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Zero–One Goal Programming for Multi-Objective Vehicle Scheduling: Coverage and Cost Optimization in Flood Relief Logistics

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ABSTRACT

Flood disasters in Kelantan, particularly in Pasir Mas, frequently disrupt transportation networks and create urgent demands for the timely distribution of relief supplies to Temporary Evacuation Centres (PPS). Relief operations face significant challenges, including limited vehicle availability, time pressure, and operational constraints, which in turn lead to inefficient vehicle scheduling and uneven service coverage. To address this issue, this study proposes a Zero–One Goal Programming (ZOGP) model to optimize assignment-based vehicle scheduling for flood relief distribution. The ZOGP framework incorporates multiple and conflicting objectives, namely, maximizing the number of PPS served, minimizing total travel distance and time, and minimizing transportation cost. The model employs binary variables for vehicle-to-PPS assignments and service status. LINGO optimization software is implemented with secondary data. Results demonstrate that the ZOGP model serves all selected PPS locations while satisfying all operational constraints. Overall, the proposed ZOGP model offers a practical and effective decision-support approach for enhancing flood relief vehicle scheduling.

Keywords: Flood relief distribution, Zero One Goal Programming (ZOGP), Optimization, Travel distance, Transportation cost.

INTRODUCTION

Flooding is a common and damaging phenomenon in Malaysia. The eastern coastal states of Peninsular Malaysia are particularly vulnerable to such events each year during the northeast monsoon season. These recurring floods, often require the evacuation of large populations and the establishment of Temporary Evacuation Centers (Pusat Pemindahan Sementara, PPS) (Nasir et al., 2023). The severity of these disasters highlights the critical need for prompt and effective humanitarian response (Oloruntoba and Gray, 2022).

The success of flood relief efforts hinges on the timely delivery of necessities, such as food, water, and shelter to the affected communities within a critical period. Therefore, planning the logistics for distributing relief supplies is very important (Balcik et al., 2021). Despite its importance, the execution of relief operations often faces considerable challenges. Decision makers face the challenge of balancing competing goals, such as maximizing service area coverage, minimizing travel distance/time, and minimizing transportation costs; thus, making the flood relief distribution problems into a multi-objective optimization problem (Habib et al., 2022). The use of single objective optimization methods may fall short in meeting many of the complex and conflicting demands of humanitarian logistics management due to resource deficiencies during times of emergency (Rahman and Hossain, 2023).

Multi-objective optimization methods offer a way to assess trade offs between different, often conflicting goals. This makes them useful for supporting effective decision-making in humanitarian logistics management (Govindan etal., 2020). In this regard, this study developed a goal programming model to optimize vehicle scheduling for distributing flood relief in Pasir Mas, Kelantan. The goal was to achieve effective and efficient service area coverage from the identified PPS, as suggested by Rani and Gulati (2021).

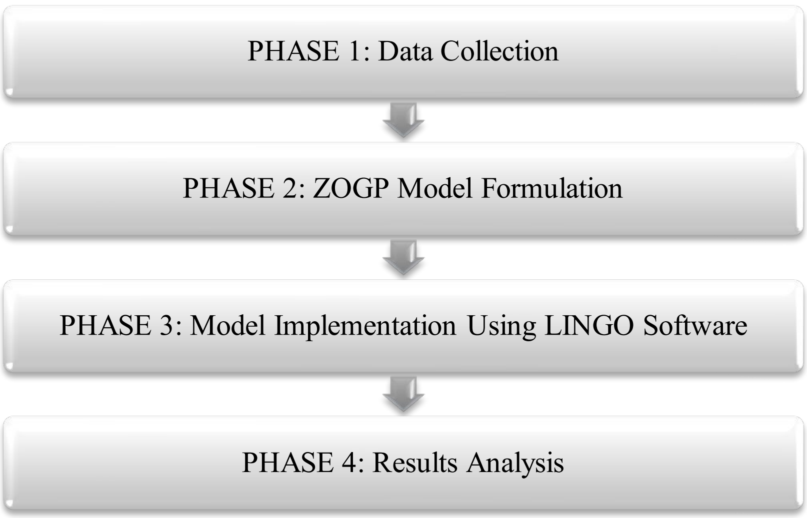
METHODOLOGY

Methodology Overview

The proposed framework follows a systematic optimization approach. The process begins by identifying the selected PPS locations and collecting the required data such as distances, travel times, and vehicle information. The collected data are then used to formulate the ZOGP model, which is implemented and solved using LINGO to generate an efficient delivery schedule. This methodology is designed to help plan flood-relief distribution more effectively and within limited operating time. The procedural flow of this research is visualized in Figure 1.

