Candidate Declaration

Project/Study: Military Logistics Planning

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Under the supervision of Mrs. Shubhi Saini, Scientist 'D'

July 27, 2024

Candidate Declaration

I hereby declare that the work which is being presented by me in this Project/Study entitled **"Military Logistics Planning"** is an authentic record of my own work carried out during the period from 27th May 2024 to 29th July 2024 under the supervision of Mrs. Shubhi Saini, Scientist 'D', Institute for Systems Studies and Analyses, Defence R&D Organisation, Ministry of Defence, Metcalfe House, Delhi 110054.

Acknowledgment

I would like to thank Dr. Sujata Dash, Director of ISSA and Head of HRD, for giving me the chance to work on this project at such a respected organization. I am also very grateful to Shubhi Saini, Scientist 'D' at ISSA, DRDO, for her helpful guidance and support throughout the project. Additionally, I appreciate the technical staff for their assistance and for providing the facilities needed to complete my project.

Military Logistics Planning: An approach using Genetic Algorithm

Animesh Mishra, Mentor: Shubhi Saini, Scientist 'D', Director ISSA: Dr. Sujata Dash

***Abstract*— This study presents a novel approach to optimize fuel replenishment strategies for a fleet of continuously patrolling vehicles over a 15-day period. The simulation involves four vehicles, each assigned to a specific patrol area, with the objective of maintaining at least 30% fuel capacity to avoid operational downtime. Fuel replenishment is facilitated by dedicated refueling vehicles dispatched from three strategically located hubs, two of which impose a 10% surcharge on fuel costs.**

I. Introduction

In the field of Military logistics and operations research, one of the core challenges is developing an optimal refueling schedule for a fleet of continuously patrolling vehicles. These vehicles, each operating within a predesignated area over a period of 15 days, require efficient fuel management to avoid downtime and maintain seamless operations. Each vehicle has a specific fuel capacity, and to ensure continuous patrolling, it is imperative that each vehicle maintains at least 30% fuel at all times.

Fuel replenishment can be performed by dispatching a refueling vehicle from one of three available hubs. Of these three hubs, two charge an additional 10% fee over the cost of the fuel collected. This adds a layer of complexity to the decision-making process, as the cost-effectiveness of the refueling operation is influenced not only by the fuel consumption patterns of the patrolling vehicles but also by the additional fees charged by certain hubs.

The primary objective is to devise an optimal refueling schedule that addresses two key decisions:

1) Determining the most cost-effective hub from which to dispatch the refueling vehicle.
2) Choosing between individually refueling each patrolling vehicle or adopting a group gathering approach where patrolling vehicles converge at a designated area near the refueling vehicle after it has been dispatched.

These decisions must be made while balancing the trade-offs between the time spent refueling and maintaining patrol coverage. The overall cost, influenced by fuel consumption and additional fees, serves as the criterion for evaluating the optimality of the refueling schedule.

This study investigates these complexities through the development and application of a Genetic Algorithm (GA) to optimize the refueling strategy. The GA evaluates various dispatch and gather strategies, refuel thresholds, and emergency thresholds to identify the most cost-effective solution.

II. Significance of the Study

This study holds substantial significance in the domain of logistics and operational management, particularly for organizations that rely on continuous vehicle operations. The primary aim is to enhance the efficiency and effectiveness of refueling schedules, which can be critical in several high-stakes applications.[**5**]

A. Applications

The findings and methodologies developed through this study are applicable to various sectors[**6**], including but not limited to:

- Law enforcement patrols
- Security services
- Emergency response units
- Commercial fleet operations with time-sensitive deliveries

B. Benefits

Implementing the optimized refueling strategies proposed in this study can yield numerous benefits:

- **Reduce operational costs**: By optimizing fuel consumption and minimizing additional fees from certain hubs, organizations can achieve significant cost savings.
- **Minimize vehicle downtime**: Ensuring that vehicles maintain at least 30% fuel reduces the risk of downtime, thereby improving the reliability and consistency of operations.
- **Improve overall patrol efficiency**: Efficient refueling schedules allow for better time management, ensuring that patrol coverage is maintained without unnecessary interruptions.
- **Enhance resource allocation**: Optimal scheduling helps in better utilization of available resources, including refueling vehicles and hubs, leading to more strategic deployment.

