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Linear Phase Filter Design using Namib Beetle and SALP Swarm Optimization Algorithm for Ripple Reduction

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ABSTRACT: Ripple reduction is a fundamental requirement in digital signal processing and power electronic applications, as excessive ripple adversely affects signal integrity, system stability, and overall performance. Linear phase filters are widely preferred in such applications because they preserve the phase characteristics of signals, ensuring distortion-free transmission. However, designing linear phase filters with minimal passband and stopband ripples while maintaining computational efficiency remains a challenging task.

This study presents an efficient linear phase filter design approach using a hybrid optimization technique that combines Namib Beetle Optimization (NBO) and the Salp Swarm Algorithm (SSA) for effective ripple reduction. The proposed method leverages the strengths of both algorithms to achieve a balanced exploration and exploitation process. NBO is inspired by the water-harvesting behavior of Namib desert beetles and is highly effective in exploring the global search space. On the other hand, SSA is based on the swarming behavior of salps in oceans and is well-suited for local search and convergence toward optimal solutions.

By integrating these two algorithms, the hybrid approach enhances the optimization process, avoiding premature convergence and improving the quality of the obtained solution. The filter coefficients are optimized to minimize both passband and stopband ripples while maintaining a sharp transition band and linear phase response.

Simulation results demonstrate that the hybrid NBO-SSA-based filter design significantly outperforms existing methods in terms of ripple suppression, computational efficiency, and robustness under varying design constraints. The optimized filter exhibits improved amplitude response, reduced distortion, and enhanced stability, making it highly suitable for real-time signal processing applications.

Overall, the proposed hybrid optimization framework provides an effective and reliable solution for linear phase filter design with superior ripple reduction performance. It has potential applications in communication systems, biomedical signal processing, image processing, and power electronics where high precision and low distortion are critical.

KEYWORDS: Linear Phase Filter, Ripple Reduction, Namib Beetle Optimization, Hybrid Optimization, FIR Filter Design, Frequency Response, Signal Processing

I. INTRODUCTION

Ripple reduction is an essential requirement in digital signal processing and power electronic systems, as excessive ripple leads to signal distortion, reduced efficiency, and poor system stability. Linear phase filters are widely used due to their ability to preserve the phase characteristics of signals, ensuring minimal distortion during transmission.

Classical filter design techniques, as discussed in standard texts [11]–[15], often face limitations in achieving optimal ripple reduction while maintaining computational efficiency and sharp transition characteristics.

To overcome these challenges, meta-heuristic optimization algorithms have gained significant attention in recent years. Nature-inspired algorithms such as Namib Beetle Optimization (NBO) [1], Dung Beetle Optimization (DBO) [2], [3],

