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Multi-Depot Dispatch Deployment Analysis on Classifying Preparedness Phase for Flood-Prone Coastal Demography in Sarawak

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Abstract

Multi-Depot VRP (MDVRP) is a metaheuristic approach with concurrent vehicle rendezvous across various depots within a demanded regulation, where the task assignment would eventually end up at the same initial depot. A review of the relief commodities distribution patterns among flood-prone areas in the underlying layouts of Sarawak residential areas has been conducted in retrospect and in light of common real-world routing problems. The purpose of this research is to demonstrate the benefits of multi-path route selection in task distribution to cater to simultaneous demands for adhering to strict constraint settings, including load dispatch dynamism and deployed vehicle quantities. Shortest path algorithms are improvised as an alternative to select the most optimum traveled routes during relief commodity distribution. This is done by determining critical allocation nodes, where solution steps are optimized using a genetic algorithm with predefined parameters. The experimental output displays the strong correlation between the number of prioritized customers and assigned depots to optimize the route complexity and natural affluence on generated final solution cost. The approach is seen as viable for further addressing problem-specific instances in vehicle routing problems such as adjusting parameter settings to generate rapid solution steps, including pathfinding shortest coverage distance and sorting out trade-offs between space covered and the time limitations of task distribution efforts.

Keywords: vehicle routing problem, MDVRP, genetic computation, optimization, routing complexity.

INTRODUCTION

In disaster preparation and response, logistics scheduling is a key element. Therefore, constant monitoring of the surrounding environment, rehearsal of actions to be undertaken under a certain circumstance, and the level of danger directly affect the logistics to be provided. Currently, there are no credible techniques to devise optimal strategies to distribute emergency resources in a way that is both efficient and effective in responding to disasters under minimized effort, and an urgent need to develop a model that would enhance decision-making on the critical variables for successful disaster response.

Sarawak is a region with population demography encompassing annual heavy precipitation during monsoon seasons, particularly interlinked with coastal underlying areas that are dense with civilization activities. Due to the variance in development progress among urban and rural areas, there had been difficulties in addressing the traversal network interjecting the priority areas with considerable population density for disaster relief routing scheduling. The current solution strategy of manual dissemination for

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relief distribution conducted by local authorities is seen only beneficial for instances before a disaster occurs, where the efficacy becomes ambiguous with the unpredictable type of eminent natural disaster. The decision-making aspects for planning stages of impending catastrophes could be improved with an automated solution strategy for determining the logic and credibility of distribution variables, among these include important areas that need to be covered during relief deployment, total permissible routing distance, the quantity of participating vehicles for smooth distribution, demand levels according to priority superiority, and the number of maximum allowed resource allocation. The formulation of a better-synergized scheduling system to resolve managerial instances for routing distribution during natural disaster situations such as flooding is seen as beneficial for long-term purposes, particularly in terms of advanced prediction and response towards any unforeseen circumstances.

The Vehicle Routing Problem (VRP) and its various variants have been innovated as an alternative to resolve several issues impeding the efficacy of scheduling systems, particularly when working with specific restrictions such as time and resource limitations. The multi-depot vehicle routing problem (MDVRP), a variant of the basic VRP, supports the simultaneous execution of multiple vehicle distributions across all participating routes while simultaneously responding to planning constraints. Previous iterations of MDVRP on problem instances, such as disaster logistics incorporated communion across the participating vectors, however, this approach requires further iteration cluster segregation to improve the relevancy of interlinking participants mainly customers and their associated depots. This research attempts to incorporate the familiarity of customer clusters with their neighboring nodes in terms of approximating the closest relative distance to improvise the estimation of the traveling distance between distribution depots with deployed vehicles to maximize cost optimality during a single deployment of relief distribution.

PROBLEM STATEMENT

No credible solution had been found to address the logistical aspects of scheduling relief commodities across multiple instances of demand priority. As an example, flood-prone demography is classified similarly to disaster logistics. During the preparation stage for natural disasters such as flooding woes in Sarawak, routing scenarios with niche features such as determining effective scheduling strategies have not been widely made available and practical. By establishing an effective disaster logistics routing system, preparedness and response levels could be improved in the event of floods. To formulate a better-synergized scheduling strategy that can enhance the efficacy of existing distribution strategies for disaster-stricken areas such as flood mitigation, it is necessary to take into account scheduling variables for routing instances involving limitations such as cost allocation and permitted coverage areas. Further improvement of the welfare state of unexpected victims could be achieved by initiating an in-depth analysis on planning efficient routing schedules and priority distribution paths. The establishment and identification of appropriate solution strategies for improving the effectiveness of relief deployment are also problematic for scheduling systems such as relief distribution for flood preparedness. There is no widely used intelligent analytic system to resolve routing instances for disaster logistics such as flooding in Sarawak. The development and incorporation of a new relief strategy augmented with a computational intelligence application are essential for optimizing resource allocation and ensuring the quality of relief distribution cycles among those affected and their respective distribution centres.

