Using a Genetic Algorithm for Telemedicine Network Optimal Topology Synthesis

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Abstract: A method based on a genetic algorithm is proposed for synthesizing the optimal topological structure of telemedicine network, ensuring that the distribution of users (with a known location) by telemedicine stations (the number and location of which are also known) is optimal in terms of signal delay time during transmission and the cost of network deployment. The method uses: random generating of a base population, a tournament selection of chromosomes among two pairs for crossover, and a homogeneous crossover operator. The results of benchmarking the proposed method are presented. The experiment reveals that the resulting solution is indeed close to optimal, i.e. due to the use of a genetic algorithm, the method avoids falling into the trap of a local extremum. While the current study focused on a specific telemedicine network, future research could explore the scalability of this genetic algorithm approach for larger-scale networks and consider additional factors such as energy efficiency and fault tolerance.

1 INTRODUCTION

Ensuring a healthy lifestyle and accessibility of medical care is an important component of the sustainable development of humanity [1]. The concept of telemedicine was developed to ensure and to increase the accessibility of medical services. In essence, telemedicine refers to the delivery of medical services using information and communication technologies, particularly when distance poses a significant barrier. [3]. The experience of recent years has shown that telemedicine is often the only solution for providing assistance to people who do not have the physical opportunity to visit a medical facility.

The provision of telemedicine services is implemented through a telemedicine network (TMN). TMN can be classified as distributed information and communication network. In most cases, TMN is built on a hierarchical principle and includes telemedicine centers and telemedicine stations at the network core level, and in turn telemedicine service consumers and their access terminals to information networks establish the access level (Figure 1) [3].

In practice, stationary telemedicine stations are often located on the territory of existing medical institutions or in places equipped with ready-made telecommunications and engineering infrastructure. As a result, their location and number are known, mainly determined by the number of suitable locations and the amount of funding. Each telemedicine station can serve a limited number of patients, which is determined by the class of the telemedicine station [2, 3].

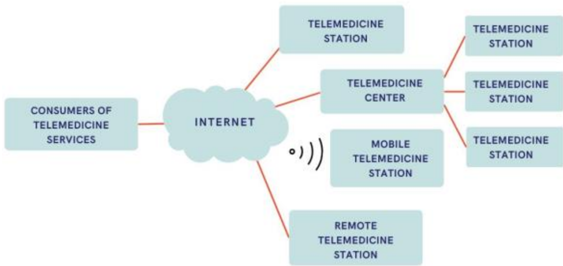

Figure 1: Basic layout of a telemedicine network.

As a rule, employees of telemedicine services can connect to only one telemedicine station (the one with which they have signed a contract). The location of user terminal is determined by the places of deployment (residence, study, work) or public places provided with access to information networks.

Thus, in practice, synthesizing the optimal topological structure when designing a new TMN or optimizing the topology of an existing TMN often implies the optimal distribution of users (with a known location) by telemedicine stations (the number and location of which are also known) and is an actual task.

2 STATE OF THE ART AND PAPER GOAL

When conducting a feasibility study to choose a network topology, characteristics such as throughput, reliability, quality of service, and the cost of all its elements are usually taken into account. It's worth mentioning that parameters like signal delay time, which characterize the quality of service, also directly affect the resulting data transfer rate. Thus, as criteria for optimizing the topological structure of the TMN in the scope of this work we propose to use the minimum signal delay time and the minimum cost of network deployment.

In terms of optimization theory, the problem can be formulated as follows. Let there be a certain set of nodes of two types: telemedicine stations and terminal equipment for telemedicine service consumers. Each node is specified by certain coordinates in space and a number. Terminal equipment corresponds to the maximum amount of traffic that it can generate per unit of time. In turn, telemedicine stations are specified by the maximum amount of traffic that they can process without additional delay. Also, each telemedicine station has a certain capacity, i.e. it can serve a limited number of patients.

It is necessary to synthesize a TMN topology that has a minimum total weight of all connections between nodes and a minimum total average delay when a signal passes through the TMN. In this case, the following restrictions are imposed on the topology: each patient can be connected to only one telemedicine station and there should be no unconnected patients in the network.