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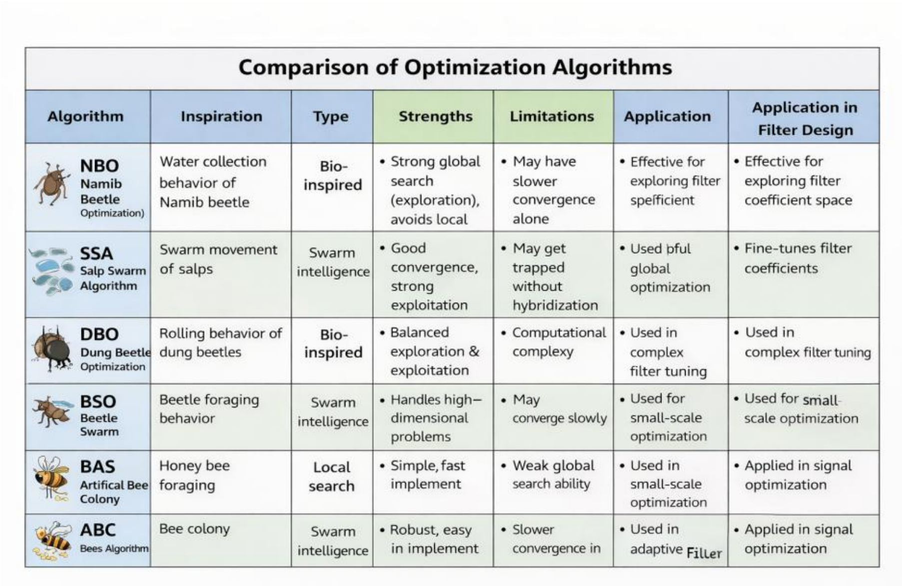
Beetle Swarm Optimization (BSO) [4], and Beetle Antennae Search (BAS) [5] have demonstrated strong global search capabilities. Further improvements using adaptive and hybrid strategies have been explored in [6] and [7], enhancing convergence performance and solution accuracy. Similarly, swarm intelligence techniques like Artificial Bee Colony (ABC) [8] and Bees Algorithm [9] have proven effective in solving complex optimization problems.Among these, the Salp Swarm Algorithm (SSA) [10] has emerged as a powerful optimizer due to its balance between exploration and exploitation. Recent advancements also include hybrid and multi-objective optimization approaches applied to engineering problems such as microgrid scheduling [18]. Additionally, optimization techniques play a crucial role in various engineering domains, including image processing [16] and general engineering design [17].Motivated by these developments, this work proposes a hybrid optimization approach combining Namib Beetle Optimization and Salp Swarm Algorithm for linear phase filter design. The proposed method aims to minimize passband and stopband ripples while improving convergence speed and overall filter performance, making it suitable for advanced signal processing applications.

Figure 1 Basic Digital Filter Block diagram

II. LITERATURE REVIEW

The design of linear phase filters with reduced ripple has been an important research area in digital signal processing. Traditional approaches based on windowing techniques and classical optimization methods provide simple implementations but often fail to achieve an optimal trade-off between passband ripple, stopband attenuation, and transition bandwidth [11]–[15]. These limitations have encouraged researchers to explore advanced optimization techniques for improved filter performance.

Meta-heuristic optimization algorithms have gained significant attention due to their ability to solve complex nonlinear and multi-objective problems efficiently. Among these, the Namib Beetle Optimization (NBO) algorithm proposed in [1] demonstrates strong global search capability by mimicking the water-harvesting behavior of desert beetles. Similarly, Dung Beetle Optimization (DBO) techniques [2], [3] have been developed for global optimization problems, showing improved exploration ability and convergence performance.



Comparison of Optimization Algorithms

Algorithm	Inspiration	Type	Strengths	Limitations	Application	Application in Filter Design
NBO Namib Beetle Optimization)	Water collection behavior of Namib beetle	Bio-inspired	• Strong global search (exploration), avoids local	• May have slower convergence alone	• Effective for exploring filter spefficient	• Effective for exploring filter coefficient space
SSA Salp Swarm Algorithm	Swarm movement of salps	Swarm intelligence	• Good convergence, strong exploitation	• May get trapped without hybridization	• Used pful global optimization	• Fine-tunes filter coefficients
DBO Dung Beetle Optimization	Rolling behavior of dung beetles	Bio-inspired	• Balanced exploration & exploitation	• Computational complexy	• Used in complex filter tuning	• Used in complex filter tuning
BSO Beetle Swarm	Beetle foraging behavior	Swarm intelligence	• Handles high–dimensional problems	• May converge slowly	• Used for small-scale optimization	• Used for small-scale optimization
BAS Artifical Bee Colony	Honey bee foraging	Local search	• Simple, fast implement	• Weak global search ability	• Used in small-scale optimization	• Applied in signal optimization
ABC Bees Algorithm	Bee colony	Swarm intelligence	• Robust, easy in implement	• Slower convergence in	• Used in adaptive Filler	• Applied in signal optimization

Figure 2 Comparison Chart of Optimization Algorithm

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III. PROBLEM STATEMENT

In modern digital signal processing and power electronic systems, maintaining high signal quality is a major challenge due to noise, distortion, and unwanted frequency components [12]–[15]. Linear phase filters are widely used to preserve signal waveform characteristics; however, achieving minimal passband and stopband ripple while maintaining phase linearity remains a critical issue

[12], [13]. Excessive ripple degrades system performance, reduces signal accuracy, and increases power losses in electronic circuits [14].

