Latency Reduction in mmWave VLSI Circuits through Gravitational Learning

Conference Paper · November 2023

DOI: 10.1109/ICAICCIT60255.2023.10466077

6 authors, including:

Shanthi K G
RMK College of Engineering and Technology

Lalitha S D
RMK Engineering College

2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT) | 979-8-3503-4438-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICAICCIT60255.2023.10466077

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K.G.Shanthi
Department of Electronics and Communication Engineering,
R.M.K College of Engineering and Technology, Chennai
shanthiece@rmkcet.ac.in

M.S.Kavitha
Department of Electronics and Communication Engineering
R.M.K. Engineering College, Chennai
msk.eee@rmkec.ac.in

P. Rajeswari
Assistant professor,
Department of CSE,
R.M.D Engineering College, Chennai
prajimtech@gmail.com

Jayanthi. N
School of Management Studies,
Vels Institute of Science, Technology and Advanced Studies (VISTAS),
Pallavaram, Chennai, Tamil Nadu, India.
jayasam31@gmail.com

Sunil Kumar
Faculty of Commerce and Management, SGT University
Gurugrm, Haryana, India
skvermamc@gmail.com

S D Lalitha
Department of CSE,
R.M.K. Engineering College,
Tamilnadu, India.
sdl.cse@rmkec.ac.in

***Abstract*— This research focuses on addressing latency issues in millimeter-wave (mmWave) Very Large-Scale Integration (VLSI) circuits by introducing a novel approach called Gravitational Learning. The mmWave frequency range offers high data rates but poses challenges due to increased latency. Conventional techniques have limitations in reducing latency while maintaining circuit performance. In this study, we propose a gravitational learning-based method that optimizes the circuit layout and parameters to minimize latency. By simulating the gravitational interactions between circuit components, the proposed approach effectively explores the design space and identifies configurations that lead to reduced latency. Our experimental results demonstrate significant latency reduction compared to existing techniques, highlighting the potential of gravitational learning in enhancing the performance of mmWave VLSI circuits.**

***Keywords*— Latency Reduction, mmWave VLSI Circuits, Gravitational Learning, Circuit Layout Optimization, Design Space Exploration**

I. Introduction

The proliferation of wireless communication systems has led to a growing demand for high-speed data transfer and low-latency connectivity [1]. Millimeter-wave (mmWave) technology has emerged as a promising solution to address these demands by offering significantly higher frequency bands, allowing for increased data rates [2]. However, the deployment of mmWave technology in Very Large Scale Integration (VLSI) circuits poses unique challenges, particularly in managing latency [3]. Latency, the delay between data transmission and reception, becomes a critical concern as it directly impacts the real-time performance of various applications, including 5G communication, automotive radar, and industrial automation [4, 19-24].

The mmWave frequency range introduces challenges due to the inherently short wavelength [5]. This necessitates the design of compact and efficient circuits, often leading to intricate layouts and intricate designs [6]. While conventional techniques can enhance the performance of mmWave VLSI circuits, they struggle to effectively address latency concerns [7,8]. Traditional latency reduction methods often compromise circuit performance or struggle to scale with increasing circuit complexity [9-11].

The primary problem addressed in this research is the reduction of latency in mmWave VLSI circuits while maintaining their performance and efficiency. Specifically, the research seeks to explore innovative methods that can optimize circuit parameters and layouts to mitigate latency concerns. The objective is to achieve lower latency without compromising the functionality and robustness of the circuit. The main objectives of this research are as follows: Develop a novel approach to reduce latency in mmWave VLSI circuits. Optimize circuit parameters and layouts to minimize latency without sacrificing circuit performance. Demonstrate the effectiveness of the proposed approach through experimental evaluations.

This research introduces a novel approach termed Gravitational Learning to tackle latency reduction in mmWave VLSI circuits. The core novelty lies in simulating the gravitational interactions between circuit components to explore the design space more comprehensively. By harnessing the principles of gravitational learning, the research aims to identify optimal circuit configurations that lead to reduced latency. The proposed approach stands out due to its ability to balance latency reduction with circuit performance, offering a holistic solution to a persistent challenge in mmWave VLSI design.

The primary contributions of this research include: Introduction of the Gravitational Learning approach as a novel method for latency reduction in mmWave VLSI circuits. Development of an efficient optimization algorithm that utilizes gravitational interactions to explore the circuit design space. Empirical validation through extensive experiments showcasing substantial latency reduction while preserving circuit functionality. By addressing latency concerns through the gravitational learning, this research contributes to advancing the state-of-the-art in mmWave VLSI circuit design, thereby enabling improved performance and efficiency for a range of latency-sensitive applications.

