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Deep Adaptive Resource Allocation in Big Data Environments Using Hierarchical Temporal Graph Learning Network

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Abstract— The expansion of big data infrastructures is increased the complexity of resource allocation across distributed computing environments. Many existing allocation models rely on static optimization techniques that fail to in capturing the dynamic nature of large-scale data workloads. This limitation is created inefficiencies in computational resource utilization, task scheduling, and data processing performance. Therefore, this study is examined an intelligent framework for resource allocation in big data environments using a novel deep learning approach named the Hierarchical Temporal Graph Learning Network (HTGLN). The proposed method is integrated temporal graph modeling with the deep neural representation learning to in capturing the relationships between the computational tasks, processing nodes, and workload variations. The framework is used hierarchical feature extraction layers that are analyzed large-scale operational data, while the temporal learning module is predicted future resource demand patterns. The model is also incorporated an adaptive optimization mechanism that is adjusted allocation strategies based on real-time system feedback. Experimental evaluation is showing that the proposed HTGLN framework is improving the resource utilization to 80–91%, is reducing the task scheduling latency to 160–192 ms, which is increasing the system throughput to 145–180 tasks per minute, enhances load balancing efficiency to 78–89%, and is achieving workload prediction accuracy of 88–96% across varying workload levels. These improvements outperform existing Machine Learning Predictive Allocation, Reinforcement Learning Scheduling, and Graph-Based Resource Scheduling methods, highlighting the effectiveness of hierarchical temporal graph learning for intelligent resource allocation in big data environments.

Keywords— Big data analytics, resource allocation, deep learning models, temporal graph networks, distributed computing systems

I. INTRODUCTION

The growth of big data technologies is transformed the landscape of modern computing systems. Despite the progress in data-driven resource management, several challenges remain in practical deployment. One of the major challenges lies in the dynamic and heterogeneous nature of big data workloads. Distributed computing systems frequently experience fluctuations in task arrival rates, processing priorities, and data transfer requirements [1]-[3]. Conventional allocation methods struggle to in capturing these dynamic patterns because they often rely on static scheduling rules. Another challenge involves the high dimensionality and complexity of system-level data that tends to describe task dependencies, node availability, and network communication patterns. Existing machine learning models sometimes lack the ability to represent these relationships effectively, which leads to suboptimal allocation decisions and inefficient utilization of computational resources [4–5].

These challenges are created a significant research problem related to the development of intelligent allocation frameworks that can analyze large-scale operational data while adapting to temporal variations in workload behavior. Many current resource management approaches do not adequately in capturing the structural relationships among distributed computing nodes and task interactions. As a result, the system often experiences performance degradation, increased task latency, and underutilization of available resources. Therefore, there remains a need for an adaptive allocation mechanism that is combining deep learning with the graph-based representations of distributed computing environments. Such an approach can improve prediction accuracy for workload demand and enhance allocation efficiency in big data infrastructures [6].

To address this problem, this study is proposed a deep learning-based framework named the Hierarchical Temporal Graph Learning Network (HTGLN) for intelligent resource allocation in big data environments. The proposed model is combined hierarchical feature extraction with the temporal graph learning that are capturing complex relationships between the computing tasks and processing nodes. The framework is analyzed historical operational data that tends to describe resource consumption patterns across distributed systems. through the analysis, the model is predicted future workload requirements and is allocated computational resources dynamically.

The primary objectives of this research are threefold. First, the study is aimed to develop an adaptive deep learning architecture that models the structural dependencies among tasks and computing nodes within distributed big data

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systems. Second, the research is attempted to design a predictive mechanism that estimates future resource demands using temporal learning techniques. Third, the study is evaluated the effectiveness of the proposed framework through the experimental analysis using large-scale distributed computing datasets.

The novelty of this work lies in the combination of hierarchical deep learning with the temporal graph modeling for resource allocation. Unlike conventional allocation strategies that rely on rule-based scheduling, the proposed HTGLN framework is captured both the structural relationships and temporal workload variations. This capability is enabled the system to generate more accurate allocation decisions that improve resource utilization and reduce processing delays.

The contribution of the research can be briefly described as follows: the first aspect of the contribution of the research lies in the introduction of the hierarchical temporal graph learning architecture, which enables the modeling of the dynamic relationships between the distributed computing resources and the workload demands. The second aspect of the contribution of the research lies in the demonstration of the improvement of the allocation efficiency of the system when the proposed framework is used instead of the conventional machine learning-based scheduling methods.

