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METHOD OF MULTI-CRITERIA OPTIMISATION OF DATA FLOW DISTRIBUTION IN SELF-ORGANISED TELECOMMUNICATIONS NETWORKS

Abstract. Relevance. Self-organising networks operate under variable topology and resource availability. It is necessary to jointly reduce delay and load imbalance while increasing resilience to failures and topology changes. This requires adaptive optimisation with near real-time decision-making. **Object of the study**: distribution processes of complex-structured data flows in self-organising telecommunications networks under node resource constraints. **Purpose of the article:** to develop a multi-criteria optimisation method for flow distribution that jointly reduces delay and load imbalance and increases resilience to failures and topology changes, taking into account heterogeneous QoS requirements and limited node resources. **Research results.** Each flow is represented as a set of subflows with heterogeneous QoS requirements. The limitations of computational and bandwidth resources of nodes are formalised as a multidimensional knapsack problem. The optimisation loop combines global evolutionary search with local refinement of solutions. Adaptive route restructuring is applied in response to traffic variability and network state changes. Simulation results confirm a reduction in inter-cluster and end-to-end delays, a decrease in critical-flow delays, improved load distribution uniformity, and shorter convergence time after topology changes. At the same time, the method increases the frequency of route reconfigurations and the computational cost of the optimisation cycle, and degrades the performance of low-priority flows, which is interpreted as a controlled compromise inherent to multi-criteria optimisation. **Conclusions.** The proposed method improves the efficiency of flow distribution in dynamic self-organising networks, providing the greatest benefits for critical flows and convergence after topology changes. The improvement is achieved at the cost of higher computational overhead and more frequent route reconfigurations, with reduced performance for low-priority flows. The method is suitable for Fog, Edge, and Cloud environments where adaptive real-time decisions are required under topology changes and resource variability.

Keywords: self-organising telecommunications networks; multi-criteria optimisation; data flow distribution; load balancing; multidimensional knapsack problem; evolutionary algorithms; resource optimisation.

Introduction

The purpose of the work. The development of telecommunications technologies has led to the emergence of systems in which traditional centralized resource management schemes no longer provide adequate efficiency. In practice, distributed and self-organised telecommunications systems are increasingly being used, characterised by the absence of a single decision-making centre; heterogeneity of computing network resources; high data flow dynamics; and multi-criteria service requirements [1, 2].

In related studies, the problem of improving the efficiency of self-organised telecommunications systems is considered from different perspectives. In works devoted to hierarchical clustering of distributed network nodes, graph-based methods for cluster formation are proposed, which allow reducing topology fragmentation and inter-cluster delays. Such approaches improve the structural organisation of the network, but do not solve the problem of optimal distribution of flows within clusters [3, 4].

Another area of research focuses on selecting and maintaining a coordinator or master node for the cluster. The proposed methods of local rating selection and gossip exchange metrics ensure rapid recovery of control in case of failures and reduce service traffic compared to classical selection algorithms. However, such methods do not take into account the multi-criteria optimisation of the distribution of complex data flows [5].

A separate group consists of works devoted to predictive-adaptive control of coordinator stability in Fog/Edge environments, where neural network models are used to predict node degradation. They allow proactive responses to load growth or failure risk, but do not consider the detailed distribution of flows and sub-flows, taking into account multidimensional resource constraints.

Classic routing and load balancing models are designed primarily to work with aggregated flows, which are described by a small number of parameters – volume, arrival rate, and acceptable delivery time. However, modern systems produce complex structured data flows (CSD flows), which have a hierarchy of sub-flows with different characteristics [1–3]. For example, an analytical flow may contain telemetry traffic, video data, service messages, and local computation results – each of these components has its own requirements for latency, throughput, and reliability.

In practical scenarios with high structural complexity of traffic, the application of these methods leads to a decrease in decision-making accuracy, local distribution optimisation, and degradation of service quality indicators. This is because they are focused on aggregated flows, take into account a limited number of criteria, and do not support the multidimensional resource constraints characteristic of modern self-organising networks.

Complexly structured data flows have a hierarchical nature, which significantly affects the process of optimising their distribution in self-organised networks. Recent studies have shown that taking into account the internal structure of flows provides significantly higher load balancing accuracy and reduces delays in heterogeneous networks [6, 7].

