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Article

Reverse Logistics Network Design with a 3-Phase Interactive Intuitionistic Fuzzy Goal Programming Approach: A Case Study of Covid-19 in Pathum Thani, Thailand

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Abstract. During outbreaks, a vast quantity of Infected Medical Waste (IMW) can be substantially generated in a short period, which poses a massive risk to medical personnel and surrounding communities. This study proposes an Intuitionistic Fuzzy Multi-Objective Multi-Period Mixed-Integer Linear Programming (IFMOMILP) model for effective IMW management in outbreaks under uncertainty, considering financial and risk factors subject to a priority from Decision Makers (DMs). The primary emphasis is on determining the optimal locations and capacity levels for temporary facilities, including temporary storage and treatment centers, as well as the optimal transportation routes. A 3-phase interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) approach is developed to solve this IFMOMILP model. First, the Jiménez approach is applied to handle the uncertainties. Then, the problem is solved by Intuitionistic Fuzzy Goal Programming (IFGP). An actual case study of the COVID-19 outbreak in Pathum Thani province in Thailand was carried out to demonstrate the effectiveness of the proposed approach. The proposed approach yields solutions with varying feasibility degrees and scaling factors, providing alternatives for DMs. Then, the score function is utilized to imply DMs' satisfaction with the outcomes, which is a concrete measure since it can reflect the intention of the DMs.

Keywords: Epidemic reverse logistics, intuitionistic fuzzy goal programming, medical wastes, multi-objective fuzzy programming, operational risks.

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1. Introduction

The impact of disease outbreaks generates significant economic disruption and seriously threatens human life. A disease outbreak was defined by the World Health Organization (WHO) as an event where the number of illness cases surpasses normal expectations [1]. Without proper monitoring of the disease's spreading, an outbreak can quickly escalate into an epidemic that threatens a large proportion of the population in a particular region. In the worst-case scenario, it may become a pandemic, spreading across multiple countries and thus causing panic among the global population.

During an outbreak, the number of cases increases exponentially, resulting in a significant increase in Infected Medical Waste (IMW), which raises a crucial issue in outbreak situations. Thus, an effective IMW reverse logistics design is critical in reducing disease spreading, as inappropriate collection and treatment can put medical personnel, patients, and populations around healthcare facilities and waste treatment centers at risk.

Coronavirus Disease (COVID-19) is the latest pandemic caused by a newly identified coronavirus spread from individual to individual. The first case was confirmed in Wuhan, China, on December 31, 2019, and quickly escalated into a global catastrophe [2]. A rise in cases generates a vast amount of IMW, which should be promptly and adequately managed to reduce the possibility of the disease spreading. Unfortunately, as the quantity of IMW keeps increasing, the capabilities of existing treatment and storage centers are insufficient, resulting in IMW harmfully building up in inappropriate places. Thus, establishing temporary facilities is essential in planning effective IMW reverse logistics under such a crisis.

Regarding actual outbreaks, the accessibility and accuracy of gathered information are always a big concern. Due to such unpremeditated events, some spontaneous information needs to be evaluated by specialists. Because the problem is no longer fully deterministic, failing to account for these uncertainties might result in poor network design. In this circumstance, the intuitionistic fuzzy theory can help to deal with uncertainty in information and hesitation in the decision-making process of humans [3].

In this study, an Intuitionistic Fuzzy Multi-Objective Multi-Period Mixed-Integer Linear Programming (IFMOMILP) model is developed for the reverse logistics network design of IMW management in outbreaks to enhance the decisions of establishing temporary facilities with optimal locations and sizes and determining transportation strategies in uncertain environments, using an actual situation in a province in Thailand, Pathum Thani.

The remainder of this study is arranged as follows: Section 2 presents a literature review on relevant topics. Section 3 contains the problem description and mathematical formulation. Section 4 proposes a 3-phase interactive intuitionistic fuzzy goal programming approach. Section 5 validates the proposed model and approach via a case study of COVID-19 in Pathum Thani province, Thailand. Section 6 discusses and analyses the results. Lastly, section 7 concludes the study and states limitations and further research directions.

2. Literature Review

The literature review in this section focuses on three main related topics, i.e., (1) Risks in the supply chain, (2) Multi-objective fuzzy programming, and (3) Reverse logistics network model for IMW management.

2.1. Risks in the Supply Chain

A thorough understanding of the risks associated with the supply chain is addressed here. There are two significant types of supply chain risks: operational and disruptive risks [4]. Operational risks are those posed by ambiguous internal procedures or external forces, such as demand uncertainty and material shortages, whereas disruptive risks are associated with disasters such as earthquakes. Epidemic outbreaks, e.g., SARS, Ebola, and the most recent COVID-19, are a particular type of supply chain disruptive risks in which the risk has spread dynamically across multiple areas. In outbreaks, inappropriate IMW management, which incorporates highly infectious diseases, can produce substantial risks of disease transmission to waste staff, healthcare providers, and the community by being exposed to contagious diseases [5]. The risks from transportation around the treatment facilities have been mentioned in several studies such by Samanlioglu [6] and Tirkolaee et al. [7], as well as risks at healthcare facilities, are addressed in Kargar et al. [8] and Yu et al. [9]. Since the healthcare staff has to work closely with the IMW, there is a high possibility of disease contracting.

To keep the supply chain operating smoothly, it must be capable of responding to unexpected circumstances. Risk measurement enables supply chains to establish appropriate risk-mitigation strategies. Cheng and Yu [10] presented a fuzzy comprehensive risk assessment using the Delphi method to analyze risks in urgent logistical challenges. In the framework of multi-objective issues, Nolz et al. [11] introduced a post-disaster problem with transportation and location risk as objectives. Three risk-measurement techniques were applied, with the unreachability approach proving the best fit for this problem. Abkowitz and Cheng [12] developed a method for estimating costs and risks in optimizing hazardous waste management. Multiple accident causes, and their consequences were considered when assessing the risk. Rianmora et al. [13] developed a new waste-classifying system to reduce the risk of the disease exposure.

2.2. Multi-objective Fuzzy Programming

In real-world problems, information is only sometimes precisely known since there are a variety of unanticipated consequences from the environment and operations. Crisp values can no longer withstand such uncertainties. Subsequently, the fuzzy set theory was developed by Zadeh [14] to deal with problems involving uncertain information. Later on, The fuzzy concept has been used in several optimization studies to deal with uncertainty and imprecision ([15], [16], [17]). Furthermore, issues in realistic situations are often complex, with multiple objectives. In several multi-objective optimization problems, the financial aspect is usually considered along with other conflicting objectives, such as the environmental aspect [18], [19], social aspect [20], [21], and risk aspect [7]-[9]. The problem of conflicting objectives is a prevalent issue in several cases, so no ideal solution can concurrently improve all objectives [22]. Preliminary approaches to producing compromise solutions, such as weighted max-min, weighted additive, and Zimmermann, methods have been used to solve fuzzy programming problems. These methods, however, may deliver inefficient or impractical solutions [23]. As a result, several new approaches have been developed to produce better results. Interactive Fuzzy Linear Programming (*i*-FLP) is one of the approaches proposed to produce efficient outcomes based on DMs' preferences. Recently, several *i*-FLP methods have been proposed, such as Jiménez et al. [24], Lai and Hwang [25], Selim and Ozkarahan [26], and Torabi and Hassini [27].

Due to an increase in fuzzy problems involving inaccurate and vague data, various extensions of fuzzy sets have emerged. Atanassov [28] proposed the intuitionistic fuzzy set to deal with DMs' hesitation due to the uncertainties and incomplete information by employing the concept of degree of acceptance and rejection. Later, it was developed and implemented in many studies, such as multi-attribute decision-making ([29], [30]), transportation problems ([31], [32]), and portfolio optimization problems ([33]).

2.3. Reverse Logistics Network Model for IMW Management

Infected medical waste management during disease outbreaks has recently gained popularity among researchers due to its ability to reduce disease spreading. The concept of Reverse Logistics (RL) was first defined by Stock [34] as a backward process of managing resources, material recycling, and waste disposal. In other words, reverse logistics involves the activities starting from End-Of-Life (EOL) products to their recovery. Fleischmann et al. [35] investigated the impact of the flow back. They constructed a Mixed-Integer Linear Programming (MILP) model widely employed in subsequent Closed-Loop Supply Chains (CLSC) problems.

Shih and Lin [36] proposed the first study of multi-objective reverse logistics in waste management, using the developed MILP and a dynamic programming model to establish optimal transportation routing and scheduling in handling IMW in Taiwan. Their models were widely employed in subsequent studies and incorporated ecological concerns and transportation risks. Shi et al. [37] developed a MILP model for the IMW reverse logistics network's cost minimization using an improved genetic algorithm method. Budak and Ustundag [38] proposed a MILP model to determine an appropriate number and location of facilities for implementing an effective waste reverse logistics system in Türkiye. Concerning environmental issues, Alshraideh and Abu Qdais [18] created a stochastic model to optimize a capacitated vehicle routing schedule for medical waste collection, considering both delivery costs and the number of pollutant emissions. Mantzaras and Voudrias [39] proposed a nonlinear model to reduce the costs associated with IMW management in Greek. Wang et al. [40] developed a two-stage reverse IMW network to allocate facilities while considering environmental and cost aspects. According to recent research, properly managing temporary facilities such as temporary treatment and storage centers is a significant strategic decision [9]. Furthermore, the danger of disease transmission from hospitals or transportation has become a critical issue in IMW management studies [8].

The fuzzy concept has been conducted to address these concerns regarding data uncertainty caused by a lack of data availability and inaccurate processes. For instance, Göçmen [41] studied optimizing the distribution and inventory of personal protective equipment under uncertainty while keeping a low cost. The Jiménez approach and clustering heuristic methods solved the model containing fuzzy parameters. The findings emphasized the significance of healthcare supply chain management. Tirkolaee, Abbasian, and Weber [7] developed a MILP model to solve the location-routing problem of IMW in COVID-19, considering travel time and infectious risk. The fuzzy chance constraint approach was employed to deal with uncertainty, and the model was solved using the weighted goal programming method. Negarandeh and Tajdin [42] employed robust fuzzy programming for managing medical wastes while considering profit, environmental impact, social consequences, and resilience in uncertain situations.

A summary of the literature on the reverse logistics of IMW management is presented in Table 1. This study aims to develop an IFMOMILP model for designing an effective reverse logistics network with an emphasis on establishing temporary facilities of appropriate size and the flow of the IMW. The proposed approach involves prioritizing conflicting objectives between the costs and the risks. A 3-phase interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) approach is employed. Thereby, the optimal outcomes can be generated according to the preference of DMs under different feasibility degrees (α), scaling factors (ρ), and allowed percentage deviations (d). This study would help DMs improve managerial decisions when developing the reverse logistics network for IMW outbreaks in uncertain circumstances subject to uncertainty in information and hesitation in decision-making. The main contributions of this study can be summarized as follows:

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- An IFMOMILP model is developed for designing an effective reverse logistics network for IMW in outbreaks, taking into account uncertainty in data and decision-making processes, as well as conflicting objectives (both financial efficiency and risks in operations) to determine suitable locations and sizes of temporary facilities as well as optimal transportation strategies.
- To determine the necessity of having temporary facilities (i.e., storage centers and treatment centers) during this outbreak by showing the outcomes of both total costs and total risks prioritization from setting these temporary facilities and comparing them with the actual situation where there are no temporary facilities.
- To tackle the uncertainties and balance the trade-off between prioritized conflicting objectives, a 3-phase interactive intuitionistic fuzzy approach is applied. Jiménez approach is utilized to handle the intuitionistic data with the feasibility concept in the first phase, and the Intuitionistic Fuzzy Goal Programming (IFGP) method is applied in the second and third phases to generate effective outcomes under an optimal solution that help DMs in making effective strategic decisions.
- To the best of our knowledge, this study is the first study of its type, which takes into account the intuitionistic fuzzy goal programming and combines the Jiménez approach with the Intuitionistic Fuzzy Goal Programming (IFGP) method subject to the optimal allowed percentage deviation from the first goal to solve the reverse logistics network of IMW in outbreaks under an uncertain environment.