III. Algorithm Definition

It is inspired by the biological theory of evolution by means of natural selection. Specifically, the new synthesis that combines an understanding of genetics with the theory. These algorithms are frequently used to create high-quality solutions to optimize and search concerns by focusing on bio-inspired operators such as selection, convergence, or mutations [**4**]. The author John Holland developed GAs based on Darwin's evolutionary theory in 1988 . Subsequently, in 1992, he expanded the GA [**3**]. This algorithm falls under the heading of evolutionary algorithms. The evolutionary algorithms are used to solve problems that do not already have a well-defined efficient solution. This approach is used to solve optimization problems (scheduling, shortest path, etc.) One iteration of the algorithm is like an evolutionary generation. The algorithm usually ends when either a maximum number of generations or satisfaction has been generated. Therefore, every successive generation is more suitable for the environments of the population. Genetic algorithms (GAs) are search heuristics

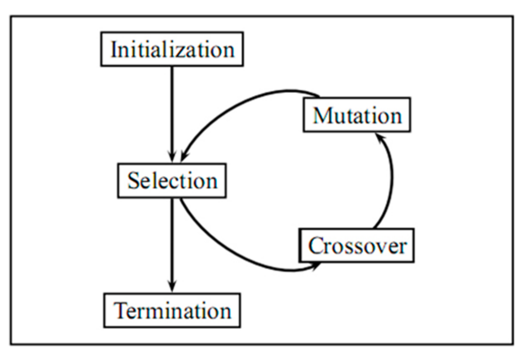


Fig. 1. Basic Algorithm

that mimic the process of natural selection. They operate on a population of potential solutions, evolving them over generations to optimize a given objective function. In the context of GAs, the fundamental units are genes, chromosomes, and populations, analogous to biological genetics. We define our own fundamental units as follows:

Gene A gene represents one of the following:

Fig. 2. Individual Strategy

- **Element in the "dispatch_strategy" list**: This is a hub ID assigned to a specific vehicle.
- **Element in the "gather_strategy" list**: This is a boolean value (True or False) for a specific vehicle.
- **"refuel_threshold" value**: A single float value used across all vehicles.
- **"emergency_threshold" value**: A single float value used across all vehicles.

Chromosome A chromosome (or individual) is the entire dictionary containing all these genes. It includes:

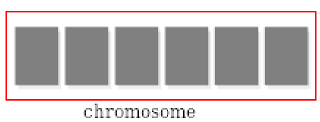


Fig. 3. Combined Strategy as a Chromosome

- The "dispatch_strategy" list for all vehicles.
- The "gather_strategy" list for all vehicles.
- The "refuel_threshold" value.
- The "emergency_threshold" value.

Population The population is a list of these chromosomes, with a size of 50 for this implementation. Each chromosome represents a potential solution in the search space.

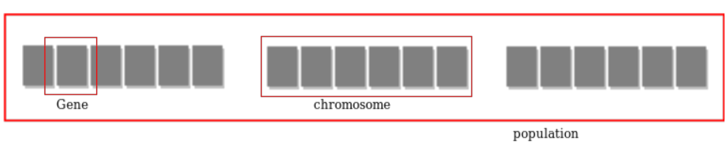


Fig. 4. Population of strategies

IV. Genetic Algorithm Operators

In our genetic algorithm, the key operators include the dispatch strategy, gather strategy, refuel threshold, and emergency threshold.[**2**] These operators define the attributes of each individual solution in the population and play a crucial role in evolving the population towards optimal solutions. The dispatch strategy determines the sequence and priority of which vehicles should be dispatched for refueling. The gather strategy decides whether vehicles should individually go to a refueling hub or gather at a designated location for group refueling. The refuel threshold sets the minimum fuel level at which a vehicle should be refueled, while the emergency threshold defines a critical fuel level that triggers immediate refueling actions.

Operator	**Parent 1**	**Parent 2**
Dispatch Strategy	{2, 1, 3, 1}	{1, 3, 2, 3}
Gather Strategy	{T, F, T, F}	{F, T, F, T}
Refuel Threshold	0.3	0.4
Emergency Threshold	0.15	0.2

TABLE I
Attributes of Parent Individuals

Operator	**Child 1**	**Child 2**
Dispatch Strategy	{2, 1, 2, 3}	{1, 3, 3, 1}
Gather Strategy	{T, T, F, F}	{F, F, T, T}
Refuel Threshold	0.35	0.35
Emergency Threshold	0.175	0.175

TABLE II
Attributes of Offspring Individuals after Crossover

Operator	**Mutated Child 1**	**Mutated Child 2**
Dispatch Strategy	{2, 1, 2, 2}	{1, 3, 3, 2}
Gather Strategy	{T, T, T, F}	{F, F, T, F}
Refuel Threshold	0.4	0.3
Emergency Threshold	0.2	0.15

TABLE III
Attributes of Offspring Individuals after Mutation

A. Crossover and Mutation Example

In the example provided, the genetic algorithm performs crossover and mutation operations on two parent individuals to generate new offspring.