A matrix is introduced for the formal description of internal dependencies:

$$D = [d_{ij}], d_{ij} = \begin{cases} 1, & \text{if } f_i \text{ depends on } f_j, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The existence of dependencies between sub-threads imposes additional constraints on the permissible solution space in the optimisation problem. For example, a high-priority sub-thread that depends on the results of a previous sub-thread cannot be assigned to a node that is too far away or has insufficient bandwidth to interact with the predecessor node. In video analytics systems, such constraints can affect the quality of event recognition, and in industrial systems, they can affect the accuracy of early warning systems.

Well-known sources indicate that modelling flows with dependencies can reduce average latency by up to 35% and improve resource utilisation uniformity in multi-level topologies. Thus, formalising dependencies is a key factor in developing an optimisation method for CSD-flow [8, 9].

Thus, the current scientific problem is to create a method for distributing complexly structured data flows that simultaneously takes into account the internal structure of flows, multidimensional resource constraints of nodes, and the dynamic nature of self-organised networks. Existing approaches are either limited to optimising aggregated traffic or solve individual control sub-tasks without providing comprehensive multi-criteria distribution of sub-flows in real time.

Thus, there is a need to create a model capable of reflecting the internal structure of flows, as well as optimisation methods that simultaneously take into account several criteria and adapt to changes in network topology in real time.

Statement of the problem. In modern telecommunications systems, traffic distribution is traditionally modelled through routing, latency minimisation, or load balancing tasks between nodes. With the growing number of sub-flows and the variability of their requirements, classical routing and load balancing models lose their scalability because they do not ensure coordination of decisions at the level of individual flow components.

Multi-criteria optimisation methods have been developed due to the ability to simultaneously consider several service requirements [6]. Second- and third-generation evolutionary algorithms, such as NSGA-II and NSGA-III, allow the formation of a set of non-dominated solutions, giving the operator or system a choice between different compromises. Their advantage is scalability to tasks with a large number of criteria and no requirement for prior determination of weighting coefficients. However, their disadvantage is that they are focused on the distribution of aggregated traffic units and do not take into account the complex internal structure of CSD-flow.

Analysis of recent studies and publications. In Fog and Edge computing systems, the problem of optimal service placement is often considered in the context of minimising latency between the data generation point and the processing point. However, most models place tasks or services rather than sub-threads, which differs significantly from real-world telecom conditions. In such networks, computing resources are distributed among numerous heterogeneous nodes, and each subthread may have a unique route and different requirements. Therefore, it is important to build a model that allows simultaneous optimisation of routing, placement, and resource allocation based on multidimensional constraints.

A separate area is combined approximate optimisation algorithms, which combine global search and local improvement. Evolutionary algorithms provide a wide range of solutions, while local methods (hill climbing, simulated annealing, tabu search) allow for high accuracy in improving intermediate results. Hybrid methods are actively used for multidimensional problems, including MKP (Multi-dimensional Knapsack Problem), since classical LP/MIP methods are too slow with a large number of dimensions and nonlinear constraints.

Combined multi-criteria optimisation algorithms with local improvement are one of the key approaches to optimisation tasks in complex telecommunications systems [4, 5, 7]. The combination of an evolutionary core, which provides global search, with local optimisation techniques, which are responsible for the precise refinement of local solutions, allows high convergence to be achieved even in high-dimensional problems. One of the advantages of such methods is their ability to adapt to load changes in real time, making them a natural choice for self-organising networks, where traffic structure changes continuously.

Thus, modern approaches either oversimplify the mathematical model, fail to take into account the interdependence of subflows, or are unable to adapt to dynamic changes in self-organised networks. This justifies the need to improve the developed methods, which combine multidimensional optimisation, detailed flow structure modelling, and an adaptive combined optimisation algorithm.

In real Fog, Edge, and Cloud environments, the proposed method can be implemented as a sequential control loop. At the first stage, the status of nodes and communication channels is monitored, and current resource profiles are generated. Next, the network is logically organised into clusters with limited internal delays, which reduces the dimensionality of the optimisation problem.

At the level of each cluster, a coordinator is selected to provide local control and initiate the process of multi-criteria distribution of sub-threads. The optimisation module, based on a multidimensional knapsack problem and a combined approximate optimisation algorithm, generates a plan for assigning sub-threads to nodes, taking into account QoS requirements. In the event of a change in load or node degradation, re-optimisation takes place without stopping the system [10].