As the weight characteristics of the TMN communication lines we will use the Euclidean distances between the corresponding nodes.

The formulated problem is an NP-complete integer nonlinear problem, similar to the well-known traveling salesman problem. The exact solution of such problems can be found by brute-force search, however, for solving large-scale problems, finding a solution requires a significant time resource. To solve similar problems, heuristic methods are usually used, which allow to get a solution as close as possible to the exact one, but at the same time with the minimization of time costs. Known heuristic methods for solving nonlinear optimization problems include [4]: Penalty Function Method, Projected Gradient Method, Interior Point Method, Branch and Bound Method. The principle of operation of these methods consists in a pseudo-random search with constant analysis and evaluation of the accumulated data on the already reviewed part of the solution space. In Figure 2 the traveling salesman problem solution space with at five nodes is shown in different projections.

As can be seen from Figure 2, the set of solutions contains a significant number of local extremums, which could be the potential solutions to the problem.

All the above-mentioned methods have a common drawback - they can fall into the trap of a "local" extremum, and thus provide a non-optimal solution.

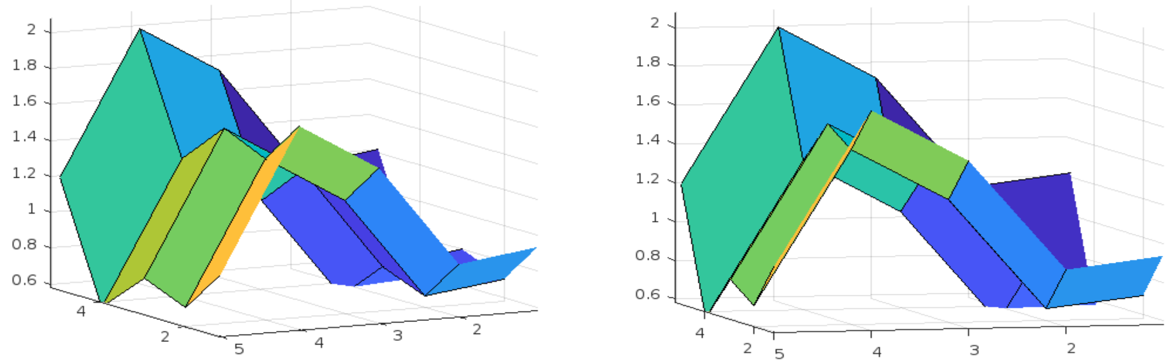

Figure 2: Projections of traveling salesman problem solution space.

It is known that Genetic algorithms do not have this drawback. In such algorithms, a mutation operation is used, which randomly changes the current parameters of the problem, and thus "bypasses" local extremums. Also, the advantages of genetic algorithms include: the ability to work with a large number of variables, the absence of the need to calculate derivatives, the possibility of parallelization [5-7].

Genetic algorithms are actively used to solve various optimization problems in the field of information communications. Thus, work [8] investigates the issue of optimizing the routing process, for the solution of which authors have developed a genetic algorithm, which, unlike the Dijkstra and Depth-First Search algorithms, allows you to find a set of shortest routes that have the same cost. The work [9] solves the problem of creating a resource scheduler to maximize the bandwidth of network channels. The problem of optimizing the structure of a wireless network using genetic algorithms in order to achieve an optimal balance between network performance and resource consumption is studied in [10]. The paper [11] analyzes the possibility of using genetic algorithms to solve the problem of energy efficiency of a wireless network. In [12] the problem of load balancing is considered during data transmission in a telemedicine network, which is built on the basis of a modified adaptive genetic algorithm.

From the above it follows that the development of method empowered by genetic algorithm for synthesizing the optimal topological structure of TMN, ensuring that the distribution of users (with a known location) by telemedicine stations (the number and location of which are also known) being optimal in terms of signal delay time and the cost of network deployment is an actual scientific problem. Solving this scientific problem is the goal of this work.

3 PROPOSED METHOD

Genetic algorithms use combinations of such genetic operations as selection, crossing and mutation [6-8]. In terms of genetic algorithms, the solution of a formalized problem is called a chromosome, i.e. coded TMN topology.