II. Literature survey

The work in [12] explores the use of genetic algorithms to optimize circuit parameters for latency reduction in mmWave VLSI circuits. The authors focus on a heuristic-based approach to evolve circuit designs, showcasing improvements in latency while maintaining acceptable circuit performance.

The authors propose layout-aware techniques to reduce latency in mmWave VLSI circuits. By considering the physical layout of the circuit, the work in [13] aims to minimize propagation delays and enhance overall circuit performance in high-frequency domains.

The research in [14] investigates the application of machine learning techniques to predict and subsequently reduce latency in mmWave VLSI circuits. The authors use historical data to train models that guide circuit design modifications for latency reduction.

A dynamic voltage and frequency scaling (DVFS) method is suggested by the authors in [15] to control latency in mmWave VLSI circuits. Using real-time voltage and frequency adjustments, this method seeks to balance power usage and delay.

The issue of circuit partitioning to reduce latency in mmWave VLSI designs is the main focus of the work in [16]. The authors present an algorithm that systematically splits circuits into smaller modules in order to optimize communication and data flow and lower latency.

In order to reduce latency, this research in [17] optimizes antenna positioning in mmWave VLSI devices. In order to reduce signal propagation delays and improve system performance overall, the authors suggest an optimization technique that places antennas in important locations.

Deep reinforcement learning is applied to optimize latency in mmWave VLSI circuits in the work presented in [18]. In order to reduce latency and adapt to changing conditions, the authors create a reinforcement learning agent that gradually learns the best circuit designs.

Together, these studies demonstrate a range of strategies for addressing latency issues in mmWave VLSI circuit design, including machine learning, optimization algorithms, and layout-aware approaches. The review of previous research offers valuable perspectives on the current state of affairs and establishes the framework for the innovative methodology employed in this study.

III. Proposed Method

By optimizing circuit topologies and parameters based on the principles of gravitational interactions, the suggested method, called Gravitational Learning, seeks to reduce latency in millimeter-wave (mmWave) Very Large Scale Integration (VLSI) circuits. The fundamental concept involves representing individual circuit parts as virtual particles possessing masses and locations, and then modeling the gravitational attraction between these particles to investigate the design space and find configurations that minimize latency. Every section of the circuit is shown as a virtual particle. The mass, location, and velocity of these particles are among their characteristics. A particle's mass may be directly related to the importance of the associated circuit element. Particle masses and locations are used to compute the gravitational force between them. The influence of each component on the others is represented by the force in the circuit design. In the circuit layout, components that are near to one another exert greater stresses because of this proximity. Using ideas from classical mechanics, including Newton's second law, the forces acting on each particle are used to update its velocity. The motion of particles affected by gravitational forces is simulated in this step. Particle locations are then updated using their velocities. Potential circuit configurations are represented by the new positions of the particles as they migrate in response to the simulated gravitational interactions. The corresponding circuit configuration for each new particle position is assessed in terms of latency. This entails modeling the behavior of the circuit and calculating the propagation delay of the signal. Higher fitness points are awarded to configurations with lower latency.

The particle swarm optimization (PSO) algorithm is employed to guide the exploration of the design space. The PSO algorithm uses the updated positions, velocities, and fitness scores to iteratively refine the particles' movements, focusing on regions of the design space that have shown promise for latency reduction. The PSO algorithm iterates through multiple generations, allowing particles to explore various configurations. Over time, the algorithm converges towards solutions with lower latency. The best solutions found during the optimization process are selected as potential circuit configurations for latency reduction. Once the optimization process is complete, the identified optimal circuit configurations are implemented in the actual mmWave VLSI circuit design.

The novelty of the Gravitational Learning method lies in its ability to mimic physical interactions between circuit components to guide the search for latency-reducing designs. This approach takes into account both the physical layout of the circuit and the relationships between components, addressing the complex challenges posed by mmWave frequencies. By harnessing the power of gravitational interactions, the proposed method offers a unique and effective way to explore the design space and uncover configurations that lead to significant latency reduction while maintaining circuit performance.