1) Crossover: Crossover involves combining the genetic information of two parents to create offspring. In this example:

- Parent 1 has the dispatch strategy {2, 1, 3, 1}, gather strategy {T, F, T, F}, refuel threshold 0.3, and emergency threshold 0.15.
- Parent 2 has the dispatch strategy {1, 3, 2, 3}, gather strategy {F, T, F, T}, refuel threshold 0.4, and emergency threshold 0.2.
- During crossover, segments of the dispatch and gather strategies are swapped, and the refuel and emergency thresholds are averaged to create the child individuals.
- For example, Child 1 inherits dispatch strategy {2, 1, 2, 3} and gather strategy {T, T, F, F} from a combination of the parents' strategies.

2) Mutation: Mutation introduces genetic diversity by randomly altering the genes of the offspring:

- In the mutation process, Child 1's dispatch strategy changes from {2, 1, 2, 3} to {2, 1, 2, 2}, and gather strategy changes from {T, T, F, F} to {T, T, T, F}.
- The refuel threshold of Child 1 changes from 0.35 to 0.4, and the emergency threshold changes from 0.175 to 0.2.
- Similarly, Child 2 undergoes mutations, resulting in new dispatch and gather strategies, and adjusted thresholds.

These operations help explore the solution space and find more optimal refueling schedules by combining and varying the attributes of parent individuals.

V. Algorithm Implementation

The Genetic Algorithm is a stochastic global search optimization algorithm.

It is inspired by the biological theory of evolution by means of natural selection. Specifically, the new synthesis that combines an understanding of genetics with the theory.

Genetic algorithms borrow inspiration from biological evolution, where fitter individuals are more likely to pass on their genes to the next generation.

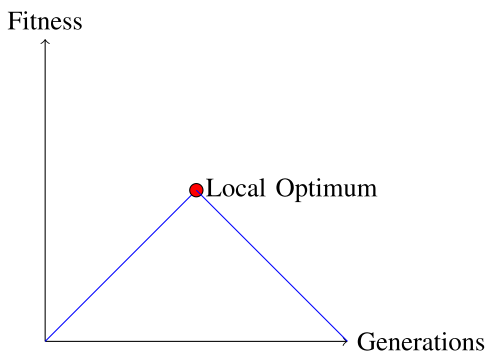
GA works on a population consisting of some solutions where the population size is the number of solutions. Each solution is called individual. Each individual solution has a chromosome. The chromosome is represented as a set of parameters (features) that defines the individual. Each chromosome has a set of genes.

A. Population Initialization

$P_0 = \{I_1, I_2, \ldots, I_n\}$ where $n = 50$ (population size)
Each I_i is an individual solution

- P_0: Initial population
- I_i: Individual solution
- n: Population size

B. Fitness Evaluation



$f(I_i) \rightarrow \mathbb{R}$, where f is the fitness function

- $f(I_i)$: Fitness of individual I_i
- $\mathbb{R}$: Set of real numbers

C. Parent Selection

$S = \{s_1, s_2, \ldots, s_n\}$ where $s_i \in P_t$, selected with probability $p(s_i) \propto f(s_i)$

- S: Set of selected parents
- s_i: Selected parent
- P_t: Population at generation t
- $p(s_i)$: Selection probability of s_i

D. Crossover

$C(s_i, s_j) \rightarrow (c_1, c_2)$, where C is the crossover operator

- C: Crossover operator
- c_1, c_2: Offspring produced by crossover

E. Mutation

$M(c_i) \rightarrow c_i'$ with probability $p_m = 0.1$, where M is the mutation operator

- M: Mutation operator
- c_i': Mutated offspring
- p_m: Mutation probability

F. Elitism

$I^* = \arg\max_{I_i \in P_t} f(I_i)$
$P'_{t+1} = \{I^*, I_1, I_2, \ldots, I_{n-1}\}$

- I^*: Best individual in a generation
- P'_{t+1}: Intermediate population for next generation

