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Graph Neural Network-Based Organizational Decision Optimization Algorithm for Dynamic Resource Allocation in Enterprises

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Abstract

Resource allocation remains a critical consideration within the domain of business administration due to changing demands, interdependence between organizational units, and conflicts among objectives. Traditional optimization techniques, including linear programming, heuristic algorithms, and rule-based systems, have limited ability to model the relationship dynamics inherent in modern organizations. In this paper, we propose GNN-ODOA (Graph Neural Network-Based Organizational Decision Optimization Algorithm), a new technique that represents organizations using heterogeneous attributed graphs and uses message-passing neural networks for transferring contextual data through organizational structures. The proposed model employs a temporal attention module to learn time-dependent demand trends from allocation histories, a multi-objective reinforcement learning algorithm to optimize trade-offs between cost-effectiveness, processing capacity, and fairness requirements, and a conflict-resolution mechanism to solve conflicts between simultaneous resource allocations. Evaluations of the proposed algorithm, GNN-ODOA, will be conducted using three real-world enterprise environments, including one multinational manufacturer, one large-scale IT service provider, and one distributed logistics company. Our experiments show that our model achieves 23.7% higher resource utilization compared to the best baseline, 41.2% lower allocation latency, and Pareto-optimal allocation in terms of constraints. The ablation study reveals the role of all components of the architecture, and scalability test verifies the linear increase in the time complexity to process inference when increasing the number of nodes up to 10,000.

Keywords: Graph Neural Networks; Organizational Decision-Making; Dynamic Resource Allocation; Multi-Objective Reinforcement Learning; Heterogeneous Graphs; Enterprise Optimization; Temporal Attention; Message Passing Neural Networks

1. Introduction

Large organizations of all sorts ranging from SME manufacturers to large multinational technological corporations are adaptive systems where a lot of decisions related to resource allocations are required to be made on a daily basis by different individuals independently. "Resources" may include people resources, i.e., human capital and employees' skills, computational resources, e.g., servers, cloud computing nodes, computation pipelines, budget, hardware, and time. Any erroneous decision will have repercussions for a company: delayed delivery, increased expenses, staff overload, and thus reduced competitiveness.

The traditional way to address resource allocation problems involves operations research (OR) techniques, such as linear programming (LP), integer programming (IP), and constraint satisfaction problems (CSPs). Although these OR techniques guarantee optimal solutions in the static setting with a completely defined problem instance, they fail to perform well under partially observable and evolving settings that are typical for enterprise settings. First, they require complete and accurate specification of the problem at hand, which is difficult to achieve. Second, they do not scale well in terms of decision variables. Third, they cannot take advantage of organizational structure. Fourth, they consider each resource allocation as an independent event.

The evolution of deep learning has led to the advent of a new breed of data-driven resource allocation approaches. RNN and Transformer-type architectures are capable of modeling temporal demands, whereas MARL architectures learn cooperative allocation policies. Nonetheless, most of these approaches tend to represent organizational structure in flat vector form, losing all the geometric complexity associated with an organization's hierarchical structure, teamwork, and supply chain structure, which determine resource allocations.

GNNs represent the ideal choice. Using learnable message-passing algorithms, GNNs operate on graph data directly and can model organizations in terms of attributed graphs and propagate context information such as workload, capacity, priority, and urgency throughout the graph structure. Current research efforts in heterogeneous GNNs, temporal graph learning, and graph-based reinforcement learning indicate that GNNs are more likely than their predecessors to overcome their structural limitations.

This paper makes the following principal contributions:

- formulate enterprise resource allocation as an optimization problem for dynamic graphs, offering a common mathematical language that unifies workforce scheduling, IT infrastructure provisioning, and logistics as one modeling class.
- propose the GNN-ODOA framework, which integrates heterogenous graph attention networks (HGATs), a multi-head temporal attention encoder, a MO-PPO optimizer, and a priority-aware conflict resolution module.
- construct three benchmarks of enterprise datasets using anonymous operation logs, namely ManuGraph, ITServGraph, and LogiGraph, and publish them publicly for the academic world.
- conduct extensive empirical evaluations showing the superiority of the proposed method in terms of resource usage efficiency, allocation speed, cost-effectiveness, and fairness, as well as perform ablation analysis and scalability tests.
- prove theoretically the convergence of the training algorithm and infer the computational complexity of the inference process.

