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AN ALGORITHM FOR SOLVING A TWO-STAGE CONTINUOUS-DISCRETE LOCATION PROBLEM FOR MEDICAL LOGISTICS OPTIMIZATION

Abstract. The research paper focuses on logistics optimization, a critical component in supply chain management across various sectors, including healthcare. Efficient coordination of medi cal logistics is essential for maintaining public health and welfare, particularly during global emergencies where quick and effective distribution of medicine is crucial. This study aims to cre ate and analyze a model and algorithm for a two stage continuous discrete location problem within medical logistics applications. We present a mathematical model tailored for a two stage continuous discrete location problem in medical logistics, considering the unique aspects of this field. The solution algorithm combines genetic methods with the optimal partition of sets theo ry. Additionally, we demonstrate the algorithm's effectiveness through a software application, using it to solve a representative model problem.
Keywords: continuous discrete two stage location problem, optimal set partitioning, genetic al gorithm, medical logistics

Introduction. The optimization of logistics processes constitutes a critical component of supply chain management across various industrial sectors, notably in the healthcare domain. Effective medical logistics management is imperative in safeguarding public health and well-being, a priority that becomes paramount during global crises necessitating rapid and efficient distribution of medicinal products. Furthermore, proficient logistics organization is vital for delivering humanitarian aid, where the prompt provision of medical supplies and resources is often critical for survival. Contemporary technologies and algorithmic advancements are pivotal in enhancing medical logistics processes. A notable strategy that has garnered considerable acceptance is the utilization of genetic algorithms to address two-stage location challenges, optimizing the distribution and location of facilities. This methodology enables medical institutions and suppliers to make informed decisions, thereby augmenting the efficacy, expediency, and economic viability of medical logistics operations.

Literature review. Metaheuristic algorithms find extensive application in research about problems similar to those in medical logistics. The authors of [1] utilized a genetic algorithm to examine a two-stage transportation problem that involved a fixed route fee and the transport of goods. Research [2] introduced an iterative algorithm for a similar two-stage transportation challenge, incorporating a customer shuffling mechanism and an efficient method for duplicate elimination, proving effective across diverse data sets. Publication [3] is dedicated to a multi-stage reverse logistics network employing a genetic algorithm with priority encoding. The objective of enhancing spatial planning for public health services via the development of location-allocation and accessibility models is explored in [4]. This study aims to identify optimal locations for hospitals and other healthcare facilities, considering factors such as population demand, accessibility, and proximity to other medical establishments. The research, exemplified by the healthcare system in Lisbon, Portugal, demonstrated that the application of these methods significantly improved healthcare quality and cost efficiency. Article [5] discusses a two-stage transportation problem to minimize logistics expenses, considering the costs associated with establishing distribution centers and transportation charges between businesses, distribution centers, and customers. Research [6] addresses the complex issue of ICU bed allocation. The described problem is approached by decomposing it into two different stages to handle multiple sources of uncertainty effectively. The study [7] focuses on hospital capacity allocation planning for operating rooms. It presents an integrative solution approach combining a two-stage stochastic recourse programming model and a stochastic optimization model with a mean absolute deviation risk measure. Publication [8] assesses a location-allocation model for healthcare services. It employs a two-stage optimization strategy using a multi-period capacitated maximal-covering model, considering interservice referral and equity access. Research [9] aims at optimal demand coverage in healthcare facility location problems. It is proposed to primarily use optimization techniques with a focus on stochastic characteristics important for facility location decisions. The paper [10] explores capacity allocation and scheduling in two-stage service systems. The authors propose a simple and easy-to-implement capacity allocation and scheduling policy, establishing its asymptotic optimality for the stochastic system. Article [11] presents a new idea for the ambulance location problem in environments under uncertainty: it addresses the problem with a focus on robust planning for path and average speed uncertainty. The work [12] investigates resource allocation optimization in natural disasters with multiple secondary hazards. A two-stage stochastic optimization model is proposed

