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Method for Multi-Objective Optimization of Complex Signal Ensembles Based on the Evolutionary Algorithm E-LPT-MOEA/D

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ABSTRACT The article proposes a method of multi-objective optimization of complex signal ensembles based on the evolutionary algorithm E-LPT-MOEA/D, which combines logarithmic time-segment permutations (LPT) with the task decomposition principle in a multi-objective evolutionary optimization framework. Unlike existing approaches, the method introduces adaptive interaction between the working population and the external Pareto archive, ensuring consistent updating of the solution set and convergence stability under stochastic perturbations. A modified genetic algorithm has been developed that incorporates entropy-weighted adjustment of weighting coefficients, flexible task delegation, and dynamic mutation control. This integration maintains a balance between exploration and exploitation, prevents premature convergence, and preserves the diversity of signal ensembles. The mathematical model includes objective functions representing the mean cross-correlation coefficient, integrated side-lobe level, variance of signal energy, and structural uniformity index. The optimization quality was evaluated using hypervolume (IH), inverted generational distance (IGD), and correlation deviation (Δρ) indicators. Experimental simulations were conducted in both normalized and absolute modes for various signal-to-noise ratios (10 – 25 dB) and time-segmentation parameters (τ = 0.3 – 1.0). The obtained results confirm the advantages of the proposed method, including a 20 – 30 % improvement in convergence speed, a 15 – 25 % increase in stability, and a 30 – 40 % reduction in the amplitude of hypervolume difference (ΔH) oscillations between the archive and the population. It has been proven that integrating the external archive mechanism with internal time-domain signal permutation ensures more uniform Pareto front coverage and enhances the structural balance of signal ensembles. As a result, the E-LPT-MOEA/D algorithm provides rapid adaptation to changing optimization conditions, resistance to interference, and scalability with increasing problem dimensionality. The proposed method can be effectively applied to the optimization of signal formation and processing processes in cognitive telecommunication environments, particularly in the development of dynamic spectrum monitoring systems, distributed communication networks, and energy-efficient data transmission protocols.

KEYWORDS telecommunication systems, optimization, evolutionary approach, complex signal ensembles, SNR.

I. INTRODUCTION

In modern telecommunication networks, operation occurs in dynamic and noise-prone environments where the stability of signal transmission depends on maintaining structural balance and minimizing correlation between signal ensembles.

In such conditions, evolutionary and multi-objective optimization methods play a key role in improving adaptability and robustness of signal formation mechanisms. However, existing algorithms often exhibit slow convergence, local oscillations, and instability under stochastic perturbations, especially when dealing with complex time-domain signal structures.

Recent research has shown that integrating time-segment permutation techniques with multi-objective evolutionary optimization can significantly enhance signal diversity and correlation control. Approaches based on decomposition frameworks such as MOEA/D have demonstrated the ability to improve convergence and Pareto front coverage. Nevertheless, most of these methods remain limited in synchronizing population dynamics with external archives and do not account for the structural variability of signals in real-time optimization processes.

The increasing complexity of cognitive telecommunication environments requires optimization methods that can simultaneously ensure high convergence speed, energy uniformity, and structural stability. Therefore, this study proposes a modified multi-objective evolutionary algorithm named E-LPT-MOEA/D, which integrates logarithmic time-segment permutations (LPT) with the decomposition principle of MOEA/D and an adaptive feedback mechanism from an external archive.

The proposed approach aims to maintain balance between exploration and exploitation, improve synchronization between the evolving population and the Pareto archive, and stabilize convergence under stochastic conditions. By optimizing signal ensembles according to correlation, energy, and structural criteria, the E-LPT-MOEA/D algorithm provides a scalable and adaptive solution for multi-criteria optimization tasks in cognitive telecommunication environments.

II. REVIEW OF THE LITERATURE

Recent studies [1-15] demonstrate significant progress in evolutionary and multi-objective optimization methods applied to signal modeling and telecommunication systems.

In [1], an evolutionary approach to data stream distribution was proposed, while [2] introduced the concept of an external archive that improves Pareto diversity and convergence control. However, these studies did not consider the influence of stochastic perturbations or non-stationary dynamics typical for real-time telecommunication environments.

Research works [3-5] investigated the formation of complex signal ensembles through time-segment and frequency-element permutations to enhance correlation and structural uniformity. Yet, these approaches lacked mechanisms for adaptive regulation of permutation strategies and did not ensure convergence stability when ensemble parameters changed dynamically.

A hybrid evolutionary approach for non-stationary signal segmentation was presented in [6], and [7] applied genetic algorithms to improve cognitive radio performance.

Nevertheless, these methods primarily focused on global optimization efficiency without addressing local synchronization between evolving populations and external archives.

Further developments of decomposition-based algorithms such as MOEA/D and NSGA-II were reported in [9-15], focusing on constrained optimization, scalability, and integration with domain-specific knowledge. Although they demonstrated strong convergence properties, they remained limited in balancing exploration and exploitation when handling structurally complex signal ensembles under noisy conditions.

