Smart Logistics for Textile Waste: Intelligent Recycling and Dynamic Path Optimization for Sustainable Development

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ABSTRACT To improve the recycling efficiency of textile waste and reduce environmental pollution, this paper constructs a smart logistics system based on Deep Reinforcement Learning (DRL). Considering that large-scale intelligent logistics networks increasingly rely on distributed sensing, wireless communication, and reliable information transmission in electromagnetically complex environments, a Graph Neural Network (GNN) is employed to encode the state of a dynamic network composed of recycling points, vehicles, and sorting centers, capturing both node features and topological relationships. A Proximal Policy Optimization (PPO) algorithm is adopted to train multiple agents for collaborative path planning and task allocation. The model convergence is guided by a reward function that maximizes recycling benefits while minimizing energy consumption and idle distance. Experimental results demonstrate that the average recycling rate reaches 0.954, the task completion time is 65.5 minutes, and the energy consumption per unit of recycling is approximately 1.25 kWh/ton. The proposed method exhibits strong adaptability in dynamic environments and provides an efficient and feasible technical framework for intelligent textile waste recycling, while offering valuable insights for resource scheduling and cooperative optimization in communication-intensive smart systems.

INDEX TERMS smart logistics, textile waste recycling, deep reinforcement learning, dynamic path optimization, intelligent communication networks

I. INTRODUCTION

GLOBAL textile consumption continues to grow, and the resulting textile waste poses a serious threat to the environment. Traditional landfill and incineration methods not only consume significant land resources but also release harmful gases, exacerbating soil and water pollution. Therefore, establishing an efficient and environmentally friendly textile waste recycling and reuse system is of great theoretical and practical significance for promoting a circular economy and achieving sustainable development.

The textile waste recycling process faces a series of practical difficulties. The dispersed sources of waste and the uncertain quantities of waste make recycling tasks highly dynamic and random [1-3]. Traditional fixed- route planning models struggle to adapt to these changes, resulting in high vehicle idle rates and high energy consumption [4,5]. Furthermore, waste accumulates at varying rates at different recycling points, and the information silo effect prevents recyclers from keeping track of the full load status of each point in real time.

This leads to missed opportunities for optimal recycling or repeated, ineffective inspections, severely restricting overall recycling efficiency [6-8].

Existing research has proposed several solutions to these difficulties. However, whether it is heuristic algorithms and genetic algorithms applied to static path planning [9,10] or mathematical programming models for solving dynamic paths [11-13], none of them has fundamentally resolved the dynamic coupling between recycling task allocation and path planning, resulting in efficiency bottlenecks and resource waste in the entire recycling system.

To address the inefficiencies of these traditional approaches in dynamic and uncertain environments, this paper proposes a DRL based smart logistics approach. This approach first uses a GNN to encode the state of the urban recycling network, capturing the complex relationships between recycling points, vehicles, and sorting centers. Subsequently, a multi agent collaborative decision making model is constructed using the proximal policy optimization (PPO) algorithm, in which each agent independently learns and executes the optimal recycling strategy. This model uses a custom reward mechanism to guide the agent to consider multiple objectives, such as recycling volume, driving distance, and energy consumption, at each decision, ultimately converging to a global optimal solution[14]. This research aims to achieve real time dynamic allocation of recycling tasks through intelligent decision making, while simultaneously completing precise vehicle route planning, thereby building an efficient and adaptive smart textile waste recycling system.

II. METHODS

A. PROBLEM MODELING AS A SEQUENTIAL DECISION PROCESS

This section abstracts the intelligent logistics system for textile waste recycling as a Markov Decision Process (MDP). The system consists of recycling stations, sorting centers, and a homogeneous fleet of vehicles. The sorting center serves as the starting point, destination, and sole unloading point for all vehicles. The amount of waste accumulated at each recycling station changes dynamically, while the vehicles have a fixed load capacity. The objective is to maximize the total recycling volume within a given time period while minimizing energy consumption and empty driving distance, thereby achieving a balance between economic efficiency and sustainable development.