RELATED WORK

The purpose of locating the shortest path possible to be traversed during a single distribution effort along a premeditated transportation network is made not only as a key determinant for enforcing rapid progression of successive commodity dispersal among the participating sectors but also improves the reliability of planning purposes in terms of approximating an optimal operating cost apart from ensuring maximized resource allotment. Determining the most minimal coverage distance for certain round trips that still closely adhere to the scheduling system's trade-off between minimizing resources and

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maximizing traveling had been the main objective for many variations of routing scheduling in corresponding research. The foundation for shortest path approximation within scheduling systems is to classify the possible best means to roam over multiple distribution points. Routing the shortest distance in urban road freight transportation under horizontal collaboration was also performed via a combination of depot location and routing variables involving strategic, tactical, and operational decision-making as a two-echelon location routing problem (Indriyono, 2021). Another work to optimize multiple distances within a single traversal is done based on a two-stage optimization method for emergency supply allocation problems involving multi-supplier, multi-affected areas, multi-relief, and multi-vehicle using earthquake threats as sampling (Foead, Ghifari, Kusuma, Hanafiah, & Gunawan, 2021). A solution method incorporating location-allocation issues was performed on several variables involving candidate hub locations, and customers, along with their clustering annotations using an endosymbiotic evolutionary algorithm (Rachmawati & Gustin, 2020). Methods of consorting identification of shortest path approximation were also performed for an evaluation model based on emergency relief to simulate delivery routes, operating hours, and running distance for the relief operations in Aichi prefecture (Talan & Bamnote, 2015). A combination of Dijkstra with the A* algorithm was improvised for a road network in city area traffic under time constraints based on bidirectional path searching (Wang et al., 2022). A similar research scope combining the heuristics of both Dijkstra and A* algorithm was also implemented on regional scale maps in Indonesia for locating the shortest path (Foead et al., 2021).

The incorporation of multi-depot instances on commodity distribution had been widely implemented in logistics scheduling, where feature implementations were amended to cater towards specific objectives in retrospect of scheduling constraints. Metaheuristic optimization algorithms had also found their forte being improvised on planning and infrastructure inspection crews in concurrence with calamity aftermath respective with urban areas via the implementation of deterministic and probabilistic districting and routing problems (Lagaros & Karlaftis, 2011). A multi-echelon MDVRP was devised for the post-disaster phase that investigates the correlation between associating central warehouses, handling damaged goods, and scheduling supplies under resource limitations (Tavana et al, 2018). Several multi-level solution phases based on the evolutionary algorithm were also introduced to address the route complexity for multiple deployment instances. These include the disaster relief routing heuristics on location-allocation tasks for pre- and post-disaster mitigation efforts and sourcing of vehicles to strategic priority locations. A modeling scheme had also been devised for VRP instances consisting of arbitrary customer points and a stochastic deployment period that allows simultaneous item delivery among systemically varied customer locations in distinct locations (Lombard et al, 2018). Along with the focus on commodity distribution under a limited time constraint, subsequent research had been conducted on emphasis for decision-making during preparedness and response stages for disaster relief efforts, as seen with the implementation of multi-echelon multi-depot VRP targeting to strategize location-allocation processes such as effective routing on rapid vehicle deployment for pre and post-disaster phases under a restricted resource scope.

The following table highlights the traits of the aforementioned works, their limitations in resolving corresponding issues, and suggestions imposed on this research work on ways to alleviate them.

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Table 1: Summary of discussed relative research works and characteristics to be addressed in this feature research

Feature	Methodology	Limitations	Proposed Solution
Shortest path traversal during a single distribution cycle	Indriyono, 2021; Foead et al., 2021; Rachmawati et al., 2020; Talan & Bamnote., 2015; Wang et al., 2022	• Need feed data for a better representation of the distribution network • Classifying the relevant neighboring distribution nodes within their clusters is needed to improve performance credibility	Perform better customer grouping within distribution clusters to enable better distribution patterns along the premeditated route
Multi-depot dispatch with scheduling constraints	Lagaros et al., 2011; Tavana et al., 2018; Lombard et al., 2018	• Due to the nature of distinct scheduling constraints aftereffects of the trade-off between maximizing route coverage and encouraging cost optimality often result in unstable performance • Functional dependence on modeling constraints such as routing variables and scheduling flexibility	Routing scheduling capability catering towards specific constraints to reduce the penalty on non-accomplished task distribution efforts, particularly regarding the proficiency of distribution cycles

RESEARCH FRAMEWORK

The motivation for suggesting the applied modeling framework as shown in Figure 1 attempts to establish several critical issues endures by common MDVRP instances, mainly constituted by: (i) reducing the total possible deployment time, (ii) cutting back on total expedited cost, and (iii) optimizing deployment proficiency under the most achievable deployment distance.

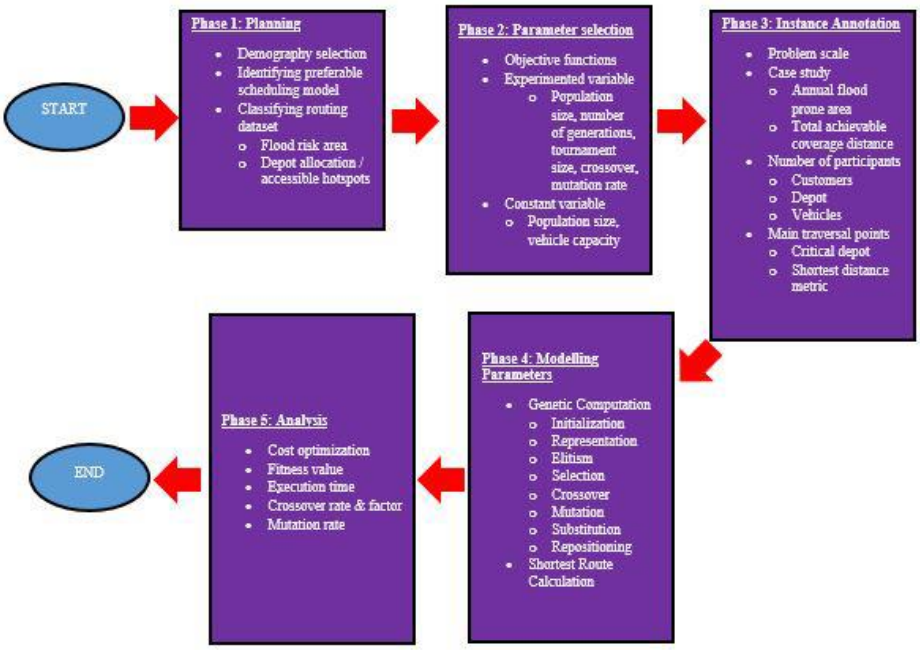

Figure 1: The framework for the implementation of the proposed amended GA using the multi-repository allocation on the flood relief routing scheme.

