Security of Infocommunication Systems and Internet of Things

2026 Vol 4, No 1

https://doi.org/10.31861/sisiot2026.1.01008

Received 06 April 2026; revised 10 May 2026; accepted 07 June 2026; published 30 June 2026

Improving the Efficiency of Data Processing and Traffic Allocation in Distributed Telecommunication Systems Based on NSGA-III and RVEA

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ABSTRACT The article presents the development and experimental validation of modified evolutionary multi-objective optimization algorithms for improving data processing and flow distribution efficiency in distributed telecommunication systems. The purpose of the study is to enhance system performance under dynamic operating conditions characterized by variable workload, interference, and limited computational resources. The scientific problem addressed lies in achieving efficient and stable multi-objective optimization of data flow distribution and processing, taking into account conflicting criteria such as processing delay, resource utilization, load balancing, and system stability. The proposed approach is based on modifications to the NSGA-III and RVEA algorithms, incorporating adaptive mechanisms, including workload prediction, hybrid constraint handling, dynamic adjustment of search directions, and adaptive mutation strategies. These enhancements enable improved adaptability of the algorithms to dynamic and uncertain operating environments. The architecture of the proposed solution integrates evolutionary optimization mechanisms into distributed data processing pipelines, allowing coordinated resource allocation and adaptive control of computational processes across network nodes. Experimental verification was conducted in two scenarios: traffic distribution in distributed telecommunication systems and object recognition in video streams under interference conditions. The results demonstrate that the modified NSGA-III algorithm provides the greatest improvement in performance, reducing processing time by up to 2.8% and increasing recognition accuracy by up to 1.4%. The modified RVEA algorithm ensures stable performance reducing processing time by approximately 2.3%, increasing accuracy by 1.1%, and reducing GPU usage by up to 2.0%. Statistical validation using the Student's t-test confirmed the significance of improvements in processing time, accuracy, and GPU utilization ($p < 0.05$), while changes in CPU, RAM, and VRAM usage were not statistically significant, indicating the absence of additional computational overhead. The obtained results confirm that the proposed modifications of evolutionary algorithms are effective for adaptive optimization of data processing and flow distribution in distributed telecommunication environments, ensuring improved efficiency, stability, and robustness under dynamic conditions.

KEYWORDS distributed telecommunication systems, NSGA-III, RVEA, multi-objective optimization, data flow distribution.

I. INTRODUCTION

In modern distributed telecommunication environments, particularly Fog/Edge infrastructures, data flow management is complicated by the decentralized nature of computation and the dynamic changes in network operating conditions. In such environments, data processing is performed across a set of heterogeneous nodes with limited and unevenly distributed resources, while traffic intensity may vary rapidly over time. Additionally, system performance is affected by interference, channel instability, and bandwidth limitations.

Under these conditions, inefficient traffic distribution leads to node overload, increased transmission delays, and degradation of overall system performance. Therefore, the key scientific and practical problem is the development of data flow distribution methods that ensure balanced resource utilization, minimize delays, and maintain system stability under dynamically changing conditions.

The solution to this problem is complicated by its multi-objective nature, nonlinear relationships between system parameters, and the presence of numerous local optima. This limits the effectiveness of conventional optimization methods and justifies the use of evolutionary multi-objective optimization algorithms, which are capable of constructing Pareto-optimal solution sets and providing trade-offs between conflicting criteria.

Among such approaches, NSGA-III and RVEA are the most widely used algorithms for solving multi-objective optimization problems in complex dynamic systems. This paper considers modified versions of these algorithms aimed at improving the efficiency of traffic distribution in distributed telecommunication environments.

The aim of this work is to study and comparatively evaluate the effectiveness of modified evolutionary multi-objective optimization algorithms for data flow distribution in distributed telecommunication systems, taking into account dynamic workload conditions, transmission delays, node overload levels, and system stability.

To achieve this aim, a comparative analysis of two approaches is performed: a modified NSGA-III algorithm, oriented toward predictive-adaptive load management, and a modified RVEA algorithm, based on geometric adaptation of the search in the objective space. The conducted study makes it possible to evaluate the effectiveness of each algorithm depending on the problem characteristics and system operating conditions.

II. REVIEW OF THE LITERATURE

Studies [1-16] address various aspects of improving the efficiency of distributed telecommunication systems, data flow distribution, and the application of evolutionary and neural network methods for control tasks in dynamic environments. In [1], a multi-objective data stream distribution method based on an evolutionary approach was proposed, while [2] presented a neural network-based method for adaptive object recognition in video streams. Works [3-4] focus on the application of intelligent methods, particularly neural networks, to optimization and cybersecurity tasks in telecommunication systems. These studies confirm the effectiveness of intelligent technologies; however, they are mainly oriented toward local data processing or classification tasks and do not provide a comprehensive solution to the global load distribution problem.

Papers [5-7] and [11-15] investigate evolutionary multi-objective optimization algorithms, including approaches for constructing Pareto-optimal solution sets, search adaptation, and load balancing in complex systems. In particular, [6] proposes a unified evolutionary optimization procedure for problems with different numbers of objectives, while [11] considers an improved version of the NSGA-III algorithm. Works [7, 12, 14, 15] demonstrate the application of genetic algorithms in load balancing, clustering, and optimization tasks in IoT and cloud environments. However, most of these approaches do not adequately account for the dynamic nature of workload changes and exhibit limited adaptability to varying network conditions.

Studies [8, 10] focus on clustering methods and structured modeling approaches in telecommunication networks, enabling improvements in data processing efficiency and node interaction organization. At the same time, these works do not sufficiently consider the multi-objective nature of resource allocation problems and lack adaptive control mechanisms for dynamic environments.