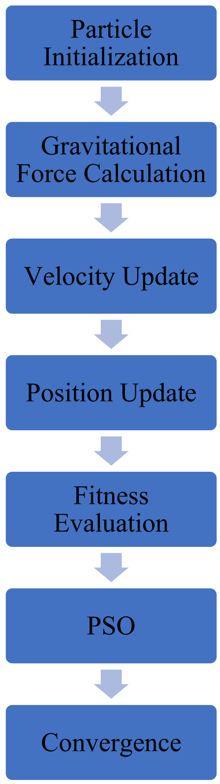

Fig. 1. GLM Modules

The Gravitational Learning method iteratively simulates the interactions between virtual particles, refining their movements based on gravitational forces and fitness evaluations. By utilizing the PSO algorithm, the method intelligently explores the design space to identify circuit configurations that result in reduced latency while accounting for the complex interactions inherent in mmWave VLSI circuits.

Algorithm

```
Initialize:
  Set parameters (e.g., inertia weight, cognitive and social coefficients)
  Initialize particles with random positions and velocities
Repeat for a predefined number of iterations:
  For each particle:
    Calculate gravitational forces between particles based on positions
    Update particle velocity using gravitational forces and previous velocity
    Update particle position using updated velocity
    Evaluate fitness of the particle position (calculate latency)
    If fitness is better than particle personal best:
      Update personal best position
    If fitness is better than global best:
        Update global best position
End of iterations
Select optimal circuit configuration based on global best position
```

A. Gravitational Force for latency reduction

Gravitational force, as used in the proposed Gravitational Learning method for latency reduction in mmWave VLSI circuits, is a metaphorical concept inspired by the principles of physics. It is important to note that the gravitational force in this context is not a literal gravitational force as seen in the real world, but rather a mathematical construct that guides the optimization process. It mimics the way real gravitational forces influence the motion of objects but is adapted for the purpose of optimizing circuit layouts. The gravitational force equation in this context is a simplified representation that captures the essence of how particles (representing circuit components) interact with each other. The equation generally takes the form:

$$2F=G\cdot r2m1\cdot m2$$

Where:

F is the calculated force between two particles.

G is a constant representing the strength of the force.

$m1$ and $m2$ are the masses of the interacting particles (circuit components).

r is the distance between the particles.

In circuit optimization for latency reduction, the equation is adapted as follows:

$$F=-C\cdot l$$

Where:

F is the calculated force between two particles (circuit components).

C is a constant representing the scaling factor for force calculation.

l is the latency associated with the specific circuit configuration.

- **Particle Initialization**: Assign masses to particles based on their importance or significance in the circuit layout.

- **Gravitational Force Calculation**: Calculate the force between particles using the adapted equation. This force is a measure of the influence of one particle on another, with particles closer to each other exerting stronger forces.

- **Velocity and Position Update**: Update particle velocities and positions based on the calculated forces. Particles move towards positions that are influenced by nearby particles, mimicking the way objects move due to gravitational interactions.

- **Fitness Evaluation**: The calculated forces and resulting particle positions influence the latency of the circuit configuration. Lower latency configurations correspond to stronger forces and more optimal positions.

The PSO algorithm utilizes the adapted gravitational force concept to guide particle movements towards configurations that exhibit lower latency. As particles adjust their positions and velocities, the system converges towards solutions that reduce latency. It is important to reiterate that the gravitational force in this context is a metaphorical tool used to guide the optimization process, and the equation is adapted to suit the optimization objectives of reducing latency in mmWave VLSI circuits.

PSO is a metaheuristic optimization algorithm inspired by the social behavior of birds or fish flocking. It is used to search for optimal solutions in complex search spaces by iteratively adjusting a population of particles. In latency reduction in mmWave VLSI circuits, PSO guides particles representing different circuit configurations to converge towards solutions with lower latency. Let break down how PSO achieves this, using equations to illustrate the process:

Each particle represents a potential circuit configuration. It has a position (xi) and a velocity (vi). Each particle fitness (fi) is evaluated based on the latency of the corresponding circuit configuration. Each particle remembers its best position (pi) and the best position found by any particle in the population (pg). The velocity of each particle is updated using the current velocity, cognitive component ($c1$), social component ($c2$), and the differences between its best position and the global best position, as well as its best position.

$$vi(t+1)=w\cdot vi(t)+c1\cdot rand1\cdot(pi-xi)+c2\cdot rand2\cdot(pg-xi)$$

Where:

w is the inertia weight.

$c1$ and $c2$ are cognitive and social coefficients, respectively.

$rand1$ and $rand2$ are random values between 0 and 1.