In MDP, system state S_t includes the amount of waste at the recycling station, vehicle location and load, and sorting center capacity; actions A_t represent the joint decisions made by vehicles, including heading to the station, returning to the sorting center, or waiting in place. After an action is executed, the system transitions to the next state based on waste generation and vehicle behavior S_{t+1}.

The reward function R_t is designed as shown in formula (1):

$$R_t = \omega_1 V_t - \omega_2 E_{\text{total}} - \omega_3 D_{\text{empty}} \tag{1}$$

In formula (1), V_t is the amount of energy recovered, E_{total} is the total energy consumption, D_{empty} is the idle distance, and ω_1, ω_2, and ω_3 are the weighting coefficients. By maximizing the cumulative reward $\sum_{t=0}^{T_{\text{total}}} \gamma^t R_t$, the agent learns the optimal vehicle cooperation strategy.

Figure 1 illustrates the system's structure and data flow: recycling stations, sorting centers, and fleets form a physical network, real time data is input into the decision model, and output commands control vehicle operation, constituting a closed-loop feedback system.

B. DYNAMIC STATE ENCODING BASED ON GNN AND RNN

To transform the dynamic textile waste recycling network into a quantifiable state understandable by deep reinforcement learning, this paper combines graph neural networks (GNNs) and recurrent neural networks (RNNs) to encode spatiotemporal features. Traditional vector representations struggle to depict the complex spatial relationships and temporal dependencies between recycling points and vehicles [15]. GNNs are used to extract spatial topological features, while RNNs are used to capture temporal dynamic changes.

The recycling network is modeled as a dynamic graph $G = (V, E)$ with a set of nodes. V includes recycling stations s_i, sorting centers D, and vehicles v_j; edge sets E represent roads and logical connections between nodes. Node features include: recycling stations: waste accumulation (amount, geographic coordinates, historical generation rate); vehicles (current location, remaining load, battery level); sorting centers (capacity and location features). These dynamic features ensure that the GNN can encode based on the real time network state at each time step.

A Graph Attention Network (GAT) mechanism is used for message passing and aggregation, iteratively updating node embeddings. The node update of the i-th layer of GAT consists of the following two parts:

AGGREGATE (aggregation): GAT uses attention-weighted summation as the aggregation function to calculate the information a node receives $m_u^{(l+1)}$ from its neighbors $\Gamma(u)$:

$$m_u^{(l+1)} = \sum_{v \in \Gamma(u)} \alpha_{uv}^{(l)} W^{(l)} h_v^{(l)} \tag{2}$$

COMBINE: The COMBINE function concatenates the old embeddings of nodes $h_u^{(l)}$ with aggregated information $m_u^{(l+1)}$, and $\sigma(\cdot)$ generates new node embeddings through a nonlinear transformation.

$$h_u^{(l+1)} = \sigma\left(\text{MLP}\left(h_u^{(l)} \| m_u^{(l+1)}\right)\right) \tag{3}$$

In Equations (2) and (3), $\alpha_{uv}^{(l)}$ represents the attention weight, $W^{(l)}$ is the shared linear transformation matrix, and $\|$ represents the concatenation operation. This structure ensures that node embeddings at each layer integrate topological and historical information from their neighbors. After extracting spatial features at each time step, the GNN uses a gated recurrent unit (GRU) to further process the node embedding sequence $h_u^{(0)}$, $h_u^{(1)}$, ... , $h_u^{(t)}$, integrating historical information to form the final spatiotemporal state representation. Ultimately, the set of node embeddings $\{H_u^{(t)}\}_{u \in V_t}$ constitutes the spatiotemporal state input of the system S_t, providing support for the decision making of the reinforcement learning agent.

