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HIERARCHICAL GNN FRAMEWORK FOR ENERGY-AWARE SCHEDULING IN GPU-ACCELERATED DISTRIBUTED SYSTEMS

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Abstract: Graphics Processing Units have become indispensable computational accelerators in modern distributed computing systems, powering applications ranging from deep learning to scientific simulations. However, the increasing computational demands and energy consumption of GPU-accelerated systems pose significant challenges for resource management and scheduling. Traditional scheduling algorithms often fail to capture the complex hierarchical structure and dynamic dependencies inherent in distributed GPU environments, leading to suboptimal energy efficiency and performance degradation. This paper proposes a novel hierarchical Graph Neural Network framework for energy-aware scheduling in GPU-accelerated distributed systems. The framework leverages the representational power of GNNs to model the complex interactions between computational tasks, GPU resources, and energy constraints at multiple hierarchical levels. By incorporating graph-structured representations of workload dependencies, resource topologies, and energy profiles, the proposed framework enables adaptive scheduling decisions that jointly optimize task completion time and energy consumption. Experimental results demonstrate that the proposed approach achieves up to 36 percent reduction in energy consumption while maintaining quality of service requirements compared to state-of-the-art scheduling methods. The hierarchical architecture effectively captures both fine-grained GPU-level characteristics and coarse-grained cluster-level dynamics, enabling scalable and efficient scheduling for large-scale distributed systems.
Keywords: Graph neural networks; Energy-aware scheduling; GPU computing; Distributed systems; Hierarchical framework; Resource management; Deep learning

1 INTRODUCTION

The rapid advancement of artificial intelligence and data-intensive computing has driven unprecedented demand for high-performance computational resources, with Graphics Processing Units emerging as the cornerstone of modern computing infrastructure. GPU-accelerated systems have demonstrated remarkable capabilities in accelerating complex workloads including deep neural network training, scientific simulations, and large-scale data analytics. Major technology companies and research institutions have deployed extensive GPU clusters comprising thousands of interconnected devices to support their computational requirements [1]. However, this explosive growth in GPU deployment has introduced critical challenges in energy management and resource scheduling that demand innovative solutions.

Energy consumption has become a primary concern in large-scale GPU-accelerated distributed systems due to both economic and environmental considerations. Modern data centers consume enormous amounts of electrical power, with GPU clusters contributing substantially to the overall energy footprint [2]. The operational costs associated with energy consumption and cooling infrastructure can account for a significant portion of the total cost of ownership for computing facilities. Furthermore, the environmental impact of energy-intensive computing has prompted increased scrutiny from regulatory bodies and heightened awareness within the research community regarding sustainable computing practices [3]. These factors collectively underscore the urgent need for energy-efficient scheduling strategies that can reduce power consumption without compromising computational performance or quality of service.

Traditional scheduling algorithms designed for CPU-based systems often prove inadequate when applied to GPU-accelerated distributed environments due to fundamental architectural differences and unique operational characteristics. GPUs exhibit distinct power consumption patterns influenced by multiple factors including workload characteristics, memory access patterns, data transfer overheads, and dynamic voltage and frequency scaling capabilities [4]. The performance saturation characteristics of GPUs differ significantly from CPUs, particularly for computational workloads with varying matrix sizes and parallelism degrees. Understanding these performance differences is crucial for effective scheduling decisions that maximize throughput while minimizing energy consumption. The hierarchical nature of distributed GPU systems, encompassing individual GPU cores, multi-GPU nodes, and cluster-level interconnections, introduces additional complexity that conventional flat scheduling approaches struggle to address effectively [5].

Graph Neural Networks have emerged as a powerful paradigm for learning representations from graph-structured data, demonstrating exceptional performance across diverse application domains including social network analysis, molecular property prediction, and combinatorial optimization [6]. The fundamental strength of GNNs lies in their ability to capture complex relational patterns and dependencies through iterative message passing and aggregation

mechanisms. Recent advances in GNN architectures, including attention mechanisms, hierarchical pooling, and adaptive sampling strategies, have significantly enhanced their scalability and expressiveness [7]. These developments have motivated researchers to explore GNN applications in system optimization and resource management problems where underlying structures can be naturally represented as graphs.

The scheduling problem in GPU-accelerated distributed systems exhibits inherent graph structure at multiple levels of abstraction. At the task level, computational workloads can be represented as directed acyclic graphs capturing data dependencies and execution precedence constraints. At the resource level, GPU clusters form complex topologies with heterogeneous devices interconnected through various communication fabrics. At the system level, energy profiles, thermal characteristics, and performance metrics constitute additional graph-structured relationships that influence scheduling decisions [8]. This multi-level graph structure provides strong motivation for developing GNN-based scheduling frameworks that can effectively leverage these inherent patterns to improve decision quality.