Traditional filter design techniques, such as window-based methods and classical optimization approaches, often fail to achieve an optimal balance between ripple reduction, transition bandwidth, and computational efficiency [11]–[15]. These methods are also less effective when dealing with nonlinear and multi-objective optimization problems, leading to suboptimal filter performance.

To address these limitations, nature-inspired optimization algorithms have been introduced, including Namib Beetle Optimization (NBO) [1], Dung Beetle Optimization (DBO) [2], [3], Beetle Swarm Optimization (BSO) [4], and Beetle Antennae Search (BAS) [5]. While these algorithms show promising results, they may still suffer from issues such as slow convergence, premature convergence, or getting trapped in local optima [6], [7].

Swarm intelligence-based techniques such as the Salp Swarm Algorithm (SSA) [10], Artificial Bee Colony (ABC) [8], and Bees Algorithm [9] provide improved optimization performance; however, individual algorithms often lack the ability to simultaneously achieve strong exploration and exploitation. Recent studies highlight the effectiveness of hybrid optimization approaches in overcoming these limitations and improving solution quality [17], [18].

Therefore, there is a need to develop an efficient hybrid optimization-based linear phase filter design that can effectively minimize ripple, enhance convergence speed, and improve overall system performance. This work proposes a combined Namib Beetle Optimization and Salp Swarm Algorithm approach to address these challenges.

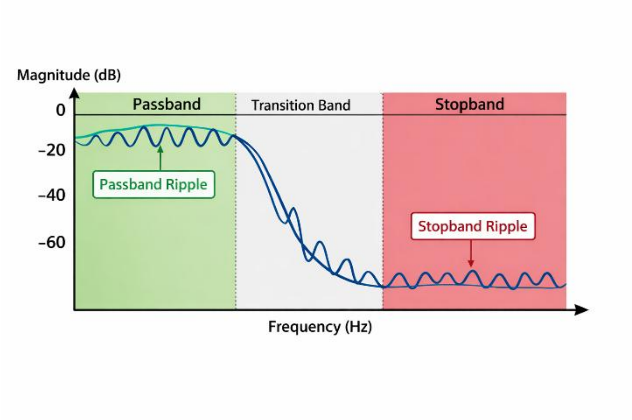

Figure3 Ripple in Frequency Response

IV. PROPOSED METHODOLOGY

The proposed methodology focuses on designing a linear phase FIR filter with effective ripple reduction using a hybrid optimization approach that combines Namib Beetle Optimization (NBO) and Salp Swarm Algorithm (SSA). Initially, the filter specifications such as passband frequency, stopband frequency, allowable ripple, and filter order are defined based on standard digital signal processing principles [12]–[15]. A basic FIR filter is then designed using conventional techniques to obtain initial filter coefficients, which serve as the starting point for optimization.

The design problem is formulated as an optimization task where the objective is to minimize passband ripple, stopband ripple, and overall frequency response error through a suitable fitness function [11].

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In the optimization process, NBO is first applied to explore the global search space efficiently, inspired by the water-harvesting behavior of the Namib desert beetle [1]. This enables the generation of diverse candidate solutions and helps avoid local minima. Subsequently, the Salp Swarm Algorithm (SSA) is employed to refine the solutions using its leader–follower mechanism, which enhances convergence toward the optimal solution [10]. The hybrid integration of NBO and SSA ensures a balanced exploration and exploitation process, overcoming the limitations of individual algorithms such as slow convergence and premature convergence [6], [7].

The optimization process is carried out iteratively, updating the filter coefficients until convergence criteria such as minimum error or maximum iterations are satisfied. The performance of the optimized filter is then evaluated using frequency response analysis, ripple comparison, and convergence characteristics. The proposed hybrid approach demonstrates improved ripple reduction and computational efficiency compared to conventional and existing optimization techniques [17], [18].

