

EVALUATING EVOLUTIONARY APPROACHES FOR THE TWO-STAGE LOCATION-ACTIVATION PROBLEM

Introduction. The events of recent years have revealed some significant loopholes in our medical logistics system that need to be addressed. The pandemic of the year 2020 demonstrated its weakness, and the need for medicines and vaccines grew many times. It showed how difficult it is to deliver supplies rapidly to the places where they are needed most during an emergency. After that, in 2022, there came the full-scale invasion, and it took things from bad to worse, compelling us even further to increase the flow of medical supplies towards humanitarian assistance. A great deal of increased demand pressure was added to an already weak system that demonstrated how vital it is to have a working logistics framework in place to cater to the emerging needs in a crisis. These episodes have illustrated an acute need for reevaluating and enhancing the processes related to the storage and transportation of medical products. Such practices are particularly required when the country is affected by conflicts. The practical problem statement and logistics aspect of our problem is shown in Fig. 1.

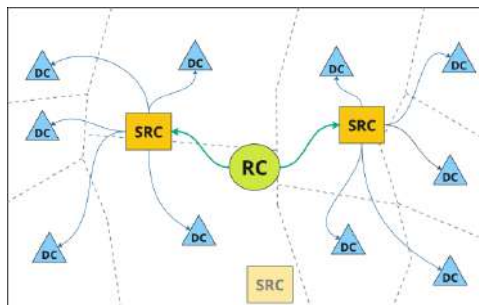


Figure 1 – Logistics problem visualization

Every region has a certain number of regional centers (RCs), some distribution centers (DCs), and subregional centers (SRCs), which serve as middle redistribution points. The general management of supply chain processes is performed by the regional centers (RCs); the transfer of supplies from the RCs to the SRCs is conducted and then to the distribution centers (DCs). Not all SRCs are

activated due to resource constraints such as fuel, vehicles, or other expenses. The focus is on providing timely service and minimizing costs simultaneously. Similar problems are researched in terms of two-stage continuous-discrete problems [1]. Let's describe our mathematical model [2] corresponding to the practical problem statement.

$$\min_{\theta(\cdot) \in \Theta, \tau^I \in \Omega^N, v \in R_{NM}^+} \sum_{j=1}^M A_j \theta_j + \sum_{i=1}^N \int_{\Omega_i} c_i^I(x, \tau_i^I) \rho(x) dx + \sum_{i=1}^N \sum_{j=1}^M c_{ij} v_{ij}^I, \quad (1)$$

under the constraints:

$$\sum_{j=1}^M v_{ij}^I \theta_j = \int_{\Omega_i} \rho(x) dx, \quad i = \overline{1, N}, \quad (2)$$

$$\sum_{i=1}^N v_{ij}^I \leq b_j^II, \quad \sum_{j=1}^M \theta_j \leq L, \quad j = \overline{1, M}, \quad (3)$$

$$\bigcup_{i=1}^N \Omega_i = \Omega, \quad \text{mes}(\Omega_i \cap \Omega_j) = 0, \quad i \neq j, \quad i, j = \overline{1, N}, \quad (4)$$

$$v_{ij}^I \geq 0, \quad i, j = \overline{1, N}, \quad \theta_j \in \{0; 1\}, \quad j = \overline{1, M}, \quad (5)$$

$$\tau^I = (\tau_1^I, \tau_2^I, \dots, \tau_N^I), \quad \tau^I \in \Omega^N. \quad (6)$$

where: Ω – customer distribution area; Ω_i – customer service for i -th DC, $i = \overline{1, N}$; N – the required number of DCs; M – the total number of SRCs available for activation; L – the maximum number of possible activated SRCs; J – set of subregional centers available for activation; b_i^I – demand of the i -th DC, $i = \overline{1, N}$; b_j^II – capacity of the j -th SRC, $j = \overline{1, M}$; A_j – activation costs for j -th SRC; $c_i^I = c(x, \tau_i^I)$ – transportation cost between DC i and customer at x ; $c_{ij} = c(\tau_i^I, \tau_j^II)$ – transportation cost between SRC (τ_j^II) and DC (τ_i^I); $\rho(x)$ – demands from medicines in point x of the area Ω ; $\tau_i^I = (\tau_{i1}^I, \tau_{i2}^I)$ – coordinates of DC ($r=I$) or SRC ($r=II$); v_{ij}^I – the volume weight units number of medicines and medical equipment transported from SRC j to DC i ; $\theta_j = 1$, if SRC j is activated; $\theta_j = 0$, otherwise.