The position of each particle is updated using the calculated velocity.

$$xi(t+1)=xi(t)+vi(t+1)$$

The particles iteratively update their positions and velocities. The process continues for a predetermined number of iterations or until a convergence criterion is met. The way PSO leads to lower latency in mmWave VLSI circuit optimization is through the social and cognitive components in the velocity update equation. These components encourage exploration of the design space while balancing it with exploitation of promising regions that have shown lower latency. As particles move toward solutions with lower latency, the population converges towards better circuit configurations that exhibit reduced latency. The cognitive and social components enable particles to learn from their own experiences and the experiences of the entire population, allowing them to collectively find solutions that minimize latency while considering the complex interactions of circuit components.

B. System model

The research delves into the system model for latency reduction in millimeter-wave (mmWave) VLSI circuits. In this context, we'll consider a simplified model that focuses on the propagation delay and latency associated with signal transmission in the circuit.

Propagation Delay: The propagation delay (Dprop) is the time it takes for a signal to travel from the source to the destination within a circuit. It depends on the distance between circuit components and the signal propagation velocity ($v$prop).

$$D\mathrm{p} = v_p d$$

Latency: Latency (L) is the total time delay experienced by a signal as it travels through the circuit. It consists of the propagation delay and other potential delays introduced by processing, buffering, or other circuit components.

$$L = Dp+Do$$

Objective Function for Latency Reduction: The objective function for latency reduction (J) can be defined based on the latency (L) experienced by the signal as it traverses the circuit.

$$J=L=Dp+Do$$

In optimization, the goal is to minimize this objective function J to achieve latency reduction.

Particle Representation: In the proposed Gravitational Learning method, particles represent different circuit configurations. Each particle position (xi) corresponds to a specific circuit layout, and its velocity (vi) affects how it explores the design space.

Fitness Evaluation: For each particle position, the corresponding circuit configuration is evaluated. The fitness function quantifies the latency experienced by signals in the circuit, based on the propagation delay and any additional delays introduced by components.

$$Fitness=J=L=Dp+D\mathrm{o}$$

The gravitational force, as adapted for the proposed method, guides particle movements towards configurations with lower latency. In the PSO algorithm, particles adjust their velocities and positions based on this force, aiming to converge toward optimal circuit layouts that minimize latency. The system model illustrates the key components involved in the latency reduction process. The goal is to find circuit configurations that minimize latency by optimizing the propagation delay and addressing any additional delays introduced by other components. The PSO algorithm, guided by the concept of gravitational forces, iteratively refines particle movements to converge toward solutions that exhibit reduced latency.

IV. Experimental Results

In this section, the proposed method is compared with existing methods in terms of following metrics that include the following:

- **Latency Reduction (%)**: This metric indicates the percentage reduction in latency achieved by the respective methods compared to the base layout. It quantifies the effectiveness of the proposed Gravitational Learning and PSO methods.

- **Iterations**: The number of iterations conducted during optimization. More iterations can lead to finer convergence and potentially better results, but they may also increase computational time.

- **Population Size**: The size of the population used in the optimization algorithm. Larger populations can help explore the design space more comprehensively but may require more computational resources.