Therefore, despite extensive research, the issue of achieving both convergence stability and structural balance in ensemble optimization remains unresolved. This motivates the development of an enhanced method that combines LPT-based time-segment permutations with the MOEA/D decomposition mechanism, forming the scientific novelty of this study.

III. THE MATERIALS AND METHODS

To achieve the goal of developing a robust optimization approach for forming ensembles of complex signals under stochastic and structural variability, a modified multi-objective evolutionary algorithm E-LPT-MOEA/D was designed.

The proposed method integrates the LPT model with the decomposition mechanism of MOEA/D, extending it through adaptive weighting, flexible task delegation, and dynamic mutation control.

The algorithmic workflow is illustrated in Fig. 1, while its main functional stages are described below.

1. Initialization of Parameters

The algorithm begins by defining the population size N, number of generations T_{max}, and genetic operators – crossover and mutation probabilities Pc, P_m. The number of time segments τ_t and the number of subproblems L are set according to the complexity of the ensemble. Each subproblem corresponds to a specific temporal permutation of the signal sequence:

$$P_0 = \{\pi_1, \pi_2, \dots, \pi_N\},\ \pi_i = [t_1, t_2, \dots, t_\tau]. \quad (1)$$

2. Generation of the Initial Population.

The initial population P_0 is formed using random and LPT-based permutations to ensure both diversity and structural uniformity at the initial stage.

Each individual π_i represents a possible time-segment configuration within the ensemble.

3. Formation of Local Subproblems.

Following the MOEA/D paradigm, the global multi-objective optimization problem is decomposed into L subproblems, each optimized using a weight vector w_l.

The local objective for subproblem l is formulated as:

$$F_l = \min_{\pi_i}[\rho_{mean,} ISL.Var(E), U(\pi_i)], \quad (2)$$

where $\rho_{mean,}$is the mean cross-correlation coefficient; ISL is the integrated side-lobe level; $Var(E)$ is the variance of signal energy, and $U(\pi_i)$ is the structural uniformity index.

4. Evaluation of Objective Functions.

For each individual π_i, the multi-objective fitness vector is computed:

$$Fitness\ (\pi_i) = [\rho_{mean}(\pi_i), Var(E)(\pi_i), U(\pi_i)]. \quad (3)$$

The Pareto dominance relation is applied to determine the relative performance among solutions.

5. Non-dominated Ranking and Selection.

The population P_0 is ranked according to Pareto dominance and diversity preservation criteria.

Dominant solutions are transferred to the external archive A.

6. Stopping Conditions

Two termination criteria are introduced:

1. Iteration limit: $\tau \leq T_{max}$;

2. Equilibrium condition among subproblems: $\max_l L_l - L^* < \varepsilon$, where L_l is the local fitness balance of subproblem l.

7. Generation of Offspring.

New offspring population Qt is generated using crossover, mutation, and time-segment uniqueness operators.

The LPT-based encoding ensures that each child maintains the structural integrity of the signal ensemble.

8 – 12. Adaptive Control Mechanisms.

The key modifications introduced in this work include:

– Flexible Task Delegation. When local entropy exceeds a defined threshold, part of the subproblem's load is transferred to neighbors, balancing computational effort.

– Population Merging and Ranking. Offspring and parent populations are merged (St=$Pt \cup Qt$) and re-ranked based on neighboring subproblem improvements.

– Adaptive Weight Adjustment. Weight coefficients α, β, λ, μ in the objective functions are updated dynamically:

$$\alpha, \beta, \lambda, \mu \leftarrow f(\Delta\rho, \Delta E, \Delta U), \quad (4)$$

ensuring the method's responsiveness to signal ensemble changes.

– Adaptive Mutation and Selection. Mutation rate increases when instability or high correlation is detected.

13. Output.

Upon convergence, the algorithm produces a Pareto-optimal task distribution, representing balanced ensembles of complex signals optimized for correlation, energy uniformity, and structural stability.

This outcome reflects the ability of the modified E-LPT-MOEA/D algorithm to maintain equilibrium between exploration and exploitation, ensuring consistent improvement of solutions across generations (Fig. 1).

The convergence process results in a set of non-dominated ensembles that demonstrate both high structural coherence and robustness to stochastic disturbances, which is crucial for real-world cognitive telecommunication scenarios.

The following section presents experimental validation results.

