{cases}$$

$$UM_z(f_z(k)) = \begin{cases} 1 & f_z(k) \le \hat{L}_z^{UM} \\ \dfrac{\hat{U}_z^{UM} - f_z(k)}{\hat{U}_z^{UM} - \hat{L}_z^{UM}} & \hat{L}_z^{UM} \le f_z(k) \le \hat{U}_z^{UM} \\ 0 & f_z(k) \ge \hat{U}_z^{UM} \end{cases}$$

$$FM_z(f_z(k)) = \begin{cases} 1 & f_z(k) \le \hat{L}_z^{FM} \\ \dfrac{f_z(k) - \hat{L}_z^{FM}}{\hat{U}_z^{FM} - \hat{L}_z^{FM}} & \hat{L}_z^{FM} \le f_z(k) \le \hat{U}_z^{FM} \\ 0 & f_z(k) \ge \hat{U}_z^{FM} \end{cases}$$

$$CM_z(f_z(k)) = \begin{cases} 1 & f_z(k) \le \hat{L}_z^{CM} \\ \dfrac{\hat{U}_z^{CM} - f_z(k)}{\hat{U}_z^{CM} - \hat{L}_z^{CM}} & \hat{L}_z^{CM} \le f_z(k) \le \hat{U}_z^{CM} \\ 0 & f_z(k) \ge \hat{U}_z^{CM} \end{cases}$$

Step 6: Now four-valued refined neutrosophic optimization method for multi-objective non-linear programming problem gives a corresponding non-linear problem as

$Max\ \alpha - \beta + \gamma + \delta$, such that

$$TM_z(f_z(k)) \ge \alpha$$

$$UM_z(f_z(k)) \ge \beta$$

$$FM_z(f_z(k)) \ge \gamma$$

$$CM_z(f_z(k)) \geq \delta$$

with

$$\alpha - \beta + \gamma + \delta \leq 4$$

and

$$\alpha \geq \beta, \ \alpha \geq \gamma, \alpha \geq \delta$$

where

$$\alpha, \beta, \gamma, \delta \in [1, 0]$$

$$a_j(k) \leq b_j \qquad j = 1, 2, ..., r$$

This corresponds to non-linear programming as:

$$Max \ \alpha - \beta + \gamma + \delta$$

such that

$$f_z(k) + (\hat{U}_z^{TM} - \hat{L}_z^{TM}) \leq \alpha . \hat{U}_z^{TM}$$

$$f_z(k) + (\hat{U}_z^{UM} - \hat{L}_z^{UM}) \leq \gamma . \hat{U}_z^{UM}$$

$$f_z(k) - (\hat{U}_z^{FM} - \hat{L}_z^{FM}) \leq \beta . \hat{L}_z^{FM}$$

$$f_z(k) + (\hat{U}_z^{CM} - \hat{L}_z^{CM}) \leq \delta . \hat{U}_z^{CM}$$

for z= 1, 2,...,r. We have

$$\alpha - \beta + \gamma + \delta \leq 4$$

and

$$\alpha \geq \beta, \ \alpha \geq \gamma, \alpha \geq \delta$$

where

$$\alpha\ ,\beta\ ,\gamma,\delta\in[1,0]$$

$$a_j(k)\le b_j \qquad j=1,2,\ldots,r$$

6.3.1 Numerical Solution

Considering our optimization problem:

$$Minz1=\sum_i^I\sum_j^J X_{ij}.d_{ij}.\alpha.\gamma+\sum_j^J\sum_k^K X_{jk}.d_{jk}.\alpha.\gamma+\sum_j^J\sum_l^L X_{jl}.d_{jl}.\alpha.\gamma+\sum_k^K\sum_m^M X_{km}.d_{km}.\alpha.\gamma$$
$$+\sum_k^K FC_k.Y_k+\sum_l^L FC_l.Y_l+\sum_i^I\sum_j^J Q_{ij}.sc_j+\sum_j^J\sum_k^K Q_{jk}.ic_k+\sum_j^J\sum_l^L Q_{jl}.rc_l$$

$$Maxz2=\sum_i^I RPN_i.Y_i$$

$$Minz3=\sum_i^I\sum_j^J X_{ij}.d_{ij}.e_f+\sum_j^J\sum_k^K X_{jk}.d_{jk}.e_f+\sum_j^J\sum_l^L X_{jl}.d_{jl}.e_f$$
$$+\sum_k^K\sum_m^M X_{km}.d_{km}.e_f+\sum_j^J\sum_k^K Q_{jk}.CO_k+\sum_j^J\sum_l^L Q_{jl}.CO_l$$

Step 1: Solve the first objective function as a single objective non-linear programming problem subjected to developed constraints, then we get the value of z1=132,607.68

Step 2: By using these decision variables, computing other objective functions, then we get z2 = 18,634.

Step 3: Now, repeating for objective function three whose value after computing is z3= 4,252.79

$$P=\begin{bmatrix} 171,085.16 & 18,634 & 4,252.79 \\ 1,561,706,006.04 & 18,634 & 16,299,863.53 \\ 167,751.16 & 18,634 & 4,252.79 \end{bmatrix}$$

Step 4: Now, find the lower and upper bounds of all objective functions.