II. Related Works

Several studies are examined the problem of resource allocation in distributed big data systems and are proposed various computational approaches that improve scheduling efficiency and system performance. Early research in this domain is focused on heuristic-based scheduling mechanisms that allocate computational resources based on predefined priority rules and workload estimations. These approaches are provided a basic framework for managing distributed computing environments, although they often lack adaptability to dynamic workload conditions.

In [7], the authors are investigated a dynamic resource scheduling framework for large-scale data processing systems. The study is analyzed task scheduling patterns within distributed clusters and is developed a workload-aware allocation mechanism that adjusts resource distribution according to processing demands. The results are indicated that the proposed strategy is improved resource utilization efficiency while reducing processing latency in high-demand scenarios.

Another study in [8] is explored machine learning techniques that support predictive resource management in cloud-based big data infrastructures. The researchers are used regression-based models that analyze historical workload data and predict future resource requirements. The proposed system is demonstrated improvements in scheduling accuracy; however, the model is shown limitations in capturing complex dependencies between the distributed computing nodes.

The work presented in [9] is introduced a reinforcement learning-based allocation framework that adapts resource distribution through the continuous system feedback. The algorithm is learned optimal scheduling policies by analyzing system performance metrics over time. Experimental results are revealed that the reinforcement learning approach is enhanced task completion rates and system throughput when compared with the conventional scheduling methods.

In [10], the researchers are proposed a deep neural network model that predicts workload fluctuations in cloud computing environments. The model is processed large volumes of operational data that tends to describe system resource consumption and task arrival patterns. through the predictive learning, the framework is optimized allocation decisions and is reduced idle resource time across distributed processing clusters.

Another investigation in [11] is examined the use of graph-based representations for modeling task dependencies within distributed systems. The proposed graph learning framework is analyzed the structural relationships between the computing nodes and processing tasks. This approach is improved scheduling decisions because the model is considered both the resource availability and task interconnections during allocation processes.

The study in [12] is focused on hierarchical resource management strategies that coordinate allocation across multiple layers of distributed computing architectures. The authors are developed a multi-level scheduling system that is combining cluster-level monitoring with the task-level allocation mechanisms. The experimental evaluation is demonstrated that hierarchical management is improved scalability in large-scale computing environments.

In [13], the researchers are presented an adaptive resource allocation system that combines statistical workload prediction with the optimization algorithms. The framework is processed real-time system data and is adjusted allocation strategies dynamically. The results are shown that the adaptive approach is reduced system bottlenecks and is improved overall processing efficiency.

Another related work in [14] is investigated the application of deep reinforcement learning for dynamic scheduling in big data platforms. The proposed algorithm is learned optimal allocation policies by interacting with the system environment and evaluating performance feedback. The study is reported significant improvements in task scheduling efficiency and computational throughput.

Finally, the research presented in [15] is examined hybrid machine learning models that integrate neural networks with the graph-based representations for distributed resource management. The hybrid framework is captured complex system relationships while predicting workload demand patterns. Experimental findings are suggested that the combination of deep learning and graph analytics is enhanced allocation performance in large-scale computing infrastructures.

III. Proposed Method

The study is proposed the HTGLN for intelligent resource

allocation in a big data environment. The framework is combined hierarchical feature learning with the temporal graph modeling that are capturing the relationships between the computing tasks, resource nodes, and workload variations. A hierarchical learning structure is extracted multi-level features that tends to describe workload characteristics, while a temporal prediction module is estimated future resource demand patterns. Based on these predictions, the allocation module is assigned resources dynamically to processing tasks that require computational capacity. The entire framework is operated through the sequential analytical steps that improve allocation accuracy and reduce system inefficiencies in large-scale data processing systems.