Figure 1

Flow Chart of The Research Methodology



A detailed breakdown of each phase is provided in the following subsections.

Phase 1 : Data Collection

The study uses secondary data, including information from digital mapping tools, government reports, and local authority information. Information regarding the locations of Temporary Evacuation Centres (Pusat Pemindahan Sementara, PPS) was retrieved from the official e-Banjir website, which provides verified records of evacuation centres activated during flood events. A central depot located in Pasir Mas Town is considered as the distribution centre in this study. Travel distances and times between the depot and PPS locations were obtained using Google Maps for practical route estimation. Additionally, vehicle-related data including capacity, availability, operating limits, and costs were defined based on realistic flood-relief scenarios. These values provide the foundational data for the optimization process.

Phase 2 : ZOGP Model Formulation

The structure of our model is built on the well-established foundations of Goal Programming and integer optimization, both of which are widely used in operations research to solve complex scheduling problems (Ignizio, 1985; Tamiz et al., 1998; Winston, 2004). This framework allows us to balance multiple, often competing, distribution goals by integrating specific sets, parameters, and binary decision variables.

A. Sets and Indices

These sets define the main elements involved in the scheduling system. The set P represents the Temporary Evacuation Centres (PPS), while the set V is for available vehicles for transportation. The indices i and j are used to identify each PPS and vehicle, respectively.

- P : Set of PPS locations, indexed by i, where $i = \{1, 2, 3, 4, 5, 6, 7\}$
- V : Set of available vehicles (4WD), indexed by j, where $j = \{1, 2, 3, 4\}$

B. Parameters

The parameters represent all known input data required by the model.

- $DIST_{ij}$: Distance (km) from the depot to PPS i served by vehicle j
- TT_{ij} : Travel time (hours) from the depot to PPS i served by vehicle j
- DEM_i : Demand requirement of PPS i
- CAP_j : Capacity of vehicle j
- $TMAX_j$: Maximum allowable operating time (hours) for a vehicle j
- G_k : Target value associated with goal k, where $k = 1, 2, 3, 4$
- $CVAR_j$: Transportation cost per kilometre for vehicle j
- ST : Service time required at each PPS (hours)
- W_p : Weights of priority goals, p, where $p = 1, 2, 3, 4, 5$

C. Decision Variables

Since the vehicle scheduling problem requires discrete assignment decisions rather than continuous values, binary decision variables are used in this model. The binary decision variable is defined as:

$$X_{ij} = \begin{cases} 1, \text{if the vehicle } j \text{ is assigned to serve PPS } i, \\ 0, \text{otherwise} \end{cases}$$

$$U_j = \begin{cases} 1, \text{if vehicle } j \text{ is used,} \\ 0, \text{otherwise} \end{cases}$$

D. Constraints

In this study, the constraints and goals are classified into two categories, namely hard constraints and soft constraints.

(a) Hard Constraints

Hard constraints represent mandatory operational requirements that must always be satisfied. Any violation of these constraints would produce an infeasible or unrealistic solution. The following constraints are treated as hard constraints:

1. Service Coverage Constraint

   Every PPS is served exactly once because to this restriction. It ensures that relief supplies are distributed completely and fairly by preventing both redundant servicing and unserved areas.

$$\sum_{j \in V} X_{ij} = 1, \qquad \forall i \in P$$

2. Vehicle Capacity Constraint

   This constraint limits the total assigned demand according to the vehicle's carrying capacity. It prevents overloading and ensures that deliveries remain physically feasible. Since $DEM_i = 1$, the capacity constraint limits the number of PPS that can be served by each vehicle.