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to simulate scenarios of random occurrence and severity of disasters. The papers [13, 14] develop a framework for supplier selection and order allocation. It introduces a hybrid multi-step long short-term memory network for demand forecasting and a new fuzzy SWOT model for supplier evaluation, followed by a multi-objective model using results from earlier stages. More information about multi-stage transportation problems for different areas, such as passenger traffic or goods transportation, can be found in [15, 16]. A more detailed analytic review of multi-stage location problems is listed in [17]. Substantial research in the field of discrete optimization is associated with genetic and stochastic approaches. However, this approach can be challenging due to the issue of scalability: in discrete scenarios, only small to medium-sized problems can be resolved efficiently. In situations requiring the location of many centers and considering population demand in facility location, continuum approaches to location problems become pertinent. Study [18] focuses on multi-stage location tasks, evaluating various facility groups and potential locations. This paper underscores the significance of considering continuum scenarios in such tasks and presents a model for two-stage location.

Problem statement. In times of crisis within a region, it becomes necessary to quickly distribute essential medical resources (medicines and medical equipment) to the people. To aid in this process, each region has a certain number of subregional centers (SRCs) that act as primary distribution points. However, due to logistical and resource constraints, only a certain number of these SRCs can be activated by the government. The chosen SRCs then redistribute the resources to multiple distribution centers (DCs) throughout the region, directly supplying the required medicines to the local population within their respective service areas. The main objective is to find the best combination of SRCs, positions of DCs and an optimal transportation strategy. The goal is to convey the medicines and medical supplies from the SRCs to the DCs and ultimately to the consumers while minimizing transportation costs. To achieve efficient distribution, careful consideration is required for factors such as transportation expenses, distance, and capacity limitations at each stage.

Figure 1 illustrates a complex transportation network, depicting a system with 4 SRCs and 8 DCs. This diagram is designed to provide a clear visual representation of the logistics and supply chain infrastructure. The active SRCs are highlighted with vibrant colors, symbolizing their operational status, whereas the inactive SRCs are differentiated by a more subdued, muted color palette, indicating their non-operational status.