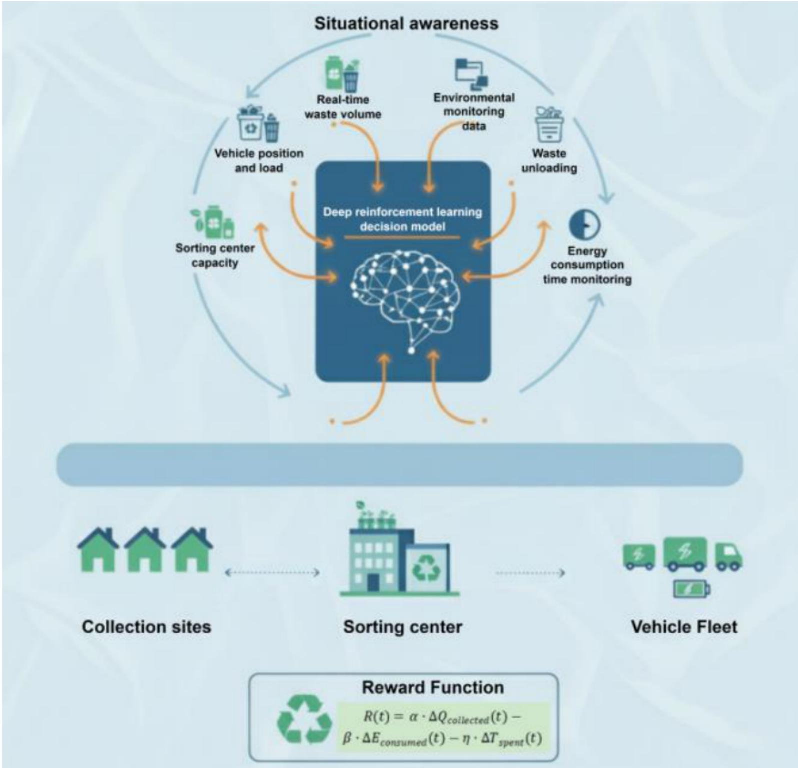

FIGURE 1. Smart Logistics System Model and Data Flow

TABLE 1. Entity and spatiotemporal feature encoding in the network model

Graph component	Node type	Feature description	information encoded	GNN operation
Collection Site (si)	Site Node	Waste accumulation, location;	local state and history	Aggregation from neighbors
Vehicle (v_j)	Agent Node	Position, load, power/battery	vehicle's physical status	Receive global context
Sorting Center (D)	Depot Node	Capacity, coordinates;	system constraint data	Hub for information flow
Connection	Edge	Road Connectivityd istance,	spatial relationship	Message passing link

Table 1 defines four core entities in the dynamic recycling network: recycling sites, vehicles, sorting centers, and network edges, and lists the role of each entity in the state encoding process. Key Feature Variables illustrate the real time key data constituting the system state. The table's key feature is the distinction between two encoding mechanisms: Spatial Encoding Mechanism clarifies that Graph Attention Networks (GATs) extract spatial topological information through node aggregation or information reception, while Temporal Integration Method specifies how Recurrent Neural Networks (RNNs) utilize hidden state updates or sequence processing to capture the temporal dependencies and historical dynamics of the system state.

C. MULTI-AGENT COLLABORATIVE DECISION-MAKING MECHANISM BASED ON PPO

This section constructs a multi agent deep reinforcement learning model based on a system state representation that integrates spatiotemporal information, achieving collaborative optimization of vehicle task allocation and dynamic path planning. The model employs a centralized training and distributed execution (CTDE) framework, modeling each recycling vehicle v_j as an independent agent A_j that learns interactively in a shared environment. Agents make independent decisions based on their global state S_t, and their actions influence overall rewards and state transitions, thus achieving implicit cooperation and global optimization.