$$\sum_{i \in P} X_{ij} \le CAP_j, \qquad \forall j \in V$$

3. Vehicle Utilisation Constraint

   This constraint links assignment decisions to vehicle act ivation. A vehicle must be activated before it can serve any PPS, ensuring logical consistency in the scheduling plan.

$$\sum_{i \in P} X_{ij} \le CAP_{ij} \cdot U_j, \qquad \forall j \in V$$

4. Operating Time Constraint.

   This constraint ensures that the total travel and service time does not exceed the allowable working hours. It reflects realistic operational limits during emergency response.

$$\sum_{i \in P} (2TT_{ij} + ST) \cdot X_{ij} \le TMAX_j, \ \forall j \in V$$

5. Binary Constraint.

   This limitation only applies different decisions. It ensures that activations and assignments are either chosen or not, preventing unrealistic fractional solutions.

$$X_{ij}, U_j \in \{0, 1\}$$

(b) Soft Constraints

Soft constraints represent desirable objectives rather than strict requirements. These goals improve system performance but may be relaxed when necessary. In the Goal Programming model, deviation variables are introduced to measure the deviation from each goal target:

- d_k^+ represents the overachievement of goal k
- d_k^- represents the underachievement of goal k

These variables allow the model to minimise deviations from the desired target values.

- Goal 1: Maximise the number of PPS served.

$$\sum_{i \in P} \sum_{j \in V} X_{ij} + d_1^- - d_1^+ = G_1$$

- Goal 2: Minimise total travel distance.

$$\sum_{i \in P} \sum_{j \in V} 2DIST_{ij} \cdot X_{ij} + d_2^- - d_2^+ = G_2$$

- Goal 3: Minimise total travel time.

$$\sum_{i \in P} \sum_{j \in V} (2TT_{ij} + ST) \cdot X_{ij} + d_3^- - d_3^+ = G_3$$

- Goal 4: Minimise total transportation cost

$$\sum_{i \in P} \sum_{j \in V} CVAR_j \cdot (2DIST_{ij} \cdot X_{ij}) + d_4^- - d_4^+ = G_4$$

where d_k^- and d_k^+ represent underachievement and overachievement deviations.

The Goal Programming framework uses deviation variables to meet these goals. The model minimizes deviations from the intended goals rather than strictly enforcing them. This results in a balanced and workable solution and enables trade-offs between competing objectives.

E. Zero-One Programming Model Formulation

The general ZOGP model can be stated as follows:

$$min\, Z = 0.40 \cdot d_1^- + 0.30 \cdot d_2^+ + 0.20 \cdot d_3^+ + 0.07 \cdot d_4^+ + 0.03 \cdot \sum_{j=1}^{4} U_j$$

where W_k represents the priority weight of each component.

d_k^- and d_k^+ are non-negative deviation variables representing underachievement and overachievement of goal k, respectively. In this model, d_1^- measures failure to serve all PPS and is restricted by setting

$d_1^- = 0$, ensuring that all PPS must be served. The positive deviations d_2^+, d_3^+, and d_4^+ represent total travel distance, total travel time, and total transportation cost, respectively, as their target values are set to zero. The term $\sum U_j$ denotes the total number of activated vehicles. The weights $W_1 = 0.40$, $W_2 = 0.30$, $W_3 = 0.20$, $W_4 = 0.07$, and $W_5 = 0.03$ reflect the relative priority of each goal, with service coverage given the highest importance.

Phase 3 : Model Implementation Using LINGO Software

The mathematical model constructed in the previous phase is converted into LINGO syntax by specifying the sets, parameters, decision variables, constraints, and objective function. Decisions on vehicle assignment and usage are represented using specified binary variables. All constraints are coded as per the specified equations in order to ensure that the scheduling plan meets the requirements. The solver will be used to obtain the best scheduling solution when the model is completely specified.

Phase 4 : Result Analysis

The final phase involves the evaluation of the optimization output of the solver to determine how well the proposed vehicle scheduling model performs. The study aims to determine whether the proposed solution achieves the intended objectives and whether it meets all the operating constraints.