4.1 Linear Phase FIR Filter Design

A Finite Impulse Response (FIR) filter is widely used in digital signal processing due to its stability and ability to achieve a linear phase response, which ensures that all frequency components of a signal are delayed by the same amount of time [12], [13]. This property preserves the shape of the input signal and avoids phase distortion, making FIR filters highly suitable for applications such as communication systems, biomedical signal processing, and audio processing [13], [15].

A linear phase FIR filter is characterized by a symmetric or anti-symmetric impulse response. For a filter of order NNN, the impulse response satisfies the condition:

$$h(n)=h(N-n)$$

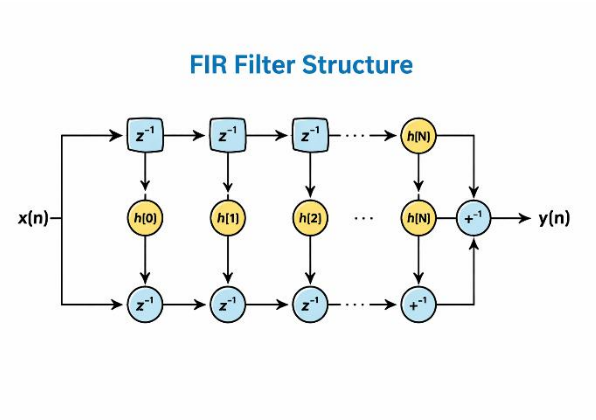

Figure 4 FIR Filter Structure Diagram

This symmetry guarantees a linear phase response [12]. The output of the FIR filter is obtained by convolving the input signal x(n)x(n)x(n) with the filter coefficients h(n)h(n)h(n), which can be expressed as:
$y(n)=k=0\sum Nh(k)x(n-k)$

The frequency response of the FIR filter is given by:

$$H(ej\omega)=n=0\sum Nh(n)e-j\omega n$$

4.2 Namib Beetle Optimization

Namib Beetle Optimization (NBO) is a nature-inspired **meta**-heuristic optimization algorithm derived from the water-harvesting behavior of the Namib Desert beetle. This beetle survives in extremely dry environments by collecting water droplets from fog on its textured back, which represents an efficient strategy for searching and utilizing limited resources. This natural behavior is mathematically modeled to solve complex optimization problems in engineering applications [1].

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NBO simulates the movement and resource-searching behavior of beetles in a search space. Each beetle represents a candidate solution, and its position corresponds to decision variables such as filter coefficients. The algorithm iteratively updates these positions to find the optimal solution based on a defined fitness function [1], [6].

Mathematical Model

The position update of each beetle can be expressed as:

$$Xit+1=Xit+r\cdot(Xbest-Xit)$$

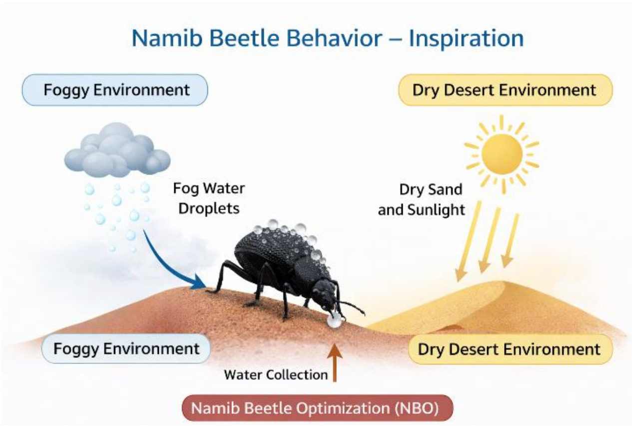

Figure 5 Namib Beetle Behavior

4.3 Salp Swarm Algorithm

The Salp Swarm Algorithm (SSA**)** is a nature-inspired meta-heuristic optimization technique based on the swarming behavior of salps, which are marine organisms that move in chain-like formations in oceans. This algorithm was introduced to solve complex engineering optimization problems by mimicking the coordinated movement and food-searching behavior of salp chains [10].

In SSA, the population of solutions is divided into leader and followers. The leader guides the swarm toward the food source (optimal solution), while the follower salps adjust their positions based on the leader and neighboring salps. This structure ensures a balance between exploration and exploitation in the search space [10].