G. Final Solution

$I_{opt} = \arg\max_{I_i \in P_T} f(I_i)$

- I_{opt}: Optimal solution found
- P_T: Final population after T generations

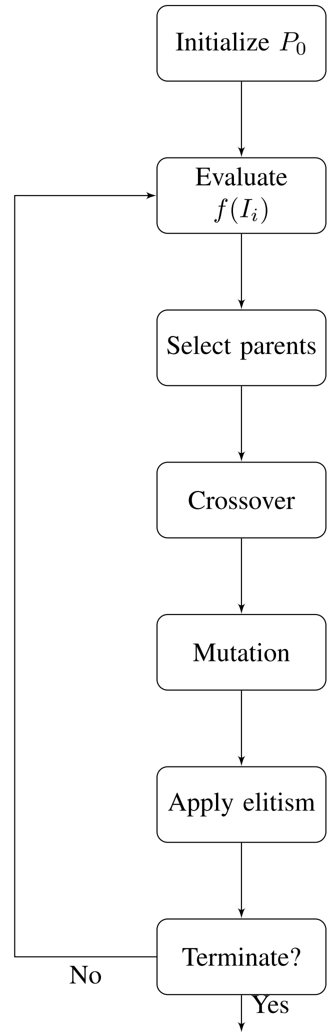


Fig. 5. Genetic Algorithm Flowchart

VI. Experimental Setup

In this study, we employed the following parameters to evaluate the performance of the genetic algorithm:

- **Population Size**: The population size was set to 50 individuals. This parameter defines the number of candidate solutions evaluated in each generation.
- **Number of Generations**: The algorithm was executed over 100 generations.
- **Mutation Rate**: A mutation rate of 0.3 was applied. This indicates a 30% probability that a mutation would occur in each gene of an individual.
- **Crossover Rate**: The crossover rate was set at 0.8. This parameter represents an 80% probability that crossover operations would be performed between pairs of individuals. A high

crossover rate promotes the recombination of genetic material and enhances the exploration of the solution space.

These parameters were selected to balance exploration and exploitation within the genetic algorithm, aiming to achieve effective optimization and convergence to high-quality solutions.

VII. Strategies

In this section, we discuss two distinct strategies employed in our system: the baseline strategy and the optimized strategy using genetic algorithms.

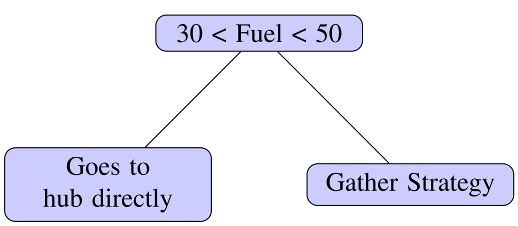
A. Baseline Strategy

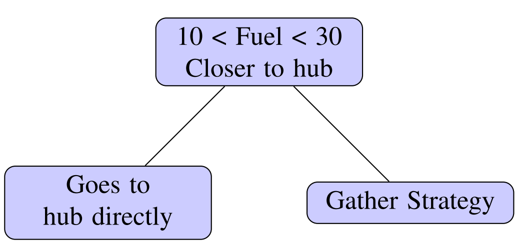
The baseline strategy represents a straightforward approach where the parameters are set with fixed values. This strategy serves as a reference for evaluating the performance of more sophisticated methods. The key aspects of the baseline strategy are:

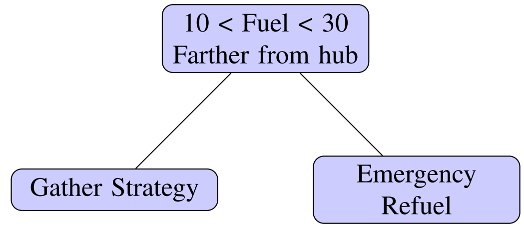
- **Dispatch Strategy**: Each vehicle is associated with a random hub from the available options, and this assignment remains constant throughout the simulation. This approach does not consider any dynamic factors or optimizations based on vehicle status or hub locations.
- **Gather Strategy**: Vehicles do not attempt to group together at any point, meaning they will not synchronize their activities or movements based on the positions of other vehicles.
- **Refuel Threshold**: The refuel threshold is set to 0.2. This means that a vehicle will initiate a refueling process when its fuel level drops to 30% of its total fuel capacity. The decision to refuel is thus based on a fixed threshold that does not adapt to varying conditions.
- **Emergency Threshold**: An emergency refuel threshold of 0.1 is used. Vehicles enter an emergency refuel state when their fuel level falls to 10% of their total capacity.

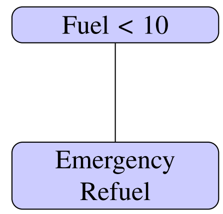
B. Optimized Strategy

The optimized strategy using genetic algorithms dynamically adjusts various parameters and adapts based on performance feedback. This approach aims to enhance vehicle management and refueling operations by evolving and refining strategies through an iterative process.









For detailed implementation and algorithmic processes of the optimized strategy, refer to **V: Algorithm Definition**.