6.3.1.1 For Objective Function (z1)

$$\hat{U}{}_1^T = 1,561,706,006.04$$

$$\hat{L}{}_1^T = 167,751.16$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T = 1,561,706,006.04$$

$$\hat{L}{}_1^F = \hat{L}{}_1^T + t(\hat{U}{}_1^T - \hat{L}{}_1^T)$$

$$\hat{L}{}_1^F = 167,751.16 + t(1,561,538,254.88)$$

$$\hat{L}{}_1^F = 468,629,227.62$$

$$\hat{L}{}_1^U = \hat{L}{}_1^T$$

$$\hat{L}{}_1^U = \hat{L}{}_1^T = 167,751.16$$

$$\hat{U}{}_1^U = \hat{L}{}_1^T + s(\hat{U}{}_1^T - \hat{L}{}_1^T)$$

$$\hat{U}{}_1^U = 624,783,053.11$$

$$\hat{L}{}_1^C = \hat{L}{}_1^T \wedge \hat{L}{}_1^F$$

$$\hat{L}{}_1^C = 7.86 \times 10^{14}$$

$$\hat{U}{}_1^C = \hat{L}{}_1^T \wedge \hat{L}{}_1^F + l(\hat{U}{}_1^T \wedge \hat{U}{}_1^F - \hat{L}{}_1^T \wedge \hat{L}{}_1^F)$$

$$\hat{U}{}_1^C = 1.46 \times 10^{18}$$

6.3.1.2 For Objective Function (z2)

$$\hat{U}{}_1^T = 18,634$$

$$\hat{L}{}_1^T = 18,634$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T = 18,634$$

$$\hat{L}{}_1^F = \hat{L}{}_1^T + t(\hat{U}{}_1^T - \hat{L}{}_1^T)$$

$$\hat{L}{}_1^F = 18,634$$

$$\hat{L}{}_1^U = \hat{L}{}_1^T$$

$$\hat{L}{}_1^U = \hat{L}{}_1^T = 18,634$$

$$\hat{U}{}_1^U = \hat{L}{}_1^T + s(\hat{U}{}_1^T - \hat{L}{}_1^T)$$

$$\hat{U}{}_1^U = 18,634$$

$$\hat{L}{}_1^C = \hat{L}{}_1^T \wedge \hat{L}{}_1^F$$

$$\hat{L}{}_1^C = 347,225,956$$

$$\hat{U}{}_1^C = \hat{L}{}_1^T \wedge \hat{L}{}_1^F + l(\hat{U}{}_1^T \wedge \hat{U}{}_1^F - \hat{L}{}_1^T \wedge \hat{L}{}_1^F)$$

$$\hat{U}{}_1^C = 347,225,956$$

6.3.1.3 Objective Function (z3)

$$\hat{U}{}_1^T = 16,299,863.53$$

$$\hat{L}{}_1^T = 4252.79$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T$$

$$\hat{U}{}_1^F = \hat{U}{}_1^T = 16,299,863.53$$

$$\hat{L}{}_1^F = \hat{L}{}_1^T + t(\hat{U}{}_1^T - \hat{L}{}_1^T)$$

$$\hat{L}{}_1^F = 4,892,936.01$$

$$\hat{L}{}_1^U = \hat{L}{}_1^T$$

$$\hat{L}_1^U = \hat{L}_1^T = 4,252.79$$

$$\hat{U}_1^U = \hat{L}_1^T + s(\hat{U}_1^T - \hat{L}_1^T)$$

$$\hat{U}_1^U = 6,522,497.08$$

$$\hat{L}_1^C = \hat{L}_1^T \wedge \hat{L}_1^F$$

$$\hat{L}_1^C = 20,808,627,869.62$$

$$\hat{U}_1^C = \hat{L}_1^T \wedge \hat{L}_1^F + l(\hat{U}_1^T \wedge \hat{U}_1^F - \hat{L}_1^T \wedge \hat{L}_1^F)$$

$$\hat{U}_1^C = 159,419,654,046,531$$

Step 5: Defining all membership functions.

6.3.2 Objective Function (z1)

$$T_1(z1) = \begin{cases} 1 & z1 \le 167,751.16 \\ \dfrac{1,561,706,006.04 - z1}{1,561,706,006.04 - 167,751.16} & 167,751.16 \le z1 \le 1,561,706,006.04 \\ 0 & z1 \ge 1,561,706,006.04 \end{cases}$$

$$U_1(z1) = \begin{cases} 1 & z1 \le 167,751.16 \\ \dfrac{624,783,053.11 - z1}{624,783,053.11 - 167,751.16} & 167,751.16 \le z1 \le 624,783,053.11 \\ 0 & z1 \ge 624,783,053.11 \end{cases}$$

$$F_1(z1) = \begin{cases} 1 \\ \dfrac{z1 - 468,629,227.62}{1,561,706,006.04 - 468,629,227.62} \\ 0 \end{cases}$$

$$z1 \le 468,629,227.62$$
$$468,629,227.62 \le z1 \le 1,561,706,006.04$$
$$z1 \ge 1,561,706,006.04$$

$$U_1(z1)=\begin{cases}1 & z1\le 7.86\times10^{14}\\ \dfrac{1.46\times10^{18}-z1}{1.46\times10^{18}-7.86\times10^{14}} & 7.86\times10^{14}\le z1\le 1.46\times10^{18}\\ 0 & z1\ge 1.46\times10^{18}\end{cases}$$