3. Problem Formulation

The principal challenge in designing an effective reverse logistics network of IMW in uncertain circumstances under uncertain environments is to balance financial efficiency and risks arising from operations, including the risk of disease spreading at the hospitals, storage centers, and treatment centers, along the transportation routes. Unlike any typical reverse logistics network design, the amount of IMW dramatically increases quickly due to the outbreak. Figure 1 presents the framework of the proposed reverse logistics network design for IMW management in outbreak circumstances, which is intended to handle this situation. The network comprises hospitals, existing treatment centers, and temporary facilities, including temporary storage and treatment centers. Considering the rapid increase of IMW generated during outbreaks, temporary facilities help provide adequate capacity for treating the IMW. An IFMOMILP model is presented to optimize the decisions of locations in establishing the temporary facilities, deciding the suitable size of temporary treatment centers, and determining the optimal flow of IMW transferred among the facilities. The problem assumptions are as follows:

- A set of capacity levels is provided to be chosen for each candidate location of temporary treatment centers. Each level is subject to a particular capacity limitation and incurs a specific installation cost.
- There is a lower limit on the utilization of facilities to be considered in each period.
- All uncertain parameters are assumed to have fuzziness under the triangular intuitionistic distribution.
- Candidate temporary facilities can be promptly installed at the beginning of the planning horizon.
- DMs have a certain mindset of a higher priority objective in which a higher priority indicates that one objective is more important than the other and should be satisfied first.

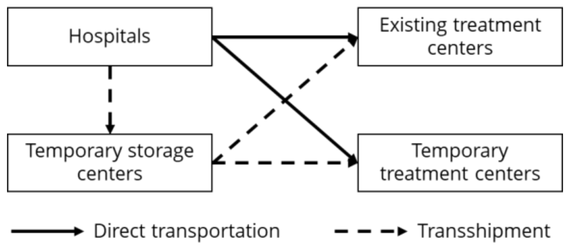

Fig. 1. The framework of the reverse logistics for IMW in the outbreak circumstance.

3.1. Model Formulation

3.1.1. Notations

The notations used in the mathematical model of the facility location problem are expressed as follows:

Please be noted that the symbol ($\tilde{}$) represents the uncertain parameters in this model.

- Indexes:

h	Hospitals, as well as other sources of medical waste
t	Candidate locations for temporary storage centers
e	Existing treatment centers
d	Candidate locations for temporary treatment centers
p	Periods
n	Capacity levels

- Parameters:

Rh_h	Risk probability at hospital h
Rt_t	Risk probability at temporary storage center t
Re_e	Risk probability at existing treatment center e

Table 1. Summary of related research.

References	Model specification			Objectives			Problem formulation	Optimization
	Multi-objectives	Multi-periods	Data uncertainty	Financial aspect	Risk	Others		
Samanlioglu [6]	x			x	x		MILP	Lexicographic weighted Tchebycheff formulation
Shih and Lin [36]	x	x		x	x		DP, ILP	Multiple criteria optimization
Shi et al. [37]				x			MILP	Genetic algorithm
Budak and Ustundag [38]		x		x			MILP	Solver software
Alshraideh and Qdais [18]	x	x		x		x	MILP	Genetic algorithm
Mantzara and Voudrias [39]		x		x			MINLP	Solver software
Wang et al. [40]	x	x		x		x	MINLP	Gray prediction
Yu et al. [9]	x	x		x	x		MOMILP	Interactive fuzzy approach
Kargar et al [8]	x			x	x	x	MOMILP	Revised Multi-Choice Goal programming method
Göçmen [41]		x	x	x			FMILP	Integrated fuzzy approach
Tirkolaee et al. [7]	x	x	x		x	x	FMOMILP	Chance Constraint Fuzzy Programming (CCFP) Weighted Goal programming
Negarandeh and Tajdin [42]	x		x	x		x	RMOMILP	Chance Constraint Fuzzy Programming (CCFP) Improved Goal programming LP-metric
This study	x	x	x	x	x		IFMOMILP	Interactive intuitionistic fuzzy goal programming approach

Abbreviations: DP: Dynamic programming, ILP: Integer linear programming, MILP: Mixed-integer linear programming, FMILP: Fuzzy mixed-integer linear programming , MOMILP: Multi-objective mixed-integer linear programming, FMOMILP: Fuzzy multi-objective mixed-integer linear programming, MINLP: Multi-objective stochastic mixed-integer nonlinear programming, RMOMILP: Robust multi-objective mixed-integer linear programming, IFMOMILP: Intuitionistic fuzzy multi-objective mixed-integer linear programming,

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Rd_d	Risk probability at temporary treatment center d
$RTht_{ht}$	Probability of transportation risk between hospital h and temporary storage center t
$RTte_{te}$	Probability of transportation risk between temporary storage center t and existing treatment center e
$RTtd_{td}$	Probability of transportation risk between temporary storage center t and temporary treatment center d
$RThe_{he}$	Probability of transportation risk between hospital h and existing treatment center e
$RThd_{hd}$	Probability of transportation risk between hospital h and temporary treatment center d
N_h^p	Number of patients in hospital h in period p
Pt_t	Population exposure at temporary storage center t
Pe_e	Population exposure at existing treatment center e
Pd_d	Population exposure at temporary treatment center d
$PTht_{ht}$	Population exposure from transportation between hospital h and temporary storage center t
$PTte_{te}$	Population exposure from transportation between temporary storage center t and existing treatment center e
$PTtd_{td}$	Population exposure from transportation between temporary storage center t and existing treatment center d
$PThe_{he}$	Population exposure from transportation between hospital h and existing treatment center e
$PopThd_{hd}$	Population exposure from transportation between hospital h and existing treatment center d
RI	Infection rate of the disease
$\widetilde{Gw_h^p}$	Quantity of IMW generated at hospital h in period p
$Caph_h$	Maximum capacity of IMW collection room in hospital h
$\widetilde{Capt_t}$	Capacity of temporary storage center t
$\widetilde{Cape_e}$	Capacity of existing treatment center e
$\widetilde{Capd_{dn}}$	Capacity of temporary treatment center d with capacity level n
LBe_e	Minimum quantity requirement of operating an existing treatment center e
LBd_d	Minimum quantity requirement of operating a temporary treatment center d
$\widetilde{inst_t}$	Cost of installing temporary storage center t
$\widetilde{insd_{dn}}$	Cost of installing temporary treatment center d with capacity level n
$\widetilde{pct_t}$	Cost of processing one unit of IMW at temporary storage center t
$\widetilde{pce_e}$	Cost of processing one unit of IMW at existing treatment center e
$\widetilde{pcd_d}$	Cost of processing one unit of IMW at temporary treatment center d
$\widetilde{tcht_{ht}}$	Cost of transporting one unit of IMW between hospital h and temporary treatment center t
$\widetilde{tcte_{te}}$	Cost of transporting one unit of IMW between temporary storage t and existing treatment center e
$\widetilde{tctd_{td}}$	Cost of transporting one unit of IMW between temporary storage t and temporary treatment center d
$\widetilde{tche_{he}}$	Cost of transporting one unit of IMW between hospital h and existing treatment center e
$\widetilde{tchd_{hd}}$	Cost of transporting one unit of IMW between hospital h and temporary treatment center d

- Decision variables:

Yt_t	1 if a temporary storage center is established at location t; 0 otherwise
Yd_{dn}	1 if a temporary treatment center with capacity level n is established at location d; 0 otherwise
$OTpe_e^p$	1 if an existing treatment center e is operated in period p; 0 otherwise
$OTpd_d^p$	1 if a temporary treatment center d is operated in period p; 0 otherwise
UQ_h^p	Quantity of uncollected IMW at hospital h in period p
Qt_t^p	Quantity of IMW stored at temporary storage center t in period p
Qe_e^p	Quantity of IMW treated at existing treatment center e in period p
Qd_d^p	Quantity of IMW treated at temporary treatment center d in period p
$QTht_{ht}^p$	Quantity of IMW transported from hospital h to temporary storage center t in period p
$QTte_{te}^p$	Quantity of IMW transported from temporary storage center t to existing treatment center e in period p

$QTtd_{td}^{p}$	Quantity of IMW transported from temporary storage center t to temporary treatment center d in period p
$QThe_{he}^{p}$	Quantity of IMW transported from hospital h to existing treatment center e in period p
$QThd_{hd}^{p}$	Quantity of IMW transported from hospital h to temporary treatment center d in period p
d	Allowed percentage deviation from the optimal value of the first goal in the third phase for *i*-IFGP models

3.1.2. Mathematical Model

A mathematical model of a reverse logistic network of IMW in an outbreak circumstance is formulated as follows:

- Objective functions

The mathematical model aims to balance the trade-off between financial performance and the total risks from operations in drastic increases of IMW in outbreak circumstances.

$$\begin{aligned} Min\ z_1 &= \textstyle\sum_{t=1}^{T} Yt_t\, \widetilde{inst}_t + \sum_{d=1}^{D} Yd_{dn}\, \widetilde{insd}_{dn} + \sum_{t=1}^{T}\sum_{p=1}^{P} \widetilde{pct}_t Qt_t^p + \sum_{e=1}^{E}\sum_{p=1}^{P} \widetilde{pce}_e Qe_e^p + \sum_{d=1}^{D}\sum_{p=1}^{P} \widetilde{pcd}_d Qd_d^p + \\ &\textstyle\sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{p=1}^{P} \widetilde{tcht}_{ht}\, QTht_{ht}^p + \sum_{t=1}^{T}\sum_{e=1}^{E}\sum_{p=1}^{P} \widetilde{tcte}_{te}\, QTte_{te}^p + \sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{p=1}^{P} \widetilde{tctd}_{td}\, QTtd_{td}^p + \\ &\textstyle\sum_{h=1}^{H}\sum_{e=1}^{E}\sum_{p=1}^{P} \widetilde{tche}_{he}\, QThe_{he}^p + \sum_{h=1}^{H}\sum_{d=1}^{D}\sum_{p=1}^{P} \widetilde{tchd}_{hd}\, QThd_{hd}^p \end{aligned} \quad (1)$$

The first objective function, as presented in Eq. (1), represents the total costs of the reverse logistics network of IMW. The first and the second terms are installation costs of temporary facilities. The third is the processing cost at the temporary storage center. The fourth and fifth terms are treatment costs. The other terms are transportation costs in the network.

The risks from operations are measured by a risk estimation model proposed by Nema and Gupta [43], which concerns the probability of occurrence and the consequence of the risk as:

$$Risk = Probability \times Consequence \quad (2)$$

Each element of risk is formulated as shown in Eq. (2). It is unitless, and the higher the risk, the greater the possibility of disease spreading.

$$\begin{aligned} Min\ z_2 &= \textstyle\sum_{p=1}^{P}\sum_{h=1}^{H} Rh_h\, UQ_h^p N_h^p RI + \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{p=1}^{P} RTht_{ht}\, QTht_{ht}^p PTht_{ht} + \sum_{t=1}^{T}\sum_{e=1}^{E}\sum_{p=1}^{P} RTte_{te}\, QTte_{te}^p PTte_{te} + \\ &\textstyle\sum_{t=1}^{T}\sum_{d=1}^{D}\sum_{p=1}^{P} RTtd_{td}\, QTtd_{td}^p PTtd_{td} + \sum_{h=1}^{H}\sum_{e=1}^{E}\sum_{p=1}^{P} RThe_{he}\, QThe_{he}^p PThe_{he} + \sum_{h=1}^{H}\sum_{d=1}^{D}\sum_{p=1}^{P} RThd_{hd}\, QThd_{hd}^p PThd_{hd} + \\ &\textstyle\sum_{t=1}^{T}\sum_{p=1}^{P} Rt_t\, Qt_t^p Pt_t + \sum_{e=1}^{E}\sum_{p=1}^{P} Re_e\, Qe_e^p Pe_e + \sum_{d=1}^{D}\sum_{p=1}^{P} Rd_d\, Qd_d^p Pd_d \end{aligned} \quad (3)$$

The second objective function, as presented in Eq. (3), represents the total risks of the reverse logistics network of IMW. The first term represents the risk at the hospitals where a significant amount of IMW is generated quickly. According to Yu et al. [9], the probability of accidental risk at hospitals is estimated by experts. The consequence of accidental risk at the hospital (Rh_h) corresponds to the uncontrolled amount of IMW (UQ_h^p), the number of patients at the hospital (N_h^p), and the spreading rate of the disease (RI). This objective aims to minimize the quantity of uncollected IMW at the hospital to reduce the risk of disease spreading to medical staff, patients, and the community around the hospital. The transportation risks, addressed from the second to fifth terms, are calculated by the probability of accidents along the route and the consequence of accidents along the route. According to Yu et al. [9], the probability of accidents along the route corresponds to the probability of accidents (PT) and the amount of IMW transported (QT). For calculating the risks at the storage and treatment centers presented from the sixth to eighth terms, the consequences correspond to the amount of IMW at the facilities (Q), and population exposure (P).