Main material

The optimisation model for sub-flow distribution is based on a multidimensional knapsack problem, which is widely used in modern research to describe resource constraints in distributed systems [11, 12]. The multidimensional backpack problem is defined as:

$$\max \sum_{i=1}^{n} v_i\, x_i, \qquad (2)$$

$$\text{s.t.} \sum_{i=1}^{n} w_{ik}\, x_i \le C_k, k = 1, \dots, K, x_i \in \{0,1\}. \qquad (3)$$

In the context of self-organised telecommunications networks: w_{ik} – determine resource consumption by sub-thread f_i, including CPU, RAM, power consumption, and channel bandwidth; C_k – maximum capabilities of the corresponding node resource; v_i – integral utility of a sub-flow, formed on the basis of QoS criteria.

Based on NSGA-II/III approaches and Fog/Edge models, the utility of a sub-thread can be defined as follows [6]:

$$v_i = \alpha_1 \cdot \frac{1}{T_i} + \alpha_2 \cdot B_i + \alpha_3 \cdot (1 - L_i) + \alpha_4 \cdot P_i. \qquad (4)$$

where T_i – delay; B_i – bandwidth; L_i – loss rate; P_i – priority.

The proposed formalisation allows obtaining an admissible sub-flow assignment plan in which each decision satisfies the set of resource constraints of nodes and QoS requirements for each sub-flow. [4, 7]. Let

$$F = \{f_1, f_2, \dots, f_n\}, \qquad (5)$$

a set of sub-threads that make up a single complex-structured thread.

Each subthread f_i has the following attributes: d_i – data volume; r_i – resource requirements (CPU, memory); τ_i – acceptable delay; p_i – priority; b_i – required channel bandwidth; e_i – energy cost of sub-stream processing.

A complexly structured flow is represented as a set of sub-flows, each of which may have requirements that are independent or partially dependent on other sub-flows. This allows for a more accurate load distribution model. For example, video analytics flows may include high-resolution traffic, service management traffic, low resource requirements but high priority, as well as processing result traffic. The network consists of nodes

$$N = \{n_1, n_2, \dots, n_m\}. \qquad (6)$$

The resource constraints of node n_j are given as

$$C_{jk}, k = 1,2, \dots, K, \qquad (7)$$

where k – denotes the type of resource: computing power, memory, bandwidth, energy consumption, etc.

Purpose of the sub-thread $f_i$per node n_j described by a binary variable:

$$x_{ij} = \begin{cases} 1, & \text{if } f_i \text{ performed on } n_j, \\ 0, & \text{otherwise.} \end{cases} \qquad (8)$$

Resource constraints are formulated as:

$$\sum_{i=1}^{n} w_{ijk}\, x_{ij} \le C_{jk}, \qquad (9)$$

where w_{ijk} – required amount of resources k for sub-thread i at node j.

Since node resources are multidimensional (CPU, memory, bandwidth, energy), the problem is formulated as a knapsack problem, where the number of dimensions k is equal to the number of resource types [13, 14]. The resource constraints of a self-organised network are presented in a multidimensional form and include the computational, bandwidth, memory, and energy parameters of the nodes [15, 16]. The sub-thread assignment problem is formulated as a multidimensional knapsack problem, which allows several types of constraints to be taken into account simultaneously for each node and correctly reflects the heterogeneity of resources in Fog/Edge/Cloud infrastructures [17–19].

This method is optimised according to the following criteria: minimising average delay; minimising load imbalance; and maximising service quality:

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} v_{ij}\, x_{ij}, \qquad (10)$$

$$v_{jk}, = \alpha_1 QoS_{ij}^{delay} + \alpha_2 QoS_{ij}^{bw} + $$
$$+ a_3 QoS_{ij}^{loss} + \alpha_4 Pri_i, \qquad (11)$$

where α_k are the weight coefficients of the criteria.

This expression allows several independent optimisation criteria to be integrated into the model.