Thus, the conducted analysis indicates that existing approaches effectively solve specific tasks such as clustering, local optimization, or data processing, but do not ensure comprehensive consideration of multi-objective requirements, workload dynamics, and system stability. This substantiates the need for developing modified evolutionary algorithms that integrate multi-objective optimization with adaptive control mechanisms and enable efficient traffic distribution in distributed telecommunication systems.

III. THE MATERIALS AND METHODS

Taking into account the formulated problem of multi-objective data flow distribution in distributed telecommunication systems, an evolutionary approach is employed to solve it, as it can handle multiple conflicting criteria.

The data flow distribution problem is considered a multi-objective optimization problem, in which it is necessary to determine a mapping of the set of data flows to the set of available computational resources (nodes, clusters, or external entities), ensuring load balancing, delay minimization, and reduction of overload risk.

To represent potential solutions, genetic encoding in the form of a chromosome is used, in which each gene corresponds to the assignment of a specific data flow to a particular resource. The chromosome structure is based on an integer representation, in which the gene value defines both the type of resource and its identifier: positive values correspond to local nodes, zero denotes the global supervisor, and negative values represent neighboring clusters (Fig. 1).

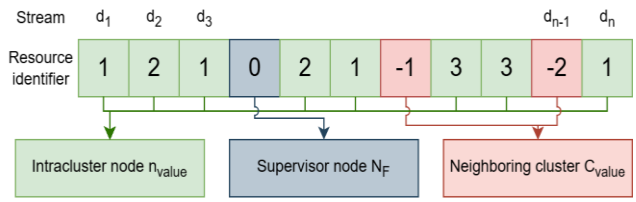

FIG. 1. Integer-based chromosome representation.

As shown in Fig. 1, the chromosome is represented as a sequence of integer values, where each position corresponds to a specific data flow di, and the gene value determines the resource to which the flow is assigned.

Positive gene values correspond to local nodes within the cluster (e.g., 1, 2, 3), enabling processing within available computational resources. A value of zero indicates that the flow is delegated to the global supervisor NF, which is utilized in cases of local cluster overload. Negative values (e.g., $-1, -2$) correspond to the assignment of flows to neighboring clusters C_i, allowing the implementation of distributed load balancing.

The interpretation of chromosome gene values is presented in Table 1.

TABLE 1. Interpretation of chromosome gene values.

Gene value	Resource type	Interpretation
> 0	Local node	Processing of the data flow within the cluster
$= 0$	Global supervisor N_F	Delegation in case of overload
< 0	Neighboring cluster C_i	Inter-cluster delegation

Such an approach makes it possible to provide a unified representation of all possible data flow distribution options within a single structure, which is essential for the efficient implementation of evolutionary operators.

The conducted analysis of modern evolutionary multi-objective optimization algorithms has shown that, for data flow distribution problems in distributed telecommunication systems, the most promising approaches are those capable of effectively handling a large number of criteria, ensuring uniform coverage of the Pareto front, and adapting to changing system conditions.

Among the considered methods, the NSGA-III and RVEA algorithms were selected, as they combine high efficiency of multi-objective optimization with the ability to scale to problems with high-dimensional solution spaces. The NSGA-III algorithm ensures stable generation of well-distributed Pareto-optimal solutions through the use of reference points, which is particularly important when dealing with a large number of criteria.

In turn, the RVEA algorithm provides effective guidance of the search process using reference vectors, enabling adaptive adjustment of search directions in the objective space.

The selection of these algorithms is determined by their ability to efficiently handle high-dimensional multi-objective problems, ensure a well-distributed set of Pareto-optimal solutions, and provide stable convergence properties under complex optimization conditions.

A comparative analysis of the selected algorithms, considering key problem requirements such as scalability, stability, and adaptability, is presented in Table 2. As shown in Table 2, both algorithms satisfy the basic requirements; however, they do not account for dynamic workload variations and the need for adaptive control, which motivates their modification.

Therefore, modified versions of the NSGA-III and RVEA algorithms are proposed, incorporating workload prediction, hybrid constraint handling, dynamic search adaptation, and adaptive mutation tuning (Fig. 2 and Fig. 3).

As shown in Fig. 2, the proposed modification of the NSGA-III algorithm is aimed at improving its adaptability to dynamic workload conditions and accounting for predicted spikes in the resource consumption of data flows. In contrast to the classical implementation, the proposed approach introduces a set of targeted modifications affecting key components of the algorithm, including initial population generation, solution evaluation, constraint handling, and adaptation mechanisms.

TABLE 2. Comparative characteristics of NSGA-III and RVEA for the data flow distribution problem.

Characteristic	NSGA-III	RVEA	Relevance to the problem
Handling a large number of objectives	High	High	Critical
Pareto front coverage	Uniform	Direction-oriented	Important
Search guidance mechanism	Reference points	Reference vectors	Key
Solution stability	High	Medium	High
Scalability	High	High	Critical
Adaptability to problem structure	Limited	Higher	Important
Sensitivity to parameters	Moderate	Moderate	Medium