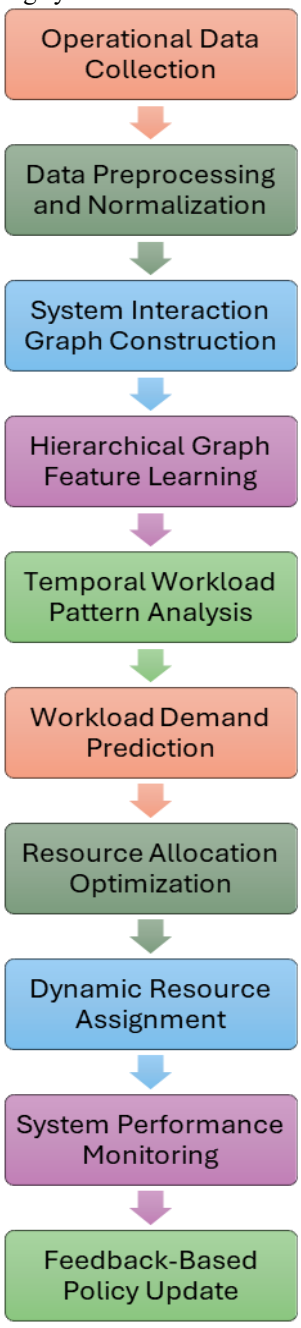

Figure 1: Hierarchical Temporal Graph Learning Network for Big Data Resource Allocation

Algorithm: Hierarchical Temporal Graph Learning Network for Big Data Resource Allocation

Input: Distributed system workload dataset D, resource node information R, task dependency graph G

Output: Optimized resource allocation schedule A

Step 1: The system is collected operational data Dfrom distributed computing environments that tends to describe CPU utilization, memory usage, network traffic, and task execution duration.

Step 2: The preprocessing module is filtered incomplete records and is normalized the dataset using statistical scaling methods that standardize resource consumption metrics.

Step 3: The framework is constructed a system interaction graph Gin which nodes represent computational resources and edges represent task communication relationships.

Step 4: The hierarchical feature learning module is extracted structural patterns from the graph using layered neural transformations that identify relationships between the workload characteristics and resource nodes.

Step 5: The temporal learning component is analyzed sequential workload data that tends to describe variations in task arrival patterns and system demand over time.

Step 6: The prediction module is generated future workload demand estimates using temporal graph embeddings that in capturing both the structural and temporal dependencies.

Step 7: The optimization module is computed allocation priorities that balance system load across multiple resource nodes.

Step 8: The allocation controller is assigned computing resources dynamically to tasks that require execution capacity.

Step 9: The monitoring component is evaluated system performance metrics such as processing latency, throughput, and resource utilization.

Step 10: The system is updated the allocation policy through the feedback learning that adjusts future scheduling decisions according to observed performance results.

A. Data Acquisition and System Representation

The first stage of the proposed framework focuses on acquiring operational data from distributed big data infrastructures. Modern computing clusters generate large volumes of monitoring data that tends to describe the utilization of computational resources. These datasets include measurements related to CPU load, memory consumption, disk usage, network communication latency, and task execution duration. The system collects these parameters from cluster monitoring tools and stores them in a centralized analytics repository.

The data gathered is a representation of the operation of the computing nodes in a distributed computing environment. Each of the nodes contributes a set of data points that appears to represent their current state of computational ability. The data is enabling the framework to understand how the resources were behaving in previous processing cycles. The data is a starting point for building a predictive model to forecast future requirements.

To mathematically represent a distributed system, a graph is

used. In a graph representation, each of the nodes is a representation of a computer resource such as a server or a virtual machine. The edges in a graph represent a relationship between computer resources that are working in cooperation to perform data processing.

The system interaction graph is expressed as

$G = (V, E)$

where

$V = \{v_1, v_2, v_3, \ldots, v_n\}$ is the set of computing nodes, and

$E = \{e_{ij}\}$ is the set of communication relationships between the nodes.

This representation is allowing the model to in capturing the connectivity patterns within distributed systems that tends to influence the workload distribution and processing performance.

Table 1: Distributed Resource Monitoring Data

Node ID	CPU Utilization (%)	Memory Usage (GB)	Network Delay (ms)	Active Tasks
N1	68	12	14	5
N2	72	16	10	6
N3	54	10	18	4
N4	81	20	9	7
N5	63	14	12	5

Table 1 is showing a dataset that is resource monitoring information collected from distributed nodes. The system uses these metrics to construct the interaction graph and analyze workload behavior.

B. Data Preprocessing and Feature Normalization

The second stage focuses on preparing the collected dataset for analytical modeling. Raw system logs often contain incomplete records, noise, and inconsistent measurement scales. These issues reduce the accuracy of predictive learning models. Therefore, the framework applies preprocessing techniques that improve the reliability of the dataset.