VIII. Refuel Vehicle Dispatch Algorithm

This section outlines the algorithm employed for dispatching refuel vehicles to those in need of refueling. The algorithm is designed to efficiently identify, process, and manage the refueling operations of vehicles. The steps involved in this algorithm are detailed below:

A. Identification of Vehicles Needing Refuel

The initial step involves identifying which vehicles require refueling. This determination is typically based on the current fuel level of the vehicles and their distance from the available refueling points. Specifically, vehicles are flagged for refueling when their fuel level falls below a predefined threshold.

B. Processing Vehicles Needing Refuel

Upon identifying the vehicles requiring refueling, the following procedural steps are executed:**[7]**

1) **Calculation of Centroid**
   - Compute the average position of all vehicles that require refueling. The centroid C of these vehicles is determined by the following equation:

   $$C = \frac{1}{n}\sum_{i=1}^{n} p_i$$

   where:
   - n denotes the number of vehicles in need of refueling ($n = |V_{\text{refuel}}|$).
   - p_i represents the position vector of the i-th vehicle needing refuel.
2) **Sorting of Vehicles**
   - Rank the vehicles needing refuel based on their distance from the calculated centroid. This sorting enables prioritization of vehicles closer to the centroid for refueling.
3) **Identification of Closest Idle Refuel Vehicle**
   - Identify all refuel vehicles that are currently idle.
   - Select the idle refuel vehicle that is closest to the centroid of the vehicles needing refuel.
4) **Selection of Vehicles for Refueling**
   - From the sorted list of vehicles needing refuel, select up to two vehicles for immediate refueling.

- Vehicles not selected in this step are classified as remaining_vehicles.

5) **Refueling Operation**
   - Determine a gathering point, which is the average position between the selected refuel vehicle and the vehicles chosen for refueling.
   - Calculate the path to the gathering point.
   - Assign the target vehicles and refuel point.
   - Reset all other refuel vehicles to an idle state, ensuring they are not engaged in refueling activities.

IX. Data preparation

A. Dashboard Features

The dashboard is designed to provide comprehensive real-time monitoring and analysis of the vehicle fleet. Key features of the dashboard include:

- **Movement Visualization:** Tracks and displays the movement of each vehicle using the most optimized algorithm over a 15-day period. The movements are plotted on a map for easy visualization.
- **Real-Time Fuel Level Monitoring:** Displays the current fuel level of each vehicle. Fuel levels are updated in real-time to ensure accurate monitoring.
- **Alert Box:** Provides alerts for various vehicle states such as:
  - **Refueling:** Alerts when a vehicle is going to refuel.
  - **Patrolling:** Alerts when a vehicle is patrolling.
  - **Idle:** Alerts when a vehicle is idle.
- **Data Logging:** All vehicle movements and states are saved in a CSV file with the following format: Frame, day, entity_type, id, x_position, y_position, fuel_level, state, refuel_point_x, refuel_point_y

B. CSV Data Format

The movements and states of each vehicle are recorded and saved in a CSV file. The format of the CSV file is as follows[**10**]:

- **Frame:** The frame number of the simulation.
- **Day:** The day of the simulation.
- **Entity_type:** The type of the entity (e.g., vehicle).
- **ID:** The unique identifier of the vehicle.
- **X_position:** The X coordinate of the vehicle's position.
- **Y_position:** The Y coordinate of the vehicle's position.
- **Fuel_level:** The current fuel level of the vehicle.
- **State:** The current state of the vehicle (e.g., refueling, patrolling).
- **Refuel_point_x:** The X coordinate of the refuel point.
- **Refuel_point_y:** The Y coordinate of the refuel point.

C. Data Analysis

The data saved in the CSV file is used for further analysis to gain insights into the performance and efficiency of the fleet management system. The analyses include:

- **Fuel Consumption Analysis:** Evaluates the fuel consumption patterns of the vehicles over the 15-day period.[**1**]
- **Movement Patterns:** Analyzes the movement patterns to identify areas with high vehicle activity.
- **State Transition Analysis:** Examines the transitions between different states (e.g., patrolling to refueling) to optimize scheduling and routing.

X. Results

A. Cost Improvement

The optimized strategy consistently results in lower daily costs compared to the baseline.