The multidimensional knapsack problem remains NP-hard already for the two-dimensional case, and its computational difficulty grows rapidly with the number of items and constraint dimensions [20]. In Fog/Edge environments, the amount of sub-threads may scale to hundreds or even thousands, while the resource vector typically includes several components (e.g., CPU, RAM, bandwidth, energy, and additional operational limits), which may increase the number of dimensions to 4–8 [21]. As a result, the search space becomes extremely large. Exact approaches such as linear/integer programming and dynamic programming-based schemes often exhibit exponential or pseudo-exponential growth of computational cost, which makes fully deterministic optimisation impractical for dynamic self-organising networks where decisions must be produced under strict latency constraints [22]. Within the CSD-flow distribution problem, this motivates a hybrid strategy that combines a global evolutionary search with local refinement steps, so that the global structure of assignments is preserved while local corrections reflect the current resource state and inter-flow dependencies [23, 24]. It is widely observed in practical optimisation tasks that evolutionary methods hybridised with local improvement can deliver higher-quality solutions and reach near-optimal results faster than purely classical exact procedures under comparable time limits [11–13].

To formalise the proposed method of multi-criteria optimisation of CSD flow distribution, an algorithm has been developed, the generalised structure of which is presented in the form of a block diagram (Fig. 1).

The main effect of the proposed approach was evaluated using temporal QoS indicators, as they directly characterise the quality of data stream service and reflect the result of coordinated global and local optimisation.

The generalised values of delays before and after applying the algorithm are shown in Table 1.

Fig. 2 shows a comparative characteristic of QoS metrics for data flows before and after optimisation.