The matrices of coordinates in space and the maximum volume of traffic for two types of nodes (telemedicine stations and terminal equipment) are used as the input data. The matrix of telemedicine stations also includes the maximum number of patients that these nodes can serve.

Also, the input data include an adjacency matrix A = (a_{ij}), where element a_{ij} =1, if there is a connection between the i-th telemedicine station and the j- th terminal device, and 0 otherwise. So, for example, the configuration of a network consisting of 4 stations and 12 terminal devices may look like Figure 3.

$$A = \begin{array}{|cccccccccccc|} 1 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{array}$$

Figure 3: Discrete network representation.

The proposed method can be described as follows:

Step 1. Building a matrix of connection weights. The structure of the weight matrix is similar to the structure of the adjacency matrix, but instead of 1 it contains the value of the distance between the corresponding nodes.

Step 2. Initializing a genetic algorithm with the base population and number of generations. In this case, the base population means a set of initial topologies in which each terminal device has a connection with one and only one telemedicine station.

Step 2.1. Setting the number of generations G (a number of iterations of the genetic algorithm).

Step 2.2. Setting the population size S (a number of initial topologies).

Step 2.3. Generating the base population. In this work, it is proposed to use a random method for generating the base topology.

Step 3. Calculating the fitness function for each topology in the population. The problem to be solved is multicriteria, therefore it is proposed to use one of the classical methods for solving such problems - the weighted function method [4].

As the fitness function F we use the sum of three functions F1, F2 and F3 with different weights:

$$FF = w_1F_1 + w_2F_2 + F_3,$$

here w_1 , w_2 are weighting coefficients such that $w_1 + w_2 = 1$; function F_1 calculates the sum of the weights of all TMN communication lines; F_2 calculates the average total delay when passing through the TMN; F_3 is a penalty function that significantly increases the value of the fitness function if in topology the number of terminal devices connected to any telemedicine station exceeds its maximum capacity.

Parents:

$$A_1 = \begin{vmatrix} 1&0&1&0&0&1&0&1&0&0&0&0 \\ 0&1&0&0&1&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&1&0&1&0&0&1 \\ 0&0&0&1&0&0&0&0&0&1&0&0 \end{vmatrix} \qquad A_2 = \begin{vmatrix} 0&0&0&0&0&1&0&1&0&0&0&1 \\ 0&0&0&1&0&0&0&0&1&0&1&0 \\ 0&1&1&0&0&0&0&0&0&0&0&0 \\ 1&0&0&0&1&0&1&0&0&1&0&0 \end{vmatrix}$$

Children:

$$A'_1 = \begin{vmatrix} 1&0&0&0&0&1&0&1&0&0&0&1 \\ 0&0&0&0&0&0&0&0&1&0&1&0 \\ 0&1&1&0&0&0&1&0&0&0&0&0 \\ 0&0&0&1&1&0&0&0&0&1&0&0 \end{vmatrix} \qquad A'_2 = \begin{vmatrix} 0&0&1&0&0&1&0&1&0&0&0&0 \\ 0&1&0&1&1&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&1&0&0&1 \\ 1&0&0&0&0&0&1&0&0&1&0&0 \end{vmatrix}$$

Figure 4 – Crossover operation.

Original chromosome: **Mutation:**

$$A = \begin{vmatrix} 0&0&0&\mathbf{0}&0&1&0&1&0&0&0&1 \\ 0&0&0&\mathbf{1}&0&0&0&0&1&0&1&0 \\ 0&1&1&\mathbf{0}&0&0&0&0&0&0&0&0 \\ 1&0&0&\mathbf{0}&1&0&1&0&0&1&0&0 \end{vmatrix} \qquad ''A = \begin{vmatrix} 0&0&0&\mathbf{0}&0&1&0&1&0&0&0&1 \\ 0&0&0&\mathbf{0}&0&0&0&0&1&0&1&0 \\ 0&1&1&\mathbf{0}&0&0&0&0&0&0&0&0 \\ 1&0&0&\mathbf{1}&1&0&1&0&0&1&0&0 \end{vmatrix}$$

Figure 5 – Mutation operator.