6.3.3 Objective Function (z2)

$$T_2(z2)=\begin{cases}1 & z2\le 18,634\\ 18,634-z2 & 18,634\le z2\le 18,634\\ 0 & z2\ge 18,634\end{cases}$$

$$U_2(z2)=\begin{cases}1 & z2\le 18,634\\ 18,634-z2 & 18,634\le z2\le 18,634\\ 0 & z2\ge 18,634\end{cases}$$

$$F_2(z2)=\begin{cases}1 & z2\le 18,634\\ z2-18,634 & 18,634\le z2\le 18,634\\ 0 & z2\ge 18,634\end{cases}$$

$$C_2(z2)=\begin{cases}1 & z2\le 18,634\\ 18,634-z2 & 18,634\le z2\le 18,634\\ 0 & z2\ge 18,634\end{cases}$$

6.3.4 Objective Function (z3)

$$T_3(z3) = \begin{cases} 1 & z3 \le 4252.79 \\ \dfrac{16,299,863.53 - z3}{16,299,863.53 - 4252.79} & 4252.79 \le z3 \le 16,299,863.53 \\ 0 & z3 \ge 16,299,863.53 \end{cases}$$

$$U_3(z3) = \begin{cases} 1 & z3 \le 4252.79 \\ \dfrac{6,522,497.08 - z3}{6,522,497.08 - 4252.79} & 4252.79 \le z3 \le 6,522,497.08 \\ 0 & z3 \ge 6,522,497.08 \end{cases}$$

$$F_3(z3) = \begin{cases} 1 & z3 \le 4252.79 \\ \dfrac{z3 - 4,892,936.01}{16,299,863.53 - 4,892,936.01} & 4252.79 \le z3 \le 16,299,863.53 \\ 0 & z3 \ge 16,299,863.53 \end{cases}$$

$$C_3(z3) = \begin{cases} 1 \\ \dfrac{159,419,654,046,531 - z3}{159,419,654,046,531 - 20,808,627,869.62} \\ 0 \end{cases}$$

$$\begin{gathered} z3 \le 20,808,627,869.62 \\ 20,808,627,869.62 \le z3 \le 159,419,654,046,531 \\ z3 \ge 159,419,654,046,531 \end{gathered}$$

Step 6: FVRN's non-linear programming problem is

$$\text{Max} \quad \alpha - \beta + \gamma + \delta$$

$$z1 + z2 + z3 \le 1,$$

$$\begin{gathered} 0 \le \alpha \le 1, \\ 0 \le \beta \le 1, \\ 0 \le \gamma \le 1, \\ 0 \le \delta \le 1, \end{gathered}$$

Chapter 7: Results and Discussions

7.1 Results and Discussions

The mathematical model has been developed as a multi-objective network design model for optimization of hazardous medical waste supply chain. The model was coded and solved using Bi-polar Neutrosophic Optimization Technique and an optimal solution was achieved. MATLAB R2022a coding tool on personal laptop with specifications of Intel Core i5-6300U CPU @ 2.40 GHz, 8GB RAM and 256GB SSD was used. The model is solved for ten waste generation points/hospitals, one central transfer station, three incineration plants, two recycling plants and two landfill sites. The model is solved for three objective functions, X constraints and Y decision variables. The model is solved using collected data and optimal values for (1) Minimization of Total Cost, (2) Maximization of RPN and (3) Minimization of Carbon Emissions.

7.1.1 Optimal Number of Vehicles Required for Medical Waste Transportation

The number of vehicles required for transporting waste from waste generation points depends upon the amount of waste generated at each generation point and the capacity of the vehicle. Each vehicle has the capacity of carrying 500 Kg of weight. The total amount of waste generated at each waste generation point throughout the day is collected, weighed, and transported to the central transfer station, the next day in the morning.

The following table shows the number of vehicles moving from each waste generation point to the central transfer station.

Table 14: No. of Vehicles moving from Waste Generation Point to the Central Transfer Station

X_{ij}	
	$j=1$
$i=1$	2
$i=2$	2
$i=3$	1
$i=4$	1
$i=5$	1
$i=6$	1
$i=7$	1
$i=8$	1
$i=9$	1
$i=10$	1

Once waste is transported to the central transfer station, it is sorted again from where hazardous medical waste is transported to incineration plants.

The following table shows the number of vehicles moving from the central transfer station to the incineration plants.

Table 15: No. of Vehicles moving from Central Transfer Station to the Incineration Plants

X_{jk}			
	$k=1$	$k=2$	$k=3$
$j=1$	0	3	3

From the transfer station hazardous waste is sent to the incineration plants, whereas the non-hazardous waste that has been sent to the transfer station along with the hazardous waste due to incorrect sortation at the waste generation points/hospitals is sent to the recycling plants.

The following table shows the number of vehicles moving from the central transfer station to the recycling plants.

Table 16: No. of Vehicles moving from the Central Transfer Station to the Recycling Plants

X_{jl}		
	$l=1$	$l=2$
$j=1$	0	1

Once the hazardous waste has been treated at the incineration plants it is converted into ash, which must be dumped at landfill sites to protect the environment and comply with WHO's regulations therefore ash from incinerated waste is then transported to the landfill sites.

The following table shows the number of vehicles moving from the incineration plants to the landfill sites.

Table 17: No. of Vehicles moving from the Incineration Plants to the Landfill Sites

X_{km}		
	$m=1$	$m=2$
$k=1$	0	0
$k=2$	0	1
$k=3$	0	1

7.1.2 Optimal Quantity of Waste Flowing Across the Network

The total quantity of waste generated daily at each waste generation point is known and all the waste is moved to the central transfer station.