Training employs the Proximal Policy Optimization (PPO) algorithm, which combines high data efficiency with policy stability. Each agent receives a state generated by a GNN RNN encoder at each time step, outputs discrete actions A_t through the policy network $\pi_{\theta_j}(A_t|S_t)$, transitions to the next state S_{t+1}, and receives a reward R_t. Policy parameters are determined by maximizing the pruning objective function $L^{\text{CLIP}}(\theta)$:

$$L^{\text{CLIP}}(\theta) = \hat{E}_t\left[\min\left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right] \quad (4)$$

In formula (4), $r_t(\theta) = \pi_\theta(A_t|S_t)/\pi_{\theta_{\text{old}}}(A_t|S_t)$ represents the probability ratio of the new and old strategies, $\hat{A}_t$ is the estimated value of the advantage function, and ϵ is the pruning coefficient.

The reward function comprehensively considers maximizing the amount of data recovered, minimizing energy consumption and idle distance, driving the multi agent system to converge to the globally optimal joint strategy, thereby achieving intelligent dynamic optimization of vehicle scheduling and routes.

D. ENSEMBLE TRAINING FRAMEWORK AND ALGORITHM FLOW

This section describes the training process of a multi agent PPO collaborative decision making model based on GNN RNN encoding to ensure the scientific validity and reproducibility of the method. The model is trained in a Python based simulation environment that simulates urban road topology, vehicle kinematics, energy consumption models, and the random generation and accumulation of textile waste. The training framework integrates the GNN RNN state encoder with the multi agent PPO algorithm: at each time step, the GNN RNN encodes the raw environmental data into a global state S_t, which is then input into the policy π_{θ_j} and value networks V_{ϕ_j} of each agent for decision making and evaluation. During training, agents collect experience trajectories and store them in a buffer, from which the PPO samples batch data to perform gradient updates.

The model convergence criterion is that the average cumulative reward growth rate is less than 0.1% over the past 100 rounds or the maximum number of training rounds is reached. Performance evaluation metrics include average recovery efficiency, vehicle energy consumption, and the proportion of idle driving, to comprehensively assess the model's practicality. The value network is trained by minimizing the value loss function:

$$L_t^{\mathrm{VF}}(\phi) = \left(V_\phi(S_t) - \hat{R}_t\right)^2 \tag{5}$$

In formula (5), $V_\phi(S_t)$ represents the value network's estimate of the current state S_t, $\hat{R}_t$ is the cumulative discounted reward actually observed in the current state S_t, and ϕ is a parameter of the value network. This process ensures accurate value estimation and improves the stability of policy updates.

In addition, parameter sensitivity analysis was performed on the weights of the reward function to verify the adaptability and robustness of the model under different optimization objectives.

III. EXPERIMENTAL SETUP

A. SIMULATION ENVIRONMENT AND DATA DESCRIPTION

The multi agent deep reinforcement learning model in this study was trained and validated on a Python- based simulation platform. The core framework used was PyTorch, which was employed to construct and train the GNN RNN state encoder and the PPO policy and value network. Experiments were run on a server equipped with an NVIDIA RTX 3090 GPU to improve parallel computing efficiency. The simulation environment was constructed based on real road networks of typical Chinese cities extracted from OpenStreetMap (OSM), rather than a simplified grid model, thus possessing higher real-world complexity.

The environment integrated a vehicle energy consumption model and a randomly driven textile waste generation model. Experimental data combined real road network topology with simulated data: recycling point locations and road network structure were derived from OSM, while waste generation rate and vehicle operating parameters were randomly generated based on industry survey data. Core experimental parameters are shown in Table 2: the number of recycling points N represents the network size, the number of vehicles M corresponds to the number of collaborative agents, the total simulation duration T_{total} determines the training round length, and the time step Δt reflects the agent decision frequency. The waste generation rate was modeled as follows:

$$P_i(t) \sim \mathcal{N}(\mu_i, \sigma_i^2) \tag{6}$$

In formula (6), $P_i(t)$ represents the rate of waste generation at time t at recycling point i. It is modeled as $\mathcal{N}(\mu_i, \sigma_i^2)$, a normal distribution with mean μ_i and variance σ_i^2, which reflects the random fluctuation characteristics of waste generation.

