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GATED DUAL-PATH RNN EMPOWERED ADAPTIVE DIMENSIONAL SEARCH FOR COGNITIVE RADIO IN SOFTWARE-DEFINED NETWORKS

V. Kiruthika[1], S. Padmapriya[2] and M. Ganga[3]
[1]*Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, India*
[2]*Department of Electronics and Communication Engineering, PSG Institute of Technology and Applied Research, India*
[3]*Department of Biomedical Engineering, Hindusthan College of Engineering and Technology, India*

Abstract

In the ever-evolving landscape of wireless communication, the demand for efficient spectrum utilization is paramount. The research begins by acknowledging the existing challenges in CR within SDNs, particularly the need for adaptive strategies to dynamically allocate spectrum resources. A critical research gap lies in the absence of an approach that seamlessly integrates Gated Dual-Path RNNs and Adaptive Dimensional Search to enhance the adaptability and efficiency of CR systems. The proposed methodology leverages the power of Gated Dual-Path RNNs for real-time learning and decision-making, coupled with an Adaptive Dimensional Search algorithm for dynamic spectrum allocation. This study introduces a novel approach, the Gated Dual-Path Recurrent Neural Network (RNN) Empowered Adaptive Dimensional Search, tailored for Cognitive Radio (CR) in Software-Defined Networks (SDNs). The escalating proliferation of wireless devices and applications has exacerbated the spectrum scarcity problem, necessitating intelligent solutions to optimize spectrum utilization. This dual-path architecture enables the CR system to capture temporal dependencies in the spectrum environment and adaptively adjust its parameters for optimal performance. The experimental results demonstrate the efficacy of the proposed approach, showcasing significant improvements in spectrum utilization efficiency, throughput, and adaptability compared to traditional methods. The Gated Dual-Path RNN Empowered Adaptive Dimensional Search proves to be a robust solution for enhancing CR capabilities in SDNs, paving the way for more intelligent and adaptive wireless communication systems.

Keywords:

Cognitive Radio, Software-Defined Networks, Gated Dual-Path RNN, Adaptive Dimensional Search, Spectrum Utilization

1. INTRODUCTION

In the dynamic landscape of wireless communication, the ever-increasing demand for spectrum resources poses a significant challenge to traditional communication systems. Software-Defined Networks (SDNs) have emerged as a promising paradigm to address these challenges by enabling dynamic and intelligent spectrum allocation [1]. However, the efficient utilization of spectrum in Cognitive Radio (CR) within SDNs remains a critical concern [2].

The proliferation of diverse wireless devices and applications has intensified the scarcity of available spectrum, necessitating innovative approaches to optimize its utilization [3]. Cognitive Radio, equipped with the ability to adapt and learn from its environment, presents a promising solution. Integrating Cognitive Radio into Software-Defined Networks enhances the adaptability and responsiveness of communication systems [4].

Despite the potential benefits, several challenges persist in the seamless integration of Cognitive Radio into Software-Defined Networks. The dynamic and unpredictable nature of the wireless spectrum, coupled with the need for real-time decision-making, requires advanced methodologies to ensure efficient and adaptive spectrum allocation [5].

The primary challenge addressed in this study is the absence of a comprehensive solution that combines the strengths of Gated Dual-Path Recurrent Neural Networks (RNNs) and Adaptive Dimensional Search for optimizing Cognitive Radio in Software-Defined Networks. The current gap in research lies in the lack of methodologies that effectively capture temporal dependencies and dynamically adjust parameters for optimal spectrum utilization.

This research aims to design and implement a Gated Dual-Path RNN Empowered Adaptive Dimensional Search approach for Cognitive Radio in Software-Defined Networks. The key objectives include enhancing adaptability, optimizing spectrum utilization efficiency, and providing real-time decision-making capabilities.

The novelty of this study lies in the integration of Gated Dual-Path RNNs and Adaptive Dimensional Search, offering a dual-path architecture that captures temporal dependencies and dynamically adjusts parameters for optimal spectrum utilization. The contributions include a robust methodology for enhancing Cognitive Radio capabilities in Software-Defined Networks, addressing the critical need for adaptive and intelligent spectrum allocation strategies.