The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 formulates the problem. Section 4 introduces the GNN-ODOA architecture. Section 5 describes the experiments. Section 6 presents results and discussion. Section 7 concludes.

2. Related Work

2.1 Classical Resource Allocation Methods

The optimization of resource allocation has been widely studied in operations research. Simplex, suggested by Dantzig [1][24], and its improvements are employed in the ERP approach through the application of LP/IP models. Although they have the potential for generalization, they require extensive fine-tuning, and nonlinear objectives are hard to manage [9][25]. While CP models can offer more flexibility to business rules, their complexity is of an exponential order in the worst case. The meta-heuristic approaches like genetic algorithm, simulated annealing, and ant colony optimization are able to provide almost optimal results.

2.2 Machine Learning for Resource Allocation

Supervised and reinforcement learning techniques have gained ground in their application to resource management in recent years. Successful implementation of Deep Q-learning in Atari games, leading to applications such as cloud computing resource scheduling and network routing [5][7][15]. Use of actor-critic algorithms [8][26] and proximal policy optimization techniques (PPO) in multi-resource cluster scheduling problems. Multi-agent reinforcement learning techniques have been extended to solve problems involving decentralized learning [10]. Attention models based on transformers [4][11] learn long-range temporal dynamics of demand data. However, none of these studies incorporate organizational topology in managing enterprise resources.

2.3 Graph Neural Networks

Only a limited amount of research utilizes graph learning techniques for enterprise management. Graph neural networks for project portfolio optimization [19][21]. Workforce skill graphs with graph attention techniques [6]. Temporal graph neural networks for demand prediction in logistics. What makes our approach unique is its ability to consider: (1) the entire enterprise, not just one process, as a dynamic and heterogeneous graph; (2) graph representation learning in combination with multi-objective reinforcement learning in a unified framework; and (3) extensive experiments on three different enterprise scenarios.

2.4 Graph-Based Optimization for Enterprise Systems

A small but growing body of work applies graph learning to enterprise management. GNNs for project portfolio selection [21][27]. Workforce skill networks with graph attention mechanisms [22] [23]. Temporal GNNs to demand forecasting in supply chains. Our work differentiates itself by: (1) treating the full enterprise—not a single process—as a dynamic heterogeneous graph; (2) integrating graph representation learning with multi-objective RL in an end-to-end trainable system; and (3) providing comprehensive empirical evaluation across three distinct enterprise domains.

3. Problem Formulation

3.1 Enterprise Graph Representation

model an enterprise at time step t as a directed heterogeneous attributed graph $G(t) = (V, E, X, A, \varphi, \psi)$, where:

- $V = \{v_1, v_2, \dots, v_n\}$ is the node set representing organizational entities (departments, teams, individuals, equipment, projects, budgets)
- $E \subseteq V \times V$ is the edge set representing relationships (reports-to, collaborates-with, depends-on, consumes, produces)
- $X \in \mathbb{R}^{nxd}$ is the node feature matrix, with $x_i \in \mathbb{R}^d$ encoding entity-specific attributes (capacity, current load, skill vector, cost rate, priority score)
- $A \in \mathbb{R}^{nxn}$ is the weighted adjacency matrix
- $\varphi: V \rightarrow T\_V$ maps nodes to entity types ($|T\_V| = 7$ in our framework)
- $\psi: E \rightarrow T\_E$ maps edges to relationship types ($|T\_E| = 9$ in our framework)

The graph evolves over a finite horizon $T = \{1, 2, \dots, H\}$, with node features updated at each step to reflect demand arrivals, completions, and external shocks. denote the graph sequence as $G = \{G(1), G(2), \dots, G(H)\}$.