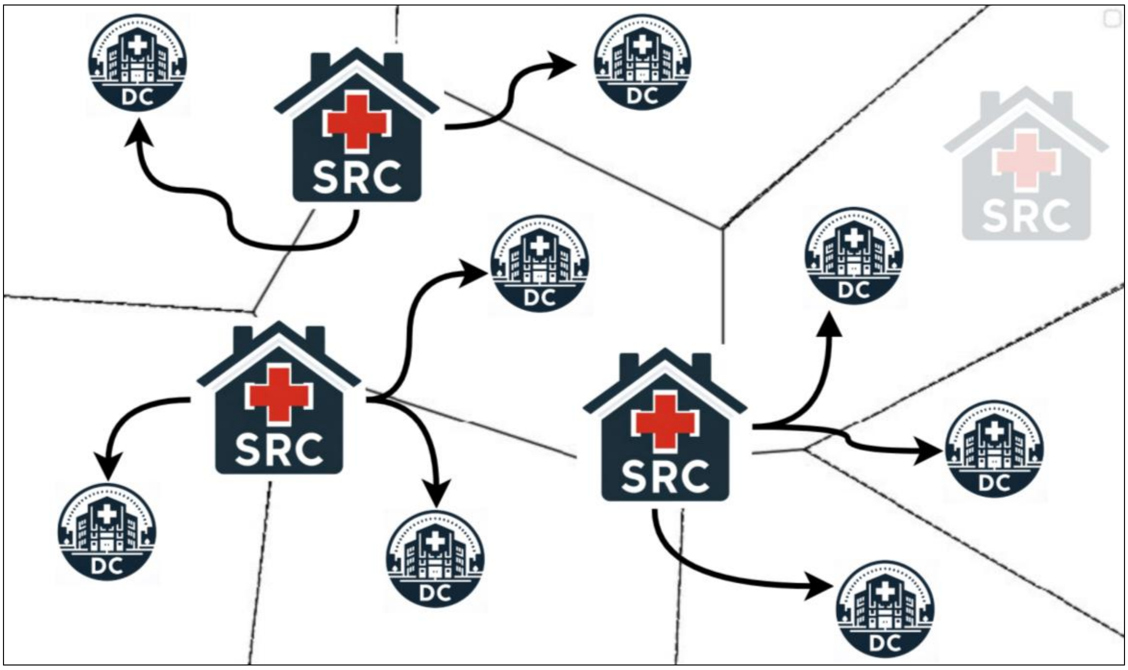

Figure 1 – Transportation schema for problem statement

Mathematical model. Moving forward, let us proceed with developing a mathematical model. We introduce the following definitions.

Ω – the area where medical products are distributed to consumers.

Ω_i – service area of the *i-th* DC, $i = \overline{1, N}$.

N – the required number of DCs.

b_j – capacity of *j-th* SRC, $j = \overline{1, M}$.

J – set of SRCs that are available for activation: $J = \left\{ \tau_1^{II}, \tau_2^{II}, \dots \tau_M^{II} \right\}$.

$c_i^I = c\left(x, \tau_i^I\right)$ – transportation costs for volume weight unit of medicines and medical equipment from DC with coordinates τ_i^I to consumer $x \in \Omega$, $i = \overline{1, N}$.

$c_{ij} = c\left(\tau_i^I, \tau_j^{II}\right)$ – transportation costs for volume weight unit of medicines and medical equipment from SRC with coordinates τ_j^{II} to DC with coordinates τ_i^I, $i = \overline{1, N}$. $j = \overline{1, M}$.

$\rho(x)$ – demand for medicines and medical equipment at the point x in area Ω .

A_j – operating expenses associated with the activation of a subregional center *j*, $j = \overline{1, M}$.

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$\tau_i^r = \left(\tau_{i1}^r, \tau_{i2}^r\right)$ – DC's coordinates *(r=I)* or SRC's coordinates *(r=II)*.

v_{ij}^I – the volume weight units number of medicines and medical equipment transported from SRC *j* to DC *i*, $i = \overline{1, N}$, $j = \overline{1, M}$.

$$\lambda_j = \begin{cases} 1, & if \;\; DC \;\; j \;\; is \;\; activated, \\ 0, & otherwise \end{cases}, \;\; j = \overline{1, M} .$$

The total expenses for activating sub-regional centers and transportation of medicines and medical equipment can be expressed as follows:

$$\sum_{j=1}^{M} A_j \lambda_j + \sum_{i=1}^{N} \int_{\Omega_i} c_i^I \left(x, \tau_i^I \right) \rho \left(x \right) dx + \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} v_{ij}^I \lambda_j .$$

Under the following constraints:

The number of volume weight units of medicines and medical equipment delivered from *i-th* DC is equal to its demands:

$$\sum_{j=1}^{M} v_{ij}^I \lambda_j = \int_{\Omega_i} \rho \left(x \right) dx, i = \overline{1, N} .$$

The number of volume weight units of medicines and medical equipment transported from *j-th* SRC does not exceed its capacity:

$$\sum_{i=1}^{N} v_{ij}^I \le \lambda_j b_j, \;\; j = \overline{1, M} .$$

The maximum number of activated SRCs does not exceed L, $\left(L > 0 \right)$:

$$\sum_{j=1}^{M} \lambda_j \le L .$$

The service areas of distribution centers include the entire region Ω :

$$\bigcup_{i=1}^{N} \Omega_i = \Omega .$$

Each customer is served by only one distribution center:

$$\Omega_i \cap \Omega_j = 0, i \ne j, i, j = \overline{1, N} .$$

Considering this, the mathematical model can be expressed as follows.