- Constraints

$$UQ_h^p = \widetilde{Gw}_h^p + UQ_h^{p-1} - \textstyle\sum_{t=1}^{T} QTht_{ht}^p - \sum_{e=1}^{E} QThe_{he}^p - \sum_{d=1}^{D} QThd_{hd}^p, \quad \forall h, p \quad (4)$$

$$Qt_t^p = Qt_{t-1}^p + \textstyle\sum_{h=1}^{H} QTht_{ht}^p - \sum_{e=1}^{E} QTte_{te}^p - \sum_{d=1}^{D} QTtd_{td}^p, \quad \forall t, p \quad (5)$$

$$Qe_e^p = \textstyle\sum_{t=1}^{T} QTte_{te}^p + \sum_{h=1}^{H} QThe_{he}^p, \quad \forall e, p \quad (6)$$

$$Qd_d^p = \textstyle\sum_{t=1}^{T} QTtd_{td}^p + \sum_{h=1}^{H} QThd_{hd}^p, \quad \forall d, p \quad (7)$$

Equations (4) and (5) balance the flow among facilities in the network. Equations (6) and (7) calculate the amount of IMW received at existing treatment centers and temporary treatment centers, respectively.

$$UQ_h^p \le Caph_h, \quad \forall h, p \quad (8)$$

$$Qt_t^p \le Yt_t \widetilde{Capt}_t, \quad \forall t, p \quad (9)$$

$$Qe_e^p \le OTpe_e^p \widetilde{Cape}_e, \quad \forall e, p \quad (10)$$

$$Qe_e^p \ge LBe_e OTpe_e^p \widetilde{Cape}_e, \quad \forall e, p \quad (11)$$

$$Qd_d^p \le OTpd_d^p \widetilde{Capd}_d, \quad \forall d, p \quad (12)$$

$$Qd_d^p \ge LBd_d\, OTpd_d^p\, \widetilde{Capd}_d, \quad \forall d, p \quad (13)$$

Equation (8) ensures that the quantity of uncollected IMW does not exceed the storage capacity of the hospitals. Equations (9), (10), and (12) ensure that the amount of IMW does not exceed the storage or treatment capacity of the facilities. Equations (11) and (13) represent the lower limit of IMW receiving at each facility.

$$OTpd_d^p \leq \sum_{n=1}^{N} Yd_{dn}, \qquad \forall d, p \quad (14)$$
$$\sum_{n=1}^{N} Yd_{dn} \leq 1, \qquad \forall d \quad (15)$$

Equations (14) ensures that a temporary facility cannot operate if not established. Equation (15) imposes that only one capacity level is chosen for a temporary treatment center. Equations (16) – (20) are non-negativity and binary constraints.

$$Yt_t, Yd_{dn}, \in \{0,1\}, \qquad \forall t, d, n \quad (16)$$
$$OTpe_e^p, OTpd_d^p \in \{0,1\}, \qquad \forall e, d, p \quad (17)$$
$$UQ_h^p, Qt_t^p \geq 0, \qquad \forall h, t, p \quad (18)$$
$$Qe_e^p, Qd_d^p \geq 0, \qquad \forall e, d, p \quad (19)$$
$$QTht_{ht}^p, QTte_{te}^p, QTtd_{td}^p, QTtd_{td}^p, QThd_{hd}^p \geq 0 \qquad \forall h, t, e, d, p, n \quad (20)$$

4. 3-Phase Interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) Approach

In the IMW reverse logistics network in an outbreak, the uncertainty parameters, including the quantity of IMW generated, the costs incurred, and the capacity of facilities, are described by the triangular intuitionistic fuzzy numbers. A 3-phase interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) approach addresses such uncertainties. Before doing so, a Fuzzy Multi-Objective Mixed-Integer Linear Programming (FMOMILP) model solved by a traditional Fuzzy Goal Programming (FGP) approach is used as a benchmark for comparison with the proposed approach. Considering the proposed approach, in the first phase, an equivalent auxiliary crisp model developed by Jiménez et al. [24] is utilized to convert intuitionistic fuzzy numbers to crisp numbers. In the second phase, the FGP approach is used to develop the optimum solution considering the priorities of the objectives. Then, in the third phase, the optimal allowed percentage deviation from the optimal value of the first goal is identified, and a comparison between the traditional FGP approach and 3-phase *i*-IFGP approach and a comparison between the cases with and without temporary facilities are made. The flow chart of the 3-phase *i*-IFGP approach is presented in Fig. 1.

The crisp MOMIILP model is used to identify the objectives' Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS). In this model, the most likely value represents the crisp value. The payoff table technique, as shown in Table 1, determines each objective's PIS and NIS. Each row shows the result of minimizing each objective. Since there are only minimization objectives, in this study, PIS is determined by minimizing each objective, and the NIS is the maximum or worst value of each objective in the column.

Table 1. Payoff table.

	v_1	v_2	…	v_k
Min z_1	$z_1(v_1)$	$z_1(v_2)$	…	$z_1(v_k)$
Min z_2	$z_2(v_1)$	$z_2(v_2)$	…	$z_2(v_k)$
…	…	…	…	…
Min z_j	$z_j(v_1)$	$z_j(v_2)$	…	$z_j(v_k)$

where $z_j^{PIS} = \min\{z_j(v_k)\} = v_k^*$ and $z_j^{NIS} = \max\{z_j(v_k^*); j \neq k\}$.

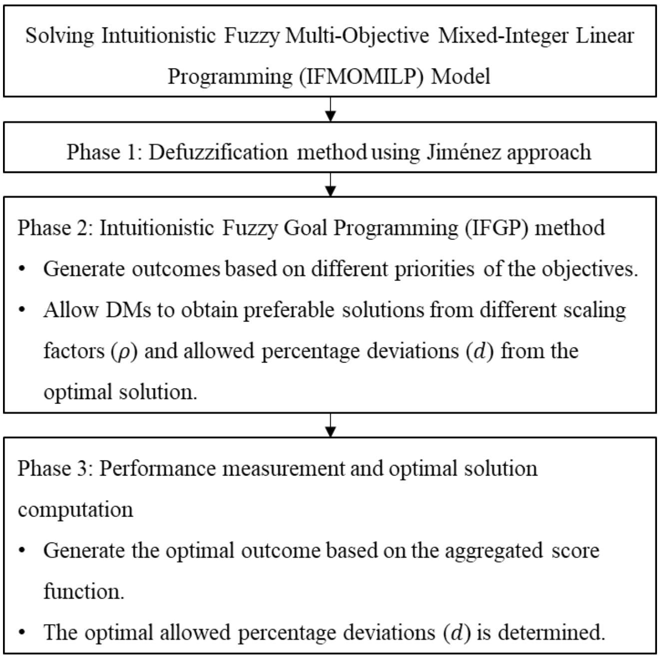

Fig. 1. Flowchart of the proposed approach.

4.1. Solving the IFMOMILP Model

This study represents the uncertain parameters using triangular intuitionistic fuzzy numbers. A 3-phase *i*-IFGP approach is also utilized to solve the IFMOMILP model. A triangular intuitionistic fuzzy number $\tilde{a}$ in X is defined as $\tilde{a} = \{\langle x, \mu_{\tilde{a}}(x), \nu_{\tilde{a}}(x): x \in X\rangle\}$, where $\mu_{\tilde{a}}(x)$ and $\nu_{\tilde{a}}(x)$ are in the range of [0,1] and denotes the degree of membership and non-membership, respectively. For each element x in X, $0 \leq \mu_{\tilde{a}}(x) + \nu_{\tilde{a}}(x) \leq 1$ and $\pi_{\tilde{a}} = 1 - \mu_{\tilde{a}}(x) - \nu_{\tilde{a}}(x)$, where $\pi_{\tilde{a}}$ denotes the degree of the hesitancy of x in $\tilde{a}$. In other words, $\pi_{\tilde{a}}$ indicates inadequate information as to whether x belongs to $\tilde{a}$ or not.

Each triangular intuitionistic fuzzy number is composed of five prominent points including a_1, a_2, a_3, a_1', and a_3', where $a_1' \leq a_1 \leq a_2 \leq a_3 \leq a_3'$. The membership and non-membership of $\tilde{a}$ is shown in Fig. 2.

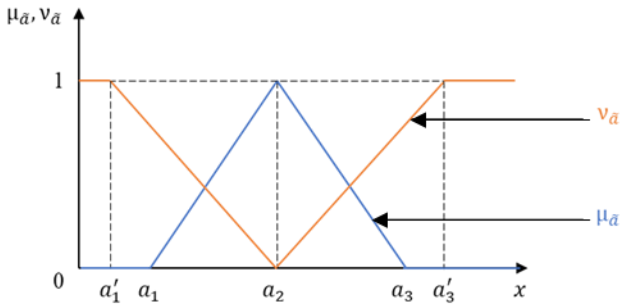

Fig. 2. Triangular intuitionistic fuzzy number $\tilde{a}$.

4.1.1. Phase 1: Defuzzification Method Using Jiménez Approach

The proposed model contains intuitionistic fuzzy parameters, which describe the unpredictable nature of outbreak scenarios and provides information on each parameter's membership and non-membership degree. Jiménez's approach is applied to transform the IFMOMILP model into a crisp model. This interactive method allows DMs to tailor the feasibility degrees (α) to their preferences. Furthermore, this approach is computationally efficient since it retains the models' linearity without adding additional objective functions.