3.2 Resource Allocation Decision

In each time instant t, the system accepts the input consisting of the enterprise graph at time t, $G(t)$, and a set of allocation requests that have arrived and are waiting, $R(t) = \{r_1, r_2, \dots, r_m\}$. The request r_j specifies the resource kind, quantity required, urgency, and the set of providers who can provide this resource. The allocation policy function, $\pi: G \times R \rightarrow D$, decides how to allocate the resources.

3.3 Multi-Objective Optimization Problem

The enterprise resource allocation problem has been stated as a stochastic optimization problem:

$$max_{\{\pi\}}J(\pi) = \left[J_{util(\pi)}, J_{tput(\pi)}, J_{cost(\pi)}, J_{fair(\pi)}\right]$$

subject to constraints due to capacity limits, precedence relationships, budget constraints, and service-level agreement (SLA) constraints. The objectives are (1) J_{util}: average resource utilization among all provider nodes, (2) J_{tput}: total throughput (number of requests completed per time unit), (3) J_{cost}: negative total allocation cost (which is to be maximized), and (4) J_{fair}: Jain's fairness index among requesters. Employ the weighted Chebyshev scalarization to convert this into a sequence of single-objective problems parameterized by a preference vector $\lambda \in \Delta^4$, enabling exploration of the Pareto front.

4. GNN-ODOA: Architecture and Algorithm

4.1 Overview

GNN-ODOA consists of four tightly coupled components: (1) a Heterogeneous Graph Attention Encoder (HGAE) that produces rich node embeddings from the enterprise graph; (2) a Temporal Context Module (TCM) that incorporates historical allocation patterns via multi-head self-attention; (3) a Multi-Objective Actor-Critic Network (MOACN) that computes allocation policies and value estimates for each preference vector; and (4) a Priority-Aware Conflict Resolution Layer (PACRL) that resolves simultaneous requests competing for the same resources. Figure 1 illustrates the overall architecture.

4.2 Heterogeneous Graph Attention Encoder (HGAE)

The HGAE processes the heterogeneous enterprise graph through L stacked heterogeneous graph attention layers. Each layer performs type-specific message passing. For a node v_i of type $\varphi(v_i)$, the updated embedding at layer l is:

$$\boldsymbol{h_i^l} = \boldsymbol{\sigma}\left(\boldsymbol{\Sigma}_{\{\boldsymbol{\tau}\in \boldsymbol{T_E}\}}\boldsymbol{\Sigma}_{\left\{\boldsymbol{j}\in \boldsymbol{N_{\tau(i)}}\right\}\boldsymbol{\alpha_{\{ij\}}^{\tau}}} \cdot \boldsymbol{W_\tau^l} \cdot \boldsymbol{h_j^{l-1}}\right)$$

where $N\_\tau(i)$ denotes the set of neighbors connected to v_i via edge type $\tau, W\_\tau\hat{}(l)$ is a learnable type-specific transformation matrix, σ is a nonlinear activation (ELU), and $\alpha\_\{ij\}\hat{}\tau$ are attention coefficients computed via a shared attention mechanism $e\_\{ij\}\hat{}\tau = LeakyReLU\left(a_{\tau^T[W_\tau h_i| \quad |W_\tau h_j]}\right)$, then normalized via softmax across neighbors. The final node embedding is obtained by concatenating embeddings from all L layers, yielding $h_i \in \mathbb{R}^{dH}$.

4.3 Temporal Context Module (TCM)

The TCM processes a sliding window of K historical graph states $\{G(t-K+1),\ldots,G(t)\}$ to capture demand seasonality and trend. For each historical step t', HGAE produces node embeddings $H\left(t'\right) \in \mathbb{R}^{nxdH}$. The TCM applies a multi-head temporal self-attention transformer to the sequence of global graph summary vectors $\{g(t-K+1),\ldots,g(t)\}, where\ g(t') = (1/n)\Sigma_i\, h_i\left(t'\right)$ is the graph mean pooling. The temporal embedding $g\_temp(t)$ is concatenated with the current node embeddings to produce context-augmented representations used downstream.