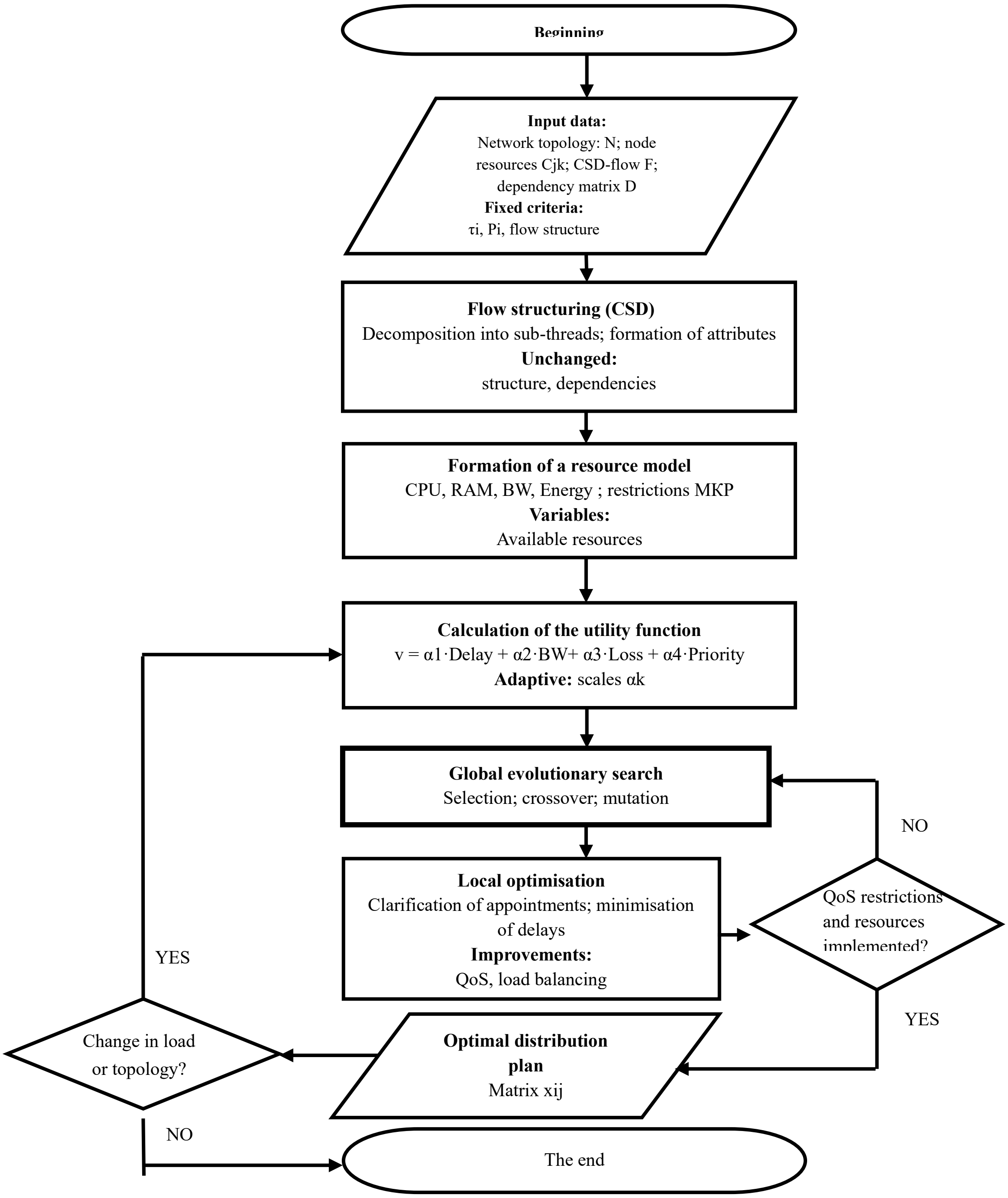

Fig. 1. Block diagram of the algorithm for multi-criteria distribution of CSD flows in a self-organised network

Table 1 – **Data flow service quality delay indicators**

№	Indicator	To optimisation, ms	After optimisation, ms
1	Final transmission delay (intercluster)	42.0	37.0
2	Average end-to-end delay	118.0	104.0
3	QoS delay of critical flows	76.0	68.0
4	QoS delay for low-priority flows	131.0	156.0

As can be seen from Table 1 and Fig. 2, after applying the algorithm, inter-cluster and end-to-end delays are reduced, as well as the delay of critical flows. At the same time, an increase in delay is observed for low-priority flows, which corresponds to the mechanism of prioritisation and redistribution of resources in favour of critical traffic. Accompanying indicators characterising the structural, control and computational consequences of optimisation are given in Table 2.

Since the accompanying indicators in Table 2 have different physical units and scales, their comparison in a single figure is presented in a normalised form. For each indicator, the baseline state "before optimisation" is taken as 100, while the value "after optimisation" is presented as a relative index. This method of presentation ensures a correct comparison of the structural, control and computational effects of the algorithm in a single graphical representation.

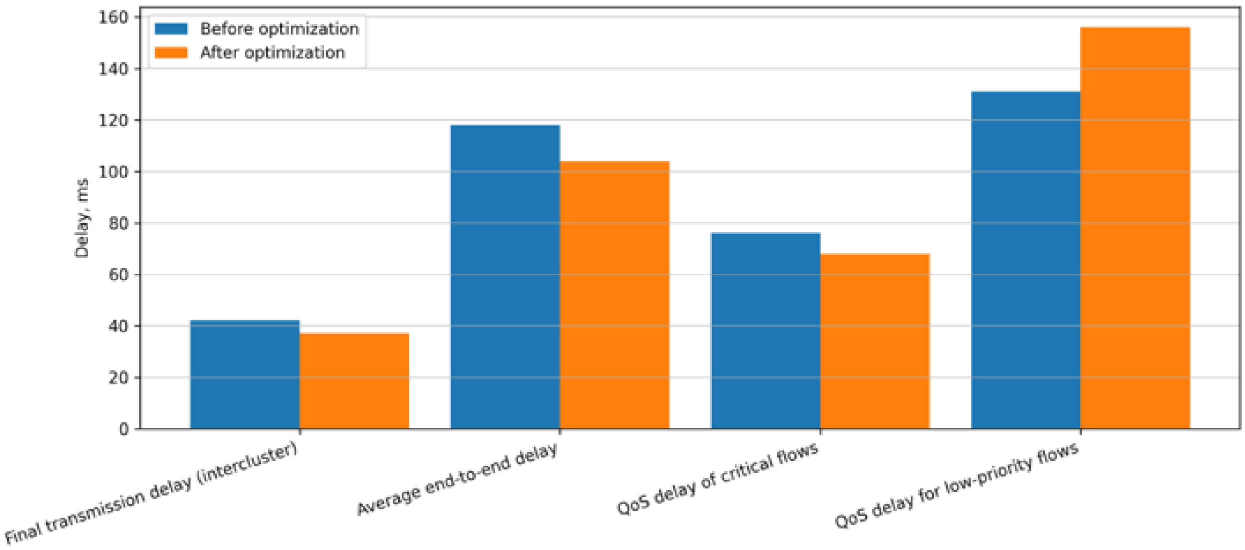

Fig. 2. Comparison of QoS delay metrics for data flows before and after optimization