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EXPERIMENTAL DEMOGRAPHY

The following characteristics are executed in mind for planning a sector of analysis, representing the demographics prone to flooding in the region of Sarawak.

i. *Description of postal code geolocation:* The purpose of assigning postal codes is to indicate the geographic location of a populated area.
ii. *Data collection*: Analysis is performed on the availability of existing distribution centers or past operational rooms such as the school compound and town hall where better dissemination of relief efforts is conducted.
iii. *The distance among traveled nodes*: Vehicle deployments operate asynchronously upon single deployment where it is ensured that task distribution possesses the highest possibility of completion within a single travel effort while deploying for a round trip under a fixed, estimated time range and receiving an equal footing of resource allocations for all participating node points.

FORMULATION OF MODELLING PARAMETERS

The first phase is the creation of quality initial solutions, whereas the second phase consisted of improvisation of the initial solution. The first phase involves plotting a set of the route into an array list, including the pick-up points to their nearest vicinity and the initial traversal routes among participating depots. For the second phase instance, local search theories are implemented in a manner of swapping candidates for better solution generation and the relocation of pick-up routes in the same or different depot with the intention of intensification and diversification of search space optimization. The genetic operators and their modified role in generating solution steps are discussed as the following.

a) **Initialization**: Random population initialization with the probable distribution.
b) **Representation**: Assignment of each individual of the customers to the depots for that particular population.
c) **Elitism**: The individuals from each population are paired with the prime fitness candidate.
d) **Selection**: This implementation applies tournament search criteria, where the prime 5 randomly selected individuals are picked as the future parent chromosome.
e) **Crossover**: Each inherited parent chromosome contains the probability of experiencing crossover.
f) **Mutation**: Individuals will proceed with mutation under a certain probability rate as soon as the new population is initiated through selection and crossover.
g) **Substitution**: The initial population is interchanged with the current generated individual replacement.
h) **Repositioning**: Interchanges were done for certain variables in the chromosome, for example, the position of the customers. Repositioning consisted of 2 types, namely insertion and swapping. Considering r represents serviceable deployment paths for a single travel cycle, and n/r consisted of median customer engagement for a single travel cycle.
    - *Insertion move*: Involves the selection of individual customers where they will be interchanged to a new position when a better candidate solution is generated. The insertion move is represented by $n\ (r - 1)\ \mathrm{n}/r = n^{2}\,(1 - 1/r)$.
    - *Swapping move*: Exchanging two engaging customers with their respective paths. These exchanges could be performed randomly. The complexity for swapping is represented by $[n\ (n - 1) / 2] \times 2\ (n / r)$.

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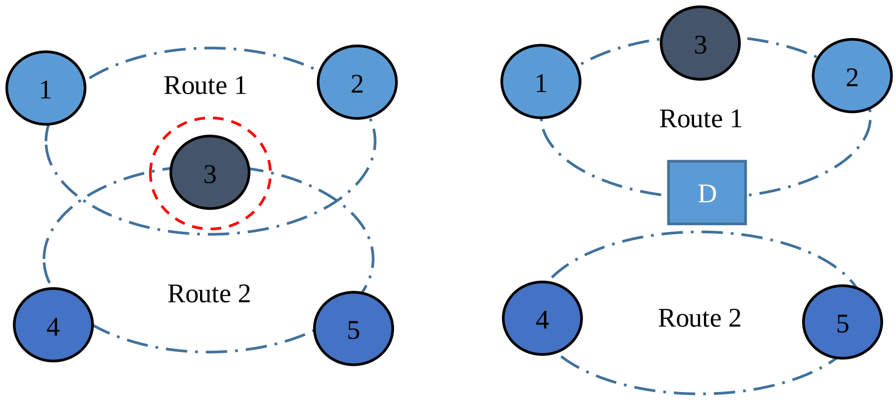
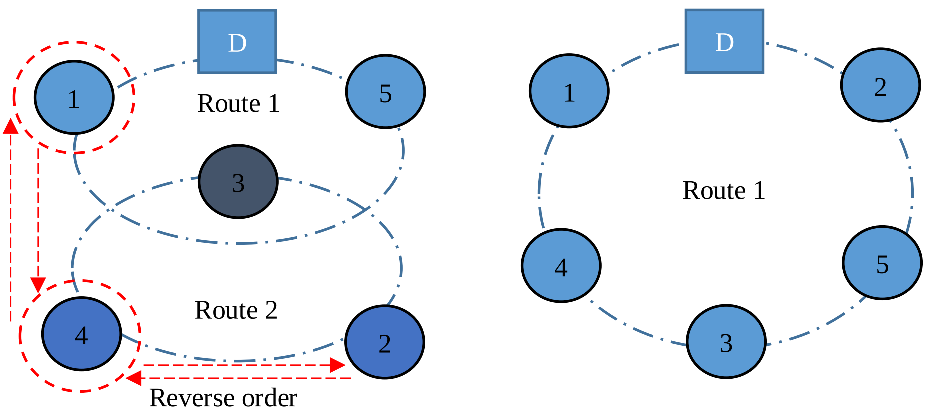
The next graphics illustrates the swapping strategy of chromosome activities to generate quality solutions to be inherited next in line. The swapping involves customer positioning when a better alternative or shorter route is allocated within the process. The selection of better customer allocation occurs between 2 routes and is executed in iteration until the fulfilled criteria are achieved.