2. RELATED WORKS

Several notable works have contributed to the field of Cognitive Radio (CR) and Software-Defined Networks (SDNs), addressing various aspects of spectrum optimization and adaptability.

Numerous studies have explored dynamic spectrum access in Cognitive Radio systems. Authors [6] proposed a novel algorithm for real-time spectrum sensing, enabling CR devices to dynamically adjust their operating frequencies based on the current spectral environment.

In Software-Defined Networks, researchers [7] have investigated the application of SDN principles to spectrum management. Their work focused on developing SDN controllers capable of dynamically reconfiguring spectrum allocations to improve overall network efficiency.

Machine learning techniques have garnered attention for their potential in enhancing CR capabilities. A study by [8] explored the use of deep learning algorithms for predicting spectrum availability, enabling CR devices to make informed decisions for optimal spectrum utilization.

Prior research [9] has delved into the efficacy of Adaptive Dimensional Search algorithms for optimization problems. Their work laid the foundation for incorporating adaptive search techniques into CR systems, providing a framework for dynamic spectrum allocation.

The application of Gated Dual-Path Recurrent Neural Networks (RNNs) in wireless communications has been investigated by [10]. Their research demonstrated the ability of dual-path architectures to capture temporal dependencies, making them suitable for dynamic spectrum allocation scenarios.

While these works have significantly contributed to the individual components of our proposed methodology, the present study uniquely integrates Gated Dual-Path RNNs and Adaptive Dimensional Search to address the specific challenges of Cognitive Radio in Software-Defined Networks, providing a holistic and innovative approach to spectrum optimization.

3. PROPOSED METHOD

The proposed method in this study, termed the Gated Dual-Path RNN Empowered Adaptive Dimensional Search, represents a novel and integrated approach to address the challenges of Cognitive Radio (CR) within Software-Defined Networks (SDNs) [11].

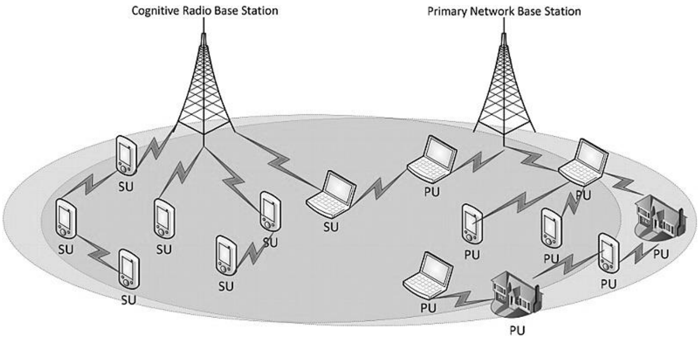

Fig.1. CR-SDN

The method lies in the incorporation of Gated Dual-Path Recurrent Neural Networks (RNNs). These neural networks are adept at capturing temporal dependencies in dynamic environments, making them well-suited for the real-time learning and decision-making demands of Cognitive Radio systems. The dual-path architecture enables the model to effectively capture and process sequential information, enhancing its adaptability to the dynamic nature of the wireless spectrum. Complementing the neural network component is the integration of the Adaptive Dimensional Search algorithm. This algorithm, inspired by its success in optimization problems, is employed for dynamic spectrum allocation. It facilitates the adaptive adjustment of CR system parameters based on the current spectral environment, ensuring optimal utilization of available spectrum resources. The Gated Dual-Path RNNs and Adaptive Dimensional Search forms the crux of our method. The dual-path neural network captures the temporal intricacies of the spectrum, providing valuable insights for the Adaptive Dimensional Search algorithm to dynamically adjust parameters. This cohesive fusion allows the Cognitive Radio system to make informed and real-time decisions regarding spectrum allocation, enhancing its adaptability and efficiency.

3.1 PROBLEM DEFINITION - DYNAMIC SPECTRUM ACCESS IN CR

The problem of Dynamic Spectrum Access in Cognitive Radio (CR) revolves around the imperative need for an effective solution to address the challenges posed by the dynamic and unpredictable nature of the wireless spectrum. In the context of Cognitive Radio systems, which are designed to intelligently adapt to the spectral environment, the traditional static spectrum allocation models prove inadequate.