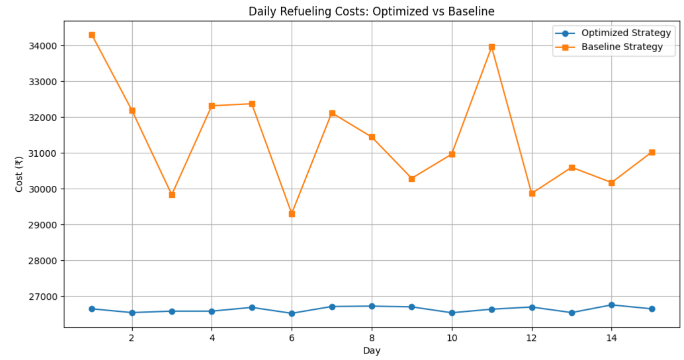


Fig. 6. Cost Comparison: Baseline vs Optimized

- Average baseline cost: ∼31,500 units
- Average optimized cost: ∼27,000 units
- Approximate cost improvement:

$$\frac{31,500 - 27,000}{31,500} \times 100 \approx 14.3\%$$

The optimized strategy offers a cost reduction of around 14-15% compared to the baseline strategy.

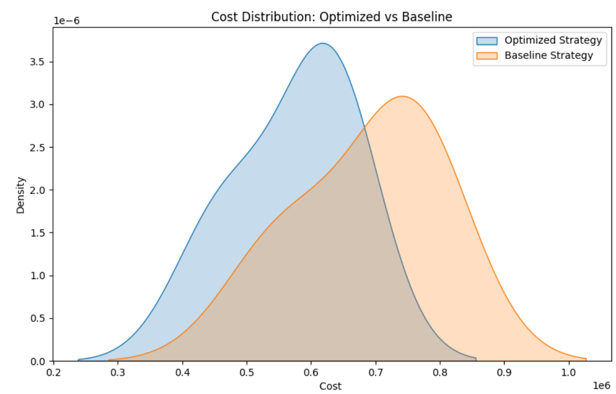


Fig. 7. Cost distribution1e6

B. K-means Clustering Analysis

K-means clustering was performed to analyze vehicle locations and movements. The analysis identified 5 distinct clusters based on the x and y positions of the vehicles.[**8**] Key findings:

- The clustering primarily reflects the spatial distribution of vehicles.
- Each cluster represents a group of vehicles in close proximity to each other.
- The analysis provides insights into geographical patterns of vehicle placement and movement within the simulation.
- A scatter plot visualization (saved as a PNG file) shows the spatial relationships between vehicles, with each cluster represented by a different color.
- The mean position (center) was calculated for each cluster, serving as reference points for strategic planning or resource allocation.[**9**]

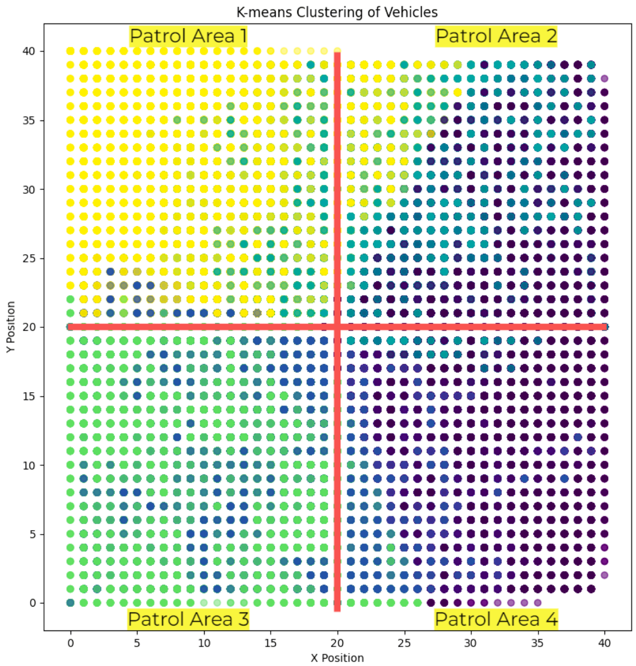


Fig. 8. Vehicle clustering

C. Insights: Optimized Strategy vs Baseline Strategy

- **Most fuel-efficient vehicle:** 3
- **Least fuel-efficient vehicle:** 1
- **Busiest refueling spot:** (20.0, 26.33) with 44 refuels
- **Stranded vehicles:** No stranded vehicles detected
- **Most efficient refuel vehicle:** 3 with 844 refuels
- **Vehicle with most complex path:** 4

The optimized strategy worked perfectly. It returns 0 stranded vehicles. All vehicles were refueled on time.

Aspect	Optimized Strategy	Baseline Strategy
Dispatch	Dynamic	Fixed
Gathering strategy	Used	Not used
Refuel threshold	Adaptive	Fixed (0.2)
Emergency threshold	Adaptive	Fixed (0.1)
Stranded vehicles	0	Likely higher

TABLE IV
COMPARISON OF DYNAMIC AND BASELINE STRATEGIES

D. Fuel Efficiency Analysis

- Calculates the fuel efficiency for each vehicle.
- Identifies the most and least fuel-efficient vehicles.
- This analysis helps in understanding which vehicles are performing optimally and which may need attention.