Route 1 is made up of Clients 1 and 2, and Route 2 is made up of Clients 3, 4, and 5. Insertion is done for customer 3 in Route 1 before customer 1 after customers 1 & 2 is considered a better quality solution.

The new route after Customer 3 is inserted into Route 1 is comprised of Customer 1-2-3 and a depot.



A cross-transfer is performed for Customers 1 and 4 when exchange testing is performed with Customers 1 and 4 with Customer 2 of Route 2 identified as compatible. The route would then be combined under a single traverse.

Following the move, the new route 1 included the depot and client 1-2-3-4-5.

Figure 2: Representation of an insertion movement amongst the possible solutions**.**

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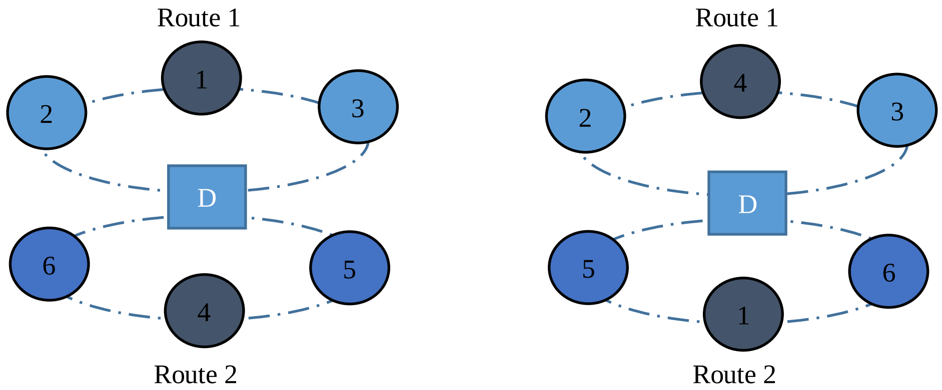
The next figure continues into the cross-over process between the interjection routes.



Crossover is done for customers 1 and 4, where their current position are interchanged between their respective routes.

Once the transition has begun, Route 1 includes customers 2-3-4 and Route 2 is represented by 1-5-6.

Figure 3: How crossover move is performed between interjecting routes.

Multi-Depot Scheduling Model

The notations applied to follow the hypothesis cases for the combination of the routing distance involved in crossing a single path across all sectors.

$$\sum_{k=1}^{\bar{k}} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij}\, x_{ijk} \tag{1}$$

$$\min_{k\in K} \sum_{(i,j)\in E} v_{ij}\, y_{ijk} \tag{2}$$

Where:

V = vehicle speed,

Y = decision variable from point *me* in front of point *j* on the path of the vehicle *k*,

E = transport capacity.

$$\sum_{i=1}^{n+m} \sum_{j=1}^{n+m} \sum_{k=1}^{K} c_{ij}\, x_{ijk} \tag{3}$$

Where:

N = Cluster of participating vehicles,

M = Number of customers involved in this single passage cycle,

K = vehicle set on a particular path.

$$\sum_{i=1}^{n+m} \sum_{k=1}^{\bar{k}} x_{ijk} = 1\ (j = 1, \dots, n)$$

$$\sum_{j=1}^{n+m} \sum_{k=1}^{\bar{k}} x_{ijk} = 1, (i = 1, \dots, n) \tag{4, 5}$$

Where:

N = Participating array of vehicles,

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M = Number of the involved customer for that single traversal cycle,
K = vehicle set on a particular path.

$$\sum_{k\in K}\sum_{i\in I\cup J} x_{ijk} = 1, j \in J \tag{6}$$

Where:
J = Path of sets represented within point *j*,
K = vehicle setting in a particular path,
K = traveling vehicle for a particular path.

$$-z_{ij} + \sum_{u\in I\cup J}\left(x_{iuk} + x_{ujk}\right) \le 1, i \in I, j \in J, k \in K \tag{7}$$

Where:
U = Reserve variable for sub-route propagation discarding constraints,
I = Total set representing all depots,
J =Total set representing all customers,
K = Total set representing all vehicles.

$$s_{i,j} = c_{1,j} + c_{j,1} - c_{i,j} \tag{8}$$

Where:
$C_{1,j}$ = Propagation path among the initiating depot and customer *j*,
$C_{1,j}$ = Sum of deployment intervals among customer *I* and *j*,
$C_{j,1}$ = Total number of propagation paths among customer *j* and the targeted depot

$$\textstyle\sum_{i=0}^{n}\sum_{k=1}^{\bar{k}} x_{ijk} = 1, j = 1, \dots, n \tag{9}$$

Where $\bar{k}$ = Traveling vehicle in that particular arc.

$$\sum_{i=0}^{n} x_{ijk} - \sum_{i=0}^{n} x_{jik} = 0, j = 0.1, \dots, n; k = 0, 1, \dots, \bar{k} \tag{10}$$

$$\sum_{j=1}^{n} x_{0jk} \le 1, k = 1, \dots, \bar{k} \tag{11}$$

$$y_{ij} + z_{ij} \le Q \sum_{k=1}^{\bar{k}} x_{ijk}, i, j = 0, 1, \dots, n \tag{12}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} d_{ij}\ x_{ijk} \le L, k = 0, 1, 2, \dots, \bar{k} \tag{13}$$