Problem I. Minimize

$$\sum_{j=1}^{M} A_j \lambda_j + \sum_{i=1}^{N} \int_{\Omega_i} c_i^I \left(x, \tau_i^I \right) \rho \left(x \right) dx + \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} v_{ij}^I \lambda_j , \qquad (1)$$

under the following constraints

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

$$\sum_{i=1}^{N} v_{ij}^{I} \le \lambda_{j} b_{j},\ \ j=\overline{1,M}\ , \quad (3)$$

$$\sum_{j=1}^{M} \lambda_{j} \le L, \quad (4)$$

$$\bigcup_{i=1}^{N} \Omega_{i} = \Omega, \quad (5)$$

$$\Omega_{i} \cap \Omega_{j} = 0, i \ne j, i, j=\overline{1,N}, \quad (6)$$

$$v_{ij}^{I} \ge 0, \lambda_{j} \in \{0;1\}, i=\overline{1,N}, j=\overline{1,M}\ , \quad (7)$$

$$\tau^{I} = \left(\tau_{1}^{I}, \tau_{2}^{I} \ldots \tau_{N}^{I}\right),\ \tau^{I} \in \Omega^{N}. \quad (8)$$

Solution approach. We propose to use a combination of a genetic algorithm and an approach from the optimal set partitioning theory. Given this, we can divide the solution of problems (1) - (8) into two stages.

At the first stage, distribution centers are located with the determination of their service areas by solving optimal partition of set problem in formulation (9) - (11), where N – required number of DCs. The solution to the optimal set partitioning problem begins with the algorithm initializing the optimization domain. This domain is bounded by a parallelepiped oriented along the coordinate axes. Initial conditions such as the grid size and the algorithm's step size are established. The parallelepiped is covered with a grid that allows for calculations at discrete points. A preliminary approximation for the variables is then set.

The core of the optimization step involves the use of Shor's r-algorithm, which employs the concept of subgradient descent with a significant variation in the calculation of the step multiplier. In classical subgradient methods, the step size often decreases following a fixed rule. In contrast, the r-algorithm adaptively updates the step size based on previous iterations, allowing the algorithm to better account for the specifics of the problem at hand.

The main innovation of the algorithm lies in its use of regularization to enhance the characteristics of the optimization problem. The addition of regularization helps to address the non-smoothness of the function and improves the convergence rate to the minimum. The r-algorithm is particularly effective for solving high-

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dimensional problems, where traditional optimization methods may need help with computational complexity and slow convergence.

The process of solving the optimal set partitioning problem is iterative, with each step updating the variable values based on prior calculations and adjusting the iterative process. The algorithm concludes its operation once a convergence criterion is met, either through the variable distance or the difference in functional values. For a more detailed version of the algorithm refer to [19].

Minimize

$$\sum_{i=1}^{N} \int_{\Omega_i} c_i^I \left(x, \tau_i^I \right) \rho \left(x \right) dx \,, \tag{9}$$

under the following constraints:

$$\bigcup_{i=1}^{N} \Omega_i = \Omega \,, \tag{10}$$

$$\Omega_i \cap \Omega_j = 0, i \neq j, i, j = \overline{1, N} \,, \tag{11}$$

At the second stage, we solve a discrete location problem (12) – (18):

$$\sum_{j=1}^{M} A_j \lambda_j + \sum_{i=1}^{N} \sum_{j=1}^{M} c(\tau_i^I, \tau_j^{II}) \lambda_j v_{ij}^I \to \min \,, \tag{12}$$

under the following constraints:

$$\sum_{j=1}^{M} v_{ij}^I \lambda_j = b_i^*, i = \overline{1, N} \,, \tag{13}$$

$$\sum_{i=1}^{N} v_{ij}^I \leq \lambda_j b_j, \; j = \overline{1, M} \,, \tag{14}$$