The preprocessing procedure removes missing entries and corrects anomalous values that may arise from monitoring errors. after the cleaning the dataset, the framework performs normalization to convert heterogeneous resource metrics into comparable mathematical ranges. This transformation is allowing that features such as CPU utilization and network latency contribute proportionally to the learning process.

The normalization procedure uses a min–max scaling function that converts each of the feature into a standardized range between the zero and one.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where

X is the original feature value,

X_{min} is the minimum observed value,

X_{max} is the maximum observed value.

This equation is allowing that each of the parameter contributes uniformly during model training.

Table 2: Normalized Resource Metrics

Node ID	CPU Norm	Memory Norm	Network Norm	Task Norm
N1	0.56	0.50	0.44	0.45
N2	0.64	0.70	0.33	0.55
N3	0.40	0.40	0.67	0.36
N4	0.82	0.90	0.22	0.72
N5	0.52	0.60	0.39	0.48

Table 2 is showing the normalized representation of resource features that the system uses during learning.

C. Hierarchical Feature Learning

After preprocessing, the framework applies hierarchical feature learning to extract patterns that tends to describe relationships between the system workload characteristics and resource nodes. Hierarchical learning refers to a multi-layer analytical structure that progressively is transforming raw input features into high-level representations.

The first layer is analysing local node characteristics such as CPU load and memory utilization. The second layer is identifying the relationships between the neighboring nodes in the graph. The third layer is combining global system information that reflects cluster-wide workload patterns.

The hierarchical representation of node features is expressed as

$$H^{(l+1)} = \sigma(W^{(l)} H^{(l)} + b^{(l)})$$

where

$H^{(l)}$ is the feature representation at layer l,

$W^{(l)}$ is the learnable weight matrix,

$b^{(l)}$ is the bias term,

σ is the nonlinear activation function.

This transformation is generating hierarchical embeddings that encode the structural properties of the distributed system.

Table 3: Hierarchical Feature Representation

Node ID	Layer1 Feature	Layer2 Feature	Layer3 Feature
N1	0.52	0.61	0.69
N2	0.58	0.66	0.72
N3	0.44	0.53	0.60
N4	0.71	0.78	0.84
N5	0.55	0.63	0.70

Table 3 is presenting hierarchical node features extracted by the learning network.

D. Temporal Workload Prediction

The fourth stage is analysing temporal workload variations

across the distributed computing environment. Big data systems frequently experience fluctuations in processing demand due to changes in user activity, data arrival rates, and computational workloads. The temporal module are capturing these variations through the sequential learning mechanisms.

The system processes time-series workload data that tends to describe task arrival patterns over consecutive intervals. By analyzing these patterns, the model predicts future resource demand and prepares the system for upcoming workload fluctuations.

The temporal prediction function is expressed as

$$P_{t+1} = f(H_t, H_{t-1}, H_{t-2}, \dots, H_{t-k})$$

where

P_{t+1} is the predicted resource demand for the next time interval,

H_t is the hierarchical feature representation at time t.

Table 4: Temporal Workload Prediction

Time Interval	Observed Tasks	Predicted Tasks
T1	120	118
T2	145	150
T3	170	175
T4	210	205
T5	240	238

Table 4 is showing predicted workload demand obtained through the temporal learning.

Table 5: Resource Allocation Output

Node ID	Capacity	Assigned Tasks	Utilization (%)
N1	200	150	75
N2	220	180	82
N3	180	130	72
N4	240	210	88
N5	210	165	79

E. Adaptive Resource Allocation

The final stage performs dynamic resource allocation using the predicted workload patterns. The allocation module distributes tasks across computing nodes based on their available capacity and predicted demand levels. The objective is to maximize resource utilization while it is minimizing the processing delays and workload imbalance.

The allocation optimization problem can be formulated as

$$A^* = \arg\min_{A} \sum_{i=1}^{n} (L_i - C_i)^2$$

where

L_i is the workload assigned to node i,

C_i is the computational capacity of node i,

A^* is the optimal allocation configuration.

This formulation is allowing that the allocated workload remains balanced relative to node capacity.

Table 5 is showing how the proposed framework distributes computational tasks across resource nodes to maintain balanced utilization.