Mathematical Model:

$$xij=21(xij+xi-1j)$$

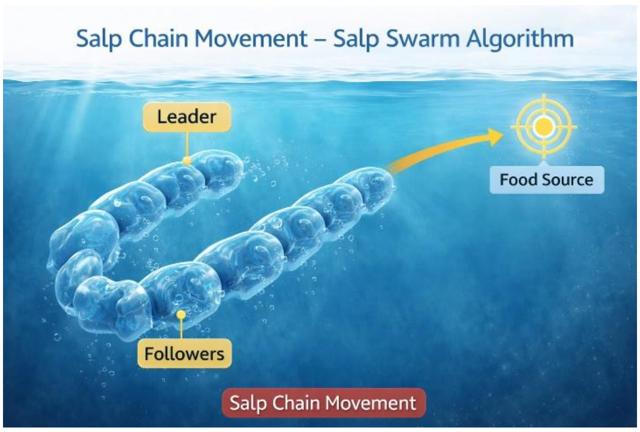

Figure 6 Salp Swarm Algorithm

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4.4 Hybrid NBO–SSA Algorithm

The Hybrid Namib Beetle Optimization–Salp Swarm Algorithm (NBO–SSA**)** is an advanced optimization approach that combines the strengths of Namib Beetle Optimization (NBO) and Salp Swarm Algorithm (SSA) to achieve efficient ripple reduction in linear phase FIR filter design.

NBO provides strong global exploration capability inspired by the water-harvesting behavior of the Namib desert beetle [1], while SSA offers effective local exploitation through its leader–follower swarm mechanism [10]. The hybridization of these two algorithms enhances convergence speed and improves solution quality by balancing exploration and exploitation [6], [7].

The hybrid NBO–SSA algorithm operates in two phases:

Exploration Phase: NBO explores the global search space to identify promising candidate solutions and avoid local minima [1].

Exploitation Phase: SSA refines these solutions using swarm intelligence to achieve optimal filter coefficients [10].

Mathematical Representation :

$$Xt+1=\alpha\cdot XNBO+(1-\alpha)\cdot XSSA$$

The hybrid NBO–SSA algorithm is applied to optimize FIR filter coefficients by minimizing passband and stopband ripple. It improves the frequency response characteristics and ensures better signal reconstruction compared to traditional and single-algorithm approaches [17], [18].