$$\sum_{j=1}^{M} \lambda_j \leq L \,, \tag{15}$$

$$v_{ij}^I \geq 0, \lambda_j \in \left\{ 0; 1 \right\}, i = \overline{1, N}, \; j = \overline{1, M} \,, \tag{16}$$

where $\tau^I = \left(\tau_1^I, \tau_2^I \dots \tau_N^I \right)$, $\tau^I \in \Omega^N$ – locations of the DCs obtained as a result of the first stage; b_i^* – determined capacity of DCs:

$$b_i^* = \int_{\Omega_i} \rho \left(x \right) dx, i = \overline{1, N} \,, \tag{17}$$

Additionally, there is a solvability condition:

$$\int_{\Omega} \rho(x)\,dx \le \sum_{j=1}^{M} b_j \lambda_j \,, \tag{18}$$

An algorithm utilizing a genetic approach with priority encoding is developed to address the issue (12) - (18). The algorithm's general description is as follows.

1. Initially, the population *P(t)* is set up through a priority-based encoding method, creating the first generation of potential solutions.

2. The fitness level of each individual chromosome within this population is then assessed.

3. For the purpose of reproduction, chromosomes are chosen based on the roulette wheel selection technique.

4. The reproductive process involves the crossover of selected chromosomes to yield new offspring.

5. The mutation process is applied to certain chromosomes to introduce new variations.

6. The next generation *P(t+1)* is created by combining these offspring with some members of the current population, effectively replacing the previous generation.

7. The algorithm checks for the termination condition. If it's not met, the process loops back to step 2, now working with the updated population *t+1*.

8. Once the termination condition is met, the genetic algorithm finishes. The most efficient chromosome is decoded to reveal the objective function's value and the proposed transportation plan.

End of the algorithm.

A more detailed description of each step can be found in [20]. The following modifications to the genetic algorithm procedures should be highlighted.

Each transportation plan between SRCs and DCs is represented as a chromosome using a priority-based coding scheme.

The chromosome is checked to satisfy all model constraints when calculating the fitness function.

A roulette selection procedure is used: a roulette wheel is created with segments proportional to these fitness scores. Selection is made by spinning the wheel and choosing individuals based on where it lands, favoring those with higher fitness but still allowing chances for less fit individuals.

The weighted crossover method is used to cross chromosomes: first, two parent chromosomes are selected based on their fitness values, then each compo-

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nent of these decisions is assigned a weight that reflects its importance or effectiveness, which is determined by past performance, knowledge of the subject area and other heuristic methods. During crossbreeding, these weights determine the combination of parental decisions to create offspring. Components with higher weights are more likely to be passed on to offspring. It results in offspring that ideally inherit the best traits from both parents.

The use of mixed mutation is proposed: with a probability of 0.5, swap or insertion mutation is used. For the first type of mutation, two unique elements are selected from each part of the chromosomes and swapped with each other. For the insertion mutation, a random index is chosen for each part of the chromosome, from which the element is rearranged to another random location.

Software implementation. We implemented a software application for numerical experiments designed to tackle the two-stage continuous-discrete location problem. This application was developed in Python 3 using the Qt5 framework for the user interface and map visualization. Qt5 provides the tools for creating interactive maps, while Python3 handles mathematical calculations and the core logic. C++ language and Eigen library are used for optimal partition numerical implementation. The development is done in PyCharm IDE. The calculations are performed using the following hardware: CPU: AMD Ryzen 7 5800X 3.8-4 GHz and 32 gigabytes of DD4-3200 RAM.

Model task. We use the proposed mathematical model, solving approaches and algorithm to optimize the medical logistics of the Dnipropetrovsk region, Ukraine. Here are the input parameters of the problem.

Number of SRCs: $M = 7$.

Number of potential DCs: $N = 25$.

SRCs maximum number limit: $L = 6$.

Vector that limits capacities of SRCs: [40, 40, 39, 40, 41, 39, 40].