Solution approach. We propose to utilize the combination of evolutionary theory and optimal set partition theory to solve our problem. We have two interconnected stages: our solution is initially represented as a permutation vector

(vector of priorities) [3] that can be encoded and decoded as a transportation plan. The initial solution will be a randomly generated vector. We have fixed but not activated SRCs for this vector, and we need to locate the DCs as their positions are unknown in advance. The location process runs during solution evaluation when we need to obtain fitness function value. To determine the final transportation plan combination, we utilize evolutionary algorithms. This work aims to compare different evolutionary algorithms applicable to the current problem. We will compare these approaches: genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization. To simplify the comparison, we compiled Table 1 to describe the differences between the approaches.

Table 1 – Comparison of different evolutionary approaches

Evolutionary Stage	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)	Ant Colony Optimization (ACO)
Population type	Randomized vectors of permutations		
Representation	Priority-based encoding of transportation tasks.		
Fitness Evaluation	Location of centers using optimal partition theory and calculation of fitness function.		
Selection	Roulette wheel selection.	Implicit in global best and local best strategies.	Ants probabilistically select paths based on pheromone concentration and heuristic information.
Reproduction	Weight Mapping Crossover.	Swap-based velocity, influenced by inertia, cognitive and social components.	Ants lay pheromone trails, with pheromone update influenced by solution quality and pheromone evaporation.
Diversity Maintenance	Dynamically adjusted mutation rate with two types of mutations (insertion and swap mutations).	Exploration encouraged by swap-based velocity updates derived from personal and global best.	Exploration is encouraged by pheromone evaporation and heuristic guidance during path selection.
Termination Condition	Fixed number of generations or fitness threshold met.		

We will run some experiments to solve model tasks using different evolutionary approaches (GA, PSO, ACO). The problems will have sizes: 4x10, 7x20, 10x25, 12x30, 15x35. As random plays a crucial role during the solution, we will rerun each experiment 20 times and find the average value for these parameters: algorithm execution time and fitness function value. The obtained results are shown in Fig. 2, 3.

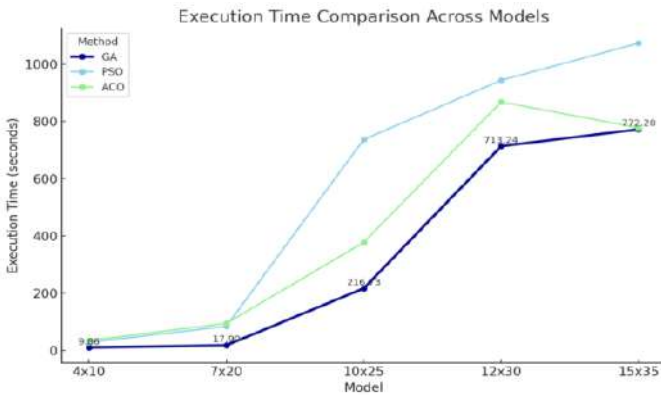


Figure 2 – Execution time for different evolutionary approaches

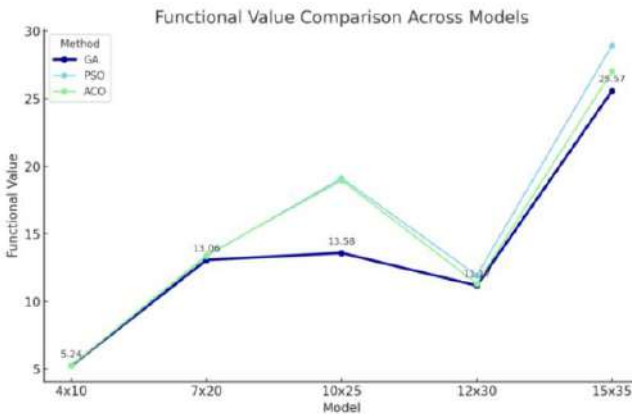


Figure 3 – Functional value for different evolutionary approaches

Conclusions. In this paper, we highlighted the importance of further improvements for a medical system at the regional level. We described a practical problem statement and mathematical model corresponding to the problem. At one of the solution stages, we utilize the evolutionary approach. To determine the best

one, our goal in this research is to compare genetic algorithms, particle swarm optimizations, and ant colony optimization. We defined a table of differences between the used approaches and ran some experiments to validate each evolutionary method during problem-solving. The results shown in Fig. 2 and 3 confirm that the GA approach outperforms PSO and ACO in both execution time and distance to the local optimum.

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