The following table shows the quantity of waste moving from waste generation points to the central transfer station.

Table 18: Quantity of Waste moving from Waste Generation Points to the Central Transfer Station

Q_{ij}	
	$j=1$
$i=1$	700
$i=2$	900
$i=3$	500
$i=4$	200
$i=5$	280
$i=6$	9
$i=7$	15
$i=8$	4
$i=9$	41
$i=10$	12

Once waste is transported to the central transfer station, it is again sorted from where hazardous medical waste is then transported to the incineration plants. According to the data collected 99% of the waste collected at central transfer station is hazardous medical waste and is moved to incineration plants for further processing.

The following table shows the quantity of waste moving from central transfer station to incineration plants.

Table 19: Quantity of Waste moving from Central Transfer Station to Incineration Plants

X_{jk}			
	$k=1$	$k=2$	$k=3$
$j=1$	0	1160	1500

From the transfer station hazardous waste is sent to the incineration plants, whereas the non-hazardous waste that has been sent to the transfer station along with the hazardous waste due to incorrect sortation at the waste generation points/hospitals is sent to the recycling plants and according to the data collected almost 1% of non-hazardous waste is segregated at central transfer station from where it is sent to the recycling plants for further processing.

The following table shows the quantity of waste moving from central transfer station to recycling plants.

Table 20: Quantity of Waste moving from Central Transfer Station to Recycling Plants

Q_{jl}		
	$l=1$	$l=2$
$j=1$	0	21

After treatment of hazardous waste, it is converted into ash which must be dumped at landfill sites. According to the data collected the amount of ash left is 30% of weight of hazardous medical waste that has been treated.

The following table shows the quantity of waste moving from the incineration plants to the landfill sites.

Table 21: Quantity of Waste moving from Central Transfer Station to Recycling Plants

Q_{km}		
	$m=1$	$m=2$
$k=1$	0	0
$k=2$	0	348
$k=3$	0	450

7.2 Cost Minimization

In the model, the objective function is centered around the minimization of costs within the hazardous medical waste supply chain, comprising several crucial components: (1) transportation cost spanning the network, (2) the fixed cost associated with operating the facilities, (3) the cost linked to storage and efficient sortation, (4) the cost of incineration, and (5) the expense of recycling. Strikingly, the model's optimization efforts resulted in a total cost amounting to **PKR 168,110**.

7.2.1 Cost Incurred in Infectious Medical Waste Supply Chain

In our comprehensive analysis of cost allocation within the Infectious Medical Waste Supply Chain, we have unveiled a detailed breakdown of the essential components that shape the overall cost structure. Transportation costs emerge as a significant factor, accounting for 20.03% (PKR 33,678) of the total cost, highlighting the importance of efficient logistical planning and execution. Storage and sortation costs, constituting 25.33% (PKR 42,576) of the total, underscore the critical role of streamlined inventory management and sorting processes in maintaining operational efficiency. The substantial allocation of 37.69% (PKR 63,356) to incineration costs showcases its relevance in specific contexts, prompting consideration of waste management strategies and environmental regulations. Additionally, the minimal percentage of 0.1% (PKR 168) assigned to recycling costs underscores its environmental significance, even though it has a relatively limited impact on the overall cost structure. The fixed cost of operating facilities, at 16.85% (28,333), remains a pivotal consideration, necessitating efficient facility management practices to optimize resource utilization. Our findings provide a comprehensive overview of the cost distribution within Infectious Medical Waste Supply Chain, offering valuable insights to inform decision-making, cost-saving initiatives, and resource allocation strategies, all of which can significantly enhance operational efficiency and financial effectiveness.

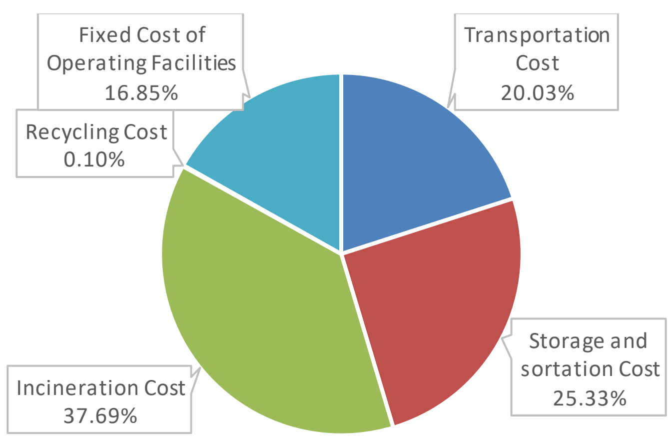

Figure 4: Total Cost of Medical Waste Supply Chain Network

7.3 RPN Maximization

Within the scope of the model RPN serves as a quantified representation of the collective risk associated with the medical waste generated by these waste generation point/hospitals. A higher sum of RPN indicates a greater overall risk level within the network, emphasizing the importance of effective waste management practices to mitigate potential adverse effects on public health, the environment, and operational continuity. An optimized value of RPN is **18,634**, which valuable insights for waste management decision-makers, allowing them to identify which hospitals pose the most substantial risks and should be prioritized in waste handling and delivery. This approach not only ensures that the highest-risk hospitals receive immediate attention but also contributes to a more efficient and risk-aware allocation of resources, ultimately enhancing the overall effectiveness of the infectious medical waste supply chain.