Total demand in DCs: 230.

Vector of SRCs activation costs: [46, 50, 41, 48, 49, 42, 50].

The coordinates of the subregional centers are shown in Figure 2 as blue markers and correspond to the locations: Verkhnodniprovsk, Bozhedarivka, Tomakivka, Novomoskovsk, Synelnykove, Prosiana, Ternivka.

In the first stage, we solve the continuous-discrete location problem: a rectangle that delimits the geographical location is defined with the following coordinates.

Left lower corner: (47.51611, 33.37109).

Right upper corner: (48.95391, 36.93066).

The map used in visualization is centered around Dnipro, Ukraine: (48.450001, 34.983334).

We use the Euclidean metric as a distance function for continuous cases for the described model task. The defined rectangle is shown as gray borders in Figure 2. As a result of the solution, we have the DCs locations as green markers in Figure 2. Along with locating each Distribution Center (DC), we also obtained its service area (optimal partition) marked as polygons with gray borders.

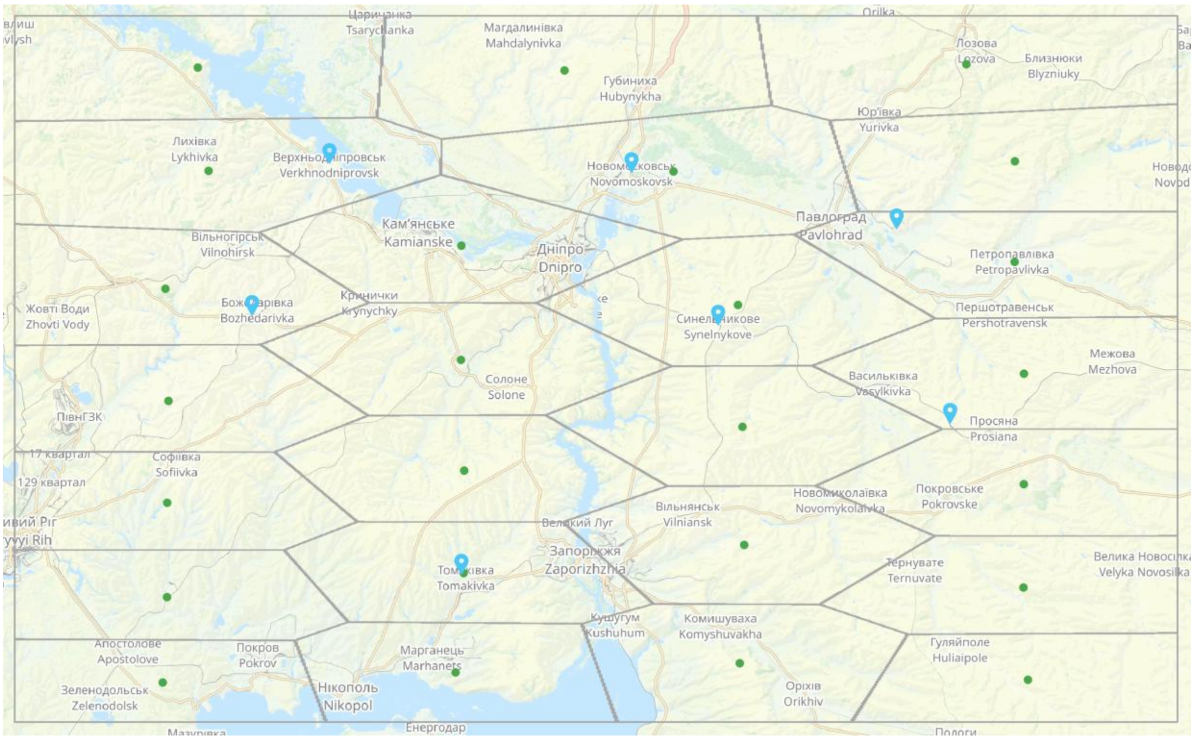

Figure 2 – Original positions of subregional centers and located distribution centers

Let's move on to the second stage. At this stage we are applying a genetic algorithm to solve discrete activation problem (12) - (18). In distance terms we use the geographic distance between the points as now we deal with geographical coordinates. The genetic algorithm will be executed with the following parameters:

Population size: 50.