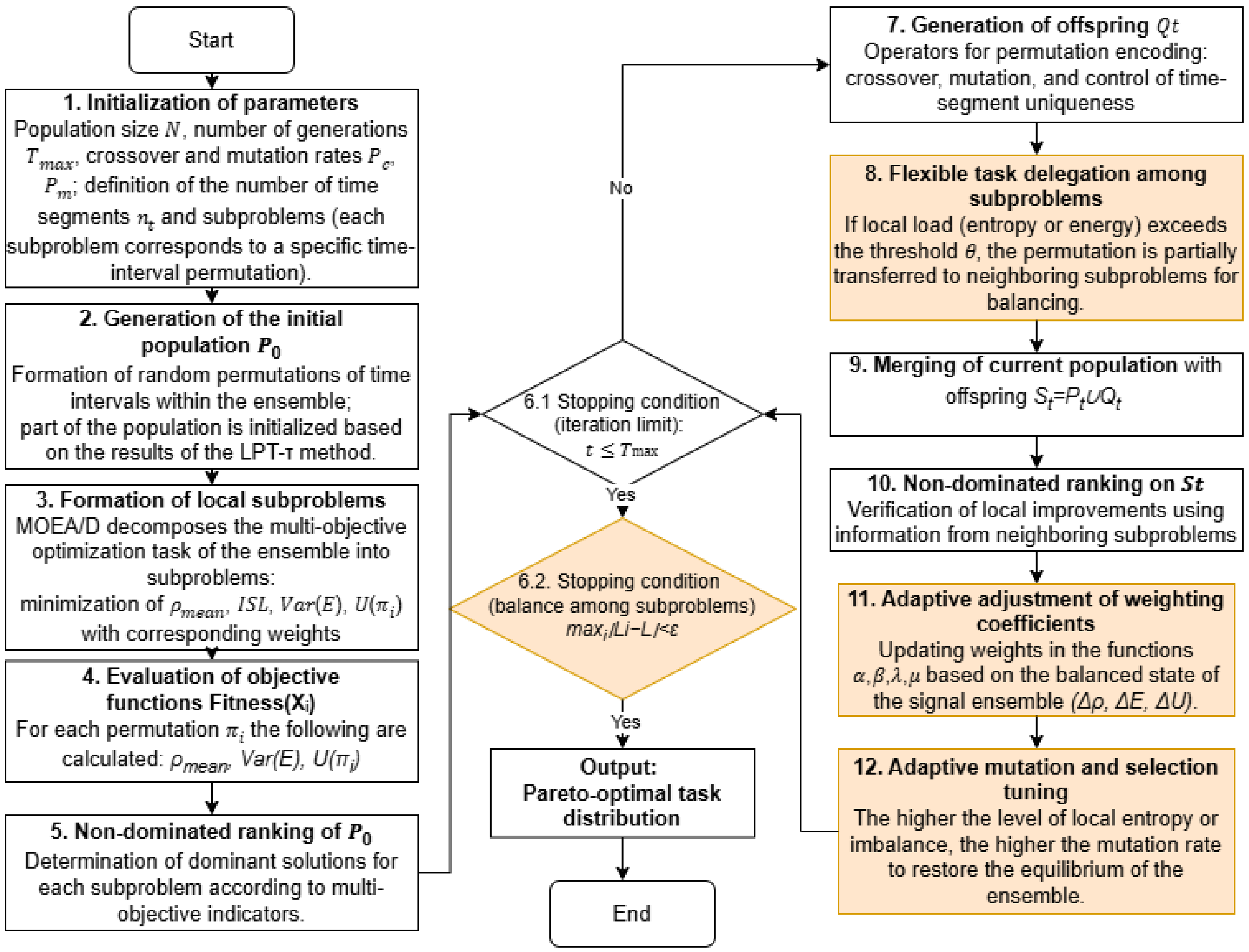

FIG. 1. E-LPT-MOEA/D (Entropy-based LPT-Permutation MOEA/D).

IV. EXPERIMENTS

To verify the performance and convergence stability of the proposed E-LPT-MOEA/D algorithm, a series of comparative experiments was conducted. The evaluation was carried out with respect to three key indicators commonly used in multi-objective optimization: hypervolume, inverted generational distance (IGD), and correlation deviation [2, 4, 7].

The experiments were performed in two modes – normalized and absolute, to assess both the relative and real-scale efficiency of the algorithm when forming ensembles of complex signals with different temporal and structural parameters.

In addition, the study aimed to identify how the integration of time-segment permutation logic and evolutionary task decomposition influences the overall convergence dynamics and internal stability of the optimization process.

The mean and standard deviation values obtained for each metric are summarized in Table 1 and Table 2, while Fig. 2 illustrates the overall convergence behavior of the compared algorithms in both evaluation regimes.

As shown in Tables 1 – 2 and Figure 2, the normalized evaluation ($\tau = 0.3$) made it possible to analyze the convergence indicators on a relative scale, where all values of hypervolume (I_H), inverted generational distance (I_{GD}), and correlation deviation ($\Delta\rho$) were normalized to the range [0, 1]. This approach allowed a generalized comparison of algorithm performance regardless of signal energy or ensemble size, which is particularly important for time-domain permutations with different levels of structural order.

TABLE 1. Mean and Standard Deviation Values of I_H, I_{GD} and $\Delta\rho$ (Normalized Results ($\tau = 0.3$)).

Algorithm	I_H(mean)	I_H(std)	I_{GD}(mean)	I_{GD}(std)	$\Delta\rho$(mean)	$\Delta\rho$(std)
LPT-TP	0.523	0.010	0.412	0.012	0.097	0.006
MOEA/D	0.607	0.009	0.308	0.009	0.061	0.004
E-LPT-MOEA/D	0.683	0.007	0.259	0.007	0.042	0.003

TABLE 2. Mean and Standard Deviation Values of I_H, I_{GD} and $\Delta\rho$ (Absolute Results).