Table 2 – **Accompanying indicators**

№	Indicator	To optimisation	After optimisation	Interpretation
1	Load dispersion of nodes	0.41	0.26	improved balancing
2	Number of congested channels	7	4	reduction of local overloads
3	Cluster fragmentation	0.28	0.18	improvement of structural integrity
4	Number of route rebuilds per interval	9	14	increase in adaptive restructuring
5	Convergence time after topology change	8.2	5.1	faster recovery
6	Computational time of the optimisation cycle	41	63	increase in computing costs
7	Traffic management during recovery	520	430	reduction in overhead costs

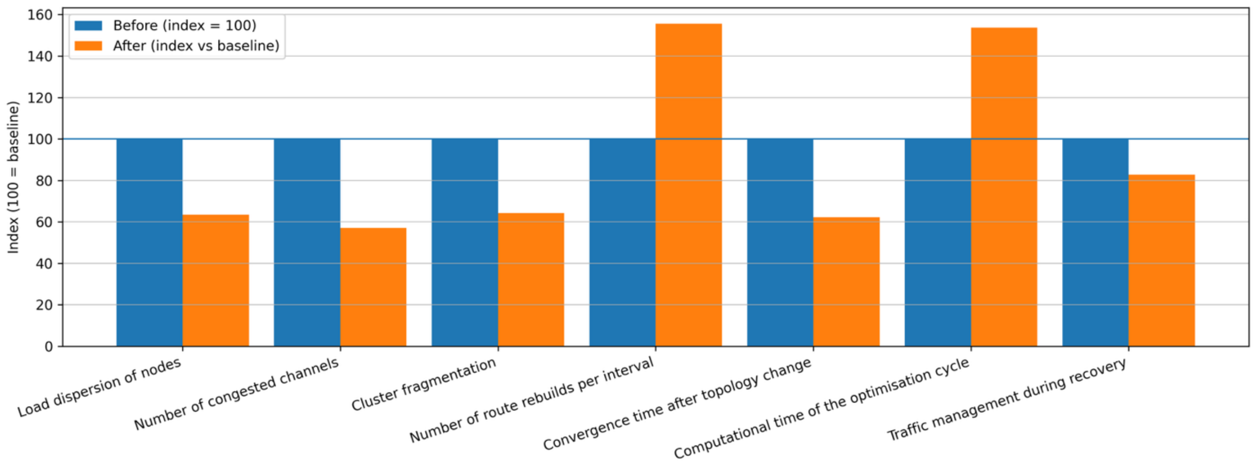

Fig. 3. Comparison of accompanying indicators in Table 2 before and after optimisation on a normalised scale

As can be seen from Table 2 and Fig. 3, after applying the method, the indicators characterising imbalance and structural degradation decrease: node load dispersion, the number of overloaded channels, and cluster fragmentation. At the same time, the convergence time after a topology change is reduced, indicating an increase in the speed of restoring the controlled state of the network. The reduction in control traffic during recovery indicates a decrease in overhead costs for coordination and reconfiguration procedures.

The gain in adaptability is accompanied by higher operational overhead. Specifically, the network performs route updates more often per interval, and the optimisation loop requires longer computation time [19]. We interpret this as a deliberate trade-off: maintaining near-optimal decisions under volatile resources and topology requires periodic re-optimisation [3]. According to Fig. 1, the main source of overhead is the hybrid workflow that combines a global scheduling phase with local refinements [11]. While this improves distribution quality and tolerance to changes, it naturally increases the reconfiguration rate and the computational cost [20].

As can be seen from Table 1, the application of the proposed algorithm leads to a reduction in QoS delay indicators, in particular, the final intercluster delay, the average end-to-end delay, and the delay of critical flows. The effect is achieved through a combination of global coordination of flow distribution, local route refinement, and adaptive reconfiguration procedures when the network state changes.

The accompanying indicators shown in Table 2 reflect the trade-offs of optimization [21]. In particular, there is an increase in the number of route rebuilds and computational costs, as well as an increase in delays for low-priority flows. These changes are consistent with the multi-criteria optimisation approach, which prioritises critical traffic and limited network resources [19]. For the multidimensional knapsack problem in the context of CSD-flow, an approximate solution search algorithm combining global search and local improvement is applied, which allows obtaining practically acceptable solutions in a limited time under dynamic conditions [7, 15].