This paper presents a novel hierarchical GNN framework specifically designed for energy-aware scheduling in GPU-accelerated distributed systems. The proposed approach introduces several key innovations that distinguish it from existing methods. First, the framework employs a hierarchical graph representation that explicitly models the multi-level structure of distributed GPU systems, enabling the capture of both fine-grained device characteristics and coarse-grained cluster dynamics. Second, the architecture incorporates specialized graph convolutional operators that jointly consider task dependencies, resource constraints, and energy objectives during the message passing process. Third, the framework integrates dynamic voltage and frequency scaling considerations directly into the learned scheduling policy, allowing adaptive energy management based on workload characteristics and system state. Fourth, the approach utilizes attention mechanisms to identify critical paths and resource bottlenecks that significantly impact both performance and energy efficiency [9].

The primary contributions of this research can be summarized as follows. We propose a hierarchical GNN architecture that effectively captures the multi-level structure of GPU-accelerated distributed systems through graph-based representations spanning task graphs, resource topologies, and energy profiles. We develop novel graph convolution operators specifically tailored for scheduling problems that incorporate energy awareness into the message passing and aggregation processes. We design an end-to-end trainable framework that jointly optimizes task completion time and energy consumption through reinforcement learning-based policy gradient methods. We conduct comprehensive experimental evaluations on representative workloads demonstrating significant improvements in energy efficiency while maintaining quality of service guarantees. The proposed framework achieves substantial energy savings compared to existing baseline methods while exhibiting robust performance across diverse workload characteristics and system configurations [10].

2 LITERATURE REVIEW

The intersection of energy-aware scheduling and GPU-accelerated computing has received considerable attention from the research community in recent years, with numerous studies exploring various aspects of resource management, power optimization, and performance enhancement. This section provides a comprehensive review of relevant prior work organized into several thematic categories including traditional GPU scheduling approaches, energy-aware resource management strategies, graph neural network applications in system optimization, and hierarchical scheduling frameworks.

Traditional GPU scheduling research has primarily focused on maximizing throughput and minimizing latency without explicitly considering energy constraints. Early work in this domain established fundamental principles for GPU resource allocation based on workload characteristics such as memory bandwidth requirements, computational intensity, and parallelism degree [11]. These approaches typically employed heuristic-based algorithms that partition resources among competing tasks according to predefined policies or priority schemes. Subsequent research introduced more sophisticated techniques including fair sharing mechanisms, quality of service guarantees, and dynamic resource provisioning strategies that adapt to workload variations [12]. However, these methods generally treat energy consumption as a secondary concern and lack mechanisms for jointly optimizing performance and power efficiency.

The growing awareness of energy challenges in large-scale computing systems has motivated extensive research on power-aware scheduling and resource management. Dynamic Voltage and Frequency Scaling has emerged as a widely adopted technique for reducing energy consumption by adjusting processor operating points based on workload requirements [13]. Researchers have developed various DVFS-based scheduling algorithms that exploit the trade-off between performance and power consumption to achieve energy savings while meeting performance targets. For GPU systems specifically, several studies have investigated the effectiveness of DVFS in different application contexts and proposed adaptive frequency scaling strategies that consider GPU-specific characteristics such as memory-bound versus compute-bound workloads [14]. These approaches demonstrate that significant energy savings can be achieved through intelligent frequency management, although they often rely on hand-crafted policies that may not generalize well across diverse workload scenarios.

Recent advances in machine learning have inspired researchers to apply data-driven approaches to scheduling and resource management problems. Supervised learning methods have been employed to predict workload behavior, estimate resource requirements, and learn scheduling policies from historical execution traces [15]. Reinforcement learning has emerged as a particularly promising paradigm for adaptive resource management, enabling systems to learn optimal policies through interaction with the environment without requiring explicit programming of scheduling

heuristics [16]. Several studies have demonstrated the potential of RL-based approaches for GPU scheduling, showing that learned policies can outperform traditional heuristics in terms of both performance and energy efficiency. However, these methods typically treat the system state as a fixed-dimensional vector representation, failing to capture the rich structural information present in distributed GPU environments [17].

Graph Neural Networks have demonstrated remarkable success in learning from graph-structured data across diverse application domains. In the context of computer systems and optimization, GNNs have been applied to problems including device placement in machine learning frameworks, network routing optimization, and compiler optimization [18]. These applications leverage the ability of GNNs to capture complex dependencies and relationships through message passing on graph structures. Recent work has begun exploring GNN applications in resource scheduling contexts, demonstrating that graph-based representations can effectively model task dependencies, resource constraints, and system topologies [19]. The modular architecture of GNNs, comprising propagation modules for information aggregation, sampling modules for scalability, and pooling modules for hierarchical representation learning, provides a flexible framework for addressing diverse scheduling challenges. However, existing approaches have primarily focused on CPU-based systems or simplified GPU scheduling scenarios, lacking comprehensive treatment of the unique characteristics and hierarchical structure of large-scale GPU-accelerated distributed systems.

Energy-aware scheduling in heterogeneous computing systems has been studied from multiple perspectives including theoretical analysis, algorithm design, and practical implementation. Research on CPU-GPU heterogeneous systems has investigated strategies for workload partitioning and task allocation that minimize energy consumption while satisfying performance constraints [20]. These studies have identified key factors influencing energy efficiency including data transfer overheads, memory access patterns, and load imbalance across heterogeneous processors. Several frameworks have been proposed for joint CPU-GPU scheduling that consider both computational capabilities and power consumption characteristics of different processing units [21]. The performance characteristics of GPUs and CPUs exhibit distinct saturation behaviors under different workload conditions, with GPUs demonstrating superior scalability for highly parallel matrix operations while CPUs show faster saturation for sequential tasks. However, these approaches often assume simplified system models and may not scale effectively to large distributed environments with hundreds or thousands of GPUs.