7.4 Carbon Emissions Minimization

Within the framework of the hazardous medical waste supply chain model, the objective function prioritizes the minimization of carbon emissions, which encompasses three key components: (1) carbon emissions stemming from transportation activities across the network, (2) carbon emissions resulting from the incineration process of waste, and (3) carbon emissions associated with the recycling of waste materials. Remarkably, the model achieved an optimal outcome, where a total of **4,269.2 Kg** of carbon was emitted while navigating the intricacies of transportation, incineration, and recycling of hazardous medical waste, all within the confines of predefined constraints.

7.4.1 Carbon Emission within Infectious Medical Waste Supply Chain

The findings reveal the distribution of carbon emissions within the overall framework. Specifically, during the transportation phase, carbon emissions account for 6.90% (294.5 Kg) of the total, signifying the environmental impact associated with the movement of vehicles. Remarkably, the process of waste incineration emerges as the dominant contributor, constituting 92.76% (3960 Kg) of the total carbon emissions, underscoring the significance of efficient waste disposal methods in the context of emissions reduction. Furthermore, carbon emissions related to recycling activities are relatively minimal, representing only 0.34% (14.7 Kg) of the total carbon emissions. Understanding this breakdown of carbon emissions is pivotal for developing targeted strategies to mitigate environmental impact and enhance the sustainability of the waste management system.

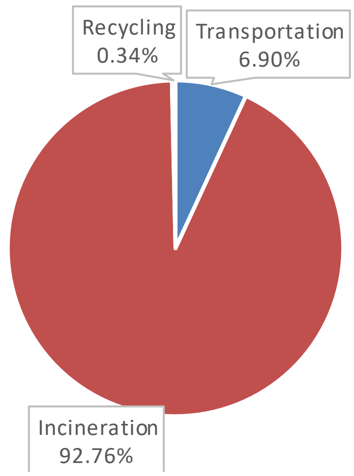

Figure 5: Emissions in Medical Waste Supply Chain Network

7.5 Sensitivity Analysis

A sensitivity analysis is performed for some key parameters that are used to develop the multi-objective mathematical model for infectious medical waste supply chain. The key parameter values are changed by a specific percentage to show the change in the optimal value of objective functions including total cost, RPN, and carbon emissions. For the sensitivity analysis, the percentage change of -50%, -25%, +25%, +50%, +70%, and +90% are considered to check the change in optimal objective function value. The sensitivity analysis is performed on distance, fuel price and segregation ratio.

The sensitivity analysis is performed to analyze the combined effect of change in all the objective functions. Table 22 shows the sensitivity analysis result for key parameters.

Table 22: Sensitivity Analysis

Parameter	Percentage Change	Percentage Change in Total Cost (PKR)	Percentage Change in RPN	Percentage Change in Carbon Emissions (Kg)
Distance	50%	0.17%	0%	0.07%
	25%	0.11%	0%	0.05%
	-50%	-0.05%	0%	-0.02%
	-25%	-0.09%	0%	-0.03%
Fuel Price	50%	0.08%	0%	0%
	25%	0.04%	0%	0%
	-50%	-0.06%	0%	0%
	-25%	-0.001%	0%	0%
Capacity of Vehicle	50%	-0.03%	0%	-0.01%
	25%	-0.01%	0%	-0.005%
	-50%	0.230%	0%	0.1%
	-25%	0.055%	0%	0.02%
Segregation Ratio	90%	-0.04%	0%	-0.06%
	70%	-0.10%	0%	-0.16%
	50%	-0.16%	0%	-0.24%

7.5.1 Change in Distance

The variations in distance have distinct repercussions on the objectives of total cost, Risk Priority Number (RPN), and carbon emissions, as demonstrated by the provided data. When the distance increases by 50%, there is a corresponding 0.17% rise in the total cost. This trend continues with a 25% distance increase resulting in a slightly lower 0.11% increase in total cost. Conversely, decreasing the distance by 50% and 25% leads to -0.05% and -0.09% decreases in total cost, respectively. These changes highlight a direct correlation between distance and total cost. In terms of RPN, all the changes in distance appear to have no effect on its value, indicating that distance alterations do not impact the RPN. Concerning carbon emissions, an increase in distance by 50% and 25% prompts 0.07% and 0.05% increases in emissions, respectively. Conversely, reducing the distance by 50% and 25% results in marginal carbon emission reductions of -0.02% and -0.03%, respectively. Therefore, while distance exerts a tangible influence on total cost and has minor effects on carbon emissions, it holds no sway over the RPN value.