To convert the IFMOMILP model to an auxiliary crisp model, the membership function $\mu_{\tilde{a}}(x)$ of $\tilde{a}$ and the non-membership function $\nu_{\tilde{a}}(x)$ of $\tilde{a}$ are defined as follows:

$$\mu_{\tilde{a}}(x) = \begin{cases} 0, & x < a_1, \\ f_a(x), & a_1 < x < a_2, \\ 1, & x = a_2 \\ g_a(x), & a_2 < x < a_3, \\ 0, & x > a_3. \end{cases} \tag{21}$$

$$\nu_{\tilde{a}}(x) = \begin{cases} 1, & x < a_1', \\ h_a(x) & a_1' < x < a_2 \\ 0, & x = a_2 \\ i_a(x), & a_2 < x < a_3', \\ 1, & x > a_3'. \end{cases} \tag{22}$$

According to Midya et al. [44], the expected interval of a triangular intuitionistic fuzzy number $\tilde{a}$, denoted EI($\tilde{a}$), and the expected value of a triangular intuitionistic fuzzy number $\tilde{a}$, denoted EV($\tilde{a}$), are calculated as follows:

$$EI(\tilde{a}) = [E_1^a, E_2^a] = \left[\int_0^1 \{f_a^{-1}(x) + h_a^{-1}\}dx,\ \int_0^1 \{g_a^{-1}(x) + i_a^{-1}\}dx\right] = \left[\frac{a_1'+2a_2+a_1}{4}, \frac{a_3'+2a_2+a_3}{4}\right] \tag{23}$$

$$EV(\tilde{a}) = \frac{E_1^a+E_2^a}{2} = \frac{a_1'+a_1+4a_2+a_3+a_3'}{8} \tag{24}$$

As determined by Jiménez [45], for any two fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the degree in which $\tilde{a}$ is larger than $\tilde{b}$ is as follows:

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 & if\ E_2^a - E_1^b < 0 \\ \frac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & if\ 0 \in [E_1^a - E_2^b, E_2^a - E_1^b] \\ 1 & if\ E_1^a - E_2^b > 0 \end{cases} \tag{25}$$

If $\mu_M(\tilde{a}, \tilde{b}) \geq \alpha$, it indicates that $\tilde{a}$ is greater than or equal to $\tilde{b}$ in a degree of α and it is represented by $\tilde{a} \geq_\alpha^i \tilde{b}$. From Eq. (25), this is equivalent to:

$$\frac{E_2^a - E_1^b}{E_2^a - E_1^b + E_2^b - E_1^a} \geq \alpha \tag{26}$$

According to Arenas et al. [46], for any two fuzzy numbers $\tilde{a}$ and $\tilde{b}$, we say that $\tilde{a}$ is indifferent to $\tilde{b}$ in a degree of α, denoted $\frac{\alpha}{2} \leq \mu_M(\tilde{a}, \tilde{b}) \leq 1 - \frac{\alpha}{2}$. This is equivalent to:

$$\frac{\alpha}{2} \leq \frac{E_2^a - E_1^b}{E_2^a - E_1^b + E_2^b - E_1^a} \leq 1 - \frac{\alpha}{2} \tag{27}$$

Fuzzy multi-objective linear programming can then be solved by the following formulations:

$$\begin{aligned} & Min\ \tilde{z} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_j) = (\tilde{c}_1 x, \tilde{c}_2 x, \dots, \tilde{c}_j x) \\ & \text{s.t.}\ \ \tilde{a}_i x \geq \tilde{b}_i, \qquad i = 1, \dots, l \\ & \tilde{a}_i x = \tilde{b}_i, \quad i = l+1, \dots, m \\ & x \geq 0 \end{aligned} \tag{28}$$

Considering Eqs (28) and (29), they are equivalent to:

$$\begin{aligned} & Min\ \tilde{z} = (\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_j) = (\tilde{c}_1 x, \tilde{c}_2 x, \dots, \tilde{c}_j x) \\ & \text{s.t.}\ \ [(1-a)E_2^{a_i} - aE_1^{a_i}]x \geq aE_2^{b_i} \\ & \quad +(1-a)E_1^{b_i}, \quad i = 1, \dots, l \\ & \quad [(1-\tfrac{\alpha}{2})E_2^{a_i} - \tfrac{\alpha}{2}E_1^{a_i}]x \geq \tfrac{\alpha}{2}E_2^{b_i} \\ & \quad +\left(1-\tfrac{\alpha}{2}\right)E_1^{b_i}, \quad i = l+1, \dots, m \\ & \quad [\tfrac{\alpha}{2}E_2^{a_i} - (1-\tfrac{\alpha}{2})E_1^{a_i}]x \geq (1-\tfrac{\alpha}{2})E_2^{b_i} \\ & \quad +\tfrac{\alpha}{2}E_1^{b_i}, i = l+1, \dots, m \end{aligned} \tag{29}$$

This method allows DMs to construct a logistic network in an interactive way using varied degrees of α. It aids DMs by providing information to assist them in determining the level of feasibility they are willing to bear.

4.1.2. Phase 2: Intuitionistic Fuzzy Goal Programming (IFGP) Method

Due to its ability to deal with data uncertainty and aspiration target levels, the Fuzzy Goal Programming (FGP) method is one of the most extensive ways to address multi-objective issues. The FGP method solves a fuzzy multi-objective problem by reducing objective deviations with a priority among the objectives. As a result, a more important goal is considered a higher priority and should be achieved first. The intuitionistic fuzzy set has become one of the most well-known extensions of conventional fuzzy optimization due to its ability to deal with uncertainties and imprecise human decision-making processes, sometimes known as hesitation. Furthermore, it simultaneously delivers knowledge of acceptable and rejective degrees so that these degrees are not complementary. In this study, the intuitionistic fuzzy concept is combined with the FGP method to develop the Intuitionistic Fuzzy Goal Programming (IFGP) method, which is used to solve an intuitionistic fuzzy multi-objective problem by using the score function (s_j) to represent DMs' satisfaction while keeping the objectives' priorities in an account. The method aims to reduce the deviation of the score function of each objective, taking into account the priority levels.

To apply the IFGP method to the problem with different priority levels of the objectives. The acceptable degree μ_j and the rejective degree ν_j should be determined. The acceptable degree is calculated from the membership degree, and the rejective degree is calculated from the non-membership degree as follows:

$$\mu_j = \begin{cases} 1, & z_j \le L_j^0, \\ \frac{U_j^0 - z_j}{U_j^0 - L_j^0}, & L_j^0 \le z_j \le U_j^0 \\ 0, & z_j \ge U_j^0 \end{cases} \quad (30)$$

$$\nu_j = \begin{cases} 0, & z_i \le L_i^1, \\ \frac{z_j - L_j^1}{U_j^1 - L_j^1}, & L_j^1 \le z_j \le U_j^1 \\ 1, & z_j \ge U_j^1 \end{cases} \quad (31)$$

where $U_j^0 = z_j^{NIS}, L_j^0 = z_j^{PIS}, U_j^1 = U_j^0, L_j^1 = L_j^0 + \rho(U_j^0 - L_j^0)$, and $0 \le \rho \le 1$. The scaling factor (ρ) indicates how much the DMs want to relax the ideal solution value. In this study, the score function $s_j(z_j)$ is presented to represent the satisfaction of DMs and it is calculated as follows:

$$s_j(z_j) = \mu_j(z_j) - \nu_j(z_j) \quad (32)$$

A multi-objective problem with j objective minimization functions intending to maximizing the acceptable degrees of objective functions can be formulated as:

$$\begin{aligned} & Min\ [\mu_1, \mu_2, \dots, \mu_j] \\ & \text{s.t. Problem constraints} \end{aligned} \quad (33)$$

To apply the FGP method to the problem with different priority levels of the objectives, suppose the first objective (z_1) is considered to have the highest priority and followed by other objectives in ascending order.

The IFGP method, which aims to maximize the score function, is employed to solve the intuitionistic fuzzy multi-objective problem. The total satisfaction of DMs is maximized by maximizing the acceptable degrees and minimizing the rejective degrees simultaneously. The IFGP method can be formulated as follows:

$$\begin{aligned} & Max\ s_j \\ & \text{s.t. Problem constraints} \\ & s_{j-1} \le s_{j-1}^* \times (1 - d_{j-1}), \quad j = 1, \dots, J \\ & \mu_j \ge \nu_j \ge 0, \ j = 1, 2, \dots, J \\ & \mu_j + \nu_j \le 1, \ j = 1, 2, \dots, J \end{aligned} \quad (34)$$

where d_j is the allowed percentage deviation of the objective function j and s_j^* is the optimal score function of z_j. The single-objective problem is solved in order of priority, with $j = 1$ being solved first, then $j = j + 1$, and so on until all objectives are solved. The constraint $s_{j-1} \le s_{j-1}^* \times (1 - d_{j-1})$ indicates how much the DMs allow the score function of the higher priority objective to deviate from its optimal value., $\mu_j \ge \nu_j$ ensures that the acceptable degree of an objective is always greater than the rejective degree, and $\mu_j + \nu_j \le 1$ ensures that the summation of the acceptable degree and the rejective degree of each objective does not exceed 1.

4.1.3. Phase 3: Performance Measurement and Optimal Solution Computation

The objective function values are typically used to evaluate and indicate the performance of solutions. However, the objective function values cannot always be directly compared due to differences in units or measurements. Hence, the aggregated acceptance degree and the aggregated score function are utilized to assess the performances of the IFMOMILP model outcomes. The aggregated score function is calculated as shown in Eq. (35).

$$\text{Aggregated score function} = \sum_{j=1}^{J} s_j \quad (35)$$

The higher the aggregated acceptance degree and the aggregated score function, the more satisfied DMs are with the outcomes.

In phase 2, the DMs choose the suitable allowed percentage deviation based on their preferences. Different allowed percentage deviations provide information about different scenarios for the DMs to obtain appropriate planning further. However, a modified model is offered if DMs desire to attain the optimal outcome based on the optimal aggregate score function. For the *i*-IFGP model, the model in Eq. (34) is as follows:

$$
\begin{aligned}
&Max\ \textstyle\sum_{j=1}^{J} s_j - d/10^6 \\
&\text{s.t.}\ \ \text{Problem constraints} \\
&\qquad s_{j-1} \le s_j\,, \qquad j = 1, \dots, J \\
&\qquad s_{j-1} \le s_{j-1}^{*} \times (1 - d_{j-1})\,, \quad j = 1, \dots, J \\
&\qquad \mu_j \ge \nu_j \ge 0, \quad j = 1, 2, \dots, J \\
&\qquad \mu_j + \nu_j \le 1, \quad j = 1, 2, \dots, J
\end{aligned}
\tag{36}
$$

where $s_{j-1} \le s_j$ represents the prioritizing of objectives. The modification is made to achieve the optimal outcomes based on the aggregated score function, as well as determine the optimal allowed percentage deviation (d) by transforming it into a decision variable.

5. Case Study

5.1. Case Description

To highlight the application of the proposed method, an actual case study of the Coronavirus Disease (COVID-19) outbreak in Pathum Thani, Thailand, is presented. The scope of the reverse logistics problem for medical waste management comprises IMW generation sources (hospitals), storage centers, and treatment centers. Pathum Thani province, a part of the metropolitan region of Thailand, had a rapid increase in the number of COVID-19 patients from July – August 2021, presented in Fig. 3.

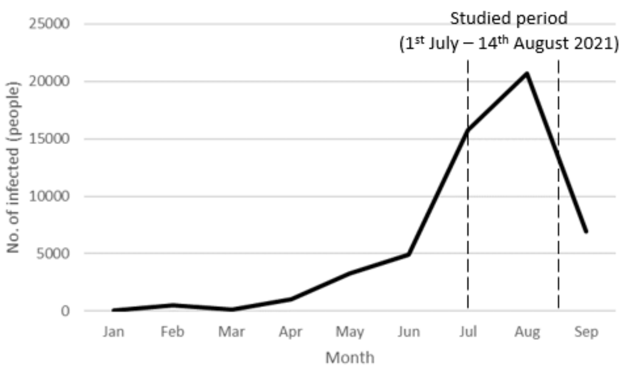

Fig. 3. No. of COVID-19 cases of Pathum Thani province from January – September 2021.

In this study, three districts of Pathum Thani province, including Muang district, Sam Khok district, and Lat Lum Kaeo district, are carried out as the case study. The planning horizon of the proposed model during the peak period of the outbreak, which is from 1st July - 14th August 2021, consists of 15 periods with 3 days each since IMW is typically picked up every 3 days.

The proposed model comprises three echelons, as presented in Fig. 4. The first echelon comprises IMW generation sources. In designing an effective reverse logistics system for IMW in this area, storage centers (the second echelon) are an alternative option to store and aggregate the IMW overflow from the hospitals. Then, the IMW is delivered to be treated at treatment centers (the third echelon). Currently, there is no storage and treatment center for IMW in Pathum Thani province. The IMW of Pathum Thani province is typically treated by two existing treatment centers in nearby provinces (one in Nonthaburi province and another in Ayutthaya province). However, these two incinerators have to be responsible for IMW from many nearby provinces. The incinerators will be unable to handle these wastes very soon since the number of patients keeps rising during this crisis. Concerning this problem, six potential locations for temporary storage centers and five potential locations for temporary treatment centers are studied to alleviate the problem by locating them in suitable areas. A digital map of the three districts of Pathum Thani province containing spatial data is analyzed using Quantum Geographic Information System (QGIS) 3.16.6 with criteria specified by Pollution Control Department (PCD) [47]. For example, a treatment center must be at least one kilometer away from residential areas and archaeological heritage sites. The locations of all facilities in the proposed reverse logistics network for IMW management can be presented in Fig. 5.