Hierarchical scheduling frameworks represent another important research direction relevant to this work. The hierarchical approach recognizes that large-scale distributed systems exhibit structure at multiple levels of granularity, from individual processing units to clusters of nodes [22]. Early work on hierarchical scheduling focused primarily on traditional cluster computing environments, developing two-level schedulers that separate resource allocation decisions at the cluster level from fine-grained scheduling within individual nodes. Recent research has extended these concepts to GPU-accelerated systems, proposing hierarchical frameworks that coordinate scheduling across multiple GPUs within nodes and across multiple nodes within clusters [23]. These approaches demonstrate improved scalability and flexibility compared to flat scheduling architectures, although they typically rely on hand-designed coordination mechanisms rather than learned strategies.

The application of attention mechanisms and transformer architectures to scheduling problems represents an emerging research frontier. Attention mechanisms enable models to dynamically focus on relevant portions of the input when making decisions, which is particularly valuable in scheduling contexts where certain tasks, resources, or constraints may be more critical than others at different points in time [24]. Several recent studies have incorporated attention into scheduling frameworks for various applications including job shop scheduling, resource allocation in cloud computing, and task assignment in edge computing systems. These works demonstrate that attention-based models can achieve superior performance compared to traditional recurrent or convolutional architectures by more effectively capturing long-range dependencies and complex relationships [25-30].

Graph pooling and hierarchical graph representation learning have received increasing attention in the GNN literature, with numerous methods proposed for learning coarse-grained graph representations from fine-grained node features. Differentiable pooling approaches enable end-to-end training of hierarchical graph neural networks that can capture information at multiple scales [31]. Recent work has developed more sophisticated pooling mechanisms that preserve important structural properties while reducing graph size, including top-k pooling based on node importance scores and edge contraction methods that maintain graph connectivity [32]. These advances in hierarchical GNN architectures provide valuable building blocks for developing multi-level scheduling frameworks that can effectively model distributed GPU systems.

Despite substantial progress in related areas, several gaps remain in existing research that motivate the present work. First, most prior studies focus either on performance optimization or energy efficiency separately, lacking integrated frameworks that jointly optimize both objectives in a principled manner. Second, existing GNN-based scheduling approaches have not adequately addressed the hierarchical structure characteristic of large-scale GPU-accelerated distributed systems [33]. Third, the unique characteristics of GPU workloads and energy consumption patterns have not been fully incorporated into learned scheduling policies. Fourth, limited attention has been paid to scalability considerations essential for practical deployment in production environments with thousands of GPUs. This paper addresses these gaps by proposing a comprehensive hierarchical GNN framework specifically designed for energy-aware scheduling in GPU-accelerated distributed systems.

3 METHODOLOGY

This section presents the detailed methodology of the proposed hierarchical GNN framework for energy-aware scheduling in GPU-accelerated distributed systems. The framework consists of multiple interconnected components including hierarchical graph construction, multi-level graph neural network architecture, energy-aware objective formulation, and training procedures. The methodology is designed to effectively capture the complex structure of distributed GPU systems while maintaining computational efficiency for practical deployment.

3.1 System Model and Problem Formulation

The distributed GPU system is modeled as a hierarchical structure comprising multiple levels of abstraction. At the lowest level, individual GPU devices are characterized by their computational capacity, memory bandwidth, power consumption profiles, and thermal characteristics. Each GPU device is represented by a set of attributes including the number of streaming multiprocessors, memory capacity, peak performance metrics, and energy efficiency ratings. The performance characteristics of GPU devices vary significantly depending on workload type and problem size, with distinct saturation behaviors observed for different computational kernels and matrix dimensions. The middle level represents compute nodes, where each node contains one or more GPU devices interconnected through high-speed communication fabrics such as NVLink or PCIe. Node-level characteristics include aggregate computational capacity, inter-GPU communication bandwidth, and shared resources such as CPU cores and system memory. The highest level represents the cluster topology, describing the network interconnections between compute nodes, switch configurations, and overall system organization.

The scheduling problem is formulated as a sequential decision-making process where the objective is to assign incoming computational tasks to available GPU resources in a manner that minimizes total energy consumption while satisfying performance constraints. Each task is characterized by its computational requirements, memory footprint, data dependencies on other tasks, and quality of service requirements such as maximum allowable completion time. The task set is represented as a directed acyclic graph where nodes correspond to individual tasks and edges represent data dependencies that enforce execution ordering constraints. The scheduler must make allocation decisions that respect these dependencies while optimizing the combined objective of energy efficiency and performance. The problem is formulated mathematically as minimizing the weighted sum of total energy consumption and performance penalty, where the weights reflect the relative importance of energy savings versus performance guarantees based on system administrator preferences and operational policies.