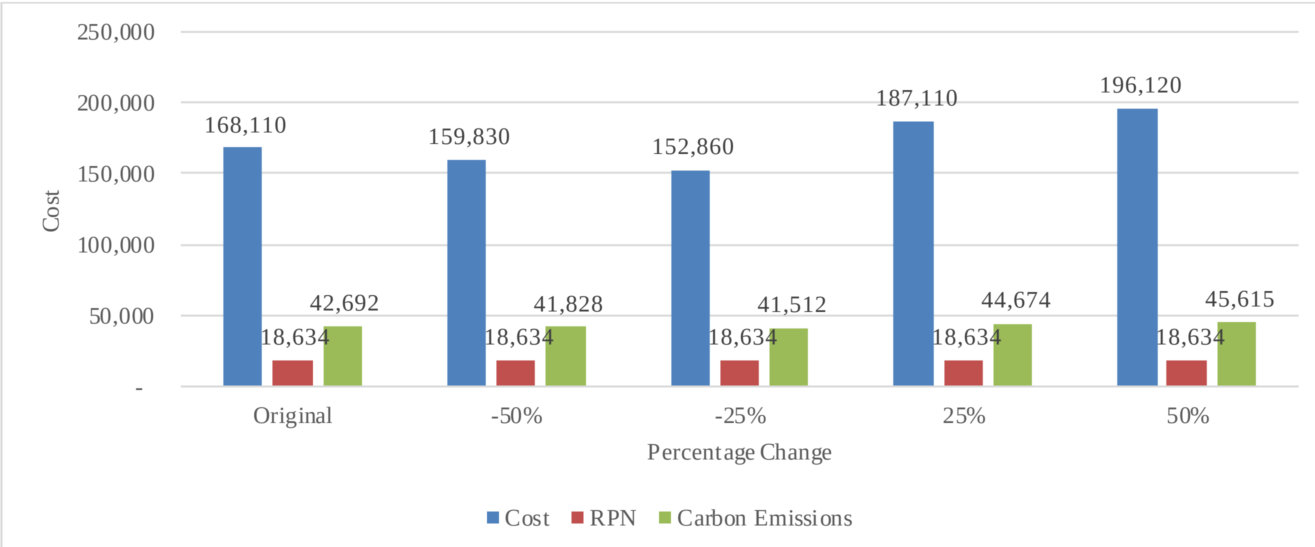

Figure 6: Change in Distance

7.5.2 Change in Fuel Cost

The adjustments in fuel prices have discernible implications for various facets of the supply chain network, including overall supply chain cost, Risk Priority Number (RPN), and carbon emissions, as illustrated by the provided data. When fuel prices increase by 50%, there is a proportional rise of 0.08% in the overall supply chain cost. A similar trend emerges with a 25% fuel price increase, yielding a slightly lower 0.04% increase in the supply chain cost. Conversely, a 50% reduction in fuel prices results in a reduction of supply chain cost by -0.06%, and a 25% reduction leads to a marginal -0.001% decrease in cost. These changes emphasize the direct correlation between fuel prices and the overall supply chain cost.

Interestingly, changes in fuel prices appear to have no effect on the RPN value, regardless of whether fuel prices increase or decrease. This suggests that fluctuations in fuel prices do not directly impact the calculated RPN within the supply chain network.

Regarding carbon emissions within the supply chain, the alterations in fuel prices do not seem to produce any changes, all registering as 0%. This implies that variations in fuel prices do not influence carbon emissions within the supply chain network.

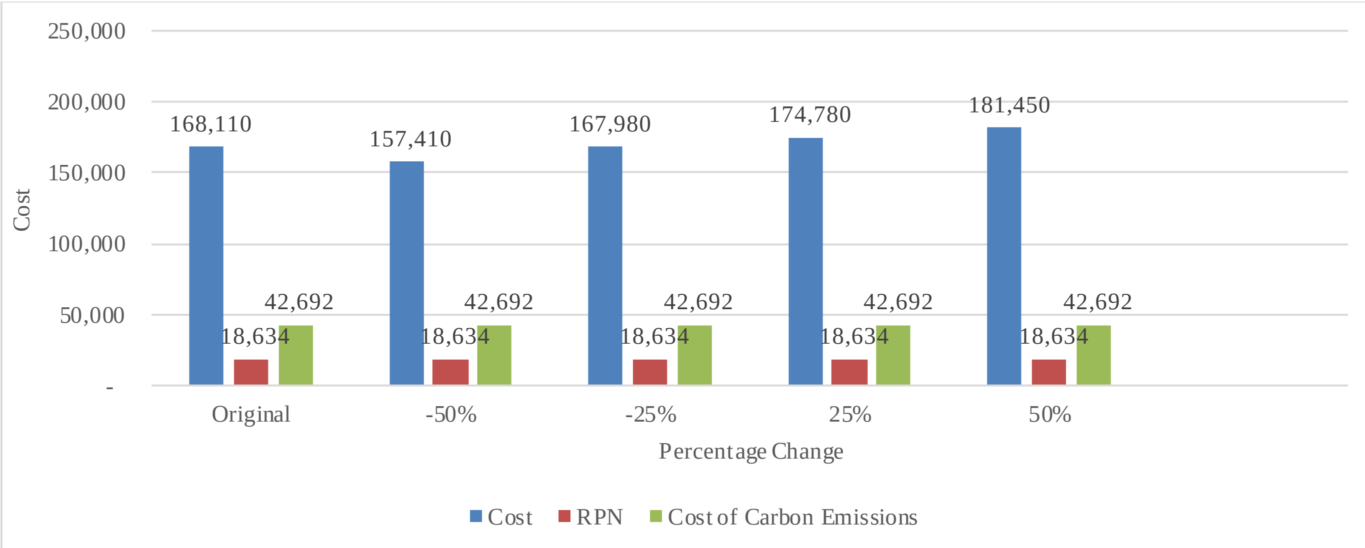

Figure 7: Change in Fuel price

7.5.3 Change in Vehicle Capacity

The investigation shows that a 50% increase in vehicle capacity resulted in a noteworthy reduction in total cost, demonstrating a decrease of -0.03%. Similarly, a more moderate 25% increase in vehicle capacity yielded a reduction of -0.01%. Conversely, a decrease in vehicle capacity had an adverse effect on total cost. A 25% decrease led to an increase in total cost by 0.230%, while a 50% decrease resulted in a cost escalation of 0.055%. This underscores the importance of optimal vehicle capacity management, with an emphasis on judicious increases to achieve cost efficiencies and the necessity to avoid excessive reductions that could potentially incur additional costs.