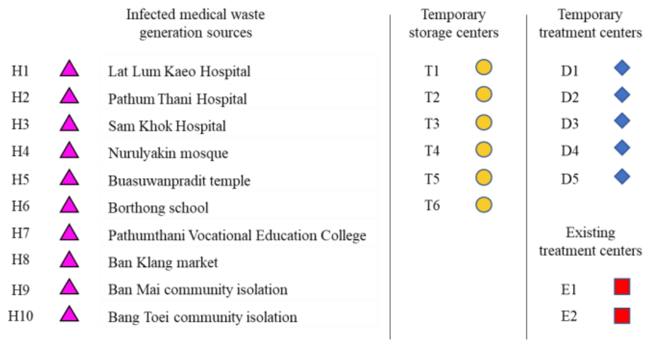

Fig. 4. Facilities in the network.

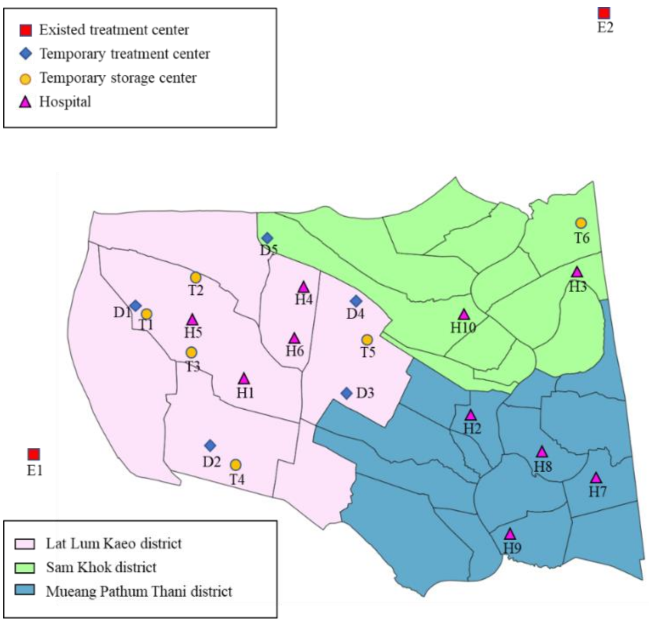

Fig. 5. The location of facilities of the reverse logistics for IMW management in Pathum Thani province.

In an outbreak situation, DMs are inevitably confronted with the challenge of trading off between financial and risk aspects to develop an effective reverse logistic network design of IMW management. Concerning this issue, two scenarios are presented in this case study, with the first case prioritizing the financial aspect and the second case prioritizing the risk aspect to provide the information for DMs to select the implementation plan according to their preferences. The scenarios and their objectives' priority are as follows:

- Scenario I: prioritizing the cost objective.
  - Priority level 1 – Minimize total costs (z_1).
  - Priority level 2 – Minimize total risks (z_2).
- Scenario II: prioritizing the risk objective.
  - Priority level 1 – Minimize total risks (z_2).
  - Priority level 2 – Minimize total costs (z_1).

In Scenario I, the total costs are regarded as more critical than the risks as a restricted budget to address the IMW management from this crisis is the primary concern. On the other hand, in Scenario II, the risks are regarded as more critical than the costs since controlling disease spreading is the most crucial issue in such a crisis. Therefore, risk management is a top priority regardless of a strict budget.

Nevertheless, compromising methods such as weightless Zimmermann's and weighted additive methods, where a weight is given to each objective to address its importance subject to DMs' preferences, can also be easily applied. However, this study considers that DMs have a particular prioritized goal one over the other. Thus, the goal programming approach is more appropriate in this circumstance.

5.2. Input Parameters

For illustration purposes, it is assumed that for the triangular fuzzy parameters representing the quantity of IMW generated, the cost parameters, and the facilities' capacity. The membership function's optimistic and pessimistic values are subject to 0.8 and 1.2 times the most likely case. For the intuitionistic triangular fuzzy parameters, the optimistic value and pessimistic value of the membership function are subject to 0.8 and 1.2 times the most likely case, while the optimistic value and pessimistic value of the non-membership function are subject to 0.7 and 1.3 times the most likely case. However, the maximum available capacity is the most likely value of the temporary facilities' capacity. Thus, its optimistic value is the same as its most likely value. Generally, the daily generation of IMW in Thailand is 0.54 kg/bed/day [48]. However, during the COVID-19 outbreak, there was an increase in the generation of IMW due to a requirement for additional medical equipment, e.g., medical masks and personal protective equipment. According to professional evaluations, the daily IMW generation in the most likely case is 2.85 kg/bed/day at hospitals and 1.82 kg/bed/day at field hospitals [49]. The IMW generated at each hospital in each period is proportional to the number of patients and the daily IMW generation. The number of hospital patients (H1, H2, and H3) was estimated based on the number of new cases reported by the Pathum Thani province public health office, and the assumption that the length of hospital stays for COVID-19 was 14 days. During this crisis, the field hospitals and community isolations (H4 – H10) were full as soon as they opened. The estimated number of patients at each IMW generation source in each period is presented in Table 2.

Table 2. Estimated number of patients at each IMW generation source in each period.

Period	Number of patients at each IMW generation sources (people/period)									
	H1	**H2**	**H3**	**H4**	**H5**	**H6**	**H7**	**H8**	**H9**	**H10**
1	464	186	39							
2	565	190	173							
3	577	145	208							
4	700	105	258				450			
5	758	89	281				1,350			
6	815	452	223				1,350			
7	922	683	352	90		90	1,350	300		300
8	1,070	825	616	90		90	1,350	450	300	900
9	1,232	1,101	1,037	90	160	90	1,350	450	300	900
10	1,291	1,348	1,241	90	240	90	1,350	450	300	900
11	1,309	988	1,715	90	240	90	1,350	450	300	900
12	1,390	725	1,511	90	240	90	1,350	450	300	900
13	1,241	654	2,036	90	240	90	1,350	450	300	900
14	1,052	446	1,924	90	240	90	1,350	450	300	900
15	915	210	1,938	90	240	90	1,350	450	300	900

Considering facilities in the network, the lists of IMW generation sources and existing treatment centers are shown in Tables 3 and 4, respectively. The capacities of the existing treatment centers in this case study are assumed to be a portion of their full capabilities since these two treatment centers must also service the IMW from other provinces. Six candidate locations for temporary storage centers and five for temporary treatment centers are selected based on the criteria specified by PCD [47]. The candidate locations for those temporary facilities and their population densities are shown in Tables 5 and 6.

Table 3. Names of IMW generation sources.

No.	IMW generation source	Maximum capacity of IMW collection room (kg/period)
1	Lat Lum Kaeo Hospital	8,160
2	Pathum Thani Hospital	4,650
3	Sam Khok Hospital	7,710
4	Nurulyakin mosque	480
5	Buasuwanpradit temple	1,320
6	Borthong school	480
7	Pathumthani Vocational Education College	7,380
8	Ban Klang market	2,460
9	Ban Mai community isolation	1,650
10	Bang Toei community isolation	4,920

Table 4. Names of existing treatment centers.

No.	Existing treatment center	Population density (people/km2)
1	Nonthaburi Provincial Administrative Organization's (PAO) waste processing facility	380.64
2	Bangpain Land company limited	4,650

Table 5. Candidate locations for temporary treatment centers.

No.	Location (Latitude, Longitude)	Sub-district	Population density (people/km2)
1	14.066303, 100.362195	Rahaeng	403.71
2	14.012116, 100.399202	Lat Lum Kaeo	183.68
3	14.032922, 100.469977	Khu Bang Luang	347.36
4	14.074859, 100.468714	Khu Bang Luang	347.36
5	14.105289, 100.423597	Bang Toei	516.05

The traveling distances between two nodes in Pathum Thani province are obtained using the fastest route in QGIS 3.16.6 and Google Map. The transportation cost is proportional to the distance traveled, and the weight of the IMW is estimated to be 0.185 Baht/kg/km [9].

Table 6. Candidate locations for temporary storage centers.

No.	Location (Latitude, Longitude)	Sub-district	Population density (people/km2)
1	14.068801, 100.374156	Rahaeng	403.71
2	14.088797, 100.395403	Rahaeng	403.71
3	14.047686, 100.393543	Rahaeng	403.71
4	13.997883, 100.413293	Lat Lum Kaeo	183.68
5	14.055485, 100.475268	Khu Bang Luang	347.36
6	14.110869, 100.573855	Chiang Rak Noi	274.74

Considering the probability of accidental risk at the IMW generation sources ($PbAh_h$), the risk is 0.003 for hospitals and 0.007 for temporary hospitals [9]. The accidental risk of storage center ($PbAt_t$) and treatment center ($PbAe_e$ and $PbAd_d$) are 0.0001 and 0.0006, respectively. According to Zhao et al. [50], the probability of risk along the route is calculated by Eq. (37). The population exposure is calculated by Eq. (38), where the affected radius is set to be 2.5 kilometers for treatment centers and 1 kilometer for storage centers. The population exposure along the route between facilities is calculated by Eq. (39).

$$PbTht_{ht}, PbTte_{te}, PbTtd_{td}, PbThe_{he}, PbThd_{hd} = \frac{0.4*10^{-6}*0.9}{(km)} \times travel\ distance\ (km) \tag{37}$$

$$Popt_t, Pope_e, Popd_d = \pi r^2 (km^2) \times population\ density\ (people/km^2) \tag{38}$$

$$PopTht_{ht}, PopTte_{te}, PopTtd_{td}, PopThe_{he}, PopThd_{hd} = 2(km^2) \times population\ density\ (people/km^2) \times travel\ distance\ (km) \tag{39}$$

The relevant costs and capacities of existing treatment centers, temporary treatment centers, and temporary storage centers are presented in Tables 7 – 9, respectively. The installation cost of the temporary storage center is composed of the costs of the land, its construction, and equipment. For temporary treatment centers, three capacity levels (S, M, and L) are provided as an alternative (decision variable), which incurs different installation costs and is subject to different capacity limitations. The installation cost is a one-time expense once the facility is chosen for establishment. In the most likely case, the processing cost of temporary storage and temporary treatment centers is set to 0.9 Baht/kg and 3.23 Baht/kg, respectively. The size and cost parameters of temporary facilities are calculated based on Yu et al. [9], Sresanpila and Sindhuchao [51], and Homchalee et al. [52].

Table 7. Cost parameters and capacity of existing treatment centers.

No.	Processing cost (Baht/kg)	Capacity (kg/period)
1	13.00	567.00
2	4.50	3021.00

Table 8. Installation cost and capacity of temporary treatment centers.

No.	Capacity level	Installation cost (Baht)	Capacity (kg/period)
1	S	9,346,550	2,400
	M	12,494,900	7,200
	L	19,915,250	14,400
2	S	10,346,550	2,400
	M	13,994,900	7,200
	L	21,915,250	14,400
3	S	10,546,550	2,400
	M	14,294,900	7,200
	L	22,315,250	14,400
4	S	10,546,550	2,400
	M	14,294,900	7,200
	L	22,315,250	14,400
5	S	8,946,550	2,400
	M	11,894,900	7,200
	L	19,115,250	14,400

Table 9. Installation cost and capacity of temporary storage centers.

No.	Installation cost (Baht)	Capacity (kg/period)
1	6,486,250	31,500
2	6,486,250	31,500
3	6,486,250	31,500
4	8,486,250	31,500
5	10,086,250	31,500
6	4,886,250	31,500

6. Result and Discussion

All optimization tasks are performed by IBM ILOG CPLEX studio IDX 12.9.0 on a computer with an Intel(R) Core (TM) i7-8550U CPU @1.80GHz and 8GB RAM. Due to the conflicting objectives, in this case study, two prioritizing scenarios are offered as an alternate network design plan for DMs to utilize based on their preferences, where Scenario I is to prioritize the cost objective and Scenario II is to prioritize the risk objective.

As previously mentioned, the crisp MOMILP model identifies the objectives' Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). In this model, the most likely value represents the value of crisp parameters. The payoff table, which is used to determine the PIS and the NIS, is presented in Table 10.