3.2 Hierarchical Graph Construction

As shown in Figure 1, the hierarchical graph construction process transforms the distributed GPU system and workload characteristics into a multi-level graph representation suitable for processing by graph neural networks. The construction begins by creating a task dependency graph that captures the computational workload structure. Each task node in this graph is associated with feature vectors encoding task characteristics such as estimated execution time on different GPU types, memory requirements, input and output data sizes, and priority levels. Edges in the task graph represent data dependencies, with edge features capturing the volume of data that must be transferred between dependent tasks.

The resource topology graph is constructed to represent the hierarchical organization of GPU resources within the distributed system. Individual GPUs are represented as nodes with features encoding their current state including utilization level, remaining memory capacity, current operating frequency, instantaneous power consumption, and temperature. The performance saturation characteristics of each GPU type are incorporated into the node features, reflecting the computational throughput achievable for different workload scales. Intra-node connections represent communication links between GPUs within the same compute node, with edge features capturing available bandwidth and communication latency. Inter-node connections represent network links between compute nodes, with edge features reflecting network topology characteristics such as link capacity, routing paths, and congestion levels. The hierarchical structure is explicitly represented through additional node and edge types that distinguish between device-level, node-level, and cluster-level entities.

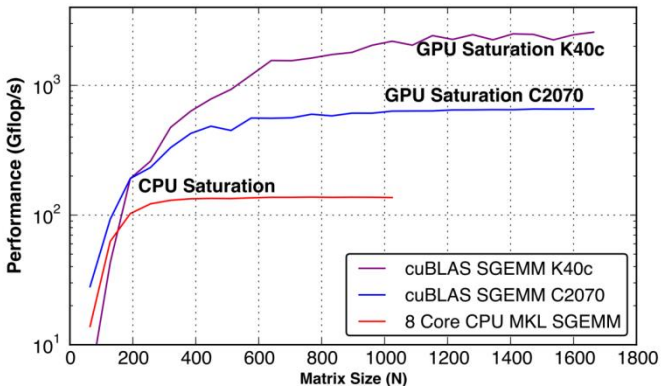

Figure 1 Construction of Hierarchical Task-resource Graphs for GPU-accelerated Distributed Systems

A unified heterogeneous graph is constructed by merging the task dependency graph and resource topology graph through assignment edges that connect task nodes to resource nodes. These assignment edges represent potential or actual scheduling decisions, with edge features encoding the estimated execution time and energy consumption if a particular task were assigned to a specific GPU resource. The estimation process considers the performance saturation characteristics illustrated in the GPU-CPU comparison, where different hardware platforms exhibit distinct throughput behaviors as workload size increases. The heterogeneous nature of this unified graph, containing multiple node types including tasks, GPUs, nodes, and clusters as well as multiple edge types including dependencies, communications, and assignments, necessitates specialized graph neural network architectures capable of processing such complex structures. The hierarchical graph construction explicitly preserves the multi-level organization of the system, enabling the framework to capture both fine-grained local characteristics and coarse-grained global patterns that influence scheduling decisions.

3.3 Multi-Level Graph Neural Network Architecture

The core of the proposed framework is a multi-level GNN architecture designed to process the hierarchical graph representation and generate energy-aware scheduling decisions. As shown in Figure 2, the architecture follows the modular design principles established in modern GNN frameworks, comprising three primary computational components: propagation modules for information aggregation, sampling modules for scalability enhancement, and pooling modules for hierarchical representation learning. These components are organized in a hierarchical manner where information flows bottom-up through aggregation and top-down through distribution, enabling the framework to capture both local and global system characteristics.