The analysis showed that changes in vehicle capacity had no significant effect on the Risk Priority Number (RPN).

The environmental implications of altering vehicle capacity revealed that a 50% increase in vehicle capacity led to -0.01% reduction in carbon emissions, emphasizing the potential environmental benefits of increased capacity. A 25% increase in vehicle capacity also contributed to a -0.005% decrease in carbon emissions. Conversely, a 25% decrease in vehicle capacity resulted in a 0.02% increase in carbon emissions, underscoring the importance of maintaining an optimal balance. Furthermore, a substantial 50% decrease in vehicle capacity increased carbon emissions by 0.1%, highlighting the environmental consequences of excessive capacity reduction.

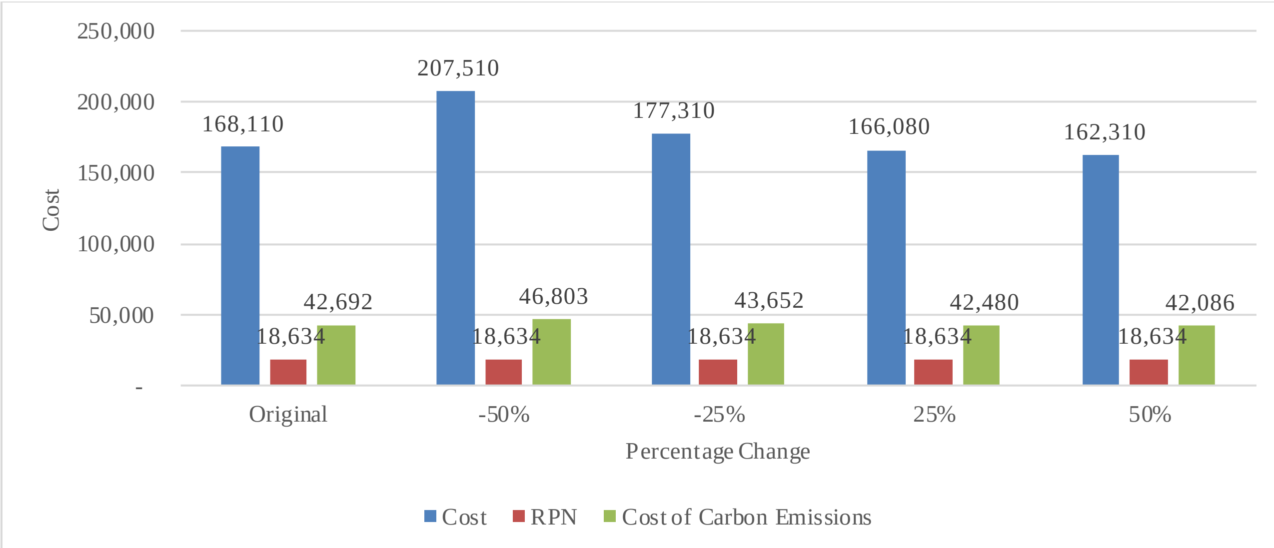

Figure 8: Change in Vehicle Capacity

7.5.4 Change in Segregation Ratio

The way waste is segregated holds notable implications for several dimensions within the context of infectious medical waste supply chain, encompassing total cost, Risk Priority Number (RPN), and carbon emissions across the supply chain network, as outlined in the provided data. When 90% of waste is designated as hazardous and 10% as non-hazardous or recyclable, there is a marginal decrease of -0.04% in total cost. This trend persists with a 70% hazardous to 30% non-hazardous/recyclable segregation ratio, resulting in a slightly larger -0.10% decrease in total cost. Furthermore, adopting a 50% hazardous to 50% non-hazardous/recyclable segregation ratio leads to a -0.16% reduction in total cost. These patterns underscore the relationship between waste segregation ratios and the total cost.

Interestingly, changes in waste segregation ratios do not seem to elicit any discernible impact on the RPN value, irrespective of the proportion of hazardous and non-hazardous/recyclable waste. This suggests that alterations in waste segregation do not directly influence the calculated RPN.

Concerning carbon emissions associated with waste management, variations in waste segregation ratios lead to proportionate changes. For instance, a 90% hazardous to 10% non-hazardous/recyclable ratio results in a -0.06% decrease in carbon emissions. Similarly, a 70% hazardous to 30% non-hazardous/recyclable ratio leads to a -0.16% decrease, and a 50% hazardous to 50% non-hazardous/recyclable ratio prompts a -0.24% decrease in carbon emissions. These shifts highlight the direct correlation between waste segregation ratios and carbon emissions across the supply chain network.