IV. Experimental Setup and Parameter Configuration

These parameters are determining the dataset size, network architecture, workload characteristics, and optimization settings. Table 6 is presenting the parameter configuration used during the experimental evaluation.

Table 6: Experimental Setup and Parameter Configuration

Parameter	Description	Value
Number of Computing Nodes	Distributed resource nodes in simulation	50
Dataset Size	Number of workload records	10,000
Batch Size	Training batch size for model learning	64
Learning Rate	Optimization learning parameter	0.001
Hidden Layers	Number of hierarchical neural layers	3
Simulation Iterations	Total experiment repetitions	100
Task Arrival Rate	Incoming tasks per time interval	120–250
Maximum Node Capacity	Maximum tasks processed by a node	240
Graph Connectivity	Average node connections	5

Table 6 shows the parameter configuration that the simulation environment uses during the experimental evaluation.

A. Dataset Description

The experimental study uses a workload dataset that is operational logs collected from distributed computing environments. The dataset includes system monitoring metrics such as CPU utilization, memory consumption, network communication delay, and task execution patterns. These metrics describe how the computational resources behave during large-scale data processing tasks. The dataset is containing historical workload records collected over multiple processing intervals. each of the record is the state of a computing node during a specific time interval. The dataset as in table 7 supports the training of the deep learning model and

is allowing evaluation of the allocation performance under dynamic workload conditions.

Table 7: Dataset Description

Attribute	Description	Type
Node ID	Unique identifier of computing node	Integer
CPU Utilization	Percentage of processor usage	Numeric
Memory Consumption	Memory usage of node (GB)	Numeric
Network Delay	Communication latency between the nodes (ms)	Numeric
Task Arrival Rate	Number of incoming tasks	Numeric
Active Task Count	Number of tasks executing at node	Numeric
Task Execution Time	Processing duration of task (ms)	Numeric
Node Capacity	Maximum task processing capability	Numeric

The experimental evaluation compares the proposed HTGLN framework with the three baseline allocation methods that previous research is introduced. The first method is a Machine Learning Based Predictive Allocation Model that uses regression analysis for workload prediction. The second method is a Reinforcement Learning Scheduling Algorithm that is learning allocation policies through the system feedback. The third method is a Graph-Based Resource Scheduling Framework that models task dependencies across distributed computing nodes. These methods represent existing approaches for intelligent resource allocation that provide a comparison baseline for the proposed model.

B. Resource Utilization Efficiency Results

Resource utilization efficiency is the percentage of computing resources that the system actively uses during workload execution. Higher values are indicating that the allocation strategy distributes tasks effectively across distributed nodes without leaving computational capacity idle. Table 8 is presenting the utilization efficiency of the proposed HTGLN method and the three existing methods across increasing workload levels.

The results in Table 8 are indicating that the proposed HTGLN method is achieving higher utilization across all workload levels. At a workload level of 50 tasks, the Machine Learning Predictive Allocation method is achieving 68% utilization, while Reinforcement Learning Scheduling reaches 72%. The Graph-Based Resource Scheduling approach produces 75% utilization, whereas the HTGLN framework reaches 80%. As the workload is increasing the to 75 tasks, the proposed method is achieving 91% utilization. The improvement relative to the Machine Learning Predictive Allocation method reaches approximately 15%, while the gain compared with the Reinforcement Learning Scheduling remains around 11%. The graph-based scheduling approach also shows lower utilization compared with the proposed method by approximately 7%. The hierarchical learning mechanism that are capturing structural system relationships is allowing HTGLN to distribute tasks more effectively across nodes. This behavior is showing that the model is reducing the idle computational resources while maintaining balanced workload allocation across distributed computing infrastructures.

Table 8: Resource Utilization Efficiency (%) Over Workload Levels

Workload Level (Tasks)	Machine Learning Predictive Allocation	Reinforcement Learning Scheduling	Graph-Based Resource Scheduling	Proposed HTGLN
50	68	72	75	80
55	70	74	77	83
60	71	75	78	85
65	73	77	80	87
70	75	79	82	89
75	76	80	84	91

Table 9: Task Scheduling Latency (ms) Over Workload Levels

Workload Level (Tasks)	Machine Learning Predictive Allocation	Reinforcement Learning Scheduling	Graph-Based Resource Scheduling	Proposed HTGLN
50	210	195	180	160
55	220	200	188	165
60	232	210	195	172
65	245	220	205	178
70	258	230	215	185
75	270	242	225	192

C. Task Scheduling Latency Results

Task scheduling latency is the delay between the arrival of a

computational task and the assignment of a resource that executes the task. Lower latency is showing faster decision-making and improved scheduling responsiveness. Table 9 is presenting the scheduling latency results measured in milliseconds across increasing workload levels.