IMPLEMENTATION

Phase 1 : Data Collection

The data used in this research are based on real situations in the Pasir Mas area and are used as inputs for the Zero-One Goal Programming (ZOGP) model. The system consists of a single central depot and six Temporary Evacuation Centres (PPS). The depot serves as a storage facility from which all the relief materials are supplied. In a flood situation, the PPS centers become evacuation centers from which food, water, and other essential items need to be supplied.

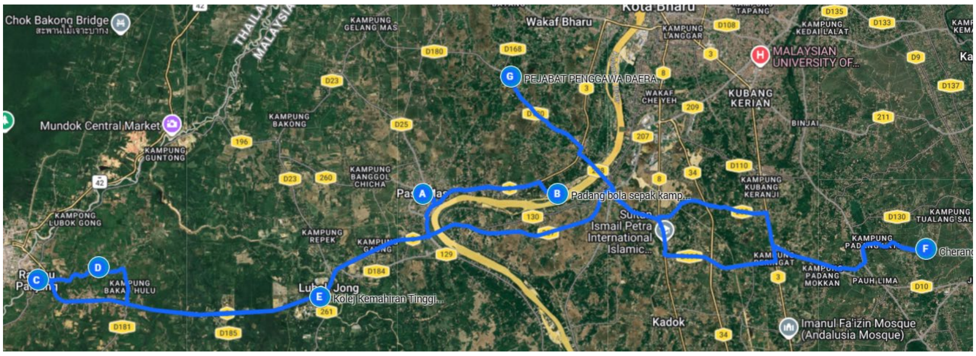
All the vehicles were assumed to start from the same depot, travel directly to their respective PPS, and then return after completing their respective deliveries. This is an emergency response situation that can realistically occur in emergency response scenarios. Google Maps was used to determine the travel time and distance between the depot and each PPS based on realistic roads that four-wheel-drive (4WD) vehicles could travel during the flood situation. The values of the travel time were converted from minutes to hours to match the optimisation model.

In addition, all the trucks are assumed to have similar operational characteristics. Four vehicles are available for the distribution process, and the capacity of each vehicle is one unit per trip. The maximum time for the operating process is restricted to seven hours for the flood relief operations. Additionally, the cost of transportation for the vehicles is assumed to be RM 0.80 for every kilometre, considering the overall cost of the delivery process. This is included in the optimisation model so that the generated schedule is realistic and feasible for the operations. Additionally, the time for the service process is assumed to be 0.42 hours (approximately 25 minutes) for every PPS, considering the average time for the unloading and distribution of the relief supplies. This is included in the model for the on-site handling of the activities during the delivery process.

A map of the study area is presented in Figure 2 to illustrates the geographical distribution of the depot and the selected Temporary Evacuation Centres (PPS) in Pasir Mas, Kelantan. Node A represents the central depot, while Nodes B, C, D, E, F, G represent PPS 1 to PPS 6 respectively. The depot acts as the main distribution centre, and the PPS serve as demand points during flood response operations. The spatial distribution of these nodes provides the basis for estimating travel distances and travel times between locations in the vehicle scheduling model.

Figure 2

Geographic locations of the depot and selected PPS in Pasir Mas, Kelantan



Tables 1 and 2 show the travel distance and travel time matrices between the depot and all PPS locations. The slight differences between certain $\boldsymbol{D_{ij}}$ and $\boldsymbol{D_{ji}}$ values are due to the use of real road network data obtained from Google Maps, which considers actual driving routes rather than straight-line distances. In some cases, route directions differ slightly due to one-way roads, road geometry, or navigation rounding, resulting in minor asymmetry. The matrices are used for providing transportation information for calculating travel distance, travel time, and cost in the optimisation model. The recorded travel times are consistent with their corresponding distances and are reflective of reasonable speeds that vehicles could travel on local roads, hence ensuring that the information is representative of real-life flood relief operations.