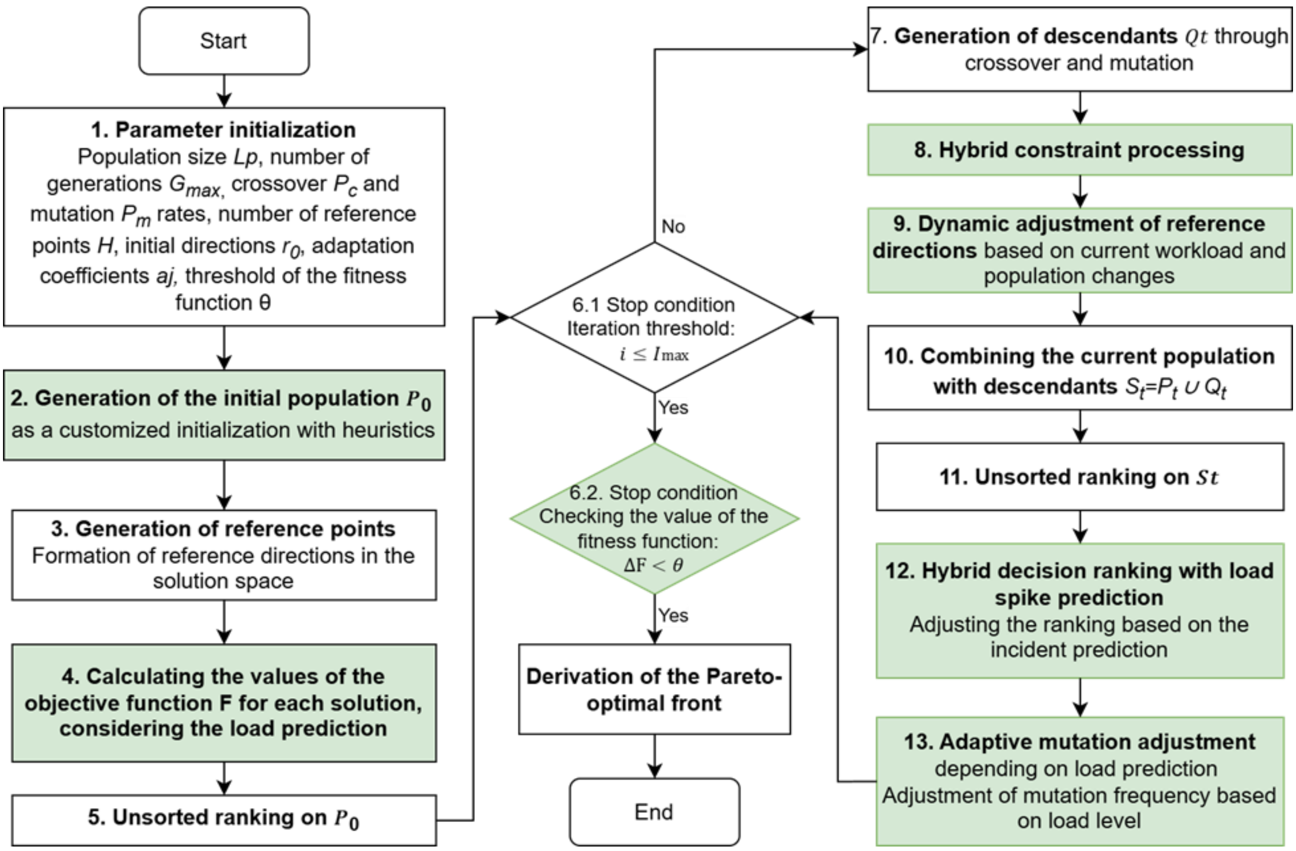

FIG. 2. Structure of the modified NSGA-III algorithm for data flow distribution.

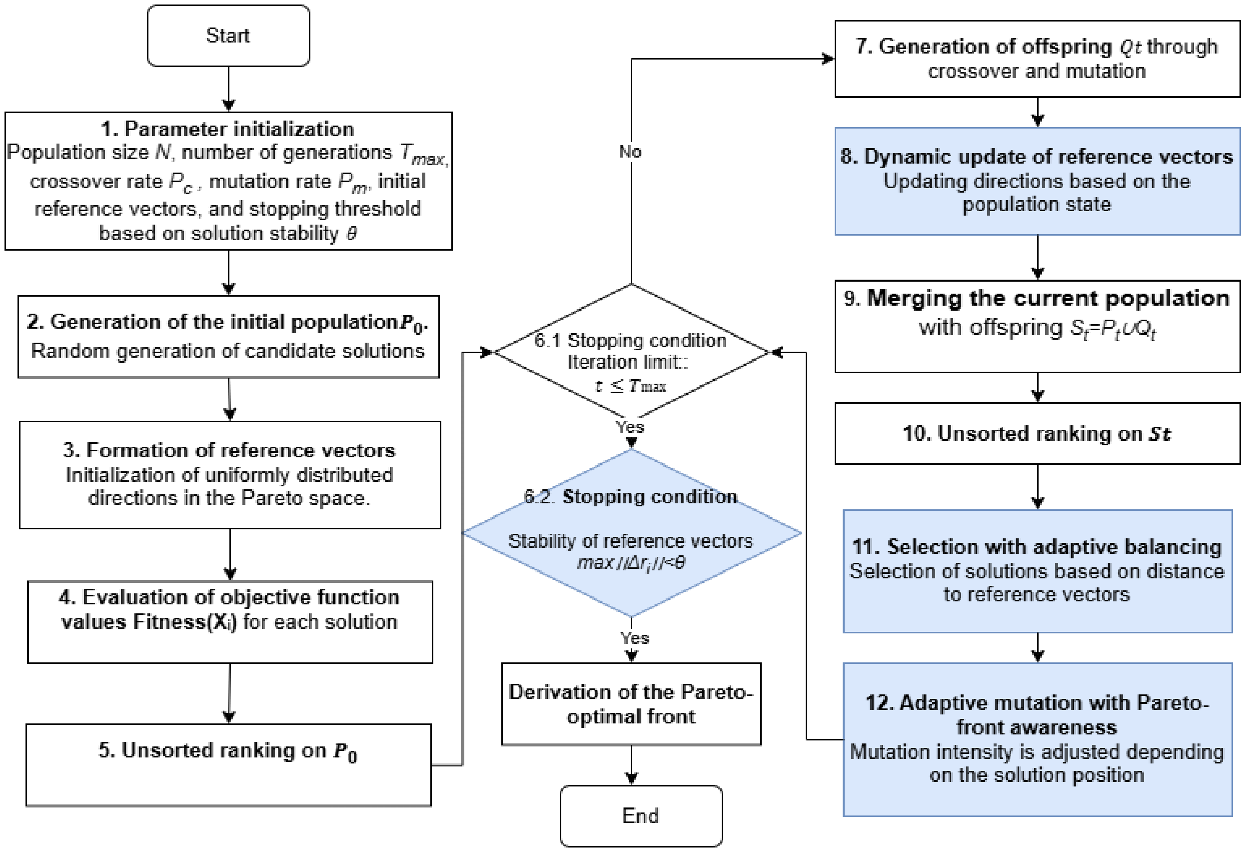

FIG. 3. Structure of the modified RVEA algorithm for data flow distribution.