Where:
D = demand load,
L = loaded capacity.

$$x_{ijk} \in \{0, 1\}, y_{ij} \ge 0, z_{ij} \ge 0, i, j = 0, 1, \dots, n, k = 0, 1, \dots, \bar{k} \tag{14}$$

The formulation of multi-depot dispatch instance of this problem instance is done with the following delimiters in mind: Constraint (1) is the minimization of the objective function, Constraint (2) ensures the maximization load proportion for the least efficient path where vehicle velocity is represented by the load proportion itself, Constraint (3) represents the minimization of the total cost, Constraint (4, 5) maintain the integrity ratio of 1 customer per 1 vehicle servicing from starting point *i* and designated point *j* respectively, Constraint (6) each customer are designated to a particular route, Constraint (7) states that the interiority of a customer to a route should the customer is not situated in the vicinity of the

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targeted depot in the array of customer allocation, Constraint (8) is the summation of travel distance among the depots and customers, Constraint (9) states that each node is frequented by only 1 vehicle, Constraint (10) makes certain that each mobile vehicles would arrive & depart from each port that it serves, Constraint (11) restricts utilization of $\bar{k}$ vehicles at certain deployment times, Constraint (12) restricts the demand's procurement and dispatch only through arcs included with the solution, Constraint (13) limits the maximal coverage within a certain routing schedule, and Constraint (14) represents the default of the decision variable.

Chromosome Representation

The chromosomes for the MDVRP solution are represented by path representation in the arrangement of the priority array list.

Customer no	Location of customers		Time elapsed	Servicing quantity	No. of visits	No. of possible visit	List of all possible visit	Beginning of the time window	End of the time window
1	37	52	0	7	1	4	2	4	8

Figure 4: An example of chromosome representation containing 1 vehicle, 4 customers, and 8 depots.

Tournament Selection

Tournament selection is applied via the running of several randomization population assortments where the candidate with the most desirable fitness is picked to proceed with crossover. Tournament selection is selected due to its independence of the scaling of the genetic algorithm and works on parallel architectures.

1: Tournament size, *k* is randomly aggregated from the population

2: From the tournament search, allocate the best individual with probability *p*

3: Identify the runner-up best individual with probability, *p** (1-*p*)

4: Pick the 2nd runner up best individual with probability *p** ((1-*p*) ^2)

Figure 5: Conceptualization steps representing tournament selection.

Crossover

The crossover operation generates a trial vector through the substitution of particular targeted vector parameters residing among the correlating randomly generated solution vector.

Behavior functions during the crossover phase are iterated as the following.

1. Regulate the mutation value which is proportional to the problem.
2. A single route is selected randomly.
3. The numbers related to the customers' genes are considered randomly from the selected route in the previous step.
4. The replacement gene is filled after the first gene. The entire next genes other than those replaced ones are taken for the next chromosome generation.

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	Before crossover		After crossover
P	8 1 **3** **5** 2 **4** 6 **7** 9	C	**1** 3 **5** 7 6 9
P_1	8 9 <u>1</u> 2 6	C_1	9 7 <u>2</u> 3 6
P_2	8 9 **2** 2 6	C_2	9 7 **1** 3 6
P_3	8 9 2 **1** 6	C_3	9 7 2 **2** 6
P_4	8 9 2 1 5 **3** **5** **4** **7**	C_4	9 7 2 3 6 **1**

Figure 6: Examples of primary crossover strategy involved in interjection routes.

Crossover swap between initial parent chromosomes (P, P_1, P_2, P_3, P_4) and child chromosome (C, C_1, C_2, C_3, C_4). To avoid problems such as premature convergence aside from improving the assortment for solution steps, the crossover probability in the MDVRP-GA proposed is done according to sequential arrays during the selected phases.

$$Trial\,(j)^{G+1} = \{v\,(j)^{G+1},\ Rand\,(j) \leq CR \text{ or } j = randn(i)$$

$$Trial\,(j)^{G+1} = \begin{cases} v\,(j)^{G+1}, & rand\,(j) \leq CR \text{ or } j = randn(i) \\ Chrome\,(I, j)^{G}, & Rand\,(j) > CR \text{ and } j \neq randn\,(I) \end{cases}$$

Where G = current iteration quantity and the probability value of the crossover factor, $CR \in [0, 1]$. Each parameter contains weightage to the crossover probability factor.

$$CR = CR_{min} + G * \frac{CRmax - CRmin}{MAXGEN}$$

Where CR_{min} is the probability of the least crossover rate, CR_{max} is the probability of the topmost crossover rate, and G is the biggest iteration number permitted across each cycle. *MAXGEN* is the highest number of permissible iterations representing each cycle.

i. Mutation strategy

The basis for the mutation steps applied is to revive genetic varsity to prevent local optima entrapment. The proposed approach attempts to improvise the probabilistic search optimizing features for evolutionary computation to improve the optimization of routing, and scheduling models with the stipulation of reduced cost and affluent delimiters such as time windows in locating a better distribution chain. This generation is mutated n-1 where the iteration undergoes subsequent application of insertion, inversion, and swapping.

Swapping operator: Two points are selected at random where the partial gene composition undergoes interchange with the partial gene composition. The swap operator randomly picks two

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organisms in the solution vector *i* and *j*, where *i≠j*. This operator is used to select critical node sets at random, where this position would eventually be swapped. The application of the swapping operator sustains the obtained neighboring information all the while retaining broken link order.