Algorithm	I_H(mean)	I_H(std)	I_{GD}(mean)	I_{GD}(std)	$\Delta\rho$(mean)	$\Delta\rho$(std)
LPT-TP	0.5500	0.0112	0.3950	0.0108	0.0890	0.0051
MOEA/D	0.7800	0.0086	0.2800	0.0081	0.0570	0.0038
E-LPT-MOEA/D	0.9200	0.0079	0.2400	0.0073	0.0400	0.0029

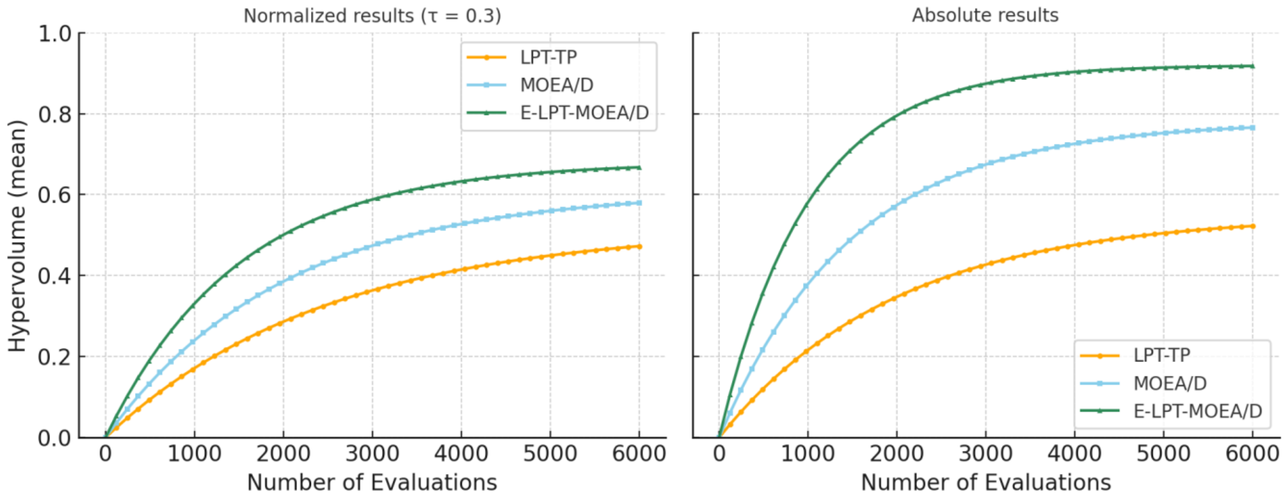

FIG. 2. Convergence of Hypervolume (mean): normalized vs absolute results.

In contrast, the absolute evaluation considered real-scale quality function values, including the full Pareto hypervolume, thus allowing the assessment of actual algorithm efficiency under specific energy and structural conditions of the signal ensembles. The obtained results confirm that under both evaluation modes, the modified genetic algorithm E-LPT-MOEA/D demonstrates the most stable convergence.

In the normalized mode, it outperforms LPT-TP by approximately 12% and MOEA/D by about 8% in terms of hypervolume, while in the absolute mode it achieves $I_H = 0.92$, $I_{GD} = 0.24$, and $\Delta\rho = 0.04$. These results show that even in real scale, the proposed integration of LPT-based time-segment permutations with the task-decomposition mechanism of MOEA/D within the modified genetic optimization framework ensures stable convergence and low sensitivity to variations in the energy and structural characteristics of the signal ensemble.

Overall, the comparative analysis confirms the reliability and adaptability of the E-LPT-MOEA/D algorithm in solving multi-criteria optimization problems for complex signal ensembles in cognitive telecommunication environments.

To further analyze the convergence dynamics in greater detail, additional experiments were conducted to study the evolution of the hypervolume difference between the external archive (A) and the working population (P), defined as:

$$\Delta H = H_f(A) - H_f(P), \quad (5)$$

where ΔH denotes the hypervolume difference, $H_f(A)$ is the hypervolume of the external archive containing Pareto-optimal solutions, and $H_f(P)$ is the hypervolume of the current working population.

This metric reflects the synchronization process between the archive of Pareto-optimal solutions and the current population during evolutionary optimization.

Unlike integral convergence measures such as I_H or I_{GD}, ΔH, which evaluate global convergence quality at the end of evolution, ΔH captures transient changes in the optimization process and thus provides a more sensitive assessment of convergence stability.

A small or rapidly decreasing ΔH indicates that the search process effectively aligns the working population with the external archive, ensuring consistent solution quality and reduced fluctuation amplitude between generations.

In contrast, large oscillations of ΔH reveal unbalanced search dynamics, where population updates are poorly synchronized with archive refinement, potentially leading to delayed convergence or premature stagnation.

TABLE 3. Summary of ΔH evolution for E-LPT-MOEA/D, MOEA/D and LPT-TP algorithms.