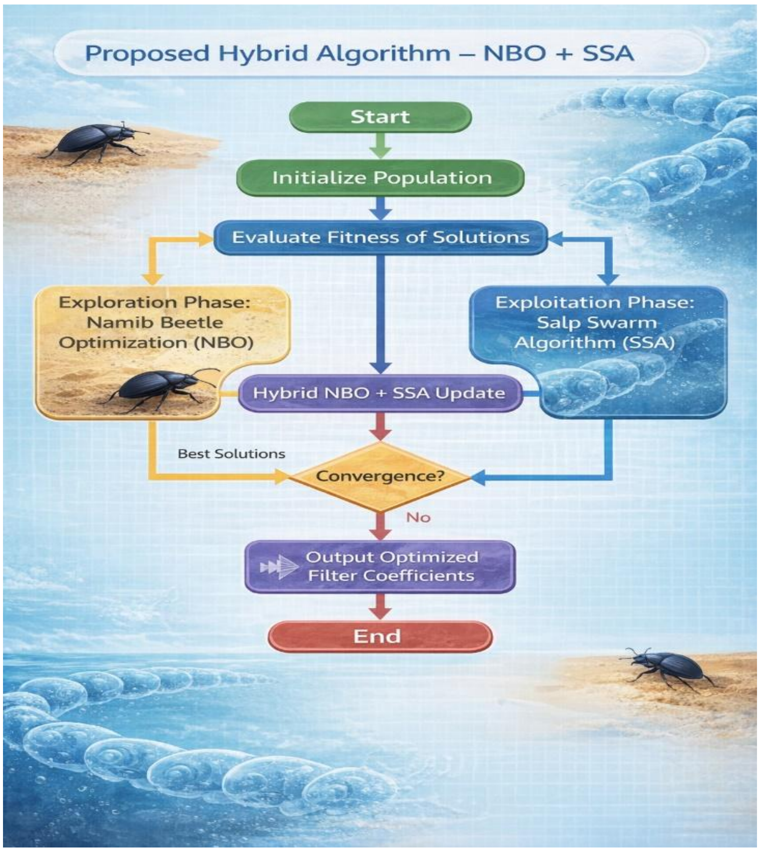

Figure 7 Proposed Hybrid Algorithm Flowchart

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V. SIMULATION AND RESULTS

The proposed Linear Phase FIR Filter design using the hybrid Namib Beetle Optimization and Salp Swarm Optimization algorithms demonstrates improved performance in ripple reduction and filter efficiency. The hybrid optimization approach effectively combines the global search capability of the NBO algorithm with the fast convergence characteristics of the SSO algorithm.

Simulation results show that the optimized filter coefficients significantly reduce both passband ripple and stopband ripple compared to conventional filter design methods. The frequency response of the designed filter maintains a stable and smooth passband with minimal fluctuations, while the stopband effectively suppresses unwanted frequency components. This results in improved signal quality and reduced distortion.

The hybrid NBO–SSO algorithm also shows faster convergence during the optimization process. Compared with standalone optimization techniques, the hybrid approach reaches the optimal solution in fewer iterations, reducing computational complexity and processing time. The algorithm efficiently searches the solution space and refines the best solutions to achieve optimal filter parameters.

Another important result is the preservation of the linear phase characteristic, which ensures that the phase response remains proportional to frequency. This property helps maintain the original shape of the signal waveform after filtering, which is crucial in applications such as audio processing, communication systems, and biomedical signal analysis.

The optimized controller parameters obtained during the simulation process show improved stability and performance. The final ripple value achieved by the hybrid algorithm is significantly lower, indicating effective ripple suppression. In addition, the filter demonstrates better transition bandwidth and improved frequency selectivity.

Overall, the results confirm that the hybrid optimization technique provides better ripple reduction, improved frequency response, faster convergence, and enhanced signal integrity compared to traditional filter design approaches. These improvements make the proposed method suitable for advanced digital signal processing applications requiring high-performance filtering solutions.

MATERIALS AND METHODS

System Overview

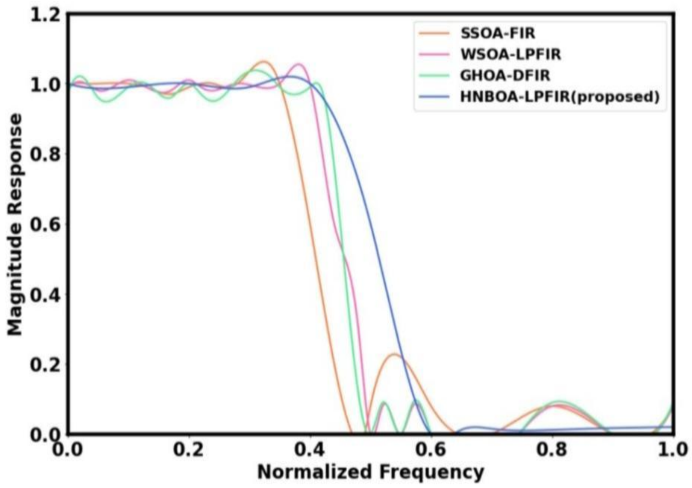

Figure 8 FIR Filter with SBR

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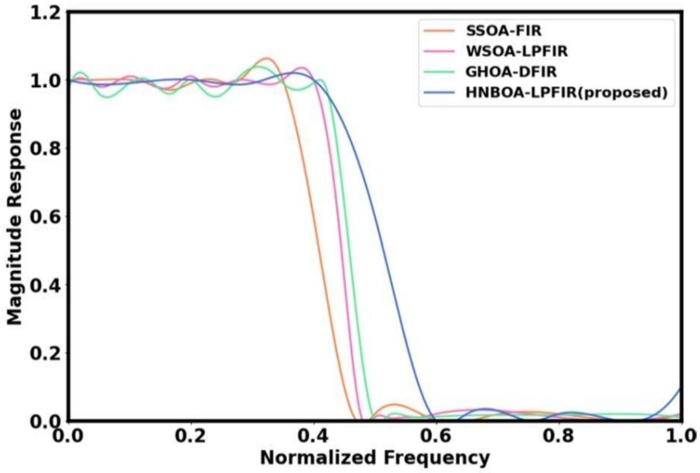