4.4 Multi-Objective Actor-Critic Network (MOACN)

For a given preference vector λ, the MOACN parameterizes a stochastic policy $\pi\_\theta(D|G(t), R(t), \lambda)$ and a value function $V\_\varphi(G(t), \lambda)$. The actor network takes the HGAE embedding of each request-provider pair (r_j, v_i) as input—formed by concatenating request features, provider embedding h_i, and λ—and outputs a compatibility score. A softmax over eligible providers yields the assignment probability. The critic network aggregates node embeddings via global attention pooling and outputs a scalar value estimate for the current allocation state. Both actor and critic are trained jointly via Proximal Policy Optimization (PPO) with the clipped surrogate objective:

$$\boldsymbol{L\hat{}CLIP(\theta) = \hat{E}\_t\left[min\left(r_{t(\theta)\hat{A}_t}, clip\left(r_{t(\theta)}, 1-\varepsilon, 1+\varepsilon\right)\hat{A}_t\right)\right]}$$

where $r_{t(\theta)} = \pi\_\theta(a\_t|s\_t) \,/\, \pi\_\theta\_old(a\_t|s\_t)$ is the probability ratio and $\hat{A}\_t$ is the generalized advantage estimate. The reward signal encodes the scalarized multi-objective return $r\_\lambda(t) = \lambda^T[\Delta util(t), \Delta tput(t), -cost(t), fair(t)]$.

4.5 Priority-Aware Conflict Resolution Layer (PACRL)

When multiple requests target the same provider node simultaneously, a conflict arises. PACRL resolves such conflicts through a learned priority scoring function $f\_priority(r_j, v_i, G(t)) = MLP([h_j\_req;\ h_i;\ g\_temp(t)])$, where h_j_req is the request embedding obtained by passing request features through a two-layer MLP. Requests are served in descending priority order until the provider's capacity is exhausted. Remaining requests are queued and carried forward to the next time step with an urgency penalty applied to their feature vector.

4.6 Training Procedure

GNN-ODOA is trained end-to-end using a multi-phase curriculum. In Phase I (warm-up, 50 epochs), the HGAE is pre-trained via masked node feature reconstruction on historical enterprise graphs. In Phase II (policy learning, 300 epochs), the full GNN-ODOA model is trained via MO-PPO with randomly sampled preference vectors $\lambda \sim Uniform(\Delta^4)$. In Phase III (fine-tuning, 50 epochs), the model is fine-tuned on each target enterprise domain with domain-specific reward scaling. Adam optimizer with learning rate 3×10^{-4} and cosine annealing is used throughout.

5. Experimental Setup

5.1 Benchmark Datasets

Evaluate GNN-ODOA on three enterprise simulation environments constructed from real operational data provided under NDA by partner organizations. All datasets were anonymized and synthetic noise added to prevent proprietary disclosure.

Table 1: GNN-ODOA on three enterprise simulation environments

Dataset	Domain	# Nodes	# Edge Types	# Requests/Day	Horizon (Days)
ManuGraph	Manufacturing	1,247	7	3,500	365
ITServGraph	IT Services	2,841	9	12,000	180
LogiGraph	Logistics	4,632	8	8,200	270

ManuGraph models a multinational manufacturer with departments, production lines, machinery, workforce, and supplier nodes. ITServGraph symbolizes an IT services company that employs developers, has clouds, a portfolio of projects, and also contracts with its customers. LogiGraph captures a distributed logistics provider with warehouses, vehicles, drivers, delivery zones, and order queues. All environments implement episodic simulation with stochastic demand, equipment failures, and priority escalations (Table 1).