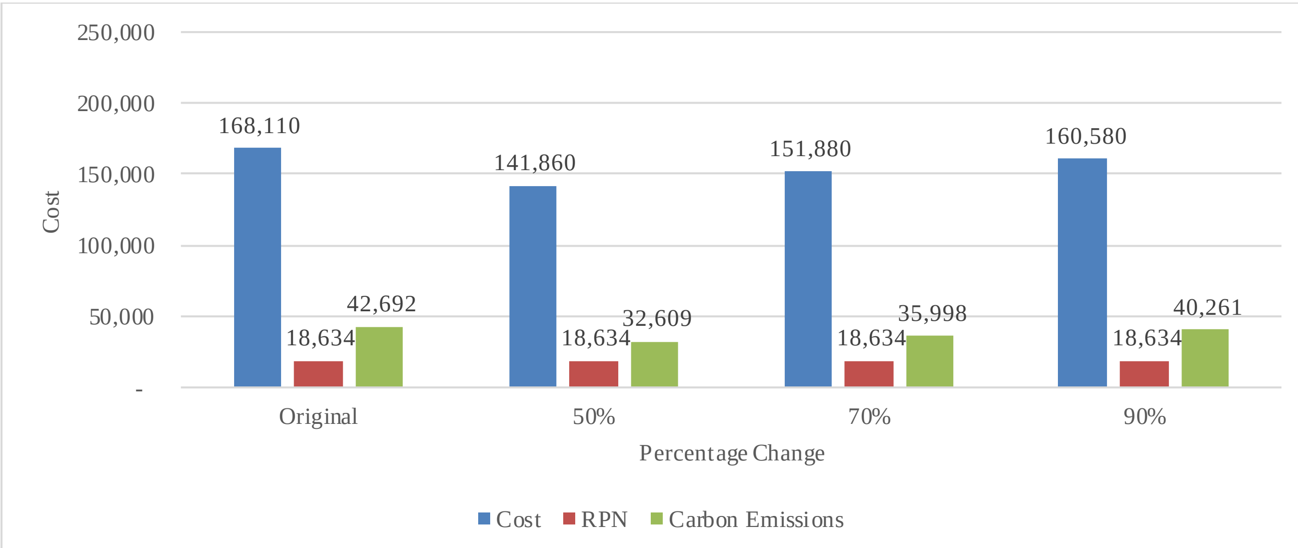

Figure 9: Change in Segregation Ratio

Chapter 8: Conclusion

The burgeoning concerns surrounding improper waste management practices, their repercussions on environmental health, and the need for sustainable solutions have driven the foundation of this research. In the pursuit of addressing these pressing challenges, mixed integer linear programming MILP model comprising of multi-objectives is developed that is used to evaluate overall supply chain cost, risk priority number (RPN), and carbon emissions. The overall cost and carbon emissions are reduced in the optimization model solved through Bipolar Neutrosophic Optimization approach. On the other hand, the risk priority number (RPN) is maximized in this model. The mathematical model was evaluated using MATLAB optimization tool and results were derived from it. The spatial arrangement of nodes within the medical waste supply chain network encompasses waste generation point, central transfer station, recycling plants, incineration plants, and landfill sites plays a critical role in both transportation cost and emissions saving. Waste segregation at sortation centers significantly contributes to emission reduction.

This research primarily emphasizes the significant role of waste recycling in achieving emission reduction objectives. Leveraging the Bipolar Neutrosophic Optimization Model, this study ensures a robust and comprehensive approach to the network design, moving beyond the limitations of traditional methodologies. The optimized model serves as an invaluable tool to evaluate the performance of the medical waste supply chain, offering decision-makers critical insights to mitigate the environmental impact of waste in the wake of global environmental challenges. Findings from the optimization demonstrate the factors primarily responsible for cost contribution within the transportation and processing. Moreover, the sensitivity analysis emphasizes the crucial role of inter-node distances in influencing both transportation costs and emissions. Comparisons made within the Bipolar Neutrosophic Optimization Model framework highlight its efficacy in addressing the research objectives. In future extensions of this work, considerations could include training programs for waste segregation, and analyzing the financial aspects for waste management companies.

In summary, this research forms a foundational basis for an optimized medical waste supply chain, employing the innovative Bipolar Neutrosophic Optimization Model to effectively address cost optimization, RPN evaluation, and emission saving, thereby significantly contributing to environmental preservation and sustainable waste management practices.

8.1 Managerial Insights

The purpose of this study was to properly manage medical waste and optimize cost and minimize the risks associated with medical waste. In addition, the proposed model can assist health center managers in strategic decisions making. By optimizing overall cost and dedicating efforts to establishing a robust MWSC network, Pakistan has the potential to significantly enhance its current situation. There is optimism that such measures could not only spur improvements within the country but also serve as a potential model for other developing nations.

The following are some recommendations for health system managers to improve MWSCN:

- Allocating a budget and demonstrating the necessary coordination for integrated medical waste management in each city. Non-integrated management increases the risks of the cleaning process, therefore in some centers the quality of the process may decrease, and cost optimization will also be very difficult.
- The amount of IMW is less than NIMW. If GMW waste is combined with IMW, they all become infectious. Therefore, if these two types of waste are combined, the volume will increase significantly, which will mean high risks and costs. Where possible, special attention should be paid to waste sorting at the source of production and these processes should be properly implemented.
- Lack of proper training plans for employees to familiarize themselves with the risks of medical waste and the methods of handling these risks can cause irreparable damage to their health. To avoid potential risks and ensure proper segregation, it is recommended to provide ongoing training to workers and the effectiveness of the training should be evaluated.
- To minimize MWSC impact on the environment and human health site selection for a set of potential new facilities should be done by experts.

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