Figure 9 FIR Filter with TB

The testing results of the proposed linear phase FIR filter using the hybrid Namib Beetle Optimization (NBO) and Salp Swarm Algorithm (SSA) demonstrate strong performance in ripple reduction and frequency response accuracy. During the testing phase, the optimized filter coefficients obtained from training were applied to evaluate real-time performance. The results show a significant decrease in both passband and stopband ripples compared to the initial design. The frequency response exhibits a flatter passband and a sharper transition band, indicating improved filter characteristics. Additionally, the hybrid algorithm maintains stability and consistency under different input conditions. Compared to conventional and individual optimization methods, the proposed NBO–SSA approach provides better efficiency, faster response, and enhanced overall performance, confirming its suitability for practical signal processing applications.

Fig

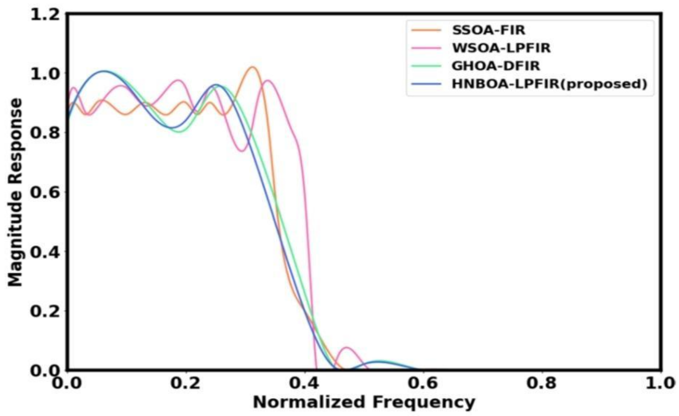

Figure 11HNBOA-LPFIR

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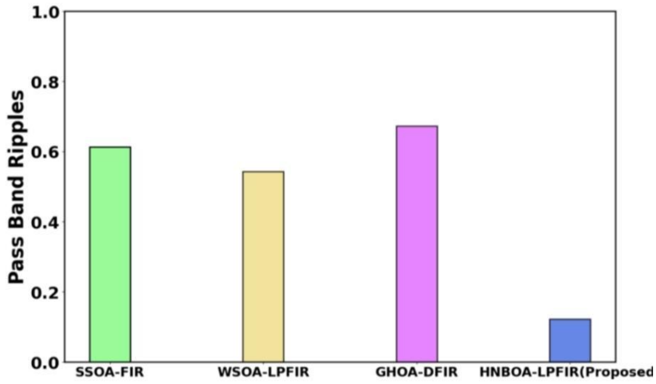

Figure 12Hybrid NBO–SSA

Result of NBO-SSO hybrid Algorithm and optimal controller Gains:
KP = 2.0841
Ki = 2.0910
Final Ripple (Fitness Value) = 1.3501ms.