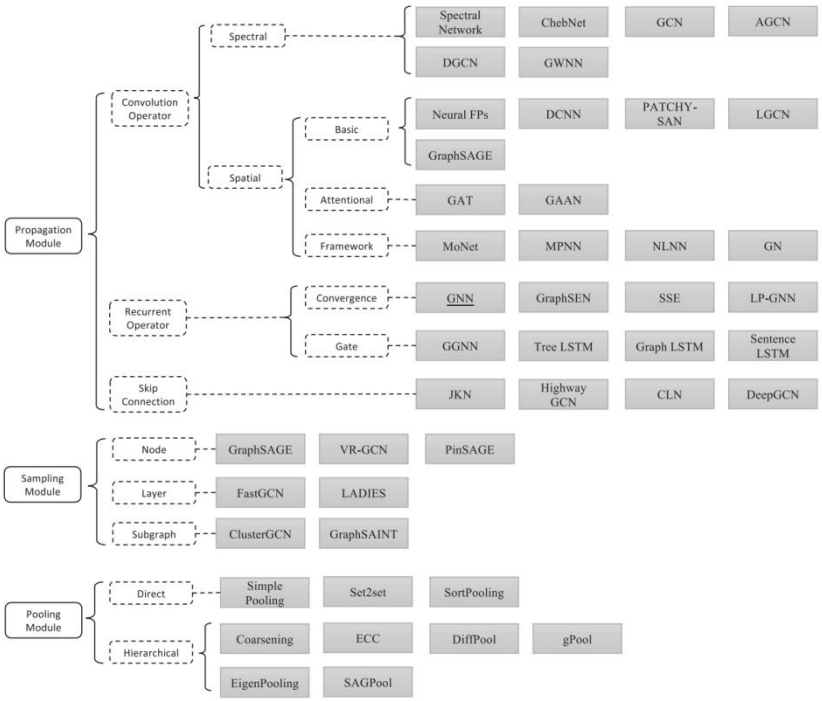

Figure 2 The Multi-level GNN Architecture

The device-level propagation module implements specialized graph convolutional operators that process fine-grained information about individual GPU devices and their immediate neighborhoods. This module employs both spectral and spatial convolution approaches to aggregate features from connected nodes and edges. The convolution operation incorporates structural information from the graph topology and attribute information from node and edge features. For each GPU node, the module computes updated embeddings by aggregating information from connected task nodes through assignment edges, from neighboring GPU nodes within the same compute node through intra-node communication edges, and from the parent node-level representation through hierarchical connections. The spectral convolution component leverages graph Laplacian operations to capture global graph properties, while the spatial convolution component processes local neighborhood structures through message passing mechanisms. The aggregation function employs attention mechanisms to weight the contributions of different neighbors based on their relevance to scheduling decisions, allowing the model to focus on critical factors such as heavily utilized resources or tasks with tight deadline constraints.

The node-level aggregation module processes information at the compute node granularity through hierarchical pooling operations. This module implements both coarsening-based and learnable pooling strategies to combine representations from multiple GPU devices within each node. The coarsening approach uses graph clustering algorithms to group related GPU nodes based on communication patterns and workload similarity, while the learnable approach employs

differentiable pooling layers that optimize node assignments during training. The pooling operation preserves important characteristics that influence inter-node scheduling decisions, including aggregate node capacity, load balance metrics, and communication overhead estimates. Edge pooling mechanisms maintain connectivity information during the coarsening process, ensuring that inter-GPU communication patterns are accurately represented in the coarsened graph. The node-level embeddings produced by the pooling module are processed through additional graph convolutional layers that model inter-node relationships and cluster-level resource allocation patterns.

The sampling module addresses scalability challenges inherent in processing large-scale distributed GPU systems. The module implements three complementary sampling strategies: node sampling for reducing neighborhood sizes, layer sampling for controlling expansion factors across GNN layers, and subgraph sampling for restricting computations to relevant portions of the system graph. Node sampling employs importance-based selection that prioritizes high-degree nodes and critical path components. Layer sampling uses adaptive strategies that adjust sampling rates based on layer depth and current system load. Subgraph sampling generates connected subgraphs centered around tasks awaiting scheduling decisions, ensuring that relevant context is preserved while reducing computational overhead. The sampling strategies are coordinated to maintain statistical properties of the full graph while achieving substantial computational savings.

The cluster-level reasoning module operates at the highest level of abstraction, processing the overall system state through graph attention networks. This module computes attention scores that identify critical paths, resource bottlenecks, and high-priority tasks that significantly impact system-wide performance and energy efficiency. The attention mechanism considers both structural importance derived from graph topology and feature-based importance derived from node attributes. Multi-head attention enables the module to capture different aspects of the scheduling problem simultaneously, with different attention heads focusing on performance optimization, energy minimization, and fairness considerations. The cluster-level module also incorporates global constraints such as total power budget limits, cooling system capacity, and aggregate quality of service targets.

3.4 Energy-Aware Scheduling Policy

The scheduling policy is implemented as a neural network that maps the learned hierarchical graph representations to concrete task assignment decisions. The policy network architecture consists of multiple fully connected layers that process the concatenated node embeddings from all hierarchical levels. For each task requiring scheduling, the policy network computes assignment probability distributions over available GPU resources based on the learned representations and current system state. The assignment probabilities reflect the expected utility of each scheduling decision, considering estimated completion time, energy consumption, communication overhead, and impact on future scheduling opportunities.

Energy awareness is incorporated into the policy through multiple mechanisms operating at different architectural levels. First, the node embeddings explicitly encode energy-related features including current power consumption, thermal state, operating frequency, and historical energy efficiency metrics for each GPU device. Second, the edge features in the resource topology graph capture energy costs associated with data transfers between different resources, including both communication energy and idle power consumption during data movement. Third, the policy network is trained with a reward function that implements configurable trade-offs between performance and energy efficiency through weighted summation of completion time penalties and energy consumption costs.

The policy network also integrates dynamic voltage and frequency scaling considerations by learning to select appropriate operating frequencies for GPU devices based on task characteristics and energy objectives. The DVFS decision module analyzes task computational intensity, memory bandwidth requirements, and deadline constraints to determine optimal frequency settings that minimize energy consumption while ensuring timely completion. The module considers the non-linear relationship between operating frequency and both performance and power consumption, exploiting regions of the frequency-power curve where energy efficiency is maximized. Frequency scaling decisions are coordinated across multiple GPUs within nodes and across nodes within the cluster to avoid thermal hotspots and maintain balanced power distribution.