Table 1

Distance Matrix (Node to Node) (km)

From/To	Depot	PPS 1	PPS 2	PPS 3	PPS 4	PPS 5	PPS 6
Depot	0	7.5	21.6	19.8	7.9	10.3	7.7
PPS 1	7.5	0	28.9	27.0	15.1	17.6	7.7
PPS 2	21.6	28.9	0	3.1	13.9	16.3	31.0
PPS 3	19.8	27.0	3.1	0	12.1	14.5	27.1
PPS 4	7.9	15.1	13.9	12.1	0	3.8	15.2
PPS 5	10.3	17.5	17.5	15.7	3.8	0	17.6
PPS 6	7.7	7.7	31.1	27.3	15.4	17.8	0

Table 2

Travel Time Matrix (Node to Node) (hours)

From/To	Depot	PPS 1	PPS 2	PPS 3	PPS 4	PPS 5	PPS 6
Depot	0	0.22	0.43	0.4	0.2	0.25	0.22
PPS 1	0.22	0	0.63	0.58	0.4	0.45	0.22
PPS 2	0.43	0.63	0	0.12	0.25	0.33	0.62
PPS 3	0.4	0.58	0.12	0	0.22	0.3	0.58
PPS 4	0.2	0.38	0.25	0.22	0	0.12	0.38
PPS 5	0.25	0.45	0.33	0.3	0.12	0	0.43
PPS 6	0.22	0.22	0.62	0.58	0.38	0.43	0

Phase 2 : ZOGP Model Formulation

The general ZOGP model can be stated as follows:

$$Minimize\ Z = 0.40 \cdot d_1^- + 0.30 \cdot d_2^+ + 0.20 \cdot d_3^+ + 0.07 \cdot d_4^+ + 0.03 \cdot \sum_{j=1}^{4} U_j \tag{1}$$

Subject to

Hard constraints

$$\sum_{j=1}^{4} X_{ij} = 1, \qquad \forall i \in P \tag{2}$$

$$\sum_{i=1}^{6} X_{ij} \leq CAP_j, \qquad \forall j \in V \tag{3}$$

$$\sum_{i=1}^{6} (2TT_{ij} + ST) \cdot X_{ij} \leq TMAX_j, \qquad \forall j \in V \tag{4}$$

$$\sum_{i=1}^{6} X_{ij} \leq CAP_j \cdot U_{j,} \qquad \forall j \in V \tag{5}$$

$$U_j \leq \sum_{i=1}^{6} X_{ij}, \qquad \forall j \in V \tag{6}$$

Goal constraint

$$\sum_{i=1}^{6}\sum_{j=1}^{4} \mathrm{X_{ij}} + \mathrm{d}_1^- + \mathrm{d}_1^+ = 6, \quad \mathrm{d}_1^- = 0 \tag{7}$$

$$\sum_{i=1}^{6}\sum_{j=1}^{4} 2DIST_{ij} \cdot X_{ij} + d_2^- + d_2^+ = 0, \tag{8}$$

$$\sum_{i=1}^{6}\sum_{j=1}^{4} (2TT_{ij} + ST) \cdot X_{ij} + d_3^- + d_3^+ = 0, \tag{9}$$

$$\sum_{i=1}^{6}\sum_{j=1}^{4} CVAR_j \cdot (2DIST_{ij} \cdot X_{ij}) + d_4^- + d_4^+ = 0, \tag{10}$$

$$X_{ij} \in \{0, 1\}, \forall i \in P, \forall j \in V$$
$$U_j \in \{0,1\}, \forall j \in V$$
$$d_k^-, d_k^+ \geq 0, k = 1,2,3,4$$

Phase 3: Model Implementation Using LINGO Software

Following the complete mathematical formulation presented in the previous subsection, the Zero–One Goal Programming (ZOGP) model was implemented using LINGO optimisation software. The implementation translates the mathematical model directly into executable syntax while maintaining consistency with all defined decision variables, constraints, and goal structures.

Phase 4: Results Analysis

This phase presents an extensive and comprehensive review of the optimization results from the proposed Goal Programming (GP) model for vehicle scheduling in Kelantan's flood relief distribution. After completing the formulation of the mathematical model and executing the optimisation procedure using LINGO software, the resulting outputs are closely studied to evaluate how effectively the available vehicles are scheduled to distribute relief supplies to all selected Temporary Evacuation Centres (PPS).

RESULTS AND DISCUSSION

Maximizing the number of PPS serviced is the most important goal in flood relief logistics. This objective ensures that no affected community is neglected and that all evacuation centres receive assistance. This goal is considered as a high-priority or required goal in the Goal Programming framework.