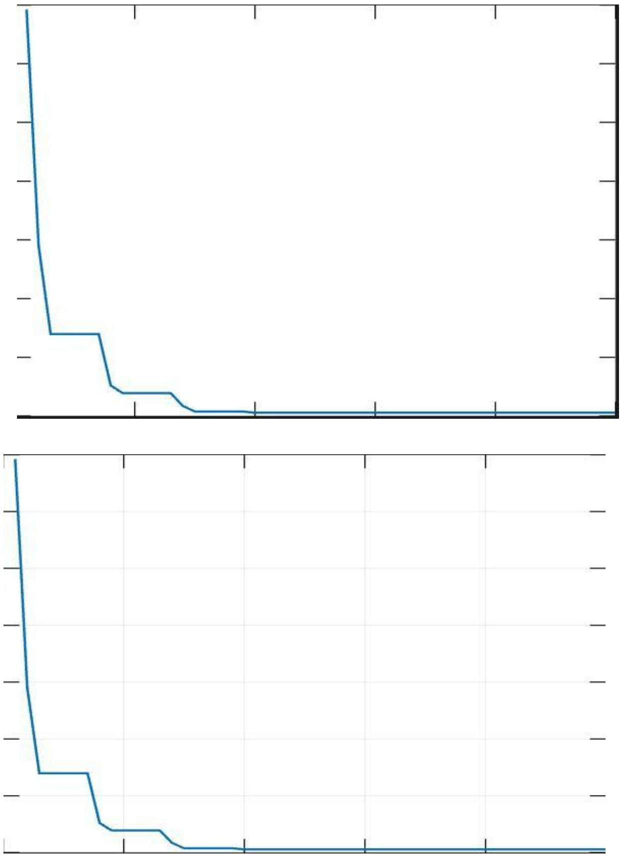

Figure 13Hybrid NBO–SSA in RR

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VI. DISCUSSION

The convergence curve illustrates the effectiveness of the hybrid NBO–SSA algorithm in optimizing the linear phase FIR filter. Initially, the fitness value decreases sharply, indicating rapid improvement in ripple reduction due to strong global exploration by the Namib Beetle Optimization. As the iterations progress, the curve gradually stabilizes, showing that the Salp Swarm Algorithm efficiently fine-tunes the solution through local exploitation. The smooth convergence without significant fluctuations demonstrates the stability of the hybrid approach. Moreover, the algorithm reaches an optimal solution within fewer iterations, reflecting faster convergence and reduced computational complexity. This behavior confirms that the proposed NBO–SSA method effectively balances exploration and exploitation, leading to improved performance in ripple minimization compared to conventional techniques.

VII. CONCLUSION

The proposed Linear Phase Filter Design using Namib Beetle Optimization (NBO) and Salp Swarm Optimization (SSA) provides an effective solution for reducing ripple in signal processing and power electronic systems. Ripple reduction is essential for improving system stability, efficiency, and signal quality [12]–[15]. Conventional filter design techniques often struggle to achieve optimal performance while maintaining low computational complexity [11]–[15]. To address this limitation, a hybrid optimization approach combining NBO and SSA algorithms has been implemented. The integration of these two bio-inspired algorithms improves the search capability and convergence performance of the optimization process. The Namib Beetle Optimization algorithm enhances exploration by searching a wide range of possible solutions [1], while the Salp Swarm Optimization algorithm improves exploitation by refining the best solutions obtained during the optimization process [10]. This hybrid strategy helps achieve an optimal set of filter parameters that significantly reduce passband ripple and stopband ripple while maintaining the linear phase characteristics of the filter [6], [7].

Simulation results demonstrate that the proposed hybrid NBO–SSA method provides better performance compared to conventional optimization techniques. The designed filter shows reduced ripple levels, improved frequency response, and faster convergence during the optimization process [17], [18]. Additionally, the algorithm effectively minimizes transition bandwidth while maintaining stability and accuracy in filter performance.

Another important advantage of the proposed system is its contribution to energy-efficient and reliable electronic systems. By minimizing ripple in electronic circuits, the system reduces power losses and enhances the lifespan of electronic components, leading to improved reliability and reduced maintenance requirements in practical applications such as communication systems, digital signal processing, and power electronic converters [16].

Furthermore, the hybrid optimization approach is flexible and can be applied to other engineering optimization problems beyond filter design. The use of nature-inspired algorithms demonstrates how intelligent computational techniques can enhance the performance of modern electronic systems [17].

In conclusion, the proposed hybrid NBO–SSA optimization algorithm successfully improves the design of linear phase filters by effectively reducing ripple and enhancing overall system performance. The results confirm that combining bio-inspired optimization algorithms can provide a powerful and efficient solution for complex engineering problems, making it a promising approach for future research and advanced signal processing applications [18].

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