Table 10. Payoff table.

Objectives	v_1	v_2
z_1 (Baht)	17,521,082.24	3,289,691.30
z_2	44,176,726.87	104,306.55

Since both objectives are minimizing objectives, the PIS, or the minimum value, is 17,521,082.24 Baht for the total costs (z_1) and 104,306.55 for the total risks (z_2). The NIS, or the maximum value, is 44,176,726.87 Baht for the total costs (z_1) and 3,289,691.30 for the total risks (z_2).

6.1. Results from Phase 2 of the 3-Phase Interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) Approach

For illustrative purposes, according to the preference of DMs, the feasibility degree (α) was set at 0.7, and the scaling factor (ρ) was set at 0.1. The sensitivity analysis to explore the effect of their variation on the outcome will be concluded later.

The *i*-IFGP approach is applied to solve the IFMOMILP model and obtain an effective solution based on the priority of the objective functions. The *i*-IFGP approach allows DMs to adjust the feasibility degree (α), the scaling factor (ρ), and the allowed percentage deviation according to their preferences. The optimal outcomes of the proposed model from various levels of the allowed percentage deviation solved by the *i*-IFGP approach with α = 0.7 and ρ = 0.1 are presented in Tables 11 – 12.

From Table 11, in Scenario I, where the costs are prioritized, increasing the allowed percentage deviation raises the total costs (z_1) while decreasing the total risks (z_2). With this outcome, the obtained results are always the same when the total costs are allowed to deviate from their optimal value beyond 10%. It is because the obtained result is the lowest possible risk generated concerning the facilities selected as the deviation exceeds 10%. On the contrary, from Table 12 in Scenario II, where the risks are prioritized, increasing the allowed percentage deviation lowers the total costs (z_1) while increasing the total risks (z_2). Allowing the risk to deviate from its optimal value beyond 25% would bring the score function of the total costs (s_1) to be higher than the score function of the total risks (s_2) and violating the priority level determined by the DMs.

6.2. Results from Phase 3 of the 3-Phase Interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) Approach

Due to unit differences, the objective values cannot always be directly compared. Hence, the aggregated score function is utilized to assess the performance of the

IFMOMILP model. A model modification is done in Eq. (36) to achieve the optimal outcomes based on the aggregated score function, as well as determine the optimal allowed percentage deviation by transforming it into a decision variable. Table 13 presents the optimal results for Scenarios I and II.

For Scenario I, which is the total costs prioritizing case, the optimal outcome, which is the case of allowing a 9.06% deviation, suggests establishing a temporary treatment center at location 2 with the capacity size M in Lat Lum Kaeo sub-district and a temporary storage center at location 6 in Chiang Rahaeng sub-district. The temporary treatment center's capacity size M is chosen since a higher capacity level incurs a higher installation cost and causes the score function of the total costs objective to deteriorate, which is consistent with the cost prioritizing case. Even if the treating capacity is insufficient to treat the IMW in each period, the excess IMW can be appropriately stored at the temporary storage center, incurring lower total costs than constructing a size L temporary treatment center. However, for Scenario II, which is the total risks prioritizing case, the optimal outcome of the IFMOMILP model, which is the case of 14.00% deviation, suggests establishing a temporary treatment center at location 2 with the capacity size L and no temporary storage center. By establishing a temporary treatment center with a capacity size L, the treating capacity of this plan is sufficient to treat the majority of the IMW, so the storage center is unnecessary. There are fewer risks due to less IMW left in hospitals and no risk of IMW storing at any storage center.

Table 11. Results of Scenario I from various allowed percentage deviation using the 3-phase *i*-IFGP approach in phase 2 with α= 0.7.

Implications	**Allowed percentage deviation**			
	5%	**10%**	**15%**	**20%**
Minimize total costs z_1 (Baht)	18,469,845.82	19,939,328.44	19,939,328.44	19,939,328.44
Score function value of the first objective s_1	0.964	0.909	0.909	0.909
Minimize total risks z_2	818,816.97	603,327.92	603,327.92	603,327.92
Score function value of the second objective s_2	0.638	0.780	0.780	0.780

Remark: The highlighted boxes present the cases of allowed percentage deviation with the same objective values.

Table 12. Results of Scenario II from various levels of the allowed percentage deviation using the 3-phase *i*-IFGP approach in phase 2 with α= 0.7.

Implications	**Allowed percentage deviation**			
	10%	**15%**	**20%**	**25%**
Minimize total costs z_1 (Baht)	25,469,878.70	22,976,810.90	22,903,870.85	19,856,568.43
Score function value of the first objective s_1	0.482	0.679	0.685	0.912
Minimize total risks z_2	422,845.02	498,288.35	573,731.67	649,174.99
Score function value of the second objective s_2	0.900	0.850	0.800	0.750

Remark: The case of priority level violation is highlighted in gray.

The aggregate score function of Scenario I, 1.690, is higher than that of Scenario II, 1.536, indicating that the optimal solution from Scenario I is more satisfying in regarding the aggregate score function. It is due to the strategy in Scenario II, which suggests that the model establishes a temporary treatment center with a higher capacity level to reduce the quantity of IMW in the system, which can reduce total risks but significantly increase the total costs. Even if Scenario II is less satisfactory, it can be helpful if DMs desire to restrict risks to reduce the potential of disease spreading, which is a crucial concern during an outbreak. On the other hand, Scenario I is suitable for a limited budget situation, which could happen in areas where a small budget is set aside for an unexpected catastrophe. The detailed strategy of the optimal outcomes from the IFMOMILP models is presented as follows:

6.2.1. Optimal Operating Policy of Scenario I: Cost Minimization

In order to explain the obtained optimal result of Scenario I, which is presented in Table 13, the total costs (z_1) are 19,936,377.02 Baht, and the total risks (z_2) are 603,429.54. The score function of the total costs (s_1) and the score function of the total risks (s_2) are relatively high at 0.909 and 0.780, respectively. Table 15 shows the allocation of IMW from each hospital to other facilities. According to Table 14, all the IMW is treated at the temporary treatment center D2 in periods 1 – 6. From period 7 onwards, the temporary treatment center D2 alone cannot treat all the increasing amount of IMW since the utilization is full, so the overflowing IMW is delivered to the existing treatment centers and the temporary storage center D2. Thus, the temporary treatment center D2 is the main treatment center, with the two existing treatment facilities, E1 and E2, serving as alternatives when the primary treatment center is overloaded. The temporary treatment center D2 is chosen over the existing ones because it is closer to the hospitals and has a lower operating cost, resulting in lower total costs and a lesser risk of disease spread. During the first seven periods, no IMW is kept at the temporary storage center T6 since the treatment centers' capacities are still sufficient to treat the waste. However, when the waste quantity increases, the treatment centers' capacities are reached, and the remaining waste is kept at the temporary storage center T6 for subsequent treatment. For a demonstration of the optimal IMW reverse logistics network design, the network flow layout of the optimal solution in period 9 of Scenario I is presented in Fig. 6.

Table 13. Optimal results for Scenario I and Scenario II.

Criteria	Scenario I	Scenario II
Objective values		
Minimize total costs z_1 (Baht)	19,936,377.02	23,015,340.30
Minimize total risks z_2	603,429.54	483,138.67
Acceptable degrees		
Aggregated acceptable degree	1.753	1.675
Acceptable degree of the first objective μ_1	0.909	0.794
Acceptable degree of the second objective μ_2	0.843	0.881
Rejective degrees		
Aggregated rejective degree	0.063	0.139
Rejective degree of the first objective ν_1	0.000	0.118
Rejective degree of the second objective ν_2	0.063	0.021
Score functions		
Aggregated score function	1.690	1.536
Score function value of the first objective s_1	0.909	0.676
Score function value of the second objective s_2	0.780	0.860
Decision variables		
Location selected for the temporary treatment center (D)	D2(size M)	D2(size L)
Location selected for the temporary storage center (T)	T6	
Allowed percentage deviation (d)	9.06%	14.00%

Table 14. Facilities utilization of the optimal result in Scenario I.

Period	E1	E2	D2	T6
1	0.00%	0.00%	28.77%	0.00%
2	0.00%	0.00%	38.75%	0.00%
3	0.00%	0.00%	38.83%	0.00%
4	0.00%	0.00%	56.38%	0.00%
5	0.00%	0.00%	83.09%	0.00%
6	0.00%	0.00%	98.21%	0.00%
7	100.00%	69.37%	100.00%	0.00%
8	100.00%	100.00%	100.00%	8.63%
9	100.00%	100.00%	100.00%	26.43%
10	100.00%	100.00%	100.00%	49.53%
11	100.00%	100.00%	100.00%	72.85%
12	100.00%	100.00%	100.00%	86.99%
13	100.00%	100.00%	100.00%	100.00%
14	100.00%	100.00%	100.00%	100.00%
15	100.00%	99.53%	100.00%	100.00%

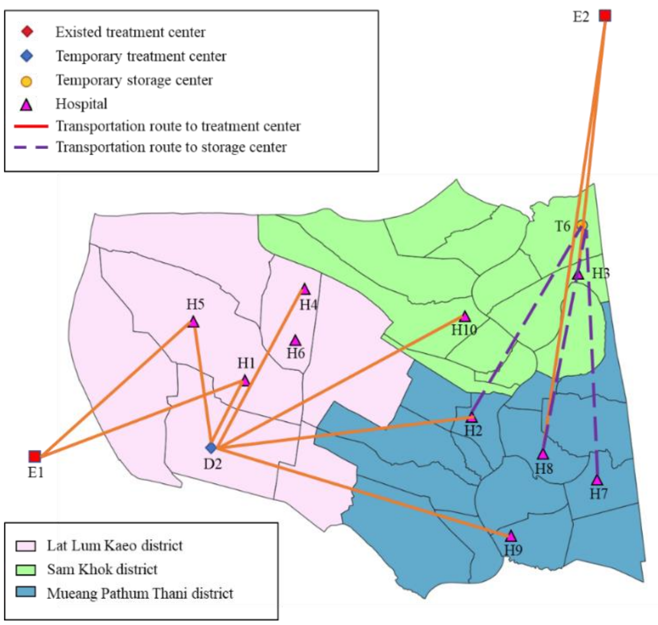

Fig. 6. Optimal network the network flow layout of Scenario I in period 9.

Table 15. Allocation of IMW in each period of the optimal result in Scenario I.

Allocation of IMW from hospitals to existing treatment centers															
Existing treatment centers	**Period**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
E1							H1	H1	H1 H5	H1	H1 H5	H1	H1	H4 H6 H10	H4 H5 H6
E2							H3 H7	H3 H8 H10	H3 H8	H3	H3	H3	H3	H3	H3
Allocation of IMW from hospitals to temporary treatment centers															
Temporary treatment centers	**Period**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
D2	H1 H2 H3	H1 H2 H3	H1 H2 H3	H1 H2 H3 H7	H1 H2 H3 H7	H1 H2 H3 H7	H1 H2 H4 H6 H7 H8 H10	H1 H2 H4 H6 H9 H10	H1 H2 H4 H5 H9 H10	H1 H2 H4 H6 H9 H10	H1 H2 H9 H10	H1 H2 H8 H9 H10	H1 H7 H8 H10	H3 H7 H8 H10	H2 H3 H4 H7 H10
Allocation of IMW from hospitals to temporary treatment centers															
Temporary storage centers	**Period**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
T6								H7 H8	H2 H7 H8	H2 H3 H7 H8	H2 H3 H7 H8	H3 H7 H8	H3 H7		

6.2.2. Optimal Operating Policy of Scenario II: Risk Minimization

For Scenario II, presented in Table 13, The total costs (z_1) are 23,015,340.30 Baht, and the total risks (z_2) are 483,138.67. The score functions of the total costs (s_1) and the score function of the total risks (s_2) are 0.676 and 0.860, respectively. Table 17 shows the allocation of IMW from each hospital to other facilities. According to Table 16, all the IMW is treated at the temporary treatment center D2 in periods 1 – 6. From period 7 onwards, the temporary treatment center D2 alone cannot treat all the increasing amount of IMW since the utilization is full, so the overflowing IMW is delivered to the existing treatment centers. Thus, the temporary treatment center D2 is the main treatment center, with the two existing treatment facilities, E1 and E2, serving as alternatives when the primary treatment center is overloaded. The temporary treatment center D2 is chosen over the existing ones due to the shorter distances among facilities, which is the same reason as Scenario I. Since the temporary treatment center has a higher capacity level and can treat the majority of IMW, fewer risks are involved, and there is no need for a temporary storage center. However, establishing a temporary treatment center with a high capacity and increased IMW treated resulted in a considerable cost increase. For a demonstration of the optimal IMW reverse logistics network design, the network flow layout of the optimal solution in period 9 of Scenario II is presented in Fig. 7.