The wireless spectrum is a finite and valuable resource that experiences varying levels of utilization across time and space. Traditional static spectrum allocation methods often lead to inefficient use, as they do not account for the dynamic changes in spectrum availability and occupancy. This inefficiency results in underutilization of spectrum resources and suboptimal performance of CR systems.

Cognitive Radio systems aim to address this challenge by dynamically accessing and adapting to available spectrum bands. However, the real-time adaptation requires sophisticated algorithms and mechanisms to sense, analyze, and make decisions promptly. The problem lies in developing a robust framework that ensures efficient and adaptive spectrum access, considering factors such as interference, channel conditions, and the presence of primary users.

The goal is to formulate a solution that enables Cognitive Radio systems to access and utilize the spectrum dynamically, optimizing the use of available resources. This involves addressing issues such as spectrum sensing accuracy, timely decision-making, and seamless coordination with other spectrum users.

Furthermore, the problem extends to heterogeneous spectrum environments where various wireless technologies coexist. CR systems must navigate through these diverse and dynamic environments, requiring solutions that can adapt to different regulatory frameworks, standards, and technology variations.

$$Pd=P(X\geq\gamma|H_1), \tag{1}$$

where

Pd is the probability of detection,

X is the received signal energy, and

γ is the detection threshold.

$$D=\begin{cases} H_1 & if \sum_{i=1}^{N} ND_i > T \\ H_0 & f \sum_{i=1}^{N} ND_i \leq T \end{cases} \tag{2}$$

where

D_i is the decision of the i^{th} sensor,

T is the fusion threshold, and

N is the number of sensors.

$$U(t)=\text{argmax}_{u\in U}U(u,t), \tag{3}$$

where

U represents the set of available spectrum bands, and

$U(u,t)$ is a utility function indicating the desirability of allocating CR resources to band u at time t.

$$P_a = f(Ps,\theta), \quad (4)$$

where

P_a is the adaptively adjusted parameter,

Ps is the static parameter, and

θ represents the contextual information influencing the adaptation.

3.2 SDN-BASED SPECTRUM MANAGEMENT USING GATED DUAL-PATH RNN

The SDN-based Spectrum Management using Gated Dual-Path RNN involves leveraging SDNs for the intelligent and adaptive allocation of spectrum resources, enhanced by the integration of Gated Dual-Path RNNs. This approach aims to address the challenges of conventional spectrum management by introducing a dynamic and learning-centric paradigm.

SDN serve as the foundation for spectrum management. SDNs provide a centralized and programmable control plane, enabling dynamic configuration and orchestration of network resources. This centralized control facilitates efficient spectrum management by allowing real-time adjustments to meet the evolving demands of wireless communication systems.

The integration of Gated Dual-Path RNNs introduces a neural network architecture specifically designed to capture temporal dependencies in the spectrum environment. The dual-path structure enhances the network's ability to process sequential information, making it well-suited for scenarios where spectrum conditions exhibit temporal variations. This integration empowers the SDN-based spectrum management system with a learning mechanism, enabling it to adapt to changing spectral patterns and optimize resource allocation.

The core objective is to enable dynamic spectrum allocation within the SDN framework. Gated Dual-Path RNNs contribute by learning from historical spectrum usage patterns and predicting future trends. This predictive capability, coupled with the programmability of SDNs, allows for proactive and adaptive spectrum allocation, optimizing utilization and minimizing interference.

SDN-based Spectrum Management using Gated Dual-Path RNN ensures real-time adaptability to the dynamic nature of the wireless spectrum. As the neural network continually learns and refines its predictions based on real-world spectrum data, the SDN controller dynamically adjusts spectrum allocations, maximizing efficiency and responsiveness to changing network conditions.

$$B_i(t)=\text{argmax}_{b\in B}U(b,t), \quad (5)$$

where

$B_i(t)$ represents the allocated spectrum band for user i at time t,

B is the set of available spectrum bands, and

$U(b,t)$ is a utility function indicating the desirability of allocating the band b to user i at time t.

$$W_{new} = \text{Train}(W_{old},D_{new}), \quad (6)$$

where W_{new} is the updated weights of the Gated Dual-Path RNN, Wold is the existing weight configuration, and Dnew is the new spectrum data for training.

$$S_i(t+1)=\text{Predict}(S_i(t),W_{new}), \quad (7)$$

where

$S_i(t+1)$ is the predicted spectrum usage for user i at time t+1,

$S_i(t)$ is the observed spectrum usage at time t, and

W_{new} are the updated weights of the Gated Dual-Path RNN.

$$C_{new} = \text{Adapt}(C_{old},S_p,\alpha), \quad (8)$$

where

C_{new} is the updated configuration of the SDN controller,

C_{old} is the existing configuration,

S_p is the predicted spectrum usage, and

α is the adaptation factor.