TABLE 2. Core Experimental Environment Parameter Settings

Parameter	Symbol	Value	Description	Unit/Type
Number of Collection Sites	N	50	Total nodes in the network graph excluding the depot.	Integer
Number of Vehicles	M	5	Total number of collaborative agents.	Integer
Total Simulation Time	T_{total}	480	Duration of one simulation episode.	Minutes
Time Step Interval	Δt	5	Interval between two consecutive agent decisions.	Minutes
Vehicle Capacity	C_{max}	15	Maximum carrying capacity of each vehicle.	Tons
Base Road Network Source	GOSM	Real City Topology	Source of the underlying road network graph.	String

B. BASELINE ALGORITHMS AND EVALUATION METRICS

This section selects representative methods as benchmarks to comprehensively verify the performance advantages and adaptability to dynamic environments of the proposed GNN

RNN PPO method. Three representative methods are selected as benchmarks: the first is the greedy algorithm... The first type is the heuristic algorithm, which selects a locally optimal path at each decision moment to reflect the lower bound of the performance of the basic heuristic strategy; the second type is the classic genetic algorithm. Algorithms (GA), as representatives of metaheuristic algorithms, are used to evaluate the solution capabilities of traditional search optimization methods in static and weakly dynamic environments; the third category is high performance methods for the Dynamic Vehicle Routing Problem (D-VRP), namely Adaptive Large Neighborhood Search. Large Neighborhood Search (ALNS). ALNS demonstrates its optimization capabilities in handling real time changing problems by dynamically selecting destruction and repair operators.

This study uses four core indicators to quantify the model's performance: total recovery volume V_{total}, energy consumption per unit recovery volume E_{unit}, average recovery task completion time $\bar{T}_{\text{finish}}$, and total vehicle mileage D_{total}. Energy consumption per unit recovery volume is a key indicator for measuring the system's sustainable development goals, and its calculation is shown in formula (7):

$$E_{\text{unit}} = \frac{E_{\text{total}}}{V_{\text{total}}} \tag{7}$$

In formula (7), E_{unit} represents the energy consumption per unit of recycling during the entire simulation cycle, E_{total} is the total energy consumed by all vehicles in the process of performing the recycling task, and V_{total} represents the total amount of textile waste collected by all recycling vehicles from various recycling points within the same cycle.

IV. RESULTS AND ANALYSIS

A. ALGORITHM CONVERGENCE ANALYSIS

To verify the effectiveness and stability of the proposed GNN RNN encoded multi agent PPO algorithm in dynamic recycling networks, this section conducts convergence experiments. The model is trained in a defined core simulation environment, with total rewards recorded per round. A moving average is used to smooth the curve and observe the long-term learning trend. Key analytical metrics include the convergence curve of training rounds versus total reward, and the changing trend of energy consumption per unit of recycling. The results are shown in Figure 2.

Figure 2, the GNN RNN PPO algorithm exhibits efficient and stable convergence characteristics, reaching a steady state in only about 3000 rounds. This indicates that the model effectively balances recycling revenue and operating costs under the PPO policy update mechanism. The energy consumption per unit of recycling decreases and stabilizes simultaneously, demonstrating that the agent, supported by precise state encoding, successfully optimizes energy consumption and idle distance. Overall, the results prove that this integrated framework possesses excellent learning efficiency and dynamic decision making stability, effectively supporting the efficient operation of the intelligent logistics system for textile waste.

B. COMPREHENSIVE PERFORMANCE COMPARISON IN DYNAMIC ENVIRONMENTS

To verify the performance advantages of the GNN RNN PPO method in dynamic textile waste recycling tasks, this section compares it with three benchmark algorithms—Greedy algorithm, Genetic algorithm (GA), and Adaptive Large Neighborhood Search (ALNS). Multiple rounds of independent testing were conducted with parameters such as waste generation rate and vehicle size adjusted. The core metrics were waste collection rate and average total recycling volume. The results are shown in Figure 3.