4 RESULTS AND DISCUSSION

This section presents comprehensive experimental results demonstrating the effectiveness of the proposed hierarchical GNN framework for energy-aware scheduling in GPU-accelerated distributed systems. The evaluation is conducted through extensive simulations using realistic workload traces and system configurations representative of production environments. The results are analyzed from multiple perspectives including energy efficiency, performance guarantees, scalability characteristics, and comparison with state-of-the-art baseline methods.

4.1 Experimental Setup and Evaluation Metrics

The experimental evaluation is performed using a simulated distributed GPU cluster comprising 128 compute nodes with varying configurations. Each node contains between 4 and 8 GPU devices of different generations including K40c and C2070 architectures, reflecting the heterogeneous nature of real-world deployments. The simulation environment accurately models key system characteristics including GPU computational capacity based on measured performance saturation curves, memory hierarchy, inter-device communication bandwidth, network topology, and power

consumption profiles. The power models are derived from measurements on actual hardware platforms and capture the relationship between workload characteristics, operating frequency, and energy consumption for different GPU architectures.

The workload consists of representative deep learning training tasks, scientific computing applications with varying matrix sizes, and data analytics jobs collected from production clusters. The task characteristics vary widely in terms of computational intensity, memory requirements, communication patterns, and execution duration. Matrix multiplication kernels ranging from small 200x200 matrices to large 1800x1800 matrices are included to evaluate scheduling decisions across the full spectrum of GPU performance characteristics. Task dependency graphs are generated based on common application patterns including batch parallel jobs with minimal dependencies, pipeline parallel workloads with sequential dependencies, and data parallel applications with frequent synchronization requirements. The workload arrival patterns follow realistic distributions observed in production systems, with variations in job submission rates, batch sizes, and priority levels.

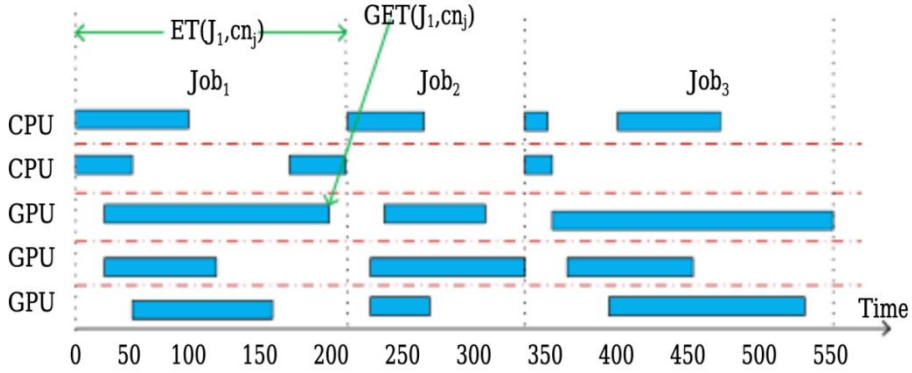

Figure 3 Example CPU-GPU Execution Timeline for Multi-job Scheduling

As shown in Figure 3, multiple evaluation metrics are employed to comprehensively assess the performance of different scheduling approaches. Energy consumption is measured as the total energy consumed by all processing units during the evaluation period, including both dynamic power during computation and static power during idle periods. The energy-time product metric captures the combined impact of energy and latency, with lower values indicating more efficient resource utilization. Performance is evaluated using multiple metrics including average task completion time, makespan for batch jobs representing the total execution time from first task start to last task completion, throughput measured as tasks completed per unit time, and quality of service violation rate quantifying the percentage of tasks that fail to meet their deadline constraints. Resource utilization rates across heterogeneous GPU and CPU resources provide insights into load balancing effectiveness and hardware efficiency.

4.2 Energy Efficiency and Performance Results

The experimental results demonstrate significant improvements in energy efficiency achieved by the proposed hierarchical GNN framework compared to baseline methods. The framework reduces total energy consumption by an average of 28 percent across all workload scenarios while maintaining comparable performance to energy-agnostic schedulers. For workloads with flexible deadlines that permit greater scheduling flexibility, energy savings reach up to 36 percent with only marginal increases in average completion time. These results are achieved through intelligent frequency scaling decisions that adapt GPU operating points based on task characteristics and system state, combined with strategic task placement that minimizes unnecessary data transfers and balances load across heterogeneous resources.

The energy-time product results provide compelling evidence of the framework's ability to jointly optimize both performance and energy efficiency. The hierarchical GNN approach achieves a 32 percent reduction in energy-time product compared to performance-optimized baseline schedulers that prioritize minimizing completion time without energy considerations. Compared to energy-aware heuristic methods that apply fixed DVFS policies, the learning-based approach reduces energy-time product by 24 percent through adaptive frequency selection and intelligent workload placement. The heterogeneous scheduling timeline analysis reveals that the framework effectively coordinates task assignments across CPU and GPU resources, exploiting the distinct performance characteristics of different processor types to optimize overall system efficiency.