Let's define the components of the fitness function:

$$F_1 = \sum_{\tau_i \in \tau} m(\tau_i),$$

here τ is the set of communication lines of the TMN graph; $m(\tau_i)$ – weight of the corresponding TMN communication line,

$$F_2 = \frac{\sum_{\theta_i \in \theta} D(\theta_i)}{N},$$

here Θ is the set of paths between any two TMN graph vertices; $D(\Theta_i)$ – delay time along the path Θ_i; $N=|\Theta|$ – total number of paths.

Step 4. Selecting chromosomes from the population for crossover. When solving this problem, we will use tournament selection of chromosomes, carried out among the two pairs [6]. Each of these two pairs is selected from the population with a probability that follows a uniform distribution. Then, from each pair, the individual with the best fitness function value is selected.

Step 5. Crossover on the winning chromosomes. The winners of each of the two tournaments held in the previous step get combined with each other. To solve this problem, it is proposed to use the homogeneous crossover operator. An element (in this case, a column of matrix) of each of the pair of descendants is selected with uniform probability from the first or second parent. If the element for the first descendant was taken from the second parent, then the same element of the second descendant should be taken from the first parent [6-8]. An example of using this operator is shown in Figure 4.

Step 6. Mutation of descendants. The mutation operator is applied to the descendants resulting from crossover in the previous step. The main purpose of using mutation in genetic algorithms is to avoid premature convergence of the population to a solution that is not good enough [6]. When solving this problem, the best results were obtained with probability $P = 1/S$. With some probability, a terminal device is selected and connected to another telemedicine station. The probability of choosing one or another telemedicine station is subject to a uniform distribution. An example of a mutation of this kind is shown in Figure 5.

Then steps 3-6 of the method are repeated until the number of generations is equal to G, as specified at the Step 1.

4 EXPERIMENTAL RESULTS

For the experiment, we the optimal topological structure of TMN from 5 telemedicine stations and 40 telemedicine service consumers was synthesized. Genetic algorithm parameters: population size – 50, number of generations – 250. Penalty function

$$F_3 = 1000*n,$$

here n is the number of terminal devices, connected to the telemedicine station in excess of its maximum capacity.

Weighting coefficients $w_1=w_2=0{,}5$. The maximum capacity of telemedicine stations is TS1=7, TS2=10, TS3=8, TS4=15, TS5=9. Genetic algorithm was emulated in the MatLab modeling environment.

Figure 6 shows one of the basic topologies, and Figure 7 - the optimal topology of the TMN, resulting from the proposed method. Table 1 presents the dynamics of changes in the population fitness function.