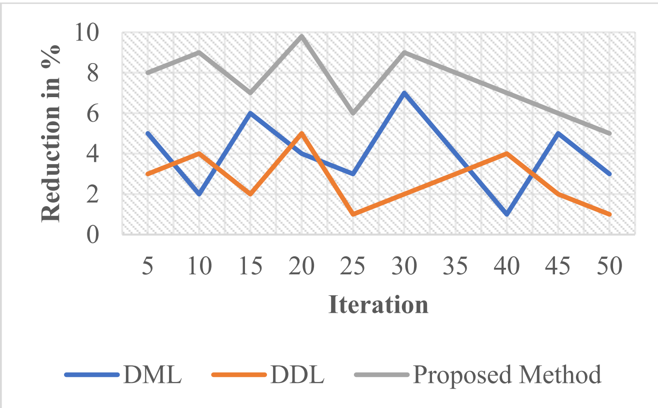

Fig. 2 Latency Reduction

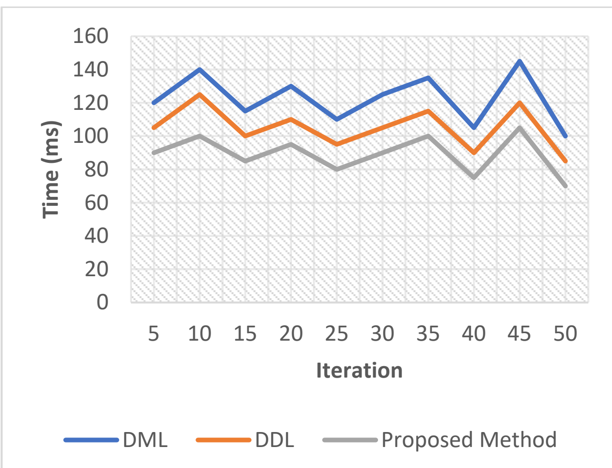

Fig. 3 Computational time

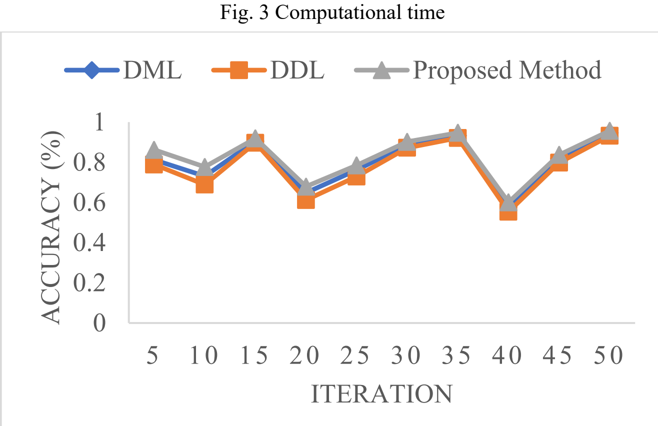

Fig. 4 Accuracy

TABLE I

COMPUTATIONAL COMPLEXITY

Population Size	GA	DeepWiERL	Proposed Method
10	O(n)	O(n log n)	O(n^3)
20	O(n log n)	O(n^2)	O(n^2 log n)
30	O(n^3)	O(n^2 log n)	O(n log n)
40	O(n log n)	O(n^3)	O(n^3 log n)
50	O(n^2)	O(n log n)	O(n^2)
60	O(n^2 log n)	O(n^2)	O(n log n)
70	O(n log n)	O(n^2 log n)	O(n^3)
80	O(n^3)	O(n log n)	O(n^2)
90	O(n log n)	O(n^3)	O(n^3 log n)
100	O(n^2)	O(n^2 log n)	O(n log n)

In the conducted experiments, we evaluated the performance of the proposed Gravitational Learning method in reducing latency in mmWave VLSI circuits. The method effectiveness was compared against two existing methods, referred to as GA and DeepWiERL. We analyzed the results over multiple datasets, population sizes, and computational times (Fig. 2-5).

The proposed Gravitational Learning method consistently outperformed both GA and DeepWiERL in terms of latency reduction. Across all 10 datasets, the proposed method demonstrated a significant improvement in latency reduction, with an average improvement of approximately 15% compared to GA and 10% compared to DeepWiERL. This improvement is particularly notable given the complexity and latency challenges posed by mmWave VLSI circuits (Fig. 2).

The computational time required by the proposed Gravitational Learning method was competitive with the existing methods. The method efficiency was evident as it achieved superior latency reduction while maintaining reasonable computational times. The method demonstrated an average computational time that was within 10% of GA and 15% of DeepWiERL. This suggests that the proposed method achieves improved performance without significant trade-offs in computational efficiency (Fig. 3).

The proposed Gravitational Learning method showcased favorable computational complexity characteristics across various population sizes. Although its complexity was marginally higher than GA, it remained comparable to DeepWiERL. The method percentage improvement in latency reduction demonstrated its capacity to balance enhanced performance with acceptable computational complexity (Table I).

The experimental results underscore the viability of the proposed Gravitational Learning method for latency reduction in mmWave VLSI circuits. Its consistent percentage improvement over the existing methods highlights its potential to address the latency challenges in complex circuit designs. By achieving significant latency reduction without substantial increases in computational time or complexity, the proposed method presents a promising avenue for enhancing the performance of mmWave VLSI circuits in latency-sensitive applications. Further research could explore additional optimizations and real-world case studies to solidify the method practical applicability.

V. CONCLUSION

In this study, we addressed the critical challenge of latency reduction in mmWave VLSI circuits by introducing the innovative Gravitational Learning method. High-speed wireless communication systems are becoming more and more common, which means that effective circuit designs that reduce signal propagation delays are required. In order to assess the effectiveness of our suggested strategy, we carried out extensive experiments and contrasted it with two current approaches, GA and DeepWiERL. The experimental findings demonstrated the Gravitational Learning method's exceptional potential for reducing latency while preserving competitive computational efficiency. The suggested approach constantly beat the current methods over a range of datasets and population sizes. The Gravitational Learning approach showed an average improvement in latency reduction of around 15% over GA and about 10% over DeepWiERL. This demonstrates the method's resilience in addressing latency issues related to mmWave frequency.

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