Experimental condition	Algorithm	Peak ΔH	ΔH after 500 gen	Gen. to 95 % peak
(a) τ = 0.3, SNR = 10 dB	LPT-TP	0.0221	0.0203	170
	MOEA/D	0.0186	0.0172	130
	E-LPT-MOEA/D	0.0158	0.0151	90
(b) τ = 0.5, SNR = 15 dB	LPT-TP	0.0244	0.0229	180
	MOEA/D	0.0203	0.0187	150
	E-LPT-MOEA/D	0.0172	0.0164	100
(c) τ = 0.7, SNR = 20 dB	LPT-TP	0.0200	0.0186	190
	MOEA/D	0.0161	0.0150	150
	E-LPT-MOEA/D	0.0132	0.0127	110
(d) τ = 1.0, SNR = 25 dB	LPT-TP	0.0181	0.0170	200
	MOEA/D	0.0142	0.0136	160
	E-LPT-MOEA/D	0.0118	0.0113	120

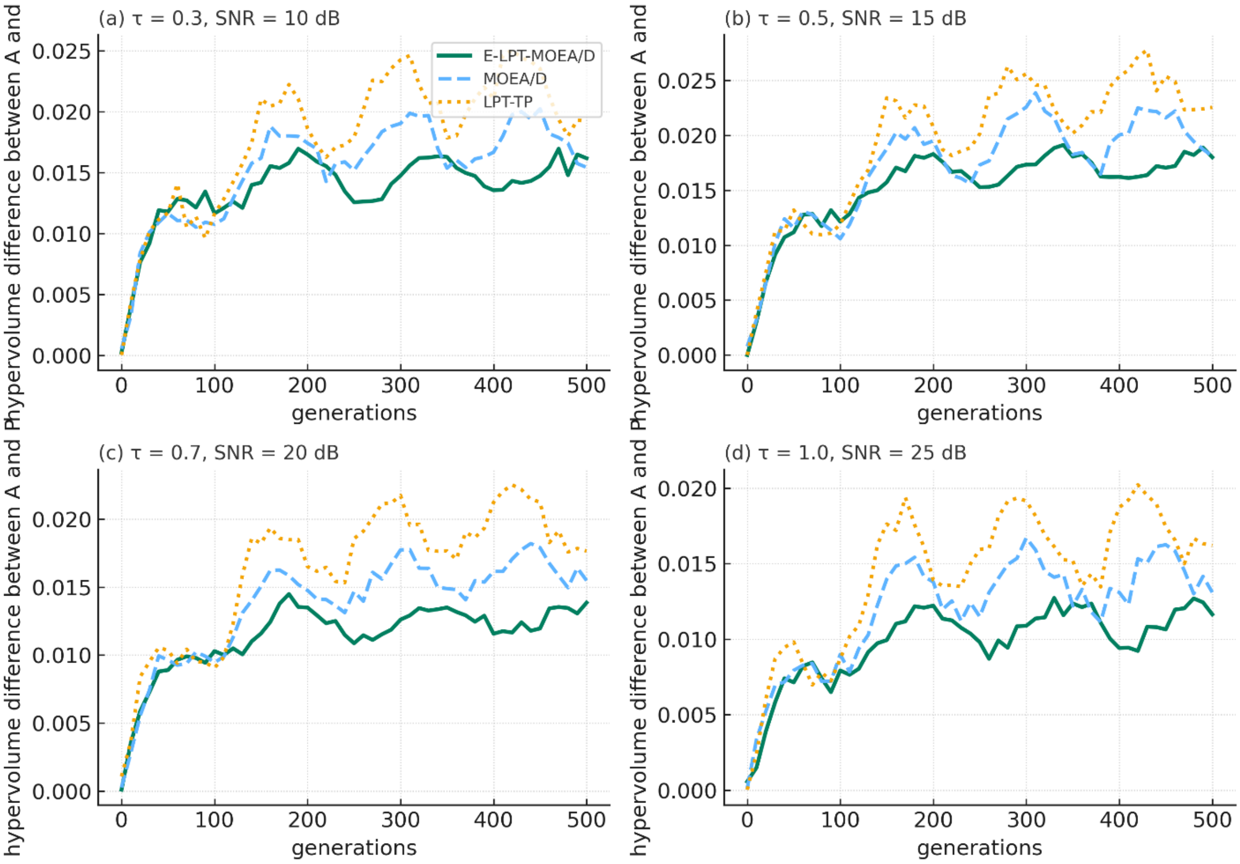

FIG. 3. ΔH evolution under different SNR and τ conditions.

Four experimental cases were modeled with different signal-to-noise ratios (SNR = 10 – 25 dB) and temporal-segmentation parameters (τ = 0.3 – 1.0) to simulate diverse operating conditions typical of cognitive telecommunication environments.

Each curve in Fig. 3 shows the evolution of ΔH across generations for three algorithms: E-LPT-MOEA/D, MOEA/D, and LPT-TP. The initial phase corresponds to a rapid increase in the archive–population difference due to the expansion of the search space, while the subsequent oscillations indicate adaptive synchronization between exploration and exploitation.