Size of the chromosome: 32.

Crossover probability: 0.9.

Mutation probability: 0.15.

Initial population generation: pseudo-randomly generated.

Termination criteria: terminates after exceeding the number of 100 generations.

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The overall result of the solution is shown in Figure 3 with the following results:

The objective function value for the most effective solution to the problem is 1298.65.

6 subregional centers were activated, except for the center in Novomoskovsk.

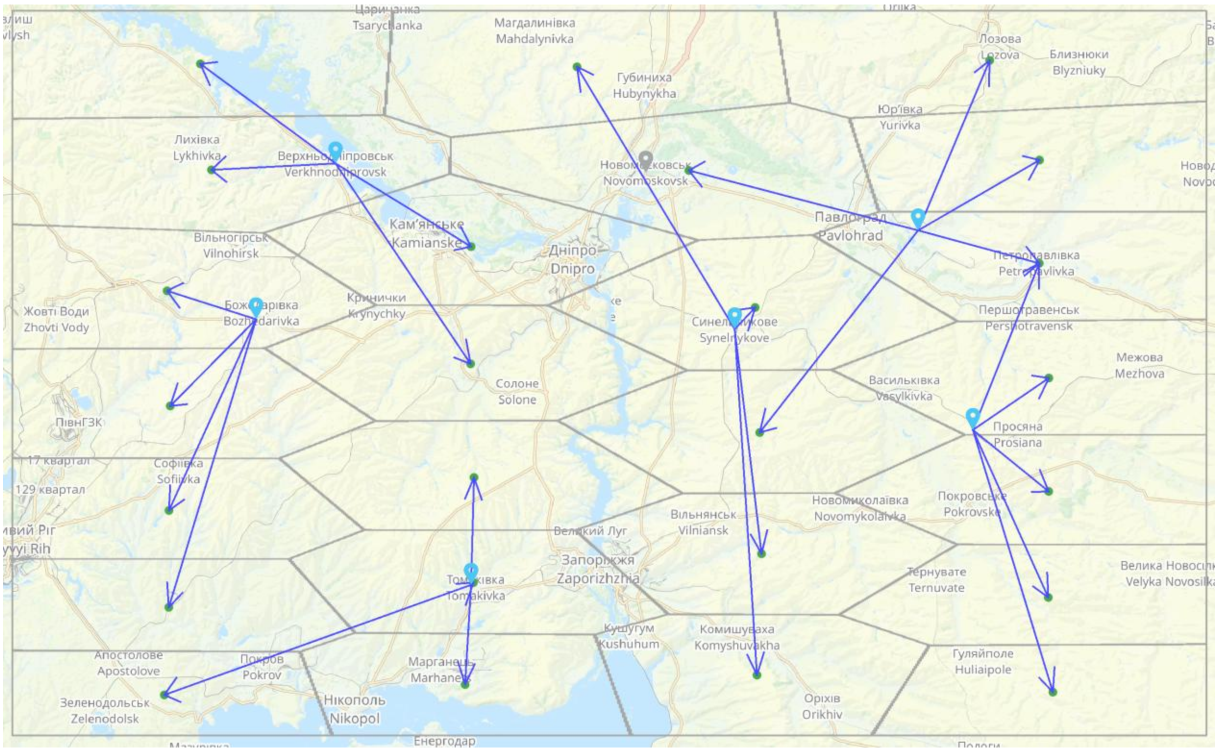

Figure 3 – Solution for the model task of two-stage continuous location problem

The total execution time of the algorithm (with visualization) took 13 seconds.