Figure 3, GNN RNN PPO performs optimally in dynamic tasks. Under standard conditions, its average waste collection rate reaches 0.954, significantly higher than ALNS (0.925), GA (0.885), and the greedy algorithm (0.821). This advantage stems from the algorithm's use of GNN to achieve accurate spatiotemporal encoding of the road network and accumulation state, and the efficient collaboration through multi agent PPO, enabling rapid task allocation when dynamic demands change. Resource sensitivity analysis shows that when the number of vehicles M increases from 3 to 6, GNN RNN PPO consistently maintains the highest total recycling volume; at that point, its recycling volume reaches 703.88 tons, significantly higher than ALNS (650.57 tons) and GA (576.92 tons). The results demonstrate that this method can maximize vehicle utilization in resource constrained environments and possesses superior dynamic intelligent recycling decision making capabilities. M=5

C. COMPREHENSIVE ANALYSIS OF DYNAMIC ADAPTABILITY AND ROBUSTNESS

This section aims to comprehensively verify the effectiveness and stability of the proposed method from three dimensions: emergency response, handling of key system constraints, and robustness of model hyperparameters.

D. DYNAMIC ADAPTABILITY ANALYSIS UNDER EMERGENCIES

To evaluate the model's adaptability in dynamic environments, this experiment pre-set time points during the middle of its operation, t_{shock}, triggering a sudden surge in data collection, i.e., forcing a critical site s_k to revert to its previous state. The amount of waste accumulation increased dramatically. A comparative analysis was conducted on the performance of the converged GNN RNN PPO agent and the baseline method based on static optimal solutions in terms of task completion time and waste collection rate after the event occurred.

The results are shown in Figure 4.

As shown in Figure 4, the GNN RNN PPO model can adjust its path in real time after a sudden event, prioritizing

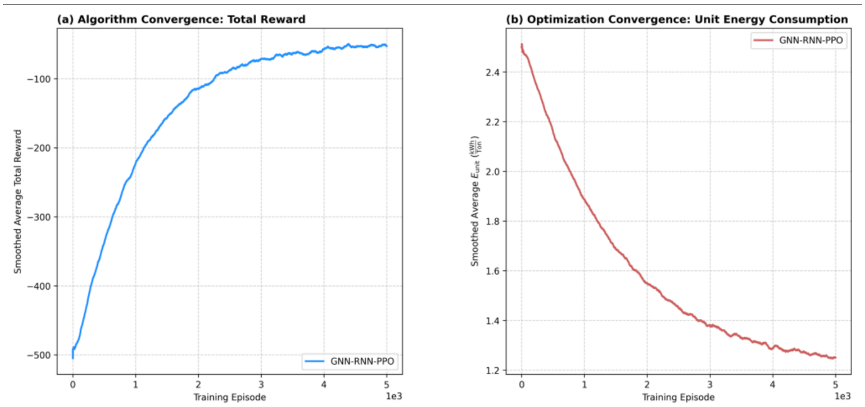

FIGURE 2. Algorithm convergence and stability analysis: (a) Algorithm convergence: Total reward; (b) Optimization convergence: unit energy consumption