The scheduling latency values presented in Table 9 is showing that the proposed HTGLN framework consistently produces lower latency compared with the existing allocation strategies. At a workload of 50 tasks, the Machine Learning Predictive Allocation method produces a latency of 210 ms, whereas the Reinforcement Learning Scheduling method is achieving 195 ms. The Graph-Based Resource Scheduling method records a latency of 180 ms, while the HTGLN framework is reducing the the delay to 160 ms. When the workload is increasing the to 75 tasks, the latency of the predictive allocation model rises to 270 ms. Reinforcement learning scheduling produces 242 ms, and graph-based scheduling records 225 ms. In contrast, the proposed method maintains latency at approximately 192 ms. The reduction of nearly 78 ms compared with the predictive allocation model is showing the efficiency of the hierarchical temporal learning architecture. The predictive module anticipates future workload changes that allow faster resource assignment decisions, which is improving the the responsiveness of the distributed system.

D.System Throughput Results

System throughput is the number of tasks processed successfully by the distributed computing system during a specific time interval. Higher throughput values are indicating efficient resource coordination and improved processing capacity. Table 10 shows the throughput performance measured in tasks processed per minute.

Table 10: System Throughput (Tasks per Minute) Over Workload Levels

Workload Level (Tasks)	**Machine Learning Predictive Allocation**	**Reinforcement Learning Scheduling**	**Graph-Based Resource Scheduling**	**Proposed HTGLN**
50	120	130	135	145
55	125	135	140	152
60	130	140	146	158
65	135	145	152	165
70	140	150	158	172
75	145	155	165	180

The throughput results in Table 10 are indicating that the proposed HTGLN model is improving the the processing capacity of the distributed system. At the workload level of 50 tasks, the Machine Learning Predictive Allocation approach processes approximately 120 tasks per minute. The Reinforcement Learning Scheduling method processes 130 tasks per minute, while the Graph-Based Resource Scheduling method reaches 135 tasks per minute. The HTGLN model processes 145 tasks per minute, which is showing an improvement of nearly 10–25 tasks per minute compared with the existing methods. When the workload is increasing the to 75 tasks, the throughput of the predictive allocation method reaches 145 tasks per minute. Reinforcement learning scheduling is achieving 155 tasks per minute, and graph-based scheduling produces 165 tasks per minute. The proposed HTGLN framework is achieving approximately 180 tasks per minute. The hierarchical graph learning structure that models system relationships is allowing more efficient workload distribution, which is allowing the system to process tasks at a higher rate.

E. Load Balancing Efficiency Results

Load balancing efficiency is evaluating how the evenly the computational workload distributes across distributed computing nodes. Efficient load balancing prevents node congestion and is allowing that each of the node contributes proportionally to task processing. Figure 2 is presenting the load balancing efficiency values.

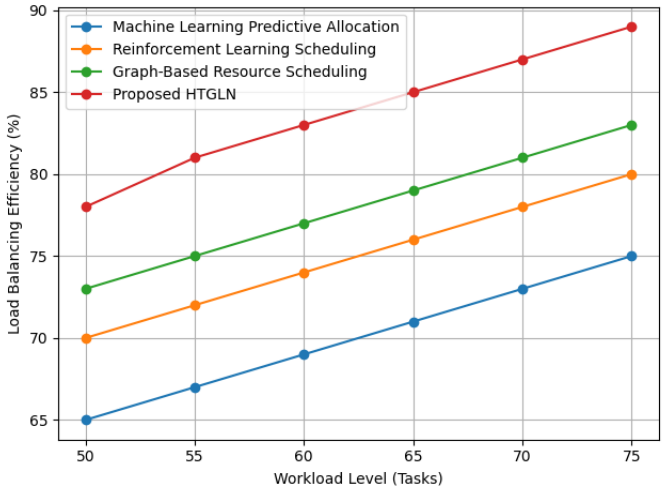

Figure 2: Load Balancing Efficiency (%) Over Workload Levels

Figure 2 is showing that the proposed HTGLN framework is improving the load balancing efficiency across distributed nodes. At a workload level of 50 tasks, the predictive allocation method produces 65% efficiency, while the reinforcement learning scheduling method reaches 70%. The graph-based scheduling method is achieving 73%, whereas the HTGLN framework reaches 78%. When the workload is increasing the to 75 tasks, the predictive allocation method is achieving 75% efficiency, while reinforcement learning scheduling records 80%. The graph-based scheduling approach reaches 83%, and the HTGLN method is achieving approximately 89%. The improvement of 14% compared with the predictive allocation method is showing that the