Each activated SRC is visually represented by a blue pin, indicating its active status and readiness to receive and process service requests. In contrast, any deactivated SRC is denoted by a gray pin, signifying its current inactivity and unavailability for handling service requests. Arrows emanate from each DC, illustrating the specific DC the particular SRC will service.

Conclusions. The research paper delves into a two-stage continuous-discrete location problem, imposing constraints on the maximal number of centers, primarily within the medical logistics sector. This area deals with distributing medicines and medical equipment, necessitating compliance with stringent requirements. The paper introduces a mathematical model that integrates optimal set partitioning with metaheuristic techniques, intending to streamline the solution process into two distinct stages. Initially, the optimal set partitioning method is employed to determine the locations of distribution centers. Subsequently, the acquired coordinates and their corresponding service areas are utilized to address a discrete activation problem. The chosen metaheuristic method is a genetic algorithm, enhanced with priority-based encoding and weight mapping crossover, alongside specific adaptations. A specially designed fitness function evaluates the adherence to the model's constraints. Moreover, a mixed mutation approach is implemented in each iteration, based on a predetermined probability. The algorithm's output encompasses the established distribution centers, activated subregional centers, and a comprehensive transportation plan. A software tool was developed in Python 3 to demonstrate the algorithm's functionality, incorporating the Qt5 framework. The paper features a case study focused on the medical logistics in the Dnipropetrovsk region of Ukraine. It exemplifies the practical implementation of the proposed model and algorithm, highlighting their potential to enhance logistics and distribution efficiency in a specific geographic context.

Future research. Future research should focus on refining the location problem by linking subregional center positions with distribution centers, optimizing algorithm complexity, and applying the model to real-world logistics, using authentic data for regional specificity. Further, the model could be expanded to include distance and time constraints, enhancing its applicability in scenarios like rapid medical supply distribution, and promoting cost-effective, sustainable logistics.

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Алгоритм розв’язання двоетапної неперервно-дискретної задачі розміщення на прикладі оптимізації медичної логістики

Оптимізація логістичних процесів є одним із важливих завдань управління ланцюгами поставок у різних сферах діяльності, включаючи медицину. Ефективна координація у сфері медичної логістики має важливе значення для забезпечення громадського здоров'я та процвітання. Це стає особливо актуальним в умовах глобальних надзвичайних ситуацій, коли швидке та ефективне розповсюдження медикаментів має вирішальне значення. Метою роботи є побудова моделі та розробка алгоритму для розв’язання двоетапної неперервно-дискретної задачі розміщення у контексті проблеми медичної логістики з подальшим аналізом їх застосування на модельних прикладах. В роботі розглянута проблема транспортування медикаментів та виробів медичного призначення в Україні та визначена

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постановка задачі в предметній області. На першому етапі необхідно активувати субрегіональні центри з набору доступних, що є дискретною задачею оптимізації. Другий етап складається з розміщення центрів дистрибуції та визначення їх зон обслуговування. Авторами запропоновано математичну модель для двоетапної неперервно-дискретної задачі розміщення у контексті медичної логістики з врахуванням особливостей галузі. Розроблено алгоритм розв'язання, що базується на поєднанні генетичних підходів та теорії оптимального розбиття множин. Використано пріоритетне кодування з міксованою процедурою мутації. На першому кроці розв'язується задача оптимального розбиття множин із розміщенням центрів підмножин у кількості, що відповідає кількості необхідних центрів дистрибуції. На другому кроці, використовуючи координати розміщених центрів та визначені зони обслуговування, застосовується генетичний алгоритм для визначення ефективного розв'язку. Авторами розроблено програмну імплементацію запропонованого алгоритму з використанням мов програмування Python3 та C++ та бібліотек Qt5 для інтерфейсу користувача та Eigen для математичних обчислень. Запропонований підхід використано для розв'язання модельної задачі медичної логістики у Дніпропетровській області, Україна.

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