Table 3 below presents the assignment variable values obtained from the LINGO solver. A value of 1 indicates that the corresponding vehicle is assigned to serve a specific PPS, while a value of 0 indicates no assignment. Based on the results, six decision variables have a value equal to 1, namely X23, X34, X43, X54, X63, and X74. All other assignment variables remain zero. This confirms that each PPS is assigned exactly once, satisfying the single-service constraint. Furthermore, the distribution of assignments indicates that only two vehicles are utilised. Each active vehicle serves three PPS, which complies with the vehicle capacity limit of three units. The deviation variable D1NEG = 0 confirms that there is no underachievement of the mandatory service coverage goal. Therefore, the service coverage target (G1 = 6) is fully achieved.

Table 3

PPS Service Coverage from LINGO Output

Variable	Value
X21	0
X22	0
X23	1
X24	0
X31	0
X32	0
X33	0
X34	1
X41	0
X42	0
X43	1
X44	0
X51	0
X52	0
X53	0
X54	1
X61	0
X62	0
X63	1
X64	0
X71	0
X72	0
X73	0
X74	1

Table 4 presents the truck activation results obtained from the LINGO solver. The binary decision variable U_j indicates whether a vehicle is utilised in the delivery operation. A value of 1 represents an activated vehicle, while 0 indicates that the vehicle remains idle. Based on the optimisation results, only Truck 3 and Truck 4 are activated (U3 = 1 and U4 = 1), whereas Truck 1 and Truck 2 are not utilised. This confirms that only two out of the four available vehicles are required to serve all six PPS locations. The result demonstrates that the optimisation model successfully minimises unnecessary vehicle usage through the penalty term included in the objective function. Despite activating only two trucks, full-service coverage is achieved while satisfying vehicle capacity and operating time constraints. This indicates efficient resource allocation and operational effectiveness.

Table 4

Truck Activation Results from LINGO Output

Vehicle	U_j Value	Status
Truck 1 (U1)	0	Not activated
Truck 2 (U2)	0	Not activated

Truck 3 (U3)	1	Activated
Truck 4 (U4)	1	Activated

Table 5 represents the total travel distance and total travel time for each truck as computed by the LINGO solver. Trucks 1 and 2 record zero distance and travel time, indicating that they are not activated. Truck 3 travels 75.2 km and operates for 3.0 hours, while Truck 4 travels 74.4 km for 2.96 hours. The relatively balanced distance distribution indicates that the workload is evenly allocated between the two active vehicles. The combined total distance of 149.6 km corresponds to the positive deviation variable D2POS, representing the total round-trip travel distance from the depot to the assigned PPS locations. The total operational time for the delivery process is 5.96 hours, which corresponds to the positive deviation variable $D3POS = 5.96$. This indicates that the model successfully controls travel time while maintaining full-service coverage.

Table 5

Total Distance and Travel Time per Truck from LINGO Output

Truck	Total Distance (TD) (km)	Total Travel Time (TTOT) (hours)
Truck 1 (TD1)	0.0	0.0
Truck 2 (TD2)	0.0	0.0
Truck 3 (TD3)	75.2	3.0
Truck 4 (TD4)	74.4	2.96

In addition to travel distance and travel time, transportation cost (see Table 6) is also evaluated to measure the financial efficiency of the proposed routing schedule. In flood relief operations, transportation cost represents an important operational consideration because fuel usage, vehicle maintenance, and manpower expenses directly depend on the total distance travelled by each truck. Minimising transportation cost allows limited financial resources to be allocated to other essential relief efforts such as food supplies, medical support, and emergency equipment.

Table 6

Total Transportation Cost per Truck from LINGO Output

Truck	Total Transportation Cost (TC) (RM)
Truck 1 (TC1)	0.00
Truck 2 (TC2)	0.00
Truck 3 (TC3)	60.16
Truck 4 (TC4)	59.52

While the total travel distance, travel time, and transportation cost are provided by the proposed technique, it is essential to determine whether these outcomes are better than traditional scheduling techniques. Therefore, to evaluate the total effectiveness of the proposed optimization strategy, a comparison with a manual distribution approach is carried out.