1. In particular, within the initial population generation process, heuristic strategies (First-Fit, Best-Fit, Least-Loaded) are applied with preliminary filtering of solutions and the introduction of a resource reservation policy:

$$\exists n \in S_C^n : CPU_n^{free} \geq \beta \cdot CPU_n , \quad (1)$$

where CPU^{free} is the amount of available computational resources of node n; CPU_n is the total computational capacity of the node; β is the resource reservation coefficient.

This approach not only improves the feasibility of initial solutions but also forms the initial population with an embedded resource reservation strategy, reducing the probability of early node overload and enhancing the algorithm's robustness to short-term workload spikes. In addition, such pre-structuring of solutions accelerates convergence by reducing the proportion of infeasible candidates in the initial iterations.

2. At the solution evaluation stage, a modification is introduced to incorporate predictive workload awareness by explicitly modeling the probability of workload spikes. This enables the evaluation function to account not only for the current system state but also for potential future overload conditions, thereby improving the robustness and reliability of the obtained solutions in dynamic operating environments:

$$P^{surge} = 1 - e^{-\lambda\tau}, \quad (2)$$

where λ is the intensity parameter of workload spike occurrence; τ is the duration of a potential workload spike.

This modification enables proactive evaluation of candidate solutions by incorporating the risk of future overload conditions. As a result, the algorithm favors solutions that remain stable under potential workload spikes, reduces the probability of resource overutilization, and improves the reliability of decision-making in dynamic telecommunication environments.

3. A hybrid constraint-handling mechanism is introduced, combining repair-based correction of infeasible solutions with adaptive penalty coefficients that depend on the degree of resource violation and predicted workload conditions. This makes it possible to maintain solution feasibility while preserving diversity within the population under dynamic constraints.

4. An adaptive adjustment of reference directions is proposed, enabling the search process to shift toward regions of the Pareto front corresponding to more stable solutions under dynamic workload conditions. This modification improves the convergence behavior of the algorithm in the presence of workload variability.

5. In addition, a hybrid ranking strategy is introduced that incorporates workload spike prediction, allowing solutions to be prioritized not only based on current objective function values but also on expected future risks. This enhances the reliability of the selection process under uncertain conditions.

6. At the final stage, an adaptive mutation mechanism is implemented:

$$P_m^{adapt} = f(P^{surge}), \quad (3)$$

where P^{adapt} is the adaptive mutation probability, and P^{surge} is the probability of workload spikes.

The function $f(\cdot)$ defines the adaptive rule for adjusting mutation intensity based on predicted workload conditions.

This modification increases exploration under high overload risk while stabilizing the search process under low variability conditions, thereby improving both robustness and convergence of the algorithm.

Table 3 summarizes the implementation scenarios and expected effects of the proposed modifications.

TABLE 3. Practical application of the modified NSGA-III algorithm in distributed telecommunication systems.

Modification	Application scenario	Expected effect
Resource reservation	Fog/Edge nodes with uneven load	Reduced overload risk
Workload prediction	Burst traffic systems (IoT, video)	Improved robustness to peaks
Hybrid constraint handling	Resource-limited environments	Fewer infeasible solutions
Dynamic search adaptation	Dynamic networks (Fog/Edge, 5G)	Improved convergence
Hybrid ranking	High variability conditions	Better solution selection
Adaptive mutation	Unstable traffic conditions	Balance between exploration and stability

The results presented in Table 3 demonstrate that each proposed modification addresses a specific limitation of classical evolutionary algorithms when applied to distributed telecommunication environments.

In particular, the integration of resource reservation and workload prediction improves system resilience to dynamic load fluctuations, while hybrid constraint handling and ranking mechanisms enhance solution feasibility and selection quality. At the same time, dynamic search adaptation and adaptive mutation ensure efficient exploration of the solution space and stable convergence under varying operating conditions.

Overall, the combined application of these modifications enables more reliable, adaptive, and efficient data flow distribution in distributed telecommunication systems.

In this regard, a modified version of the RVEA algorithm is proposed, adapted to the specific requirements of the considered problem. As shown in Fig. 3, the proposed modifications are aimed at improving the adaptability of the algorithm to dynamic changes in the solution space and system conditions.

1. Dynamic update of reference vectors based on solution distribution.

Unlike in classical approaches, reference vectors in the modified RVEA algorithm are dynamically updated according to the actual distribution of solutions in the population. This allows the search directions to be adapted to changes in the system state, including variations in workload and environmental conditions:

$$\mathrm{r}_i^{t+1} = \mathrm{r}_i^t + \vartheta \cdot (\bar{\bar{\chi}} - \chi_i), \quad (4)$$

where χ is the centroid of the current population in the objective space, χ_i is the position of the i-th solution, ϑ is the direction adjustment coefficient.

This modification enables flexible adaptation of the search process and improves the robustness of the algorithm under dynamic and uncertain conditions.

2. Selection with adaptive deviation from reference vectors.

The selection criterion is extended by incorporating a distance-based component between a solution and its corresponding reference vector:

$$S_i = S_{RVEA}(i) + \delta \cdot \|\chi_i - \mathrm{r}_i\|, \quad (5)$$

where $\|\chi i{-}ri\|$ is the distance between solution χ and the reference vector ri, δ is the weighting coefficient.