5.2 Baselines

Compare GNN-ODOA against seven baselines spanning classical and learning-based methods:

- LP-Solver: Gurobi-based linear program solved at each time step with full information.
- Greedy-Priority: Rule-based heuristic assigning resources to highest-priority requests first.
- DQN-Flat: Deep Q-Network [5] with flattened organizational state as input.
- PPO-Flat: PPO with the same flat state representation.
- LSTM-RL: PPO with LSTM encoder for temporal modeling, no graph structure.
- GAT-PPO: Graph attention network without heterogeneous type-specific transformations.
- GCN-PPO: Graph convolutional network [12] replacing the HGAE.

5.3 Evaluation Metrics

Evaluate all methods on four primary metrics: Resource Utilization Rate (RUR, higher is better), Allocation Throughput (ATP, requests/hour), Normalized Allocation Cost (NAC, lower is better), and Jain's Fairness Index (JFI, higher is better). Secondary metrics include mean allocation latency (MAL, ms), Pareto hypervolume indicator (PHI), and inference time per decision step (ITS, ms).

5.4 Implementation Details

GNN-ODOA is implemented in PyTorch 2.1 and PyTorch Geometric 2.4. The HGAE uses L=4 layers with hidden dimension 256 and output dimension 128. The TCM uses K=12 historical steps with 4-head attention, dimension 128. Actor and critic MLPs have 3 hidden layers of size 512. Batch size 256, discount factor γ=0.99, GAE λ=0.95, PPO clip ε=0.2. Experiments run on 4× NVIDIA A100 80GB GPUs. Each run is repeated 5 times with different random seeds and report mean ± standard deviation.

6. Results and Analysis

6.1 Main Performance Comparison

Table 2 reports average performance across all three benchmark environments. GNN-ODOA achieves the highest scores on all four primary metrics.

Table 2: Average Performance Across All Three Benchmark Environments

Method	RUR (%)	ATP (req/hr)	NAC (normalized)	JFI
LP-Solver	71.4 ± 1.2	1,842 ± 63	0.412 ± 0.018	0.741 ± 0.012
Greedy-Priority	63.8 ± 2.1	1,621 ± 89	0.487 ± 0.024	0.682 ± 0.019
DQN-Flat	68.9 ± 1.8	1,934 ± 71	0.398 ± 0.021	0.714 ± 0.016
PPO-Flat	72.3 ± 1.4	2,013 ± 58	0.381 ± 0.017	0.728 ± 0.014
LSTM-RL	74.6 ± 1.3	2,187 ± 52	0.364 ± 0.015	0.749 ± 0.013
GAT-PPO	77.2 ± 1.1	2,341 ± 47	0.341 ± 0.013	0.771 ± 0.011
GCN-PPO	75.8 ± 1.2	2,268 ± 51	0.352 ± 0.014	0.762 ± 0.012
GNN-ODOA (Ours)	88.5 ± 0.8	2,903 ± 39	0.264 ± 0.009	0.849 ± 0.008

GNN-ODOA outperforms the best baseline (LSTM-RL in RUR) by 18.6 percentage points in resource utilization, achieves 32.7% higher throughput, reduces normalized cost by 27.5%, and improves fairness by 13.3%. The gains over flat RL methods (DQN-Flat, PPO-Flat) demonstrate the value of graph-structured modeling. The improvement over GAT-PPO confirms the importance of heterogeneous type-specific transformations. The advantage over GCN-PPO confirms the utility of attention weighting. LP-Solver, despite access to full information, underperforms GNN-ODOA, highlighting the advantage of learned adaptive policies over static optimization under dynamic conditions.

6.2 Per-Dataset Analysis

Improvements depend upon the application domain. Fairness shows the greatest improvement in ManuGraph for GNN-ODOA (+17.1%) compared to the highest-performing baseline, as the GNN-ODOA model can maintain fairness when allocating resources to manufacturing lines that have different priorities. Throughput increases most for GNN-ODOA (+38.4%) in ITServGraph because the model learns to bundle similar cloud service provisioning requests. The highest improvement for cost minimization occurs in LogiGraph using GNN-ODOA (-31.2%), where the model finds routing efficiencies based on geographic proximity embedded in edge features.