The method consists of several stages, such as structuring the flow, in which the flow is broken down into sub-flows according to criteria: functional purpose, QoS requirements, and dependencies between components. Building a node model where a knapsack problem is created for each node, which contains resource constraints, local delay characteristics, and possible routes to other nodes. A greedy algorithm is applied: subflows are sorted by priority and delay, and each subflow is assigned to the node with the best resource and delay ratio. An evolutionary algorithm performs a global search for optimal flow assignment schemes [11]. After each iteration, a local search is performed to refine the assignment by analysing the movements of sub-threads between nodes [12, 13]. Evolutionary operators, crossover and mutation, allow us to escape local minima and explore new areas of the solution space.

The proposed method is made more efficient by detailed modelling of the internal structure of flows, which allows optimising assignments with precision down to individual sub-flows, as well as by taking into account the multidimensional resource constraints of nodes. Experimental analysis shows that the use of a combined approach reduces the number of iterations to a stable solution and increases the stability of the solutions obtained under variable load conditions. However, the effectiveness of the method begins to decline with a sharp increase in the number of sub-threads and resource types, as the search space and computation time increase. Additional performance losses are possible in scenarios with overly frequent topology changes or high overhead costs for migrating subthreads between nodes. This determines the limits of the method's applicability in real-time systems with strict constraints on decision-making delays. In modern video surveillance systems, the distribution of sub-streams between Edge nodes allows for a significant reduction in throughput load and an increase in the speed of analytical data processing [1].

In industrial IoT systems, the volume of sensor streams can reach tens of thousands. According to recent studies, traditional routing methods do not provide effective distribution at such a scale, while the multidimensional knapsack problem allows for a significant improvement in the accuracy of stream assignment [8]. In Fog networks, optimisation of streaming services reduces energy consumption and delays in data processing, as confirmed by the results of a number of experimental studies.

In the evolutionary approaches to multi-criteria flow distribution, optimisation is performed at the level of aggregated traffic units, which simplifies the model but limits its applicability in the case of complexly structured flows. [15]. Unlike evolutionary methods, in which a flow is considered as an aggregated unit of optimisation, the proposed approach operates with a multi-level CSD-flow structure. The proposed model considers a complexly structured flow as a set of subflows, each of which acts as a separate unit of destination and optimisation and is characterised by its own attributes, QoS requirements and dependencies. This decomposition provides a more accurate assessment of the load on nodes and allows you to form a distribution plan that takes into account traffic heterogeneity and service priorities. This makes it possible to take into account the dependencies between subflows and assign them to nodes, taking into account individual resource requirements and delays, which increases the accuracy of distribution in self-organising networks. It is effective for a large number of criteria, but does not take into account the internal structure of the flow [6]. In the method of multi-criteria distribution of data flows in telecommunications networks based on an evolutionary approach, the flow is modelled as an aggregated unit, which simplifies the model but limits its application to CSD-flow. The proposed method takes into account the internal multi-level structure, which allows optimising resources with sub-flow accuracy.

Unlike existing evolutionary methods, the proposed approach has the following features: takes into account the multidimensionality of resource constraints, which increases the accuracy of the model; uses a multi-criteria optimisation algorithm, which provides better convergence in complex tasks; operates in a self-organised manner, i.e. without centralised management.

Hybrid algorithms combine different optimisation principles. In the proposed method, hybridisation occurs between an evolutionary algorithm that generates many solution variants; a local search that improves the quality of each solution; and a knapsack problem that formally limits the solution space. The optimisation procedure combines global formation of a set of candidate solutions based on evolutionary search and local refinement focused on improving the quality of assignments in the immediate vicinity. This combination increases convergence stability and reduces the risk of getting stuck on locally optimal solutions in problems with a large number of sub-threads and high load variability.

Modern multi-objective evolutionary algorithms, such as NSGA-III, effectively form sets of compromise solutions, but their application in flow distribution problems has significant limitations.