This modification makes it possible to maintain a balance between solution accuracy and computational efficiency, while adapting to changes in workload conditions.

3. Adaptive mutation with Pareto-front awareness.

The mutation intensity is dynamically adjusted depending on the distance of a solution from the center of the Pareto front:

$$M_i = M_0 \cdot (1 + \gamma \cdot \|\chi_i - \chi^*\|), \quad (6)$$

where $\chi*$ is the center of the Pareto-optimal solution set, $\|\chi i{-}\chi*\|$ is the distance to this center, γ is the adaptation coefficient.

The proposed mutation mechanism accelerates convergence toward optimal solutions while preserving stability under changing system conditions.

The presented modifications of the RVEA algorithm enhance its adaptability to dynamic changes in the solution space, improve the stability of the search process, and enable more efficient handling of varying workload conditions.

Table 4 summarizes the application scenarios and expected effects of the proposed RVEA modifications.

The results presented in Table 4 indicate that the proposed modifications of the RVEA algorithm provide targeted improvements in handling dynamic and uncertain operating conditions.

In particular, the dynamic update of reference vectors enables the algorithm to adapt its search directions according to the current distribution of solutions,

TABLE 4. Practical application of the modified RVEA algorithm in distributed telecommunication systems.

Modification	Application scenario	Expected effect
Dynamic update of reference vectors	Dynamic environments with varying load	Improved adaptability of search directions
Adaptive selection (distance-based)	Systems with changing interference/load	Balanced accuracy and efficiency
Adaptive mutation (Pareto-aware)	Non-stationary conditions	Faster convergence and stability

improving responsiveness to workload variations. The distance-based selection mechanism enhances the balance between solution quality and computational efficiency, while the adaptive mutation strategy accelerates convergence without compromising stability.

Overall, the integration of these mechanisms ensures more robust and efficient optimization performance of the RVEA algorithm in distributed telecommunication environments.

IV. EXPERIMENTS

To verify the effectiveness of the proposed modified evolutionary algorithms for multi-objective traffic distribution in distributed telecommunication systems, a comprehensive simulation study was conducted based on graph models of the network. In these models, nodes represent computational elements of the distributed system, while edges correspond to communication links characterized by bandwidth and latency.

On this basis, computational pipelines were constructed to reflect the sequential processing of data flows across nodes, allowing simultaneous consideration of network topology, resource constraints, and load distribution, which is critical for solving the multi-objective traffic allocation problem in dynamic environments.

The experiments were carried out over 100 iterations, which ensured convergence to a steady-state regime and statistical reliability of the obtained results (Table 5, Fig. 4).

The following approaches were evaluated:

– no balancing – execution of predefined pipelines without optimization;

– NSGA-III – baseline evolutionary multi-objective algorithm;

– modified NSGA-III – incorporating adaptive mutation, hybrid ranking, and workload prediction;

– modified RVEA – incorporating dynamic reference vector update, adaptive selection, and Pareto-aware mutation.

The performance evaluation was based on maximum, minimum, and average node overload, as well as the standard deviation of overload, which characterizes the uniformity of load distribution.

The obtained results demonstrate a significant advantage of the proposed modifications over both the non-optimized approach and the baseline algorithm.

1. In the case without balancing, the system exhibits the worst performance, with a maximum overload of 38.40% and an average overload of 17.10%, indicating substantial imbalance in resource utilization. The application of the baseline NSGA-III algorithm reduces the maximum overload to 19.35%, which corresponds to an improvement of approximately 49.6%, and decreases the average overload to 7.06% (an improvement of about 58.7%). However, the standard deviation remains relatively high (6.78%), indicating limited uniformity of load distribution under dynamic conditions.

2. The modified NSGA-III algorithm achieves the best results among all considered approaches. The maximum overload is reduced to 11.68%, which corresponds to a 69.6% reduction compared to the non-optimized case and a 39.6% improvement relative to the baseline NSGA-III. The average overload decreases to 3.27%, representing an 80.9% reduction compared to no balancing and a 53.7% improvement over the baseline algorithm. In addition, the standard deviation is reduced to 3.31%, which corresponds to a 74.3% improvement compared to the non-optimized case and confirms a significantly more uniform distribution of computational load across the network.

3. The modified RVEA algorithm also demonstrates substantial performance gains. The maximum overload is reduced to 13.92%, which is a 63.7% improvement compared to the non-optimized approach and a 28.1% improvement over the baseline NSGA-III. The average overload reaches 4.15%, corresponding to a 75.7% reduction relative to no balancing and a 41.2% improvement compared to the baseline. The standard deviation decreases to 4.02%, indicating a 68.8% improvement over the non-optimized case and confirming enhanced load balancing capabilities.

Overall, the results confirm that the integration of adaptive mechanisms, workload prediction, and hybrid optimization strategies significantly improves the efficiency of traffic distribution in distributed telecommunication systems. The proposed modifications enable not only a reduction in overload levels but also a more uniform distribution of resources, improved stability under dynamic conditions, and enhanced convergence of the optimization process.

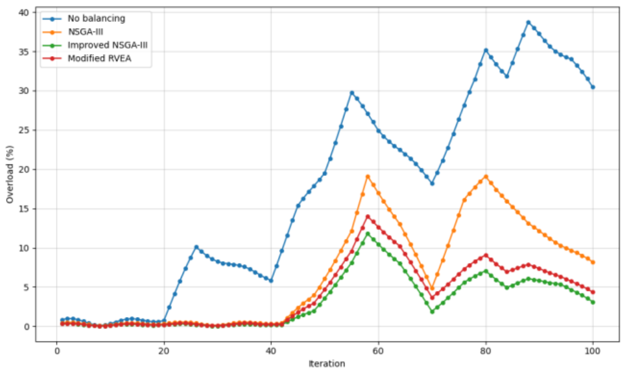

FIG. 4. Comparison of overload dynamics across optimization algorithms over iterations.