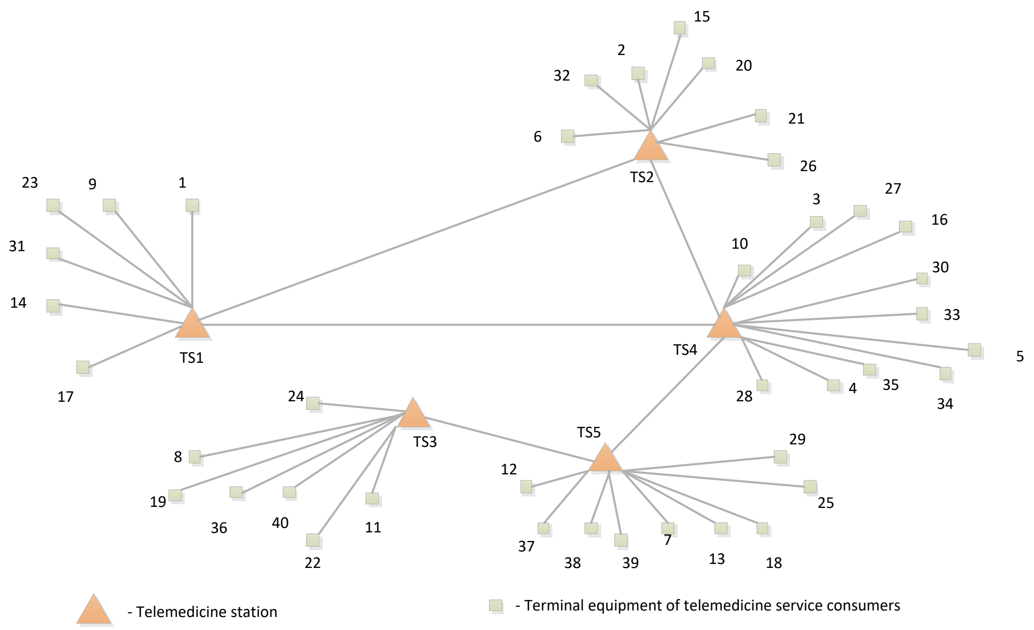

Figure 6: One of the basic topologies of TMN.

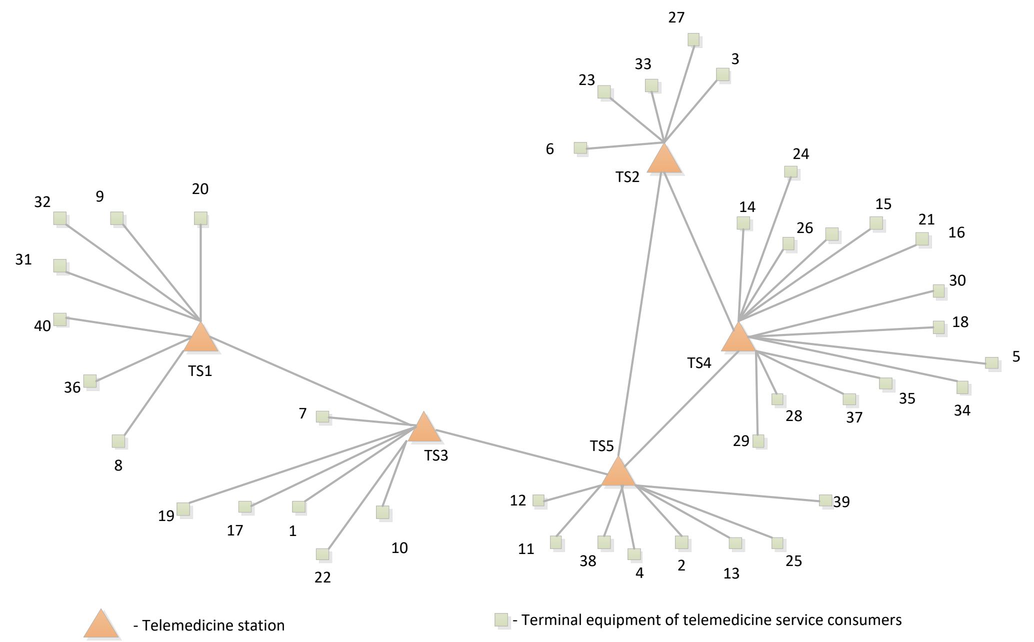

Figure 7: Optimal topology of TMN.

Table 1: Dynamics of the fitness function change.

Generation	The dynamics of changes in the average value of fitness function, %	Dynamics of changes in the best value of fitness function, %
1-10	27,00	9,2
11-20	24,30	6,8
21-30	11,15	2,14
31-40	3,4	0,95
41-50	1,17	0,02

5 CONCLUSIONS

The proposed method, based on a genetic algorithm, can be used to synthesize the optimal topological structure of a TMN. This ensures that the distribution of users (with known geographical coordinates) by telemedicine stations (whose number and location are also known) is optimized for both signal transmission delay time and the cost of network deployment. The experiment revealed that the resulting solution achieves near-optimal performance , i.e. the use of a genetic algorithm significantly reduces the risk of falling into a local extremum. In this method, the accuracy of the obtained results depends on the number of generations specified during the initialization stage of the genetic algorithm. The computational complexity of the algorithm can be further reduced by employing a more efficient method for finding the base population.

Further research will be aimed at developing a generalized method that allows synthesizing the optimal TMN topology when the required number of telemedicine stations and their location are unknown in advance. It is also important to modify the resulting method to optimize the TMN topology with reference to a larger number of parameters.

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