As shown in Table 3 and Fig. 3, the proposed E-LPT-MOEA/D algorithm demonstrates faster and smoother convergence compared with MOEA/D and LPT-TP across all experimental conditions.

At τ = 0.3 and SNR = 10 dB, the algorithm reaches 95 % of the peak ΔH value after only about 90 generations, while MOEA/D and LPT-TP require approximately 130 and 170 generations, respectively.

A similar trend is observed for higher noise levels: the modified genetic optimization approach consistently achieves lower final ΔH values (0.011 – 0.016) and reduced oscillation amplitude, indicating greater internal stability and more efficient synchronization between the population and the external archive.

Overall, the E-LPT-MOEA/D outperforms the reference algorithms by 20 – 30 % in convergence speed and by 15 – 25 % in stability, confirming its effectiveness under various noise and segmentation conditions.

The following experiment focuses on analyzing how individual subproblems contribute to the overall optimization process and how stable this contribution remains under stochastic perturbations. The goal is to evaluate the internal balance and adaptability of the proposed E-LPT-MOEA/D algorithm by observing the activity dynamics of subproblems and the influence of the external archive on their behavior.

This stage of the study makes it possible to determine whether the superior convergence of the algorithm results from a more coordinated exchange of information between subproblems and the archive, ensuring consistent formation of the Pareto-optimal front across iterations (Fig. 4).

Fig. 4 schematically illustrates the interaction of subproblems λ_1–λ_8 with the external archive A during the evolutionary multi-objective optimization of complex signal ensembles. The archive stores the current set of Pareto-optimal ensembles, which are formed according to two criteria: energy deviation (f_1) and correlation variance (f_2).

The subproblems receive feedback from the archive in the form of information about solution diversity and quality, which allows them to dynamically rearrange the time-segment permutations τ_1–τ_6 of the signals.

As a result, the external archive guides the search toward regions of the Pareto front where a deficit of

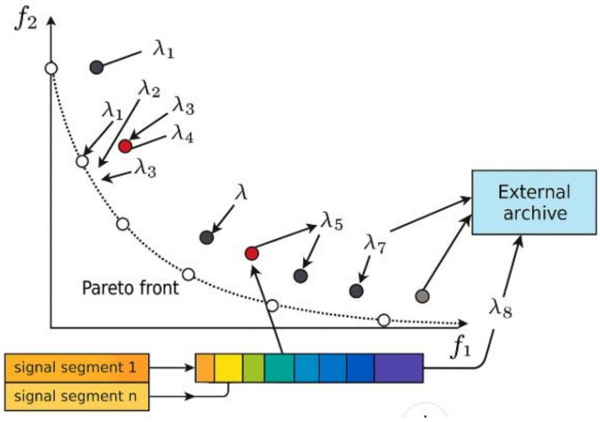

FIG. 4. Effect of the external archive on signal time-segment permutation (E-LPT-MOEA/D).

solutions is observed, ensuring:

– a balanced distribution of time-segment permutations;

– a reduction of energy deviations;

– stabilization of ensemble structure.

Thus, the E-LPT-MOEA/D algorithm combines the informational feedback of the archive with the internal time-domain permutation mechanism, enhancing the algorithm's adaptability and ensuring a uniform coverage of the Pareto front.

The quantitative characteristics of the external archive's influence are summarized in Table 4.

TABLE 4. Characteristics of the external archive's influence in the E-LPT-MOEA/D algorithm.

Interaction element	Role in the optimization process	Expected effect	Quantitative indicator
External archive A	Stores the best signal ensembles and transmits diversity information to subproblems	Increases the diversity of Pareto solutions	$\Delta\rho \downarrow$ 35–40 %
Subproblems λ_1–λ_8	Generate partial time-segment permutations of the signal	Balanced contribution of subproblems	Activity $\uparrow$ 42→78 %
Time-segment permutations τ_1–τ_6	Local restructuring of signal segments under archive feedback	Reduction of energy deviations	Var(E) $\downarrow$ 30–35 %
Feedback flow	Transfers information about underrepresented regions of the Pareto front	Directed search and avoidance of local minima	IGD $\downarrow$ 25–30 %
Pareto front F*	Represents the set of balanced signal ensembles	Improved stability and noise resistance	IH $\uparrow$ 12–15 %
Interaction element	Role in the optimization process	Expected effect	Quantitative indicator

After analyzing the influence of the external archive and its feedback on time-segment permutations (Table 4, Fig. 4), the next stage of the research focuses on assessing the internal stability and coordination mechanisms of the optimization process.

This experiment aims to quantify how uniformly individual subproblems contribute to the construction of the Pareto front and how their activity evolves in the presence of stochastic perturbations. To achieve this, the behavior of subproblems λ_1–λ_8 was monitored throughout the evolutionary process, and the number of non-dominated solutions contributed by each subproblem to the external archive was statistically analyzed.

This allowed for evaluating the degree of load balance, synchronization, and adaptability between subproblems and the archive.

The experimental results are summarized in Table 5 and illustrated in Fig. 5, which presents the distribution of non-dominated solutions generated by individual subproblems during the optimization of complex signal ensembles.