Swapping points, p1=9 and p2=2

1	2	3	4	5	6	7	8	**9**	→	**9**	2	3	4	5	6	7	8	**1**

parent → child

Figure 7: Individual gene trait swapping criteria between participating chromosomes.

SHORTEST ROUTE CALCULATION HEURISTICS

The Haversine distance metric is selected as the main evaluation metric to represent distances on a curved surface, apart from estimating the curvature of the involved route (Anisya & Swara, 2017). The metric quantifies the least distance achievable among two nodes along the equatorial line depending on the fixed latitudes and longitudes representing the location. Before applying the shortest distance metric, several hypotheses had been taken into account as decisive criteria after each successful iteration: (i) *vehicle load is unaltered and premeditated*, (ii) *the number and location of depots are made known earlier*, (iii) *number and location of customers are also predefined*, (iv) *traveling velocity for the vehicle is constant*, (v) *cost of transportation relies on the total distance cover*ed, and (vi) *symmetrical network representing in the transportation routes*.

The Euclidean distance is preferred as the distance calculator for this problem instance, where Haversine formulation is applied in the approximation of real-world location between 2 points on an equatorial point. Haversine distance approximation is averaged based on the following formulation:

$$haversine(\theta) = sin^2\frac{\theta}{2}$$

The next equation translates the formulation into a linear form.

Assumption: Radius of earth's surface = 6371km

$$a = \sin^2\left(\frac{\varphi B - \varphi A}{2}\right) + \cos\varphi A * \cos\varphi B * \sin^{22}\left(\frac{\lambda B - \lambda A}{2}\right)$$

$$C = 2 * \operatorname{atan2}(\sqrt{a}, \sqrt{(1-a)})$$

$$d = R \cdot c$$

Where:

φ = latitude, λ = longitude, and R = earth's radius (6371 km)

Some assumptions were also made known beforehand related to the implementation technique involved to approximate real-world distance from 2 points (point A to B) along an equatorial plane: (i) *Selection of key points to calculate distance*: the travel distance along the coastal areas of disaster-prone layout, consisted of red zones for the annual flood occurrence, (ii) *Getting straight line*, *road distances*: assumption of the geometrically straight line that can be visualized along the route path, and (iii) *Result analysis:* Bisection of road distance along the straight-line distance.

DATASET ANNOTATION

The fundamental disaster strategy situation selected is the flood mitigation process, where a routing schedule is targeted for flagged areas that are deemed potential to be struck with flash floods during monsoon season, where the identified location is targeted along residential areas near river banks that are

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deemed risky to experience overflowing. The research foundation references Cordeau's work on MDVRP instances to customize the testing dataset.

PROBLEM CHARACTERISTICS

The routing distribution cycle consisted of 33 pick-up cities and 23 targeted participating depots which are scattered in the vicinity or at the epicenter of the pick-up sites. The pick-up cities have a fixed capacity for relief commodities. The main cities in the region are selected as the distribution depots of traversal. Table 3.4 on the next page represents the coordinates in X-Y for the participating locations and traversable routes with respective with their distance from each other.

Simulated Problem Instances

A program script dedicated to generating multi-depot instances for the flood risk demography areas is coded in Java based on the parameter variables representing Cordeau's 23 instances. This script produces simultaneous problem instances and solution files from the selected contents consisting of p2, p3, p5, p9, p12, p15, p18, and p21.

Table 2: Dataset parameter variables applied in the flood risk routing scheduling

Parameters/Instances	Total num. of customers	Total num. of depots	Num. of vehicles in each depot	Vehicle capacity (kg)	Final Solution
p02	50	4	2	160	487.83
p03	75	5	3	140	667.89
p05	100	2	5	200	811.18
p09	249	3	12	500	2012.55
p12	80	2	5	60	1415.26
p15	160	4	5	60	2767.34
p18	240	5	5	60	4137.26
p21	360	5	5	60	6204.52

MAPPING THE PARTICIPATING DEMOGRAPHY

A Java program script is coded as a go-mapping plot tool replacing Google Maps' reliability in portraying the actual critical potential depot location for the multi-depot traversal. The heat map of flood-prone areas is devised based on an analysis of the Department of Irrigation and Drainage (DID) report on heavy precipitation areas for the past 5 years, ranging from 2017-2021. Only areas that portray water levels within 0. 3-1. 5m after a heavy rain without immediate receding is deemed as a flood risk demography study for this investigation, where the prominent pattern exhibits a higher precipitation tendency for 4 divisions, mainly Miri (2017, 2018), Sibu (2020), Betong (2019), and Kuching (2021).

i. Demography selection

- Postcode geolocation description: Allocation of postal codes is done to indicate the existence of the geographical location of a populated area.
- Data collection: Analysis is performed on the availability of existing distribution centers or past operational rooms such as the school compound and town hall where better dissemination of relief efforts is conducted. Route annotation would go through a designated central point, where the transportation would eventually pass through all sub-node points.
- The distance among traveled nodes: It is ensured that task distribution possesses the highest possibility of completion within a single travel effort while deploying for a round trip under a fixed, estimated time range and receiving an equal footing of resource allocations for all participating node points.

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ii. Node disposition

With the obtained precipitation data from the Meteorological Department (2010-2018), the area with a higher risk of flood is identified. 54 nodes are selected based on their corresponding traits with the main nodes, among the decided points include Bintulu (11), Tatau (3), Mukah (4), Dalat (5), Sarikei (7), Sibu (20), Kanowit (6), Kapit (3), and Song (4). In the final dataset, 45 areas are fixed as the node points after taking into consideration the relevancy of several sub-district aside from removing redundancy points.