E. Path Complexity Analysis

- Calculates the complexity of paths taken by vehicles.
- Identifies vehicles with the most complex paths, which might indicate areas of inefficiency or difficulty.

F. Vehicle Position Density Heatmap

- Generates a heatmap showing the density of vehicle positions.
- This visualization helps identify high-traffic areas and potential patrol route optimizations.[**11**]

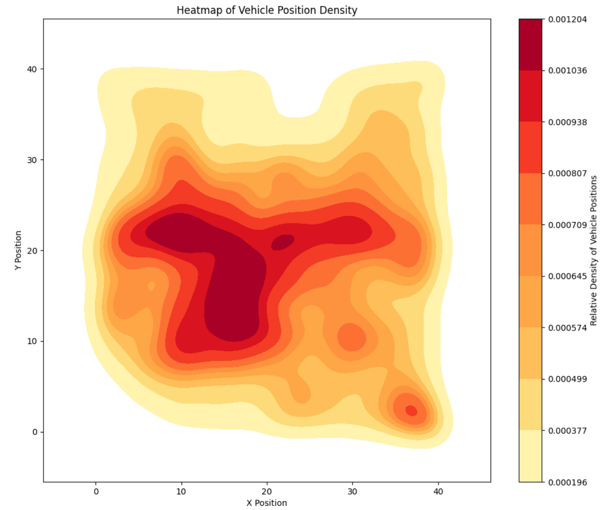


Fig. 9. Heatmap: Vehicle Density

G. Fuel Level Distribution Visualization

- Creates a kernel density estimation plot of fuel levels across different days.
- This visualization helps in understanding how fuel levels vary over time and across the fleet.

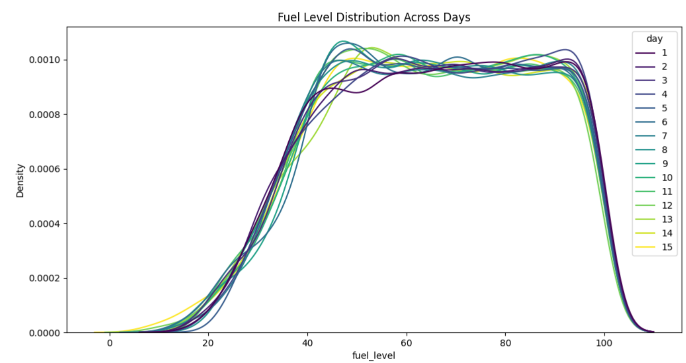


Fig. 10. Fuel level distribution

XI. Case Study

A. Scenario 1: Vehicle far from hub

[**12**] **Optimized Strategy:** When a vehicle is far from a hub and needs refueling, the dynamic strategy assesses the situation holistically. It considers the vehicle's current fuel level, distance to the nearest hub, and the presence of other vehicles in the vicinity. If the fuel level is critically low, it initiate an emergency refuel by dispatching a refueling vehicle. Alternatively, if other vehicles are nearby, it might employ a gathering strategy, where multiple vehicles converge to share resources efficiently. The strategy adapts based on real-time conditions to minimize the risk of the vehicle becoming stranded.

Baseline Strategy: In the same scenario, the baseline strategy relies on its fixed thresholds. The vehicle continues its operation until it reaches the predetermined refuel threshold (0.2). At this point, it would attempt to return to the nearest hub for refueling.

If the distance is too great and the fuel level drops below the emergency threshold (0.1) the vehicle gets stranded.

B. Scenario 2: Two vehicles need refueling

Optimized Strategy: When two vehicles require refueling, the dynamic strategy can utilize its gathering capability. It assesses the locations of both vehicles and nearby hubs. If efficient, it may direct both vehicles to a common point for simultaneous refueling, potentially by a single refueling unit. This approach optimizes resource use and minimizes overall travel time and fuel consumption for the refueling operation.

Baseline Strategy: The baseline strategy, lacking a gathering mechanism, would treat each vehicle independently. It would likely direct one vehicle to the nearest hub and the other to the next nearest hub, or have them queue at the same hub for sequential refueling. This approach is less efficient, potentially leading to longer wait times and increased fuel consumption as vehicles may need to travel further for refueling.

C. Scenario 3: Three vehicles need refueling

Optimized Strategy: In a scenario with three vehicles needing refuel, the dynamic strategy's adaptability shines. It can create a complex, optimized plan that might involve a combination of gathering and hub visits. For example, it could direct two closely located vehicles to gather for a shared refuel, while sending the third to a conveniently located hub. Alternatively, it might coordinate a rolling refuel plan, where vehicles assist each other in reaching refueling points efficiently. The strategy continuously adapts based on changing vehicle positions and fuel levels to minimize overall resource use and time.