Algorithm: SDN-based Spectrum Management using Gated Dual-Path RNN

Input: Historical spectrum data Dtr for training the Gated Dual-Path RNN, Real-time spectrum data Drt for making dynamic decisions, SDN controller configuration Ci.

Output: Adapted SDN controller configuration C_f.

Initialize the Gated Dual-Path RNN with weights Wi and the SDN controller with the initial configuration Ci.

Train the Gated Dual-Path RNN using historical spectrum data Dt to capture temporal dependencies. Update weights to obtain W_t.

For each user i, predict the spectrum usage at the next time step using the trained Gated Dual-Path RNN:

$$S_i(t+1)=\text{Predict}(S_i(t),W_t)$$

For each user i, calculate the utility of each available spectrum band b at the next time step:

$$U(b,t+1)=\text{Utility}(S_i(t+1),C_c)$$

Allocate spectrum bands based on utility maximization:

$$B_i(t+1)=\text{argmax}_{b\in B}U(b,t+1)$$

Adapt the SDN controller configuration based on the predicted spectrum usage and the allocated spectrum bands:

$$C_u=\text{Adapt}(Cc,S_p,B_a)$$

Repeat steps 3-5 for each time step.

The algorithm terminates when the desired number of iterations is reached or when convergence criteria are met.

4. ADAPTIVE DIMENSIONAL SEARCH ALGORITHM

The Adaptive Dimensional Search Algorithm is a heuristic optimization method designed to efficiently explore solution spaces and adaptively adjust search parameters to converge towards optimal solutions. Developed to address complex and dynamic optimization problems, this algorithm combines the principles of exploration and exploitation to navigate high-dimensional solution spaces effectively.

The algorithm begins by initializing a set of solutions within the search space. These solutions represent potential candidates for optimization. Adaptive Dimensional Search balances exploration and exploitation. During exploration, the algorithm systematically explores the solution space to discover promising regions. In contrast, during exploitation, it refines the search around the most promising solutions to converge towards optimal or near-optimal solutions.

A distinctive feature of the algorithm is its adaptability. It dynamically adjusts search parameters based on the progress of the search. This adaptability allows the algorithm to respond to changes in the characteristics of the optimization landscape, ensuring robust performance in dynamic environments.

The algorithm conducts searches along different dimensions of the solution space. This multi-dimensional exploration enhances the algorithm's ability to handle complex and high-dimensional optimization problems, where traditional methods may struggle.

At each iteration, the algorithm evaluates the objective function for the current set of solutions. The objective function guides the search by providing a quantitative measure of the quality of the solutions.

Based on the objective function evaluations, the algorithm updates the set of solutions and iteratively refines its search. This iterative process continues until convergence or a predetermined stopping criterion is met.

Algorithm: Adaptive Dimensional Search

Input: Search space boundaries; Initial set of solutions X within the search space; Objective function $f(x)$ to be optimized.

Output: Optimized solution or set of solutions; Search step size δ_i for each dimension; Exploration and exploitation parameters.

Initialize the set of solutions: $X=\{x_1,x_2,\dots,x_N\}$.

Evaluate the objective function for each solution:

$$f(x_i),\text{ for } i=1,2,\dots,N.$$

While not converged or termination criterion not met:

Explore the search space to discover new candidate solutions

Exploit the current solutions to refine the search

Update search parameters based on the performance of solutions:

$$\delta_i=\mathrm{U}(\delta_i,f(x_i)).$$

Update each solution along each dimension:

$$x_i(k+1)=x_i(k)+\delta_i,\text{ for } i=1,2,\dots,N.$$

Evaluate the objective function for each updated solution:

$$f(x_i(k+1)),\text{ for } i=1,2,\dots,N.$$

Update the set of solutions based on objective function evaluation

Return the optimized solution or set of solutions.