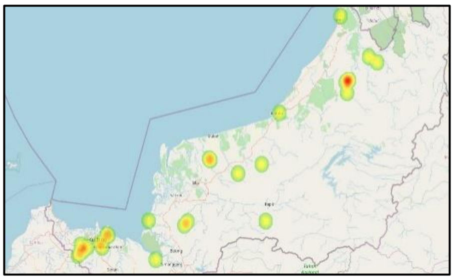

Figure 8: Location of designated depot across the strategic flood-prone locations in the simulated demography

Figure 9: Location of targeted customers across the strategic flood-prone locations in the simulated demography

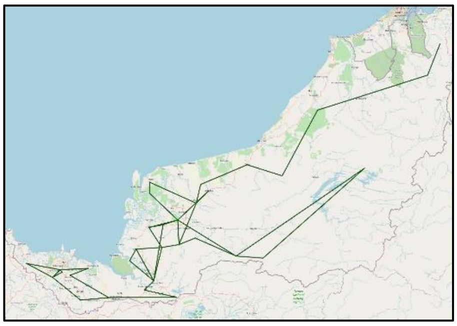

Figure 10: Plotted designated route using shortest path distance measure for the flood-prone locations along the round trip coverage

DATA INSTANCE ANNOTATION

Cordeau's (1997) dataset instance is selected as the proprietary reference for this approach. The proposed computational modeling reproduces a schematic delineation of a multi-level traversal area for the sampled demography. Testing reflective the flood relief distribution scheduling simulation model is conducted on 8 main problem instances, collectively p02, p03, p05, p09, p12, p15, p18, and p21.

Table 3: List of predetermined modeling variables for the custom problem instances

p	Num. of customers	Num. of involving depot	Num. of vehicles	Vehicle capacity	Initial cost
02	50	4	2	160	487.83
03	75	5	3	140	667.89
05	100	2	5	200	811.18
09	249	3	12	500	2012.55
12	80	2	5	60	1415.26
15	160	4	5	60	2767.34
18	240	5	5	60	4137.26
21	360	5	5	60	6204.52

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RESULTS

The simulation program code is done with Java in Eclipse, with an i7-8550 CPU with several execution delimiters being imposed. The following table illustrates the parameters highlighted in the study.

Table 4: Parameter variables for the proposed framework

Experimented Variable	Constant Variable
Elapsing time: 50000 m/s	Rate of crossover, *CR*: 0.05
Population size, *NP*: 1000	Crossover factor: 0.05
Generation number: 1000	Rate of mutation: 0.05

The scale of the problem instance is determined as follows.

Table 5: Instance size for each dataset category constituted by the number of customers and participating depots

Type	Problem Instance
Small	p2, p3, p5
Medium	p7, p9
Large	p12, p15, p18, p21

The problem modeling takes into consideration the constant variables and their influence on routing complexity be it the completion time or total coverage within a certain elapsing time. As with MDVRP problem states, positioned vehicles start and conclude at the same depot. Table 2 illustrates the comparison between normal route allocation and the application of the shortest path algorithm. From the proposed route, the total traveling distance when a round trip is achieved is approximated to be 3006.4km as compared when the total accrued distance without applying the shortest distance selection metric by the study which totals around 8387.2km.

Table 6: Comparison of actual round trip distance for a single deployment assuming the vehicle traverses through all nodes

Single Trip (without shortest path approximation)	Total overall projected deployment distance (assuming all node points is served at a specific time)	45 critical traversal point = **4193.6 km**
	Total	8387.2 km (round trip)
	Total serviceable areas (no duplicates)	43 critical traversal point = **3859.9 km**
	Total	7719.8 km
Shortest Path Algorithm for a Single Trip	Calculation: Starting Point: Limbang Ending Point: Bau	Limbang (0.0 Km) -> Marudi (199.2 Km) -> Miri (235.0 Km) -> Bintulu (436.5 Km) -> Tatau (492.2 Km) -> Mukah (635.6 Km) -> Dalat (676.8 Km) -> Julau (902.1 Km) -> Pakan (968.9 Km) -> Betong (1035.7 Km) -> Sri Aman (1110.3 Km) -> Lubok Antu (1196.1 Km) -> Simunjan (1403.4 Km) -> Serian (1432.0 Km) -> Bau (1503.2 Km)
	Total	3006.4 km (round trip)

Table 7: Final result of the simulation run

Problem instance	Population size (NP)	Mutation rate	Crossover rate (*CR*)	Completion time (ms)	Fitness		Cost
					Average	Best	
p02	1000	0.05	0.05	41000	707.536	707.152	487.83
p03	1000	0.05	0.05	38000	719.889	719.703	667.89
p05	1000	0.05	0.05	36000	656.530	655.973	811.18
p09	1000	0.05	0.05	35000	638.096	637.891	2012.55
p12	1000	0.05	0.05	34000	686.211	685.562	1415.26
p15	1000	0.05	0.05	35000	661.598	660.148	2767.34
p18	1000	0.05	0.05	35000	673.884	673.457	4137.26
p21	1000	0.05	0.05	37000	706.150	705.141	6204.52

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As with MDVRP problem states, positioned vehicles start and conclude at the same depot. From the proposed route, the total traveling distance when a round trip is achieved is approximated to be 3004km. The number of depots does not affect the allocation speed, however, increased vehicle frequency would react in parallel with the number of the participating depot as when more depot is simulated across the participating sectors the execution time obtained as compared with less depot allocation paired with less vehicle deployment. In terms of algorithm comparison, the execution speed for solution generation is rapid until a stagnation point is achieved, where the process halts and no longer extends in growth even with a further increment in population size. The fitness value will be lowered when the number of generations increases. The comparison between average and best fitness always displays a slightly lower value achieved by best fitness. This shows that the search space during the crossover strategy implementation is not explored enough. There are little to no variation values between both end fitness values. The benefits of a constant parameter can be seen if all the resources at the initiating point are the same, where should the uncertainty factor is involved in the growth rate upon achieving a certain number of generations the fluctuation & decrement would be temperamental. Some experiments on incrementing crossover threshold with the same parameter instance indicated only certain changes in fitness value could be observed only if the population size is extended exponentially.