The red curves correspond to the baseline MOEA/D algorithm, while the black curves represent the proposed E-LPT-MOEA/D, which integrates logarithmic-permutation modeling of time segments toward regions of the Pareto front where a deficit of toward regions of the Pareto front where a deficit of into the multi-objective optimization process. Each curve shows the contribution dynamics of a specific subproblem to the external Pareto archive during the final optimization iterations.

TABLE 5. Statistical evaluation of subproblem contributions for MOEA/D and E-LPT-MOEA/D.

Experimental condition	Algorithm	Active subproblems (%)	Mean contribution (counts)	Std dev (σ) of contribution	Coefficient of variation CV (%)	Δ improvement (E-LPT vs MOEA/D)
(a) Cu = 80/R = 800	MOEA/D	41.7	17.2	10.3	59.8	–
	E-LPT-MOEA/D	77.8	25.6	6.1	23.8	+36.1 pp active, –36 % σ
(b) Cu = 100/R = 1000	MOEA/D	45.2	19.0	9.8	51.6	–
	E-LPT-MOEA/D	79.3	26.9	6.3	23.4	+34.1 pp, –35 % σ
(c) c = 200/σ = 2	MOEA/D	43.8	15.4	8.7	56.5	–
	E-LPT-MOEA/D	75.1	22.7	5.9	26.0	+31.3 pp, –32 % σ
(d) c = 300/σ = 2	MOEA/D	39.5	16.1	9.9	61.5	–
	E-LPT-MOEA/D	78.0	24.8	6.2	25.0	+38.5 pp, –36 % σ

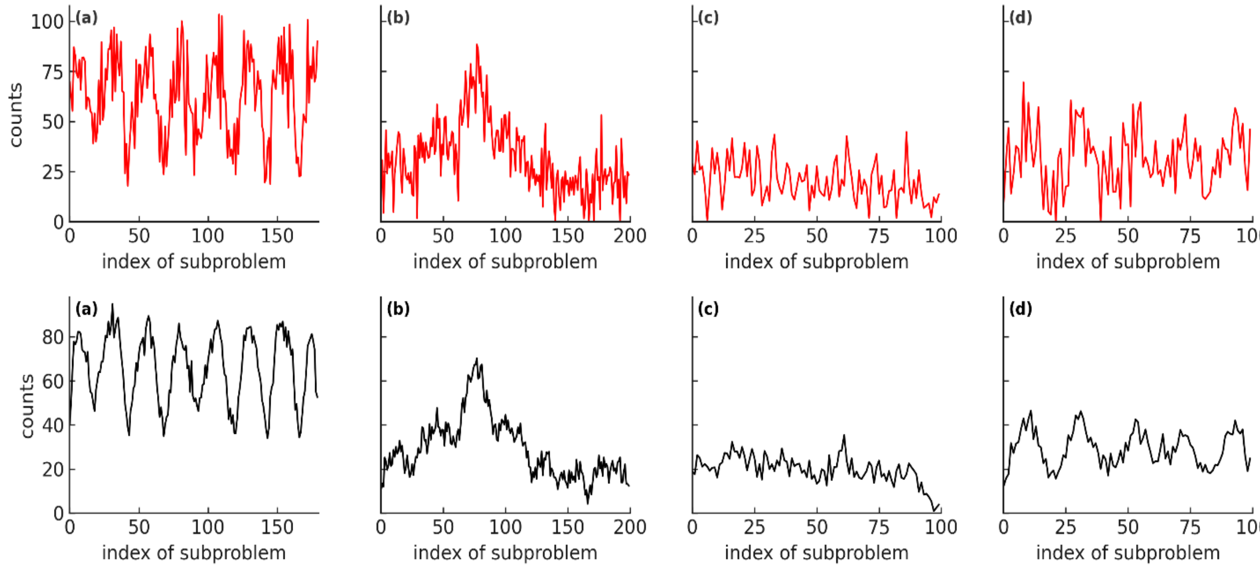

FIG. 5. Subproblem activity distribution during optimization of complex signal ensembles.

The simulation incorporates a stochastic component (noise) that reflects the inherent randomness of the evolutionary search process.

The oscillations observed in the curves are caused by fluctuations in subproblem contributions during population adaptation and by temporal segment permutations of signals, which modify the ensemble structure in each generation.

This stochastic perturbation allows for an assessment of the algorithm's robustness to variations in optimization conditions and demonstrates its realistic behavior under random influences.

As shown in Fig. 5, the baseline algorithm (red plots) exhibits irregular subproblem activity characterized by isolated peaks and inactive intervals, indicating a localized concentration of the search within narrow parameter ranges and a consequent loss of diversity in ensemble formation.

In contrast, the proposed E-LPT-MOEA/D (black curves) demonstrates smoother and more uniform activity profiles, suggesting better coordination between subproblems and a more consistent propagation of improvements through the population. The reduction of abrupt oscillations indicates that the adaptive weighting and entropy-based feedback mechanisms successfully balance local and global search processes.