Table 16. Facilities utilization of the optimal result in Scenario II.

Period	**E1**	**E2**	**D2**
1	0.00%	0.00%	14.38%
2	0.00%	0.00%	19.37%
3	0.00%	0.00%	19.41%
4	0.00%	0.00%	28.19%
5	0.00%	0.00%	41.55%
6	0.00%	0.00%	49.10%
7	0.00%	0.00%	69.25%
8	0.00%	0.00%	94.81%
9	29.27%	62.63%	100.00%
10	100.00%	100.00%	100.00%
11	100.00%	100.00%	100.00%
12	100.00%	85.82%	100.00%
13	0.00%	53.13%	100.00%
14	51.76%	0.00%	100.00%
15	0.00%	0.00%	100.00%

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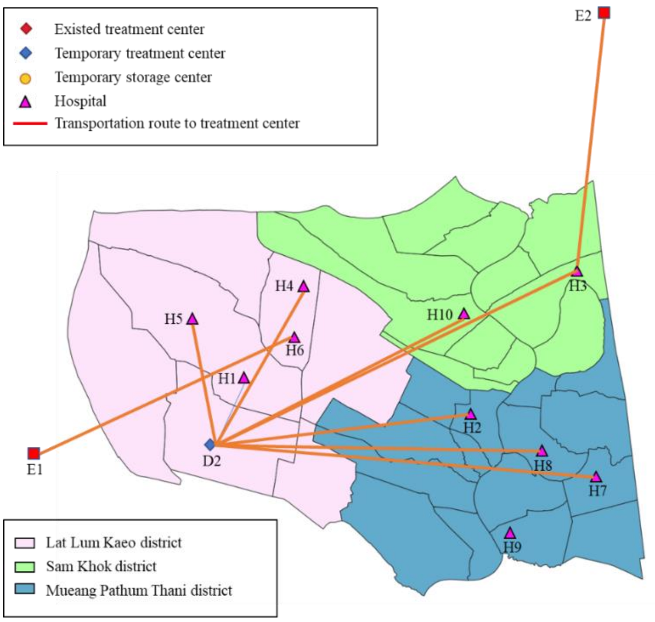

Fig. 7. Optimal network flow layout of Scenario II in period 9.

Table 18 shows a comparison with the actual situation where no temporary facility is carried out, highlighting the importance of the temporary facilities. It shows the massive damage from the actual situation's excess amount of uncollected or untreated IMW. Because of an increase in IMW during the COVID-19 outbreak, the existing treatment centers could not treat all delivered amounts of IMW, and the remaining IMW eventually started to pile up. In the actual case, the total costs are indeed lower than the proposed situation without these temporary facilities. However, the IMW would be severely accumulated at the hospitals or the existing treatment centers, causing the risks to increase tremendously beyond the acceptable level. Improper accumulation of IMW caused huge concerns about the disease spreading to communities during that time as reported in all newspapers and social medias that the IMW badly piled up across the country, especially at treatment centers in Bangkok and Nonthaburi provinces [53]. The temporary facilities can lead to far better effective management of the IMW, lowering the risk of disease spreading due to IMW piled up in inappropriate areas.

Table 17. Allocation of IMW in each period of the optimal result in Scenario II.

Allocation of IMW from hospitals to existing treatment centers															
Existing treatment centers	**Period**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
E1									H6	H5 H8	H2 H5	H5		H1	
E2									H3	H3	H3	H3	H3		
Allocation of IMW from hospitals to temporary treatment centers															
Temporary treatment centers	**Period**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
D2	H1 H2 H3	H1 H2 H3	H1 H2 H3	H1 H2 H3 H7	H1 H2 H3 H7	H1 H2 H3 H7	H1 H2 H3 H4 H6 H7 H8 H10	H1 H2 H3 H4 H6 H7 H8 H9 H10	H1 H2 H3 H4 H5 H7 H8 H10	H1 H2 H3 H4 H6 H7 H8 H10	H1 H2 H3 H7 H8 H9 H10	H1 H2 H3 H4 H5 H6 H7 H8 H9 H10	H1 H3 H5 H7 H8 H9 H10	H1 H3 H7 H8 H9 H10	H1 H3 H4 H6 H7 H8 H9 H10

6.3. Result comparison between the two approaches

A comparison between the optimal outcomes of the proposed approach, which is the 3-phase *i*-IFGP approach, and the traditional FGP approach is carried out for both scenarios to demonstrate the effectiveness of the proposed approach. Several significant differences between the FGP approach used in this comparison and the 3-phase *i*-IFGP approach are presented in Table 19.

For a fair comparison between the two approaches, the feasibility degree (α) is set at 0.7, and the scaling factor (ρ) is set at 0.1 for all cases. The outcomes are compared using the aggregated score function. For the traditional FGP approach, in this study, the DMs decided to increase the allowed percentage deviation by a step size of 5%. Selecting the case with the highest score function, allowing a 10% case deviation generates the optimal outcome for Scenario I, and allowing a 15% deviation can generate the optimal outcome for Scenario II for the traditional FGP approach. Thus, these cases are selected to compare with the 3-phase *i*-IFGP approach. Tables 20 and 21 present the result comparison of the optimal outcomes for Scenarios I and II, respectively.

Table 18. Results Comparison with actual situations.

Criteria	Actual situation		Proposed situation	
	Accumulate at hospitals	**Accumulate at existing treatment centers**	**Scenario I**	**Scenario II**
z_1 (Baht)	594,928.91	1,492,308.23	19,936,377.02	23,015,340.30
z_2	4,819,809.20	5,592,050.80	603,429.54	483,138.67
Excess amount of IMW remaining (kg)	111,107.45	111,107.45	None	None

Table 19. Differences between FGP approach and the 3-phase *i*-IFGP approach.

Criteria	Traditional FGP approach	3-phase *i*-IFGP approach
Uncertain parameter	Use the triangular fuzzy numbers (containing only membership function) shown in Eq. (21).	Use the intuitionistic fuzzy numbers (contain both membership function and non-membership function) as shown in Eqs (21) and (22).
Objective function	Multi-objective with a higher priority objective being solved first. Use the acceptance degree, calculated as shown in Eq. (30).	Modify into a single objective by setting a priority in a constraint. Use the aggregate score function (consider all acceptable degrees and rejective degrees and allow the DMs to adjust the scaling factor (ρ) as shown in Eq. (36).
Defuzzification of the objective function	Use the expected value (EV) of the triangular fuzzy numbers. The EV is calculated as follows: $EV(\tilde{a}) = \frac{a_1 + 2a_2 + a_3,}{4}$	Use the expected value (EV) of the triangular intuitionistic fuzzy number as shown in Eq. (24).
Defuzzification of the constraints	Use the expected value (EV) of the triangular fuzzy numbers. The EV is calculated as follows: $EV(\tilde{a}) = \frac{a_1 + 2a_2 + a_3,}{4}$	Use the Jiménez approach with the expected interval (EI) subject to the feasibility concept as shown in Eq. (29).

For Scenario I, by comparing the aggregated acceptance degrees, the aggregated score function of the 3-phase *i*-IFGP approach, 1.690, is slightly higher than that of the FGP approach, 1.652. For Scenario II, the aggregated score function of the 3-phase *i*-IFGP approach, 1.536, is also slightly higher than that of the FGP approach, 1.521. It indicates that the outcome from the 3-phase *i*-IFGP approach is more satisfying for DMs. The proposed 3-phase *i*-IFGP approach can generate better outcomes since it accounts for not only the acceptable degree but also the rejective degree of the objectives, which is related to the scaling factor (ρ) value determined by DMs' preferences in which he/she might not be eager to achieve the true optimal value but satisfy with relaxing the PIS to some acceptable levels. Thus, the score function can reflect more intention of DMs, and it is a more concrete way to evaluate the satisfaction of the DMs toward the outcome since it maximizes the acceptable degree and minimizes the rejective degree simultaneously. Furthermore, the model modification in phase 3 enables the proposed approach to produce the optimal outcome with compromising goals. In contrast, the traditional FGP approach can only vary the allowed percentage deviation from the best value of a higher-priority objective.

In summary, the proposed 3-phase *i*-IFGP approach has proven to be more effective since it can generate better outcomes regarding the aggregated score function. Moreover, the obtained result is more concrete by considering both acceptable and rejective degrees while reflecting the intention of DMs. On top of that, it provides flexibility to the model by allowing the DMs to adjust the scaling factor (ρ) and the feasibility degree (α) according to their preferences. This helps the DMs to effectively plan for the expected budget and the locations of the temporary facilities ahead of the unexpected catastrophe under uncertainties.

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Table 20. Results comparisons of Scenario I.

Criteria	FGP approach (10% deviation)	3-phase *i*-IFGP approach
Minimize total costs z_1 (Baht)	19,076,335.56	19,936,377.02
Minimize total risks z_2	709,151.84	603,429.54
Aggregated score function	1.652	1.690

Table 21. Results comparisons of Scenario II.

Criteria	FGP approach (15% deviation)	3-phase *i*-IFGP approach
Minimize total costs z_1 (Baht)	23,070,968.12	23,015,340.30
Minimize total risks z_2	498,877.67	483,138.67
Aggregated score function	1.521	1.536

6.4. Sensitivity Analysis

A sensitivity analysis is also performed in this section to evaluate the impact of the feasibility degree (α) and the scaling factor (ρ) on the outcomes of the proposed approach. In the 3-phase *i*-IFGP approach, the feasibility degree (α) and the scaling factor (ρ) are typically specified based on the preferences and knowledge of DMs. The α level indicates the level of feasibility that DMs are willing to acknowledge. It controls the confidence levels of ambiguous objectives and constraints. To investigate how uncertainty affects the optimal solutions for both scenarios, various feasibility levels with the scaling factor (ρ) = 0.1 under the optimal level of feasibility are applied to the IFMOMILP model. The result of varying the feasibility levels is shown in Table 22 and Fig. 8 for Scenario I and Table 23 and Fig. 9 for Scenario II.

According to Table 22 and Fig. 8, for Scenario I, it can be seen that as the α increases, the total costs (z_1) and the total risks (z_2) tend to worsen. It is because DMs prefer to tackle uncertainty more confidently in satisfying constraints. The constraints become restricted, and fewer solution sets are feasible.

According to Table 23 and Fig. 9, for Scenario II, as the feasibility level increases, the total costs (z_1) tend to worsen. However, the total risks (z_2) fluctuate. As mentioned in the sensitivity analysis of α in Scenario I, the objective value often gets worsens as the feasibility level increases due to more restrictions on the constraints However, for the total risks (z_2), there is fluctuation in the trend for various reasons. One of the reasons is the conflict among objectives. To lower the risks, there is a need to transfer a higher amount of IMW from the hospitals to other facilities for storage or treatment. This results in increased transportation among facilities, a larger quantity of IMW to be treated, and the establishment of more temporary facilities, all of which contribute to higher total expenses. Furthermore, this problem involves establishing temporary facilities, which is varied by the feasibility level. It can cause the risks to fluctuate since different facilities can treat or store a different amount of IMW and face different risks associated with transportation and treatment.

Table 22. Solutions of Scenario I with different values of α with ρ = 0.1 and d = 9.06%.