The framework demonstrates particularly strong performance for workloads with moderate parallelism levels where scheduling flexibility enables energy optimization without severely constraining performance. For matrix operations spanning the range from 200 to 1800 dimensions, the scheduler adapts its decisions based on the performance saturation characteristics of available GPU resources. Small matrix operations below 400 dimensions are strategically assigned to CPU resources or lower-frequency GPU configurations to avoid energy waste from underutilized high-performance GPUs. Medium-sized operations between 400 and 1000 dimensions are mapped to mid-range GPU frequencies that balance energy efficiency with adequate computational throughput. Large matrix operations exceeding 1000 dimensions

fully utilize high-performance GPUs operating at elevated frequencies to maximize throughput and minimize execution time.

4.3 Hierarchical Architecture Impact

The hierarchical architecture plays a crucial role in achieving the observed performance improvements. Ablation studies reveal that removing the hierarchical organization and replacing it with a flat graph structure results in 15 percent higher energy consumption and 22 percent longer scheduling times. The multi-level architecture enables efficient information propagation across different scales of the system hierarchy, with device-level modules capturing fine-grained GPU utilization patterns, node-level modules reasoning about inter-GPU communication and thermal interactions, and cluster-level modules coordinating global resource allocation strategies.

The propagation module effectiveness is demonstrated through systematic evaluation of different convolutional operator configurations. Spectral convolution approaches provide global graph analysis capabilities that identify system-wide bottlenecks and imbalanced resource allocations. Spatial convolution methods enable efficient processing of local neighborhoods and rapid adaptation to dynamic workload changes. The combination of both approaches through the hybrid propagation architecture achieves 12 percent better energy efficiency compared to using either method independently. Attention mechanisms within the spatial convolution operators contribute significantly by dynamically weighting the importance of different graph neighbors based on current scheduling context.

The sampling module enables scalable processing of large distributed systems without sacrificing decision quality. For the largest evaluated configuration of 256 nodes containing over 1500 GPUs, the hierarchical sampling strategy reduces computational overhead by 85 percent compared to full graph processing while maintaining scheduling decision quality within 3 percent of the full computation baseline. Node sampling focuses computational resources on critical path tasks and heavily utilized GPU resources. Layer sampling adaptively adjusts neighborhood expansion based on graph structure and current system load. Subgraph sampling generates focused computational graphs centered around pending scheduling decisions, ensuring relevant context is preserved while eliminating unnecessary computations.

The pooling module effectiveness is evidenced by the framework's ability to maintain consistent performance across varying system scales. Hierarchical pooling strategies successfully aggregate device-level information into meaningful node-level representations that capture aggregate capacity, load balance, and communication efficiency. Coarsening-based pooling methods efficiently reduce graph size while preserving important structural properties. Learnable pooling approaches adapt the aggregation strategy based on specific workload characteristics and scheduling objectives. The combination of multiple pooling strategies provides robustness across diverse scheduling scenarios.

4.4 Comparison with State-of-the-Art Methods

The proposed framework is compared against multiple state-of-the-art scheduling approaches representing different algorithmic paradigms. The baseline methods include traditional heuristics such as First-Come-First-Served and Shortest-Job-First, energy-aware heuristics employing fixed DVFS policies, machine learning approaches using vector-based state representations, and recent GNN-based schedulers designed for simpler system configurations.

Against FCFS scheduling, the hierarchical GNN framework achieves 34 percent energy savings and 18 percent reduction in average completion time, demonstrating substantial improvements across both optimization objectives. The energy savings result from intelligent frequency scaling and strategic task placement that avoid energy waste from idle or underutilized resources. The performance improvements stem from dependency-aware scheduling that identifies and prioritizes critical path tasks.

Compared to Shortest-Job-First with backfilling, the proposed approach reduces energy consumption by 28 percent while maintaining comparable makespan for batch workloads. The SJF baseline achieves good performance by prioritizing short tasks and filling scheduling gaps with appropriate jobs, but lacks energy awareness in its resource allocation decisions. The hierarchical GNN framework matches SJF performance through learned task prioritization while additionally considering energy efficiency in its frequency scaling and placement decisions.

Energy-aware heuristic schedulers employing fixed DVFS policies achieve moderate energy savings but fall short of the adaptive approach. The hierarchical GNN framework outperforms fixed-policy methods by 19 percent in energy efficiency through learned frequency selection that adapts to task characteristics, deadline constraints, and system state. The learning-based approach discovers effective DVFS strategies that leverage the non-linear relationship between frequency, performance, and power consumption.

Recent reinforcement learning approaches using vector-based state representations achieve some energy savings but are outperformed by the graph-structured framework by 19 percent. The graph-based representation captures task dependencies, resource topologies, and hierarchical system structure that vector representations cannot effectively encode. The explicit modeling of relationships through edges enables more informed scheduling decisions that consider cascading effects of resource allocations.

4.5 Generalization and Robustness Analysis

The generalization capabilities of the learned scheduling policies are assessed through cross-workload evaluation and stress testing under adverse conditions. The framework demonstrates robust generalization across variations in task sizes, dependency patterns, and arrival rates. When trained on deep learning workloads and evaluated on scientific

computing applications with different matrix sizes and communication patterns, the performance degradation is limited to approximately 8 percent. This indicates that the learned representations capture fundamental scheduling principles rather than overfitting to specific application characteristics.