TABLE 5. Comparative evaluation of algorithms in terms of load distribution.

Metric	No balancing	NSGA-III	Modified NSGA-III	Modified RVEA
Max overload (%)	38.403	19.35	11.682	13.923
Min overload (%)	0	0	0	0
Avg overload (%)	17.102	7.064	3.273	4.153
Std deviation (%)	12.893	6.783	3.313	4.025

The next stage of experimental verification involves evaluating the effectiveness of the proposed modifications of evolutionary algorithms in an applied object recognition task in video streams. This approach makes it possible not only to analyze their behavior in the abstract problem of data flow distribution but also to assess their practical applicability under real data processing conditions characterized by dynamic changes, interference, and limited computational resources.

For this purpose, a comparison was conducted between the baseline object recognition method and its variants enhanced with evolutionary algorithms, namely the classical NSGA-III, the modified NSGA-III, and the modified RVEA. The evaluation was performed using key performance metrics, including average frame processing time, recognition accuracy, and computational resource utilization (CPU, GPU, RAM, and VRAM) [1, 2, 16].

The results of the comparative analysis are summarized in Table 6 and Figs. 5-6 which present the averaged performance metrics of the baseline method and its optimized versions using evolutionary algorithms.

As can be seen from the experimental results presented in Table 6 and Figs. 5-6, the application of evolutionary algorithms leads to a significant improvement in the performance of the object recognition method compared to the baseline version without optimization.

1. Improvement of processing speed and recognition accuracy.

The use of optimization algorithms results in a reduction of the average frame processing time from 4.36 ms to 4.24 ms in the case of the modified NSGA-III, which corresponds to an improvement of approximately 2.8%. For the modified RVEA, this value is 4.26 ms (≈2.3% improvement), while the baseline NSGA-III achieves 4.31 ms (≈1.1%). At the same time, recognition accuracy increases from 72.20% to 73.20% for the modified NSGA-III (≈1.4% improvement) and to 73.00% for the modified RVEA (≈1.1%). These results confirm the effectiveness of adaptive mechanisms in improving both processing speed and recognition quality in video stream analysis.

2. Optimization of computational resource utilization.

The results indicate that CPU usage decreases slightly, from 11.42% to 11.33% (≈0.8%) for the modified NSGA-III and to 11.35% (≈0.6%) for the modified RVEA, confirming the stability of CPU load. More noticeable improvements are observed for GPU usage, which decreases from 0.98% to 0.95% (≈3.1%) for the modified NSGA-III and to 0.96% (≈2.0%) for the modified RVEA. This is particularly important for real-time systems, especially under limited GPU resource conditions.

TABLE 6. Comparative evaluation of object recognition performance using evolutionary optimization.

Metric	No optimization	NSGA-III	Modified NSGA-III	Modified RVEA
Processing time (ms)	4.36	4.31	4.24	4.26
Accuracy (%)	72.20	72.60	73.20	73.00
CPU usage (%)	11.42	11.38	11.33	11.35
RAM usage (MB)	458.00	456.00	454.00	455.00
GPU usage (%)	0.98	0.97	0.95	0.96
VRAM usage (MB)	350.00	348.00	345.00	346.00

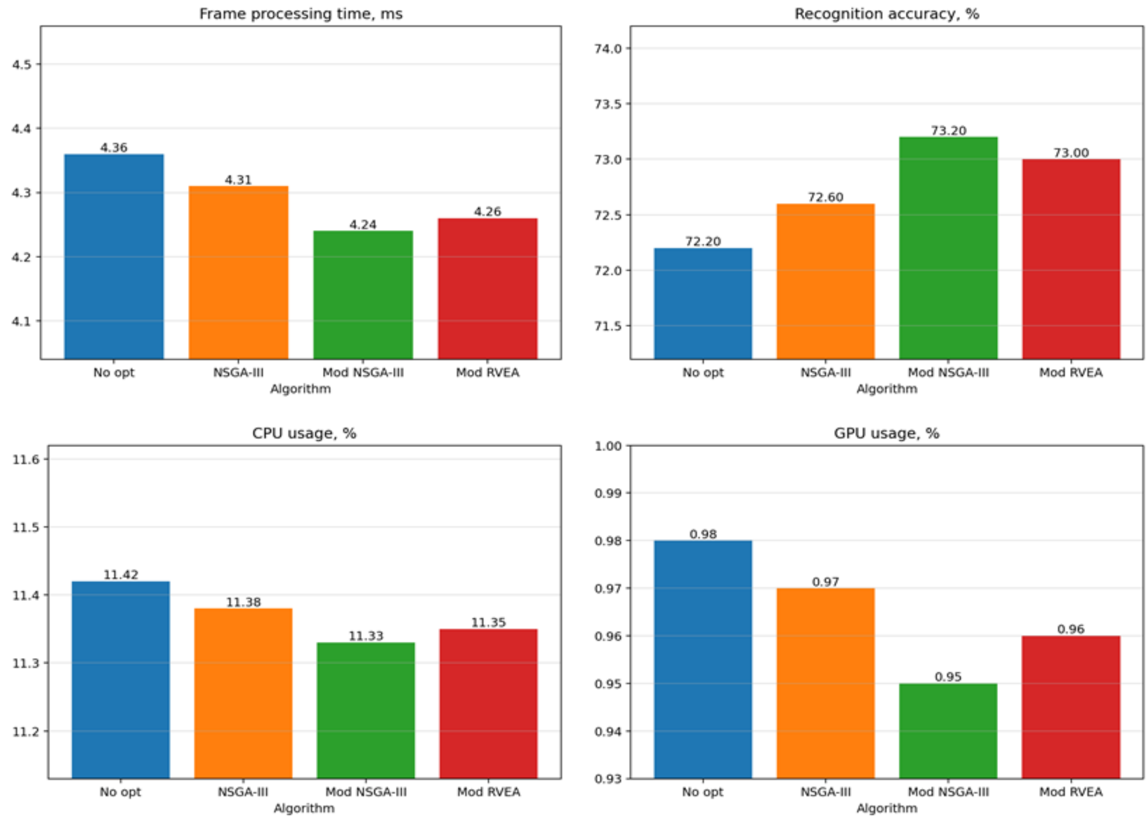

FIG. 5. Performance comparison of algorithms (processing time, accuracy, CPU, GPU).