α-level	Aggregated s	s_1	s_2	z_1 (Baht)	z_2
0.1	1.820	0.946	0.875	18,971,897.33	460,793.33
0.3	1.781	0.944	0.837	19,013,498.04	517,177.45
0.5	1.740	0.909	0.831	19,936,377.01	526,989.77
0.7	1.690	0.909	0.780	19,936,377.02	603,429.54
0.9	1.596	0.909	0.686	19,933,745.36	745,269.19

Table 23. Solutions of Scenario II with different values of α with ρ = 0.1 and d = 14.00%.

α-level	Aggregated s	s_1	s_2	z_1 (Baht)	z_2
0.1	1.732	0.866	0.866	20,616,643.95	474,230.26
0.3	1.732	0.866	0.866	20,616,643.95	474,230.26
0.5	1.564	0.677	0.887	23,006,043.53	442,168.67
0.7	1.536	0.676	0.860	23,015,340.30	483,138.67
0.9	1.348	0.473	0.875	25,575,233.00	461,150.44

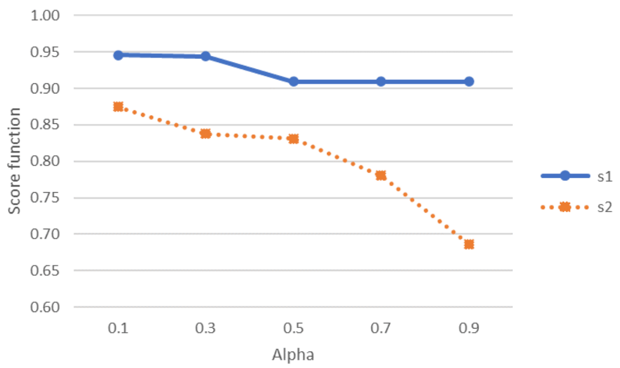

Fig. 8. Score function value of each objective function of Scenario I with different values of α with ρ = 0.1 and d = 9.06%.

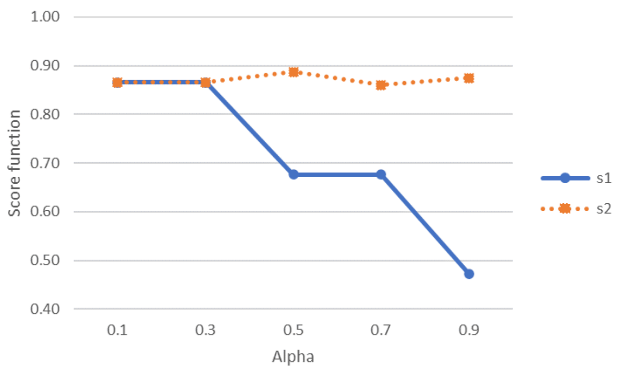

Fig. 9. Score function value of each objective function of scenario II with different values of α with ρ = 0.1 and d = 14.00%.

Various levels of the scaling factor with the feasibility degree (α) = 0.7 are also applied to the proposed model to investigate the impact of the scaling factor (ρ) on the optimal solutions. The results of varying the scaling factor for Scenarios I and II are shown in Figs. 10 and 11, respectively.

According to Figs. 10 and 11, raising the scaling factor (ρ) decreases the rejective degree (ν) while increasing the hesitation index (π). It is obvious that the increase of the scaling factor (ρ) leads the rejective degree (ν) to drop while increasing the hesitation index (π). Nonetheless, there is no significant impact on the acceptable degree (μ). The scaling factor (ρ) is usually determined by DMs to correspond with the appropriate certainty level for each problem. In this study, the scaling factor (ρ) is set to 0.1 to balance the rejective degree and the hesitation index. Since setting the scaling factor lower than 0.1 leads the hesitation index to zero, indicating that the outcome is concrete, it also raises the rejective degree since the summation of the acceptance degree, the rejective degree, and the hesitation index is equal to 1. The higher rejective degree leads to a lower score function, which means the result is less satisfactory. On the other hand, setting the scaling factor higher than 0.1 leads the rejective degree to approach zero. However, it also increases the hesitation index to a high level, which results in lower confidence in the outcome. A high scaling factor indicates that the DMs are satisfied with relaxing the PIS to an acceptable level and are not eager to achieve the optimal objective value.

The outcomes from altering the feasibility degree (α) and the scaling factor (ρ), and the allowed percentage deviation (d) can aid DMs in anticipating potential outcomes from various scenarios. Besides, this enables DMs to prepare beforehand, lowering the possible costs and risks associated with the IMW from outbreaks.

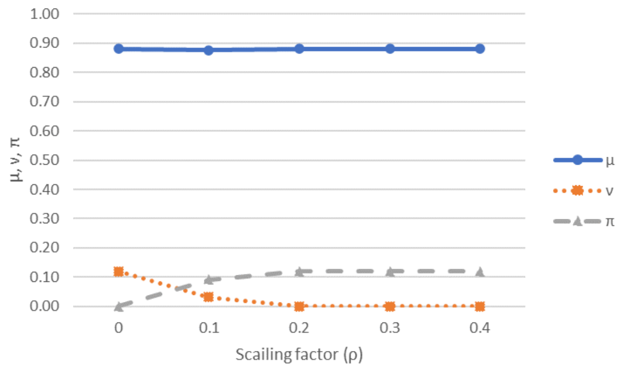

Fig. 10. Acceptable degree (μ), rejective degree (ν), and hesitation index (π) of scenario I with α = 0.7.

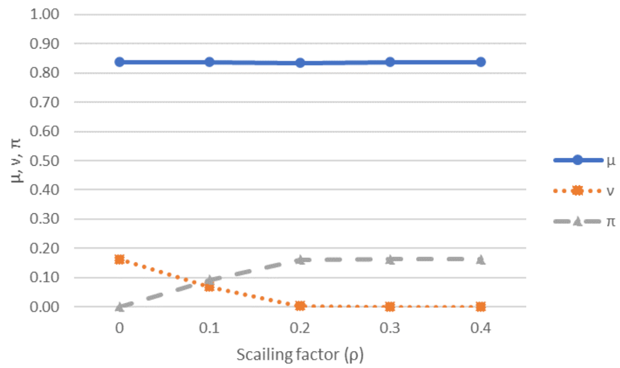

Fig. 11. Acceptable degree (μ), rejective degree (ν), and hesitation index (π) of scenario II with α = 0.7.

6.5. Managerial Implications

The primary purpose of this study is to develop a proper reverse logistics plan for IMW during outbreaks to decrease costs and avoid disease spreading from IMW by minimizing the risks in the network. Several managerial insights for healthcare managers or IMW treatment planners could be obtained from this study, as follows:

- Temporary facilities are crucial in reducing disease spreading from IMW since a vast quantity of IMW was generated during the outbreak and piled up at existing facilities. Inappropriate management can endanger the medical personnel and the communities surrounding the hospitals and existing treatment centers, as shown in Table 18, for the massive amount of IMW accumulating at hospitals and in front of existing treatment centers in case of no temporary facilities. Furthermore, the temporary facilities are still helpful even after the outbreak since Pathum Thani does not have its IMW treatment center or storage center. By establishing temporary facilities, the province does not have to rely on treatment facilities in other provinces or private treatment centers, which have higher treatment costs and transportation risks. In addition, these facilities help Pathum Thani province to be ready and prepared for future outbreaks, which are likely to occur again.

- The feasibility degree (α) could be used to demonstrate the unpredictability of the outbreak. It provides knowledge for the planner to prepare for and be aware of the best-case and worst-case scenarios. By setting a high feasibility degree, the planner emphasizes pessimistic values to assure high confidence in the results. However, greater confidence must be traded off for a better optimal solution. The planner should develop an appropriate plan that provides optimal outcomes while yielding acceptable confidence levels.
- Due to hesitation in decision-making, the proposed 3-phase *i*-IFGP approach can help handle this uncertainty. The planner can select a scaling factor (ρ) value that matches his/her preference. A higher level of the scaling factor indicates that the planner desires to relax the PIS since a slightly higher objective value might be acceptable from his/her perspective. If the planner is willing to yield a high certainty plan by choosing a low scaling factor, the score function, which is the satisfaction of the planner towards the outcomes, is lower, but there is less unknown information in the plan. Furthermore, the proposed approach provides information on the acceptable degree (μ), rejective degree (ν), and the hesitation index (π) of the outcomes, and the score function is utilized to indicate the satisfaction of the planner toward the obtained outcomes, which is more concrete in determining the satisfaction of the planner than using the acceptable degree since it can reflect the true intention of the planner.

7. Conclusions

This study provided insight into the design of the IMW reverse logistics network in outbreaks, focusing on installing temporary facilities and IMW management. Uncertainty in the data and the decision-making process, as well as the prioritized conflicting objectives, were tackled in this problem. To improve the reverse logistic of IMW, an Intuitionistic Fuzzy Multi-Objective Multi-Period Mixed-Integer Linear Programming (IFMOMILP) model was proposed. The proposed model attempted to trade off conflicting objectives, including the total costs and risks while considering DMs' priorities. To deal with such issues, a 3-phase interactive Intuitionistic Fuzzy Goal Programming (*i*-IFGP) approach was presented, which combines an auxiliary model of the Jiménez approach and the Intuitionistic Fuzzy Goal Programming (IFGP). In phase 1, the auxiliary model of the Jiménez approach was adapted to deal with the intuitionistic parameters with the feasibility concept. In phase 2, the intuitionistic fuzzy goal programming was applied to solve the conflicting objectives considering DMs' priorities by varying the allowed percentage deviation. In phase 3, the model modification is presented to obtain the optimal outcome based on the aggregated score function with the allowed percentage deviation modified as a decision variable. A comparison between the traditional fuzzy goal programming and intuitionistic fuzzy goal programming was performed to determine the best result. Besides, the proposed method provided flexibility for DMs by adjusting the feasibility degree (α), the scaling factor (ρ), and the optimal allowed percentage deviation (d). Furthermore, compared to the traditional FGP approach, the outcomes were clearly better regarding the aggregated score function in both scenarios. Moreover, the rejective degree was considered in the proposed 3-phase *i*-IFGP approach, which can better reflect the satisfaction of DMs with the results. It is unlike the traditional FGP approach, which only considers the acceptance degree.

The proposed approach's effectiveness and applicability were shown by an actual case of the COVID-19 outbreak in three districts of Pathum Thani province. This study presented two scenarios, with Scenario I prioritize the total costs and Scenario II prioritize the total risks. For Scenario I, the optimal solution, where the allowed percentage deviation is 9.06%, suggested establishing a temporary treatment center at location 2 with the capacity size M in the Lat Lum Kaeo sub-district and a temporary storage center at location 6 in Chiang Rahaeng sub-district. For Scenario II, the optimal solution, where the allowed percentage deviation is 14.00%, suggested establishing a temporary treatment center at location 2 with the capacity size L in the Lat Lum Kaeo sub-district and no temporary storage center. Both scenarios highlighted the necessity of temporary facilities (storage centers and treatment centers). They certainly help to avoid spreading disease from the vast excess amount of IMW reported in the past.

The main limitation of this study is associated with data interpretation. Because the COVID-19 outbreak is a relatively new pandemic, the collected data are subject to incompleteness, and the subjective knowledge of specialists is still required to develop the appropriate information. As a result, further possible studies can be recommended as follows:

- More advanced methods in estimating the amount of IMW generated and the risk parameters could make the outcome more practical and reflect actual circumstances.
- The assumption of using the triangular distribution to represent imprecise data can be relaxed as other appropriate distributions can be considered based on subjective judgment and historical resources.

- As the problem is a multi-objective problem, other objectives, such as sustainability and other risk measures, can be considered. Then, the problem will be investigated more extensively in different dimensions and from other points of view.
- An outbreak is an incident that incurs a high level of uncertainty. More advanced methods in handling the risks, e.g., robust programming, could be applied for better robust outcomes.
- The network design could add more facilities (e.g., different IMW sources and disposal centers). As the problems get bigger and more complex, metaheuristic algorithms such as Genetic Algorithms, Ant Colony, or other evolutionary approaches could be considered for any possibility to obtain near optimal or even optimal solution with faster computational time.

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