In particular, such algorithms: do not take into account the CSD-flow structure; do not work with multidimensional resources; poorly adapt to dynamic changes in traffic; do not take into account dependencies between subflows. A comparison with known evolutionary approaches shows that in the case of CSD-flow, explicit consideration of the sub-flow structure and multidimensional resource constraints is critically important. The transition from an aggregated representation of traffic to a representation in the form of subflows ensures the controlled assignment of flow components to nodes, taking into account QoS requirements, while the multidimensional formulation of constraints increases the adequacy of the assessment of available resources in networks with dynamic topology.

Conclusions

The article develops a comprehensive method for multi-criteria optimisation of the distribution of complex data flows in self-organised telecommunications networks. The method is based on representing each flow as a set of sub-flows with heterogeneous QoS requirements and taking into account the multidimensional resource constraints of nodes. The resource constraints of nodes are formalised as a multidimensional knapsack problem, and optimisation is implemented by combining global evolutionary search and local refinement of solutions with adaptive route restructuring when the network state. The results of simulation modelling confirmed that the application of the developed method allows reducing the delay characteristics of critical flows, increasing the uniformity of load distribution, and reducing the convergence time after topology changes. At the same time, a controlled compromise was established: there is an increase in the frequency of route reconfiguration and computational costs of the optimisation cycle with a deterioration in performance for low-priority flows. In future research, it is planned to mitigate the effect of service degradation for low-priority flows as a side effect of multi-criteria optimisation. The proposed approach can be used as a basic mechanism for adaptive flow control in Fog, Edge, and Cloud environments, as well as in other decentralised infrastructures with variable resources and topology.

Conflict of interest

The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship, or other, that could influence the study and its results presented in this article.

Using artificial intelligence tools

For the initial literature search and for shaping the review structure, the generative AI tools ChatGPT (version 5.2) and Grok 4 were used to help systematise approximately 100 sources. The final literature analysis and the writing of the manuscript were performed independently by the author.

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Метод багатокритерійної оптимізації розподілу потоку даних у самоорганізованих телекомунікаційних мережах

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Анотація. Актуальність. Самоорганізовані мережі працюють в умовах змінної топології та доступності ресурсів. Необхідно спільно зменшити затримку та дисбаланс навантаження, одночасно підвищуючи стійкість до збоїв та змін топології. Це вимагає адаптивної оптимізації з прийняттям рішень майже в реальному часі. **Об'єкт дослідження**: процеси розподілу складноструктурованих потоків даних у самоорганізованих телекомунікаційних мережах за обмежень ресурсів вузлів. **Мета статті**: розробити багатокритеріальний метод оптимізації розподілу потоків, який спільно зменшує дисбаланс затримки та навантаження та підвищує стійкість до збоїв та змін топології, враховуючи неоднорідні вимоги до якості обслуговування (QoS) та обмежені ресурси вузлів. **Результати дослідження.** Кожен потік представлений як набір підпотоків з неоднорідними вимогами до QoS. Обмеження обчислювальних та пропускних ресурсів вузлів формалізовано як багатовимірну задачу ранця. Цикл оптимізації поєднує глобальний еволюційний пошук з локальним уточненням рішень. Адаптивна реструктуризація маршруту застосовується у відповідь на зміну трафіку та зміни стану мережі. Результати моделювання підтверджують зменшення міжкластерних та наскрізних затримок, зменшення затримок критичного потоку, покращення рівномірності розподілу навантаження та скорочення часу конвергенції після змін топології. Водночас, метод збільшує частоту реконфігурацій маршрутів та обчислювальні витрати циклу оптимізації, а також погіршує продуктивність потоків з низьким пріоритетом, що інтерпретується як контрольований компроміс, властивий багатокритеріальній оптимізації. **Висновки.** Запропонований метод покращує ефективність розподілу потоків у динамічних самоорганізованих мережах, забезпечуючи найбільші переваги для критичних потоків та конвергенції після змін топології. Покращення досягається за рахунок вищих обчислювальних витрат та частіших реконфігурацій маршрутів, зі зниженням продуктивності для потоків з низьким пріоритетом. Метод підходить для середовищ Fog, Edge та Cloud, де потрібні адаптивні рішення в режимі реального часу за умов змін топології та мінливості ресурсів.

Ключові слова: самоорганізовані телекомунікаційні мережі; багатокритеріальна оптимізація; балансування навантаження; розподіл потоку даних; багатовимірна задача рюкзака; еволюційні алгоритми; оптимізація ресурсів.