Baseline Strategy: The baseline strategy would handle this situation similar to the two-vehicle scenario, but with even less efficiency. Each vehicle would be directed to a hub based solely on proximity and availability, without consideration for the overall fleet efficiency. This could result in situations where all three vehicles are traveling to different hubs, or two are queued at one hub while a second hub is underutilized. The lack of coordination and adaptive planning could lead to increased overall travel distances, longer refueling times, and less efficient use of refueling resources.

XII. Future Scope

Future research could explore several enhancements to extend the current analysis:

A. Geomap Integration

Integrate geomap technologies to map simulation grid coordinates to real-world geographic coordinates, allowing for a realistic representation of locations while maintaining grid-based mechanics.

B. Real-time Analysis

Develop real-time data processing capabilities to provide immediate insights during simulation runs, enhancing responsiveness and decision-making.

C. Weather and Environmental Factors

Incorporate weather and environmental conditions into the analysis to understand their impact on fuel consumption and vehicle performance.

D. Multi-modal Transportation

Expand the analysis to include interactions with other transportation modes or infrastructure, offering a comprehensive view of transportation dynamics.

E. API Development

Create an API to facilitate integration of the analysis tools with other systems or applications, promoting interoperability and broadening usability.

XIII. Conclusions

This study shows that using a Genetic Algorithm (GA) to optimize fuel replenishment strategies for a fleet of continuously patrolling vehicles leads to significant improvements. By considering dispatch and gather strategies, refuel thresholds, and emergency thresholds, the GA effectively reduces operational costs and minimizes vehicle downtime. Specifically, the optimized strategy achieved about a 14-15% cost reduction compared to the baseline approach. The integration of K-means clustering provided useful insights into the spatial distribution and movement patterns of the vehicles, aiding better decision-making. The results confirm that GA is effective in tackling complex logistical challenges and improving efficiency in various real-world applications, including law enforcement, security services, emergency response units, and commercial fleet operations.

Acknowledgment

I would like to thank Dr. Sujata Dash, Director of ISSA and Head of HRD, for giving me the chance to work on this project at such a respected organization. I am also very grateful to Shubhi Saini, Scientist 'D' at ISSA, DRDO, for her helpful guidance and support throughout the project. Additionally, I appreciate the technical staff for their assistance and for providing the facilities needed to complete my project.

References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.

References

[1] Roberto H. Q. Filho , "Development of a Genetic Algorithm-Based Control Strategy for Fuel Consumption Optimization in a Mild Hybrid Electrified Vehicle's Electrified Propulsion System," in Energies.

[2] Abbas K. Zaidi, Alexander H. Levis, in Soft Computing and Intelligent Systems. (2000). "Variable Structure Distributed Information Systems via Genetic Algorithms"

[3] Vijini Mallawaarachchi, "Introduction to Genetic Algorithms,Towards Data Science

[4] Albadr, M.A.; Tiun, S.; Ayob, M.; AL-Dhief, F. "Genetic Algorithm Based on Natural Selection Theory for Optimization Problems." Symmetry 2020

[5] van Fenema, Paul and Kampen, Ton. (2021). "Foundational Concepts of Military Logistics."

[6] Pînzariu, Sorin and Mînea, Costel-Dorel. (2019). "Functions of Logistics Support Management for Military Activities During Peace." Land Forces Academy Review.

[7] Shieu Hong Lin, Nate Gertsch, Jennifer R. Russell, "A linear-time algorithm for finding optimal vehicle refueling policies."

[8] Alfiyatin, Adyan and Mahmudy, Wayan and Anggodo, Yusuf Priyo. (2018). "K-Means Clustering and Genetic Algorithm to Solve Vehicle Routing Problem with Time Windows Problem." Indonesian Journal of Electrical Engineering and Computer

[9] S. B. Changalasetty, A. S. Badawy, L. S. Thota and W. Ghribi, "Classification of moving vehicles using k-means clustering," 2015 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT)

[10] GeeksForGeeks, "Working with csv files in Pythonnetworks"

[11] Rahul Awati, "Intro. to heatmaps," TechTarget

[12] Zöldy, Máté and Szalay, S and Szalay, Zsolt and Zsombók, Imre. (2019). Refueling strategies of autonomous hybrid vehicles. ANNALS OF THE ORADEA UNIVERSITY. Fascicle of Management and Technological Engineering.