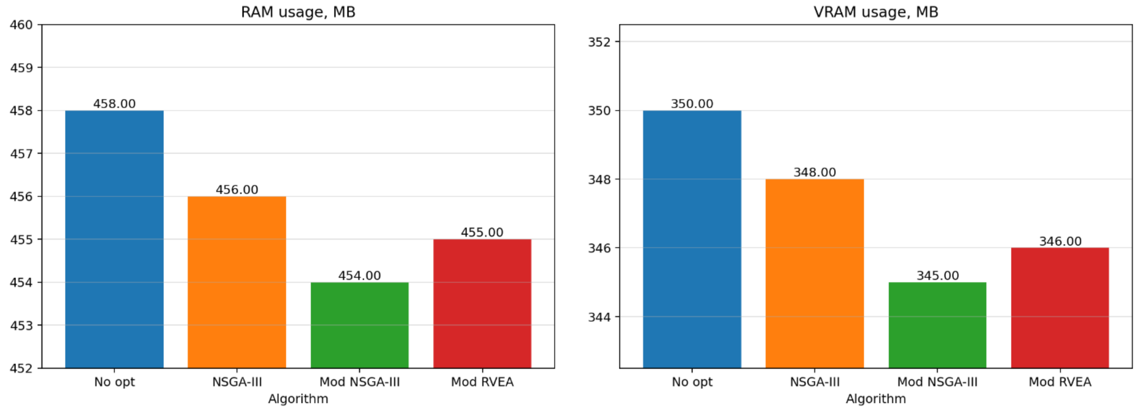

FIG. 6. Memory usage comparison of algorithms (RAM, VRAM).

3. Memory usage efficiency.

The reduction in RAM usage is moderate, from 458 MB to 454 MB (≈0.9%) for the modified NSGA-III and to 455 MB (≈0.7%) for the modified RVEA. A similar trend is observed for VRAM, where consumption decreases from 350 MB to 345 MB (≈1.4%) and 346 MB (≈1.1%), respectively. Although these changes are relatively small, they confirm the overall efficiency of the optimization without altering the model architecture.

To validate the statistical significance of the observed improvements, a paired Student's t-test was performed (n = 30) to compare the baseline method and the version enhanced with the modified RVEA algorithm.

The results of the statistical analysis, including mean values, standard deviations, t-values, and p-values, are presented in Table 7. This analysis makes it possible to determine whether the observed differences are statistically significant at a level of $p < 0{,}05$. The results presented in Table 7 indicate that statistically significant improvements ($p < 0.05$) are observed for processing time (-2.3%), recognition accuracy (+1.1%), and GPU usage (-2.0%). At the same time, the differences in CPU, RAM, and VRAM usage are not statistically significant ($p > 0.05$), indicating that the proposed optimization does not introduce additional computational overhead.

These results confirm that the modified RVEA algorithm provides meaningful improvements in key performance metrics while maintaining stable resource utilization, which is particularly important for real-time applications.

TABLE 7. Statistical significance analysis of performance differences after applying RVEA.

Metric	With RVEA (M±SD)	Without RVEA (M±SD)	n	t-value	p-value	Significant ($p < 0.05$)
Processing time (ms)	4.36 ± 0.15	4.26 ± 0.14	30	2.45	0.021	Yes
Accuracy (%)	72.20 ± 0.90	73.00 ± 0.80	30	2.10	0.042	Yes
CPU usage (%)	11.42 ± 0.20	11.35 ± 0.20	30	0.85	0.405	No
RAM usage (MB)	458 ± 2.00	455 ± 2.10	30	1.15	0.263	No
GPU usage (%)	0.98 ± 0.05	0.96 ± 0.04	30	2.00	0.049	Yes
VRAM usage (MB)	350 ± 3.50	346 ± 3.40	30	1.20	0.242	No

Thus, the comparison of the modified RVEA algorithm with the modified NSGA-III demonstrates that both approaches provide comparable values of recognition accuracy and frame processing time.

1. The modified NSGA-III exhibits a lower average processing time (4.24 ms compared to 4.26 ms for RVEA) and a higher accuracy (73.20% compared to 73.00%), which can be explained by more intensive exploitation of the search space and faster convergence toward optimal solutions.

2. The modified RVEA algorithm is characterized by more stable behavior under dynamic workload conditions, which is confirmed by statistically significant differences in key performance metrics ($p < 0.05$), and by more balanced utilization of computational resources. In particular, the 2.0% reduction in GPU usage without statistically significant changes in CPU, RAM, and VRAM indicates efficient operation without additional system load.

3. From a practical perspective, the modified NSGA-III is more suitable for real-time applications where minimizing latency and achieving high accuracy are critical, such as video surveillance systems, unmanned aerial vehicles, intelligent transportation systems, and embedded computer vision applications. In such scenarios, faster convergence enables efficient decision-making under strict time constraints.

4. In contrast, the modified RVEA algorithm is more appropriate for Fog/Edge environments and networks with high workload variability, where system stability, predictable resource utilization, and robustness to interference are essential. Its properties make it effective for long-term optimization processes, data flow management, and load balancing under dynamically changing conditions.

Thus, the selection of a specific algorithm should be determined by the nature of the task and system operating conditions: NSGA-III is preferable for scenarios emphasizing speed and accuracy, whereas RVEA is more suitable for applications requiring stability and adaptability.