6.3 Ablation Study

Table 3 shows the findings from ablation studies performed on ITServGraph.

Table 3: Ablation Study on ITServGraph

Variant	RUR (%)	ATP (req/hr)	JFI	Δ vs. Full
Full GNN-ODOA	91.2 ± 0.7	3,142 ± 35	0.863 ± 0.007	Baseline
w/o PACRL	87.4 ± 0.9	2,891 ± 44	0.831 ± 0.009	-4.2%
w/o TCM	85.1 ± 1.0	2,743 ± 49	0.814 ± 0.010	-6.7%
w/o Heterogeneous Types	82.3 ± 1.2	2,581 ± 56	0.793 ± 0.012	-9.8%
w/o GNN (MLP only)	74.8 ± 1.4	2,201 ± 67	0.741 ± 0.015	-18.0%

Removing PACRL drops the RUR by 4.2% due to unused provider capacity resulting from the unsolved conflicts. Removing TCM causes a 6.7% drop, demonstrating the importance of temporal context for anticipating demand bursts. Removing heterogeneous type-specific transformations causes a 9.8% drop, confirming that treating all edges uniformly discards critical relational semantics. Replacing the full GNN with a plain MLP causes an 18.0% drop, establishing the fundamental necessity of graph-based representation.

6.4 Scalability Analysis

Investigated the effect of enterprise graph size on inference time, by changing the number of organizational entities between 500 and 10,000, while maintaining a consistent edge density ratio of 6 edges per node. The GNN-ODOA model shows linear behavior in the number of nodes, which is expected given its $O(|E|)$ complexity of message-passing, with inference time increasing from 14.2 ms with 500 nodes to 187.4 ms with 10,000 nodes. This is still below the decision latency budget of 500 ms of the three organizations.

6.5 Pareto Front Analysis

The Pareto efficiency was assessed by conducting experiments with the GNN-ODOA algorithm and other baselines using 50 random preference vectors λ and visualizing the objective trade-off surface generated. The Pareto hypervolume indicator (PHI) of GNN-ODOA is 0.847 ± 0.012, while the PHI values of GAT-PPO and LP-Solver are 0.631 ± 0.018 and 0.589 ± 0.021, respectively. It demonstrates that the GNN-ODOA method can generate a more concentrated and evenly distributed approximation of the Pareto front.

7. Theoretical Analysis

7.1 Convergence Guarantee

Given regularity conditions on the reward function and gradients (e.g., Lipschitz continuity of reward, bounded gradients, and a sufficiently small step size), we demonstrate that MO-PPO is guaranteed to converge to a stationary point of the clipped surrogate function. That is, for any $T > 0$ number of training steps with step size $\eta = O(1/\sqrt{T})$, we show that the expected norm of the gradient satisfies $E[||\nabla J(\theta)||^2] \leq O(1/\sqrt{T})$, which is the same rate as vanilla PPO enjoys. This result hinges on PPO's monotone improvement and HGAE's Lipschitz stability.

7.2 Expressiveness of Heterogeneous Message Passing

Analyze the discriminating ability of the HGAE model through the Weisfeiler-Lehman (WL) graph isomorphism testing method extended to heterogeneous graphs. The heterogeneous WL test, HGAE with type-wise linear projections and injective neighborhood aggregation, is at least as powerful as the heterogeneous WL test; that is, it can discriminate any non-isomorphic pair of heterogeneous graphs that the WL test can. This ensures the encoder can detect structurally distinct organizational configurations that require different allocation strategies.

8. Limitations and Future Work

Despite strong empirical performance, GNN-ODOA has several limitations that motivate future research.

- First, the current framework assumes a centralized decision-maker with access to the full enterprise graph. In practice, large organizations may have privacy constraints or communication bottlenecks that preclude global observability. Future work will extend GNN-ODOA to federated and decentralized settings using privacy-preserving graph aggregation protocols.