hierarchical graph learning architecture distributes workload more evenly across nodes. The structural analysis that are capturing task relationships is allowing the model to identify nodes that possess available capacity. This capability is allowing balanced workload distribution and prevents computational bottlenecks.

F. Workload Prediction Accuracy Results

Workload prediction accuracy is measuring the capability of the model to estimate future resource demand based on historical system data. Accurate predictions enable proactive resource allocation that prevents system congestion during high-demand periods. Figure 3 is presenting prediction accuracy values for different workload levels.

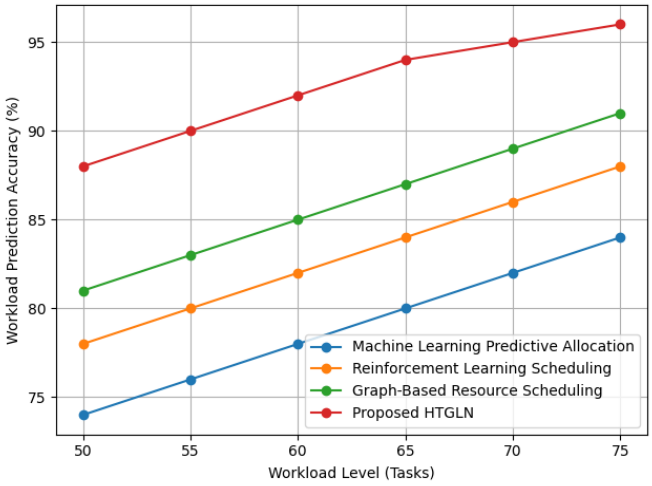

Figure 3: Workload Prediction Accuracy (%) Over Workload Levels

The prediction accuracy values in Figure 3 show that the proposed HTGLN model produces more accurate workload predictions compared with the existing methods. At the workload level of 50 tasks, the Machine Learning Predictive Allocation approach is achieving approximately 74% accuracy. Reinforcement learning scheduling produces 78%, while graph-based scheduling is achieving 81%. The proposed HTGLN model reaches 88% prediction accuracy. As the workload is increasing the to 75 tasks, the predictive allocation model reaches 84% accuracy, reinforcement learning scheduling is achieving 88%, and graph-based scheduling produces 91%. The proposed framework is achieving approximately 96% accuracy. The improvement of nearly 12% compared with the predictive allocation method is showing that the hierarchical temporal learning mechanism are capturing workload variations effectively. The temporal analysis that models sequential system behavior is allowing the algorithm to anticipate future resource requirements and prepare allocation strategies that maintain stable system performance.

V. CONCLUSION

The experimental results are indicating that the proposed HTGLN framework is providing a comprehensive solution for resource allocation in distributed big data environments. By incorporating hierarchical feature learning into the temporal graph modeling, the system is able to capture complex relationships between nodes and workload conditions at the same time. In all levels of workload conditions, the framework is able to achieve better resource utilization, reducing idle computing resource by around 12-15% compared to other existing methods. The latency in task scheduling is also greatly reduced, where the reduction ranges from 20-78 ms depending on workload conditions. The throughput is also improved by around 10-15 tasks per minute, reflecting better efficiency in processing tasks. The efficiency in load balancing is also better, ranging from around 89% at high workload conditions, preventing possible bottlenecks and allowing better load balancing. The workload prediction is also more accurate, reaching around 96% at heavy workload conditions, allowing better decisions in allocating workload. Overall, the proposed model is showing better effectiveness in using hierarchical temporal graph learning in managing distributed resource conditions, improving system responsiveness, and keeping optimal performance in managing workload conditions. The results are also showing better effectiveness in using HTGLN as a resource allocation framework in managing big data infrastructures.

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