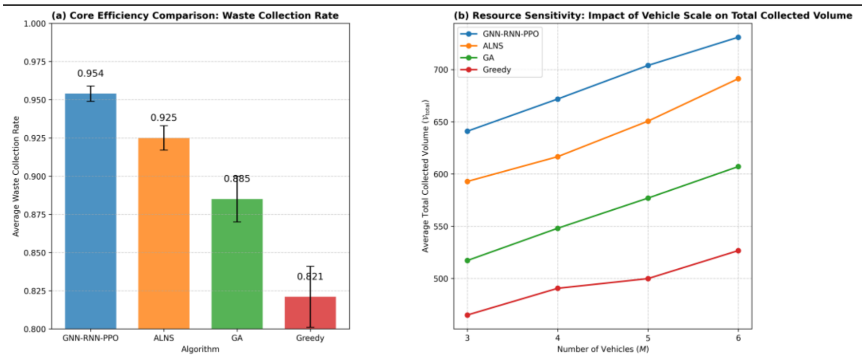

FIGURE 3. Performance comparison of different algorithms in dynamic environments: (a) Core efficiency comparison: Waste collection rate; (b) Resource Sensitivity Analysis: Impact of Vehicle Size on Total Recycling

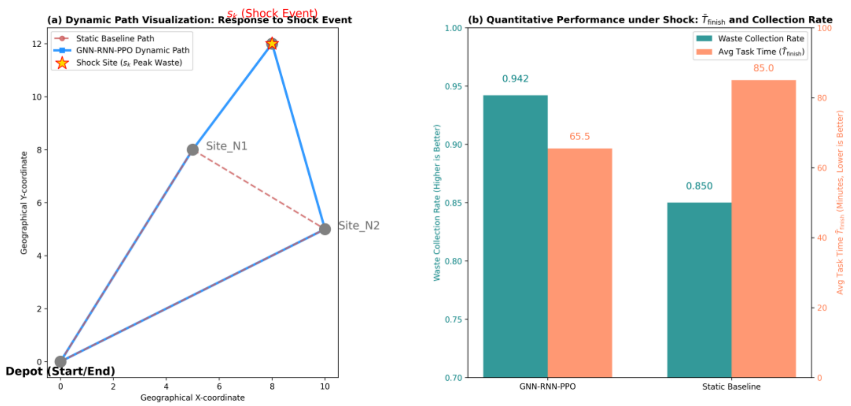

FIGURE 4. Dynamic path adaptability analysis under emergencies: (a) Dynamic path visualization: emergency response; (b) Performance quantification under dynamic shock: $\bar{T}_{\text{finish}}$ with collection rate

responses to a surge in the number of stations s_k, demonstrating significant dynamic decision making capabilities. This mechanism benefits from the real time capture of environmental state changes by the GNN RNN encoder, enabling the PPO policy network to quickly output new optimal actions. Quantitative results show that the model maintains a high collection rate and a short task completion time under sudden shocks, representing improvements of approximately 10.8% and reductions of approximately 23% compared to the static baseline, respectively. The results validate the real time adaptability and stability maintenance capabilities of this method in non-static environments.

E. ANALYSIS OF THE IMPACT OF SORTING CENTER CAPACITY CONSTRAINTS

The real time capacity of the sorting center (Depot) is a key system constraint affecting multi agent collaborative decision making. This experiment quantifies the impact of this constraint on vehicle decisions.

Experimental scheme: Two extreme scenarios are compared: sufficient capacity (constraint inactive) and compressed capacity (capacity upper limit significantly reduced).

The performance changes of the GNN RNN- PPO model and the baseline ALNS are analyzed under the compressed constraint. The results are shown in Figure 5.

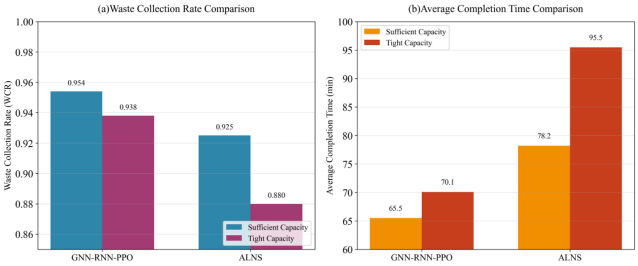

FIGURE 5. Performance comparison under tight capacity constraints: (a) Comparison of waste collection rates under different capacity constraints; (b) Comparison of average completion time under different capacity constraints