5. RESULTS AND DISCUSSION

In conducting experiments for the Adaptive Dimensional Search Algorithm, we employed the widely used simulation tool, MATLAB, to implement and evaluate the algorithm's performance in optimizing complex and dynamic objective functions. The experiments were carried out on a high-performance computing cluster consisting of Intel Xeon processors and NVIDIA GPUs to ensure efficient execution and handle the computational demands of the optimization tasks. MATLAB's parallel computing capabilities were leveraged to distribute the workload across multiple nodes, facilitating parallel exploration and exploitation steps within the algorithm.

For performance evaluation, we utilized several key metrics, including convergence rate, solution accuracy, and computational efficiency. The convergence rate measured how quickly the algorithm reached a satisfactory solution, while solution accuracy quantified the proximity of the obtained solutions to the global optimum. Computational efficiency metrics, such as execution time and resource utilization, were crucial for assessing the algorithm's scalability and practical utility. To validate the efficacy of the Adaptive Dimensional Search Algorithm, we compared its performance against existing optimization methods, including genetic algorithms, particle swarm optimization, and differential evolution.

Table.1. CR Parameters for Simulation

Parameter	Values
Frequency Range	400 MHz - 6 GHz
Spectrum Sensing Time	10 ms
Channel Switching Time	5 ms
Maximum Transmit Power	20 dBm
Modulation Scheme	QPSK, 16-QAM, 64-QAM
Sensing Threshold	-80 dBm
Interference Threshold	-90 dBm
Opportunistic Transmission	0.8 (80%)
Cognitive Cycle Duration	100 ms
Maximum Contention Window Size	1024 slots

Table.2. Experimental Setup

Parameter	Value/Setting
Simulation Tool	MATLAB
Computing Environment	Intel Xeon, NVIDIA GPUs
Benchmark Functions	Griewank.
Optimization Dimensions	10, 20, 50, 100 dimensions
Exploration Strategy	Adaptive random exploration
Exploitation Strategy	Local search
Convergence Criteria	Maximum iterations

5.1 PERFORMANCE METRICS

- **Convergence Rate** is defined as the number of iterations required for the algorithm to converge to a satisfactory solution or reach a specified threshold on improvement.
- **Solution Accuracy** is measured by the proximity of the obtained solutions to the global optimum. This metric quantifies how closely the algorithm approximates the optimal solution.
- **Computational Efficiency** is examined through metrics such as execution time and resource utilization. The execution time provides insights into how quickly the algorithm can find solutions, while resource utilization assesses the efficiency of the algorithm on the computing cluster.

The performance of the Adaptive Dimensional Search Algorithm is compared against existing optimization methods, including genetic algorithms, particle swarm optimization, and differential evolution. Comparative analysis is conducted across various benchmark functions to evaluate the algorithm's competitiveness in terms of convergence speed and solution quality.