Each vehicle serves one PPS at a time under the traditional scheduling technique before returning to the depot to go on to the next location. Every delivery consequently requires a round trip from the depot to the appropriate PPS, resulting in more frequent trips and greater total distances. The total travel distance for the traditional method is determined using the depot-to-PPS distances listed in Table 2.

Table 7 presents the comparison between the existing manual scheduling method and the proposed Zero-One Goal Programming (ZOGP) model. The results indicate that the total travel distance for both methods is 149.6 km, while the total travel time remains 5.96 hours, and the total transportation cost is RM119.68. This is because the study assumes independent depot-return trips for each PPS. Under this assumption, once all PPS are served exactly once, the total distance becomes fixed and cannot be further reduced through truck reassignment alone. However, a significant improvement is observed in terms of vehicle utilisation. The existing manual scheduling method utilises four trucks, whereas the proposed model requires only two trucks to serve all six PPS while satisfying capacity and operating time constraints.

Table 7

Comparison Between Existing and Proposed Scheduling Methods

Measure	Existing Schedule	Proposed Scheduling	Percentage Improvement
Total distance (km)	149.6	149.6	Maintained
Travel Time (hours)	5.96	5.96	Maintained
Transportation Cost (RM)	119.68	119.68	Maintained
Vehicle Utilised	4	2	50% reduction
Service Coverage	All	All	Maintained

Authors should clearly describe the research design, data collection methods, sampling or participant selection (if applicable), and any software, instruments, or platforms used to carry out the study. For technical or computational research, the algorithmic steps or system architecture should be explicitly described, preferably with flowcharts or pseudocode for clarity. If datasets are used, state their source, size, format, and pre-processing methods. For empirical studies, outline the procedures, instruments, and any statistical or analytical techniques used for data analysis. A well-structured Methodology section not only improves transparency but also strengthens the credibility of the research by showing that the approach is sound, appropriate, and repeatable.

Although the total travel distance, time, and cost remain unchanged, the proposed ZOGP model demonstrates higher scheduling efficiency by optimally allocating PPS to fewer vehicles without compromising service coverage. Furthermore, the model ensures systematic decision-making and automatic compliance with operational constraints, which may not be guaranteed under manual scheduling. Overall, the proposed technique improves resource utilisation efficiency while maintaining equivalent operational performance.

CONCLUSION

The required operational and logistical data were identified and structured into distance and travel time matrices, ensuring that the model accurately represents the scheduling environment. The constructed Goal Programming formulation incorporated binary decision variables and multiple objectives, including minimizing travel distance, travel time, transportation cost, and the number of vehicles utilized. Based on the LINGO optimization results, all PPS locations were successfully served while satisfying vehicle capacity and operating time constraints. Under the independent depot-return assumption, the total travel distance, travel time, and transportation cost remained unchanged compared to the existing scheduling method. However, a significant improvement was observed in vehicle utilization. The proposed model reduced the number of trucks required from four to two, representing a 50% reduction in vehicle usage while maintaining full-service coverage. In conclusion, the proposed ZOGP model enhances scheduling efficiency by optimizing resource allocation and ensuring systematic decision-making under operational constraints. Although routing distance remains fixed under the study assumptions, the model provides a structured and reliable decision-support tool for vehicle scheduling during emergency relief operations.

Although the proposed model has shown promising results, there are several improvements that can be considered to enhance its applicability and realistic in future studies. First, in order to the better applicability of the porposed model to the real-world scenario of floods, future studies may take into account the factors of uncertainty such as changing travel times, road conditions, and changing demand levels. The scheduling decisions might be more realistic if they were made using a random or dynamic optimization approach. Second, the porposed model can be extended to a larger-scale problem with more depots, more vehicles, and more PPS locations to make it more applicable to a wider range of disaster operations. Third, besides quantitative objectives such as distance, time, and cost, qualitative factors including urgency level, priority of vulnerable groups, and coordination constraints may also be considered to improve decision-making effectiveness. Finally, collaboration with disaster management agencies is 50 recommended to test the model using real operational data, ensuring its practicality and reliability for actual flood relief planning.

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Conflict of Interest
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