As shown in Figure 5, under the tight capacity constraint, the ALNS model's task completion time increased by approximately 22.1%, and the collection rate decreased by approximately 4.9%, exhibiting a significant efficiency degradation. In contrast, the GNN RNN PPO model showed a smaller performance decline, only 7.0% and 1.6%, respectively. This is attributed to the GNN RNN encoder's ability to incorporate the real time capacity of the sorting center as a global constraint into the state S_t, enabling the PPO agent to be forward- looking and strategically embed unloading tasks in path planning. This analysis demonstrates that the sorting center capacity variable is active and crucial in the model.

F. SENSITIVITY ANALYSIS OF REWARD FUNCTION WEIGHTS

To verify the robustness of the model performance to the reward function weights (ω_1: recovery amount, ω_2: energy consumption, ω_3: idle distance), this section presents a sensitivity analysis. Experimental scheme: The weight for maximizing the recovery amount was kept ω_1 fixed at 1.0, and nine different combinations of ω_2 and ω_3 within the range of [0.5, 2.0] were tested. The fluctuations of the core indicators (waste collection rate (WCR) and unit recovery energy consumption E_{unit}) were analyzed. The results are shown in Figure 6.

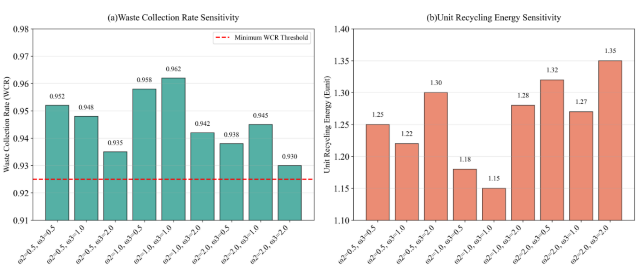

FIGURE 6. Sensitivity analysis of reward function weights: (a) Changes in waste collection rate under different weight combinations; (b) Changes in unit recovered energy consumption under different weight combinations

Figure 6 illustrates the performance fluctuations of the model under different weight combinations. In all tested parameter combinations, the waste collection rate (WCR) consistently remained above 0.925, with a relative fluctuation of no more than [percentage missing] ±3.5%. This result strongly suggests that the intrinsic mechanisms of GNN RNN state encoding and PPO policy optimization are the fundamental reasons for the superior performance. Even when the weight settings of the reward function are not "optimal," the model can still robustly converge to a high-quality suboptimal policy, demonstrating the good robustness of the model's hyperparameter selection.

V. CONCLUSION

This paper addresses the dynamic and uncertain challenges of textile waste recycling by constructing a smart logistics system based on deep reinforcement learning. The method utilizes a GNN RNN hybrid architecture to encode the spatiotemporal state of a dynamic network composed of recycling points, vehicles, and sorting centers, abstracting the recycling task into a Markov decision process, ensuring real time and accurate decision making. The PPO algorithm is used to train the multi agent system, achieving collaborative decision making for path planning and task allocation. The model converges by guiding it through a reward function that maximizes recycling benefits while minimizing energy consumption and idle distance, and experiments verify the superior performance of the proposed method. Under standard conditions, the model achieves an average waste collection rate of 0.954. Under the dynamic impact of simulated sudden recycling peak events, the average recycling task completion time reaches 65.5 minutes, demonstrating the method's strong dynamic adaptability. Multi-objective optimization brings the energy consumption per unit of recycling volume down to a low level of approximately 1.25 kWh/Ton. This research achieves real time dynamic allocation of recycling tasks and precise optimization of path planning through intelligent decision making, providing an efficient and feasible decision making model and technical solution for promoting resource recycling and sustainable management of textile waste.

AUTHOR CONTRIBUTIONS

Zhihuan Liu designed, collected and analyzed the data, and drafted the manuscript. Zhihuan Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Zhihuan Liu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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