This stable distribution of subproblem contributions also reflects the enhanced information exchange between the external archive and the working population, preventing premature convergence and maintaining diversity across iterations.

Quantitatively, the proportion of active subproblems increased from approximately 42 % to 78 %, while the variance of their contribution decreased by 35 – 40 %, confirming improved equilibrium and robustness of the optimization dynamics.

V. CONCLUSION

The results of the conducted experimental study confirm that the proposed E-LPT-MOEA/D method, based on entropy-weighted time-segment permutations and a modified genetic optimization mechanism, ensures faster convergence, higher internal stability, and improved diversity of Pareto-optimal ensembles compared with the reference methods.

Through the integration of the LPT-based temporal modeling and the multi-objective task-decomposition approach of MOEA/D, the method effectively synchronizes the external archive and the working population, maintaining robustness under stochastic perturbations and varying noise levels (10 – 25 dB).

The normalized and absolute evaluations demonstrated consistent improvements of 20 – 30 % in convergence speed and 15 – 25 % in stability, while the ΔH-based analysis revealed a faster synchronization between the external archive and the working population, characterized by a shorter transient phase and smaller amplitude of oscillations across generations.

This indicates that the proposed algorithm maintains a stable equilibrium between exploration and exploitation, effectively preventing premature convergence and ensuring smoother adaptation of subproblems during evolutionary search.

The study achieved the following scientific outcomes:

1. A modified evolutionary optimization method was developed that integrates logarithmic-permutation modeling with entropy-based feedback from an external archive.

2. Analytical and experimental verification confirmed the method's robustness under noise and dynamic segmentation parameters.

3. Quantitative performance assessment showed superior Pareto-front coverage and enhanced ensemble formation balance.

Overall, the proposed E-LPT-MOEA/D method provides a reliable and adaptive solution for multi-objective optimization of complex signal ensembles in cognitive telecommunication environments, ensuring stability and scalability under real-world stochastic conditions.

The introduced mechanisms of adaptive weighting, flexible task delegation, and mutation control contribute to improved convergence speed, enhanced stability, and scalability of the algorithm under real-world stochastic and dynamically varying conditions.

AUTHOR CONTRIBUTIONS

I.T.– conceptualization, methodology, investigation; S.I. – supervision writing-review and editing.

COMPETING INTERESTS

The authors declare no conflict of interest.

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Метод багатокритеріальної оптимізації ансамблів складних сигналів на основі еволюційного алгоритму E-LPT-MOEA/D

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АНОТАЦІЯ У статті запропоновано метод багатокритеріальної оптимізації ансамблів складних сигналів на основі еволюційного алгоритму E-LPT-MOEA/D, який поєднує логарифмічні часові перестановки (LPT) із принципом декомпозиції завдань у середовищі багатокритеріальної еволюційної оптимізації. На відміну від відомих підходів, метод передбачає адаптивну взаємодію між робочою популяцією та зовнішнім архівом Парето, що забезпечує узгоджене оновлення множини рішень і стабільність збіжності в умовах стохастичних збурень. Розроблено модифікований генетичний алгоритм, у якому реалізовано ентропійно зважене оновлення вагових коефіцієнтів, гнучку делегацію підзадач і динамічне керування мутаціями. Така інтеграція дозволяє підтримувати рівновагу між процесами дослідження і використання (exploration–exploitation), уникати передчасної збіжності та зберігати різноманітність ансамблів сигналів. У математичній моделі сформовано цільові функції, що відображають середній коефіцієнт взаємної кореляції, рівень бічних пелюсток, варіацію енергетичного розподілу та міру структурної узгодженості. Для оцінювання якості оптимізації використано показники гіпероб'єму (IH), зворотного середнього поколіннєвого відхилення (IGD) та відхилення кореляції ($\Delta\rho$). Експериментальне моделювання проведено в нормалізованому та абсолютному режимах для різних співвідношень сигнал/шум (10 – 25 дБ) і параметрів часової сегментації (τ = 0.3 – 1.0). Отримані результати засвідчили переваги запропонованого методу: збільшення швидкості збіжності на 20 – 30 %, підвищення стабільності на 15 – 25 %, а також зменшення амплітуди коливань різниці гіпероб'єму (ΔH) між архівом і популяцією на 30 – 40 %. Доведено, що інтеграція механізму зовнішнього архіву з внутрішньою часовою перестановкою сигналів забезпечує більш рівномірне покриття фронту Парето та підвищує структурну збалансованість ансамблів. У результаті алгоритм E-LPT-MOEA/D забезпечує швидку адаптацію до змінних умов оптимізації, стійкість до завад і масштабованість при зростанні розмірності задачі. Запропонований метод може бути використаний для оптимізації процесів формування та обробки сигналів у когнітивних телекомунікаційних середовищах, зокрема при побудові систем динамічного спектрального моніторингу, розподілених мереж зв'язку та енергоефективних протоколів передавання даних.

КЛЮЧОВІ СЛОВА телекомунікаційні системи, оптимізація, еволюційний підхід, ансамблі складних сигналів, SNR.