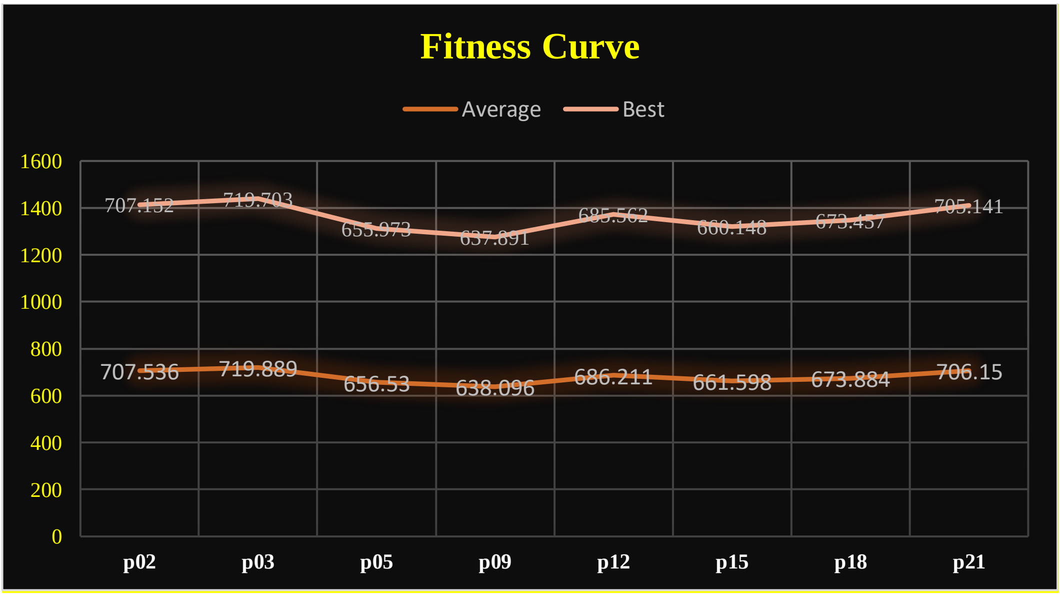

Figure 11: The fitness value for the 8 tested instances

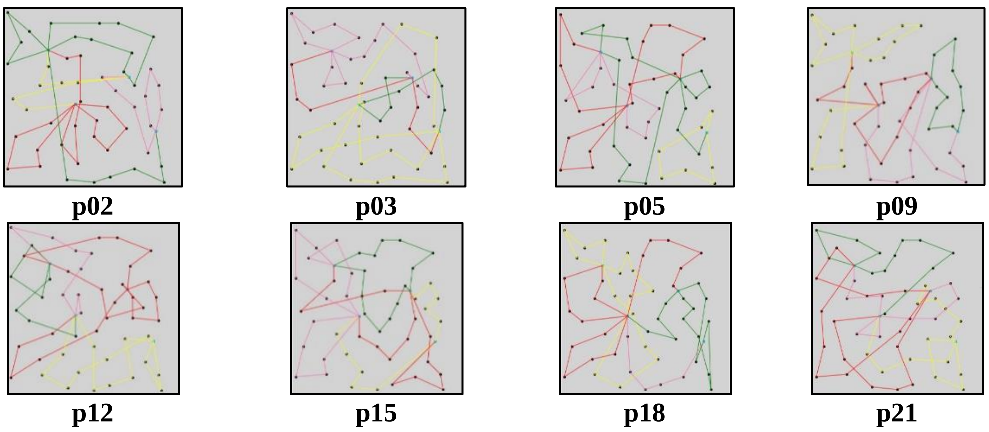

Figure 12: Output value of the simulated run for the tested instances (p02, p03, p05, p09, p12, p15, p18, p21)

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CONCLUSION

This paper performs an investigation of the application of multi-depot dispatch based on VRP instances for distribution purposes involving the transportation of relief items for highly risky areas as an effort to augment the existing preparedness phases in managing unforeseen disasters. Through applying the proposed genetic computation approach and route optimization measures, it is concluded that the modified genetic algorithm combined with the Haversine distance measure could assist in improvising better route selection features based on the retrenching of participating route distance. Some of the suggested endeavors already in the works is an improvement of the search space during the selection & mutation strategies by embedding perpendicular measures such as route relocation strategies and classifying a better-optimized vertex to highlight the priority vertex points in the distance matrix to formulate a better simulation of neighboring nodes crucial in annotating shorter round trip distance. It is also suggested for further investigation that adaptive measures be implemented into parameter selection measures to prevent an unstable fitness trend and to observe a better crossover to generate featured solution chromosomes. It is a good recommendation to augment optimization measures for exploration and exploitation purposes involving route latency, better cost function handling, and rapid minimization of local optima for generated solution steps.

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