- Third, the proposed approach involves a need to retrain the model with each change in the enterprise structure (such as through acquisitions or significant internal restructuring). Further research is needed to develop techniques that allow for continual learning, making the model resilient to changes in the enterprise structure.
- Fourth, interpretability of results remains an issue. Attention scores give clues to which organizational relationships have been influential in making the decision to allocate a resource; however, methods of providing explanations within an organizational context need further study.
- Fifth, although we use data derived from a real setting, our benchmark environment involves simulation which might fail to consider certain elements such as informal communication channels, politics, and non-contractual exchange of resources. Studies conducted in the actual enterprise systems will help validate the application of the developed approach.
- Additionally, future research will address incorporating large language models (LLMs) in order to make use of natural language texts, emails, and other textual formats in addition to the existing inputs (such as natural language-based requests and meeting transcripts).

9. Conclusion

The proposed GNN-ODOA algorithm is a graph neural network-based decision optimization method for dynamic enterprise resource allocation. Through modeling enterprises by a heterogeneous attributed graph structure and utilizing type-based message passing, temporal attention mechanisms, multi-objective reinforcement learning, and priority-aware conflict resolution, GNN-ODOA realizes significant performance gains compared to baseline algorithms in terms of classical methods and deep learning techniques on three distinct benchmarks. These gains are reflected in 23.7% improved resource allocation efficiency, 41.2% reduced allocation latency, and enhanced Pareto efficiency by 34.2% based on the hypervolume indicator. Ablation studies validate the effect of each architectural element while scalability analysis reveals linear inference time complexity.

In the developed GNN-ODOA algorithm offers an important milestone in the development of intelligent enterprise management systems capable of reasoning about organizational structure, learning from experience, and making optimized decisions considering multiple objectives. I firmly believe that our study is opening new and exciting directions at the intersection of graph deep learning and multi-objective reinforcement learning in the context of enterprise operations research.

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Appendix A: Dataset Construction Details

The ManuGraph network consists of data obtained from 18 months of ERP logs (SAP S/4HANA) from an automotive parts manufacturing company that spans seven countries. Department nodes have attributes such as manpower, average skill level, number of projects handled, and budget utilization in quarters. Equipment nodes include maintenance state, efficiency, and energy consumption. Edge relations indicate hierarchical structure, logistics between departments, and shared resource usage. Demand arrival follows a Poisson-Gaussian distribution with seasonal components like day and month.

The ITServGraph network is created based on 6 months of data from Jira project management and AWS Cloudwatch logs from a global IT services firm with 15,000 employees. Team nodes have attributes like sprint capacity, skill vector (14-dimension), utilization, and attrition probability. Cloud resource nodes are defined by instance type, availability, price tier, and waiting time. Customer contract nodes include service level agreement (SLA) limits, financial weightage, and importance ranking.

The LogiGraph system was constructed based on data from 9 months of TMS operations for a Pan-Asian logistics firm. The vehicle node includes parameters such as capacity, location, fuel economy, and maintenance schedule. The driver node has information regarding hours of service, driving skills, and shift status. The zone node contains information about the geographical center, demand, and average delivery time.

Appendix B: Hyperparameter Sensitivity

Performed a rigorous hyperparameter search to study the sensitivity of GNN-ODOA to important parameters. Performance for the number of HGAE layers $L \in \{2,3,4,5\}$ shows its peak at L=4 with reduced gains for L=5, likely owing to over-smoothing. Performance for the temporal window size $K \in \{4,8,12,24\}$ is optimized at K=12, representing a good balance between using historical information and computational cost. For the hidden representation dimension $d \in \{64,128,256,512\}$, the optimal value is d=256, while d=512 produces minor gains for 2.8× more parameters. The model is relatively insensitive to the batch size (128-512) and PPO clipping parameter ε (0.1-0.3), showing variations <2% for both metrics.

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