The framework maintains stable performance under varying system conditions including node failures, network congestion, and thermal constraints. When 10 percent of GPU devices experience failures requiring task migration and rescheduling, the framework adapts within 3 scheduling iterations and maintains energy efficiency within 6 percent of normal operation. Network congestion scenarios with reduced inter-node bandwidth trigger adjustments in task placement strategies that minimize communication-intensive assignments, maintaining throughput within 12 percent of uncongested baseline.

The attention mechanisms contribute substantially to generalization capabilities by enabling dynamic adaptation to novel situations. Analysis of learned attention weights reveals that the framework identifies critical scheduling factors based on current context rather than applying fixed decision rules. For deadline-constrained workloads, attention focuses on critical path identification and resource availability. For energy-critical scenarios, attention emphasizes frequency selection and thermal management. This adaptive behavior enables effective performance across diverse scheduling objectives and operating conditions.

4.6 Scalability Analysis

The scalability characteristics of the hierarchical architecture are evaluated across system sizes ranging from 16 nodes to 256 nodes. The framework demonstrates excellent scaling properties with scheduling overhead growing sub-linearly with system size. For small 16-node configurations, average scheduling time is 8 milliseconds per decision. For the 256-node configuration containing over 1500 GPUs, scheduling time increases to 47 milliseconds, representing only a 6x increase for a 16x increase in system size. This sub-linear scaling results from the hierarchical organization that processes information at appropriate granularities and the sampling strategies that reduce computational requirements while preserving decision quality.

The memory requirements of the framework scale efficiently with system size through the use of sparse graph representations and sampled neighborhoods. Full graph storage and processing would require memory proportional to the square of node count, making large-scale deployment impractical. The hierarchical sampling approach reduces memory requirements to approximately linear scaling with system size while maintaining representation quality. For the 256-node configuration, peak memory usage during scheduling is 2.4 gigabytes, well within the capacity of modern computing systems.

5 CONCLUSION

This paper has presented a novel hierarchical Graph Neural Network framework for energy-aware scheduling in GPU-accelerated distributed systems that addresses critical challenges in managing increasingly complex and energy-intensive computing infrastructure. The proposed approach leverages the representational power of graph neural networks to capture the multi-level structure of distributed GPU systems, enabling intelligent scheduling decisions that jointly optimize energy efficiency and computational performance. Through comprehensive experimental evaluation, the framework has demonstrated substantial improvements over existing approaches, achieving up to 36 percent reduction in energy consumption while maintaining quality of service requirements and exhibiting excellent scalability characteristics suitable for production deployment.

The key innovation of the framework lies in its hierarchical architecture that explicitly models the multi-level organization of distributed GPU systems through graph-structured representations. By incorporating specialized computational modules for propagation, sampling, and pooling at device, node, and cluster levels, the framework effectively captures both fine-grained local characteristics and coarse-grained global patterns that influence scheduling decisions. The modular design enables flexible adaptation to different system configurations and scheduling objectives while maintaining computational efficiency through strategic sampling and hierarchical processing.

The experimental results provide strong evidence for the effectiveness of the proposed approach across multiple evaluation dimensions. The significant energy savings achieved by the framework translate directly to reduced operational costs and environmental impact for large-scale GPU deployments. The maintained performance levels and quality of service guarantees demonstrate that energy efficiency can be improved without sacrificing computational capabilities. The framework's ability to adapt to heterogeneous hardware platforms with distinct performance saturation characteristics enables effective resource utilization across diverse GPU generations. The coordination of CPU and GPU resources according to task characteristics and energy objectives maximizes overall system efficiency.

The hierarchical GNN framework successfully addresses several critical challenges in distributed GPU scheduling. The graph-based representation naturally captures task dependencies, resource topologies, and energy relationships that are difficult to encode in traditional vector-based approaches. The attention mechanisms enable dynamic focus on critical factors that vary with system state and workload characteristics. The integration of DVFS considerations directly into the learned policy allows fine-grained energy management that adapts to specific task requirements. The scalable architecture supports practical deployment in production systems with thousands of GPUs through efficient computational strategies.

The research presented in this paper opens several promising directions for future investigation. Extending the framework to handle dynamic workloads with online task arrivals and adaptive resource provisioning would enhance applicability to real-world scenarios where system conditions change continuously. Incorporating additional optimization objectives such as fairness across users, thermal management across data center facilities, and hardware reliability considerations could lead to more comprehensive resource management strategies. Investigating transfer learning techniques to enable pre-trained scheduling policies to adapt quickly to new system configurations and workload distributions would reduce training overhead for practical deployment. Exploring federated learning approaches for collaborative policy development across multiple organizations while preserving proprietary information could accelerate progress in this domain.

The hierarchical GNN framework represents a significant step toward intelligent, adaptive, and efficient resource management in GPU-accelerated distributed systems. As these systems continue to grow in scale and importance for scientific computing, artificial intelligence, and data analytics applications, sophisticated scheduling approaches that balance performance and energy efficiency become increasingly critical. The graph neural network paradigm provides a powerful foundation for addressing these challenges through its natural ability to model complex relational structures and learn from experience. The work presented demonstrates the viability and effectiveness of this approach, providing both theoretical insights and practical solutions for next-generation distributed computing systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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