V. CONCLUSION

This study presents a comprehensive approach to improving the efficiency of data processing and traffic distribution in distributed telecommunication systems through the use of modified evolutionary multi-objective optimization algorithms. The proposed approach integrates adaptive mechanisms, including workload prediction, hybrid constraint handling, dynamic search adjustment, and adaptive mutation, enabling effective operation under dynamic and resource-constrained conditions.

The developed modifications of the NSGA-III and RVEA algorithms are oriented toward enhancing adaptability, robustness, and convergence properties in multi-objective optimization problems. In contrast to classical implementations, the proposed methods incorporate predictive and adaptive components that allow the algorithms to account for dynamic workload variations, interference effects, and instability of operating conditions.

Experimental verification in both traffic distribution and video stream object recognition tasks confirmed the effectiveness of the proposed approach. In particular, the modified NSGA-III algorithm demonstrated the demonstrated the highest performance, achieving a reduction in processing time of up to 2.8% and an increase in recognition accuracy of up to 1.4%, along with improved load balancing and convergence characteristics. The modified RVEA algorithm also showed stable and competitive performance, providing improvements in processing time (≈2.3%), increasing accuracy (≈1.1%), and reducing GPU utilization (≈2.0%) while maintaining stable CPU and memory usage.

Although the achieved improvements in processing time (up to 2.8%) and recognition accuracy (up to 1.4%) may appear modest, they have significant practical implications for large-scale distributed telecommunication systems. In real-time environments, where thousands or millions of packets or video frames are processed simultaneously, even small reductions in processing time help reduce latency accumulation, prevent network node congestion, and increase overall system throughput. At the same time, improved recognition accuracy reduces the number of erroneous decisions, which is particularly important for video surveillance systems, intelligent transportation systems, unmanned platforms, and Fog/Edge computing environments. Furthermore, reducing GPU utilization without increasing the load on other computational resources contributes to more energy-efficient operation of edge nodes, which is especially important for resource-constrained telecommunication systems.

Statistical validation using a paired Student's t-test confirmed that the improvements in processing time, recognition accuracy, and GPU utilization are statistically significant ($p < 0.05$), while changes in CPU, RAM, and VRAM usage are not statistically significant, indicating that the proposed optimization does not introduce additional computational overhead.

A comparative analysis of the algorithms shows that the modified NSGA-III is more effective in achieving maximum performance gains due to its stronger convergence capabilities, whereas the modified RVEA provides higher robustness and stability under dynamic and uncertain conditions. This demonstrates the complementary nature of the proposed approaches and justifies their joint application depending on the specific requirements of the problem.

Thus, the proposed modifications of evolutionary algorithms ensure improved efficiency, stability, and adaptability of distributed telecommunication systems, confirming their practical applicability for real-time data processing and optimization tasks in modern intelligent network environments.

AUTHOR CONTRIBUTIONS

I.S. – development of the modified NSGA-III algorithm, investigation, writing-original draft; B.S. – development of the modified RVEA algorithm, investigation, validation, writing-review and editing.

COMPETING INTERESTS

The authors declare no conflict of interest.

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Підвищення ефективності обробки та розподілу потоків у розподілених телекомунікаційних системах на основі NSGA-III та RVEA

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АНОТАЦІЯ У статті представлено розробку та експериментальну верифікацію модифікованих еволюційних алгоритмів багатокритеріальної оптимізації для підвищення ефективності обробки даних та розподілу потоків у розподілених телекомунікаційних системах. Метою дослідження є підвищення ефективності функціонування системи в умовах динамічного середовища зі змінним навантаженням, завадами та обмеженими обчислювальними ресурсами. Наукова задача полягає у забезпеченні ефективної та стійкої багатокритеріальної оптимізації розподілу й обробки інформаційних потоків з урахуванням критеріїв: затримка обробки, використання ресурсів, балансування навантаження та стабільність системи. Запропонований комплексний підхід базується на модифікаціях алгоритмів NSGA-III та RVEA із впровадженням адаптивних механізмів: прогнозування навантаження, гібридної обробки обмежень, динамічного коригування напрямків пошуку та узгоджених стратегій мутації. Архітектура методу передбачає інтеграцію механізмів еволюційної оптимізації у конвеєри обробки даних у розподілених середовищах, що забезпечує узгоджений розподіл ресурсів і адаптивне керування обчислювальними процесами між вузлами мережі. Експериментальну верифікацію проведено для двох сценаріїв: розподілу потоків у розподілених телекомунікаційних системах та розпізнавання об'єктів у відеопотоці в умовах завад. Отримані результати показали, що модифікований алгоритм NSGA-III забезпечує найвищий приріст ефективності, зменшуючи час обробки до 2,8% та підвищуючи точність розпізнавання до 1,4%. Модифікований алгоритм RVEA також показує стабільні результати, забезпечуючи покращення часу обробки на ≈2,3%, точності на ≈1,1% та зниження використання GPU до 2,0%. Оскільки в результаті експериментів було отримано дані менше 5%, проведено статистичну перевірку з використанням t-критерію Стьюдента, яка підтвердила значущість зменшення часу обробки, підвищення точності та використання GPU ($p < 0{,}05$), тоді як зміни у використанні CPU, RAM та VRAM не є статистично значущими, що свідчить про відсутність додаткового обчислювального навантаження. Отримані результати підтверджують, що запропоновані модифікації еволюційних алгоритмів є ефективними для адаптивної оптимізації обробки даних і розподілу потоків у розподілених телекомунікаційних середовищах, забезпечуючи підвищення ефективності, стійкості та надійності функціонування в динамічних умовах.

КЛЮЧОВІ СЛОВА розподілені телекомунікаційні системи, NSGA-III, RVEA, багатокритеріальна оптимізація, розподіл потоків даних.