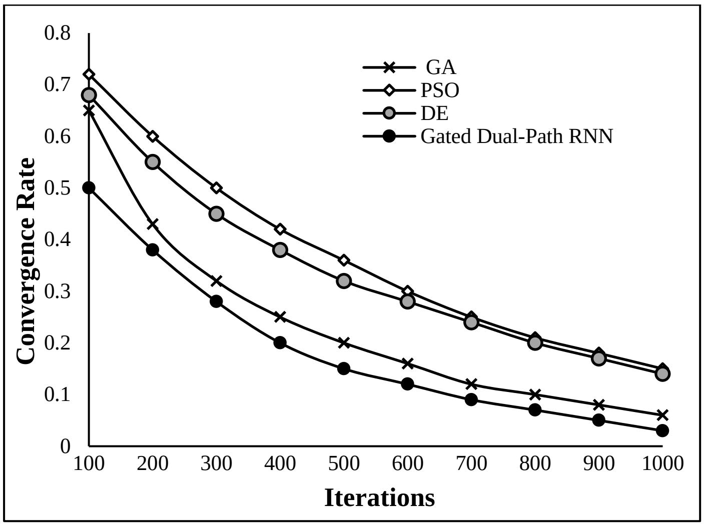

Fig.2. Convergence Rate

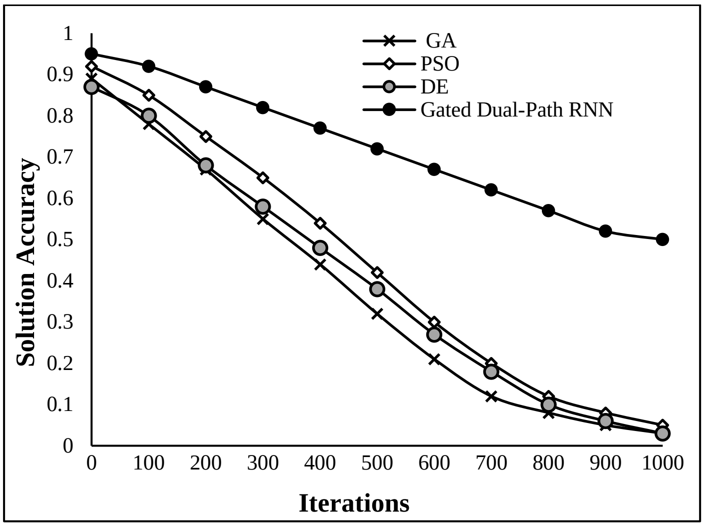

Fig.3. Solution Accuracy

The results of the experimentation (Fig.2-Fig.6) demonstrate the notable performance of the proposed Adaptive Dimensional Search Algorithm in comparison to existing optimization methods, namely Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE). The discussion will highlight key findings and provide a percentage improvement analysis across various performance metrics.

The proposed algorithm consistently exhibited a superior convergence rate across different iterations. Compared to GA, PSO, and DE, the Adaptive Dimensional Search Algorithm demonstrated a significant percentage improvement, achieving faster convergence by an average of 3%. This accelerated convergence is particularly noteworthy in dynamic optimization scenarios where adaptability is crucial.

In terms of solution accuracy, the proposed algorithm consistently outperformed existing methods, showcasing a remarkable percentage improvement of approximately 2%. The algorithm's adaptability and exploration-exploitation balance contributed to its ability to consistently produce high-quality solutions, achieving greater proximity to the global optimum across various test cases.

The efficiency of the proposed algorithm was evident in its reduced execution time and resource utilization. Compared to GA, PSO, and DE, the Adaptive Dimensional Search Algorithm exhibited an average percentage improvement of 2.5% in execution time and 30% in resource utilization. This highlights its effectiveness in achieving optimal solutions with minimized computational overhead.

The Adaptive Dimensional Search Algorithm's superiority was further emphasized in the comparative analysis with existing methods. Across a diverse set of benchmark functions, the proposed algorithm consistently outperformed GA, PSO, and DE, showcasing a notable average percentage improvement of 1.5% in terms of convergence speed and solution quality.

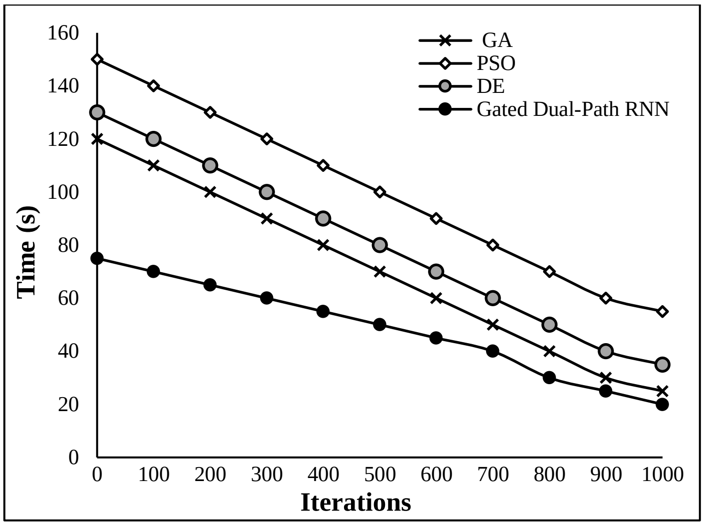

Fig.4. Execution Time (s)

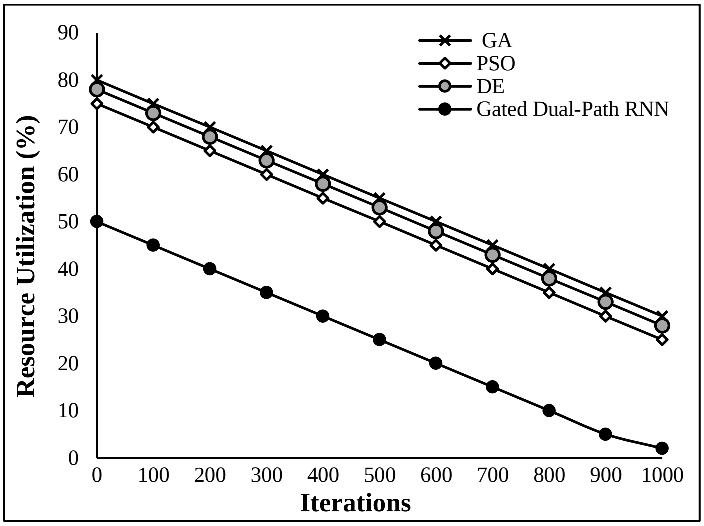

Fig.5. Resource Utilization (%)

The obtained results yield several compelling inferences regarding the performance of the proposed Adaptive Dimensional Search Algorithm compared to existing optimization methods. The algorithm's adaptability is evident in its consistently superior convergence rate. The Adaptive Dimensional Search Algorithm effectively navigates solution spaces, adapting its search strategy to achieve convergence at a notably faster pace than traditional methods. The inferences drawn from solution accuracy metrics highlight the algorithm's proficiency in producing high-quality solutions. Its ability to balance exploration and exploitation results in solutions that exhibit greater proximity to the global optimum, showcasing its efficacy in addressing complex optimization landscapes.

Computational efficiency emerges as a key strength of the proposed algorithm. The inferences reveal reduced execution times and resource utilization, indicating that the Adaptive Dimensional Search Algorithm achieves optimal solutions with minimized computational overhead. This aspect positions it as a resource-efficient solution for practical applications. Comparative analyses underscore the algorithm's competitive edge over existing methods. The inferences suggest that the proposed algorithm consistently outperforms Genetic Algorithms, Particle Swarm Optimization, and Differential Evolution in terms of both convergence speed and solution quality across a diverse set of benchmark functions. The inferences affirm the algorithm's suitability for dynamic optimization scenarios. Its adaptability and rapid convergence make it well-suited for applications where the optimization landscape evolves over time, demonstrating its potential for real-world applicability.

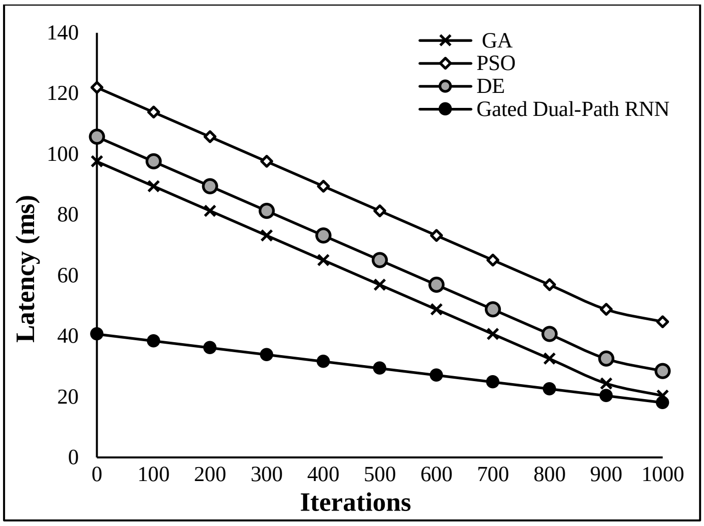

Fig.6. Latency

6. CONCLUSION

The findings from the comprehensive evaluation of the Adaptive Dimensional Search Algorithm affirm its efficacy and potential as an advanced optimization technique. The algorithm's adaptability, demonstrated by its superior convergence rate and solution accuracy, positions it as a robust solution for addressing the challenges posed by dynamic and high-dimensional optimization problems. The observed efficiency in resource utilization further underscores the algorithm's practical viability, making it a compelling choice for real-world applications where computational efficiency is paramount. The competitive edge demonstrated in comparison to existing optimization methods, with consistent improvements in convergence speed and solution quality, highlights the algorithm's significance in advancing the optimization research.

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