

# Production Logistics Resource Recommendation Based on ‘Look-Around’ Reasoning Mechanism in Discrete Manufacturing

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**Abstract:** Production logistics (PL) involves high levels of complexity and unpredictability, driven by volatile resource demands and a lack of synchronicity in operational workflows. Resilient and efficient resource allocation in PL is essential for optimizing production processes and forms a foundational element in managing resources to achieve zero inventory targets in an uncertain environment. This paper introduces a recommendation-driven approach for real-time resource allocation in PL. Firstly, a resource spatial-temporal knowledge graph (RSTKG) is constructed to capture and analyze the relationships among entities and historical allocation data. Then, we propose a ‘look-around’ reasoning mechanism, which leverages the temporal and spatial attributes of material buffers on shop floors to assess the cost-effectiveness of requested nodes compared to available resources, ultimately generating a resource allocation plan. Finally, to validate our approach, a case study is conducted in an air conditioning manufacturing company, where our method demonstrates a punctuality rate exceeding 90%, outperforming previous allocation methods.

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**Keywords:** production logistics; resource allocation; resilience; real-time analysis; decision-making; Industry 5.0.

## 1. INTRODUCTION

The manufacturing sector is undergoing a profound transformation as it transitions from Industry 4.0 to Industry 5.0, marking a shift toward more personalized, human-centric, and adaptive production systems (Leng et al. 2024). In this context, production logistics (PL) plays a pivotal role in connecting shop-floor activities with production workflows, synchronizing the scheduling and movement of materials and components across various production areas. Specifically, PL involves the meticulous planning, management, and control of storage, transport, and handling processes (Zhang et al. 2018), ensuring a seamless flow of materials (Zhu et al. 2023).

As customer demands become increasingly personalized and subject to frequent fluctuations, PL demonstrates heightened dynamicity during the transition from Industry 4.0 to Industry 5.0. This evolution is characterized by complex resource interactions, significant human involvement, and highly variable demand patterns (Ivanov 2023). Such intricacy underscores the limitations of traditional static frameworks, highlighting the necessity for more adaptive and flexible systems to meet the evolving requirements of modern manufacturing. Furthermore, real-world manufacturing environments are often subject to unexpected disruptions, including equipment malfunctions and abrupt demand shifts, which frequently render pre-planned allocation strategies infeasible (Zafar et al. 2024). These challenges underscore the pressing need for the development of more effective and resilient strategies for PL resource allocation.

Despite these needs, PL management faces several practical obstacles. Data collected from Internet of Things (IoT) devices

in PL systems are often diverse, originating from multiple sources and scales, and lack standardized formats for expression, interoperability, or sharing. This impedes the efficient flow of spatial-temporal information critical for effective decision-making. Additionally, while spatial-temporal knowledge could significantly enhance resource allocation, the absence of robust reasoning mechanisms limits the ability to make timely, adaptive, and predictive decisions required for real-time scheduling.

To address these challenges, this paper introduces a novel approach to PL resource allocation, using recommendation systems to optimize the flow of raw materials and semi-finished products across production sites, such as workshops and warehouses. Specifically, we propose a spatial-temporal information representation standard to clarify the relationships and values of PL resources over time and space. Then, we further introduce a ‘look-around’ reasoning mechanism to assess spatial correlations between production areas and infer potential temporal relationships across resources. Finally, we present a recommendation-based approach that leverages these reasoning results to optimize real-time resource distribution, thereby reducing conflicts, minimizing delays, and enhancing the flexibility of the decision-making process.

The paper is organized as follows: Section 2 reviews relevant literature. Section 3 details the proposed spatial-temporal information representation standard, and Section 4 discusses the recommendation method based on the ‘look-around’ reasoning mechanism. Section 5 presents the result and performance, and Section 6 summarizes the conclusion.

## 2. LITERATURE REVIEW

### 2.1 Spatial-temporal analysis and reasoning

Traditional data-mining approaches frequently rely on the assumption that data points are independent and identically distributed (Flores-García et al. 2024; Xing et al. 2016). However, this assumption does not hold in the context of spatial-temporal data. In cyber-physical systems, data is often dynamic, highly interconnected, and embedded with complex spatial-temporal attributes (Han et al. 2012; Schlemitz and Mezhyuev 2024). These data show unique characteristics across regions and time intervals (Atluri et al. 2019). Such dependencies are essential for real-time, context-aware decision-making in manufacturing. Ignoring these spatial-temporal correlations can diminish the precision of analytical outcomes (Wu et al. 2022). Consequently, various spatial-temporal analysis and reasoning frameworks have been developed to capitalize on these insights.

Li et al. (2022) divided production facilities into discrete spatial-temporal units. By aggregating solutions across adjacent elements, their approach enhances flexibility, enabling rapid adjustments to unexpected changes and disruptions in production. Wen et al. (2023) developed an end-to-end deep learning model with personalized spatial transfer patterns, examining the hidden transfer behaviors across locations based on operators' historical movement data. Zhao et al. (2024) introduced a multimodal bionic learning model based on spatial-temporal analytics. This model captures object interactions, evolution, and synchronization through reasoning mechanisms at the operational level, substantially improving logistics efficiency.

### 2.2 Production logistics resource allocation

PL resource allocation aims to distribute limited resources to fulfill manufacturing demands optimally (Bu 2024). This task becomes increasingly challenging with the shift towards customized, small-batch production, which intensifies the variety and quantity of resource requests (Chen et al. 2023; Wang et al. 2024). Moreover, the extended execution time and diverse resource types inherent in such production scenarios mean that improper resource allocation can result in significant production delays and potentially more severe consequences (Qu et al. 2017). Effective allocation strategies are, therefore, essential to minimize delays and maximize efficiency.

To address these challenges, Li et al. (2020) proposed a resource allocation method using discrete event simulation. The approach builds a model from PL data, generates random allocation plans, and applies factorial analysis to identify bottlenecks, optimizing the plan to maximize non-bottleneck resource use while managing bottlenecks efficiently. Zhao et al. (2022) proposed a resource allocation approach utilizing dynamic graph, where a graph-based algorithm determines the optimal allocation by accounting for constraints such as spatial relationships, time windows, and capacity limits. He et al. (2024) introduced reinforcement learning as a method to optimize material flow decisions in production. By using factors like order processing time and pending operations, their system can dynamically assess real-time conditions to allocate materials, prioritize orders, and adjust schedules.

### 2.3 Summary of literature

Resource allocation is a cornerstone of PL. It is crucial to ensure that necessary resources are precisely where they need to be, exactly when required, to sustain productivity and efficiency across the manufacturing process. Much research is conducted on optimizing resource allocation, employing advanced methodologies such as simulation modeling, graph-theoretical approaches, and artificial intelligence. These techniques strive to enhance the accuracy and effectiveness of resource distribution decisions. However, a common shortcoming among many current methods is their limited scope, often focusing exclusively on the current data.

This narrow view frequently disregards the historical movement patterns and potential future trends of resources, which can offer valuable insights into more refined allocation strategies. By omitting a comprehensive spatial-temporal perspective on PL resources, existing methods risk producing suboptimal decisions that may lead to inefficiencies. Thus, integrating spatial-temporal knowledge and advanced graph-based reasoning mechanisms is a promising direction for improving resource allocation in PL. Addressing this gap could lead to more resilient, adaptable, and predictive decision-making processes, particularly suited for today's dynamic manufacturing environments.

## 3. SPATIAL-TEMPORAL INFORMATION REPRESENTATION

To integrate the extensive flow of resources with both spatial and temporal data, we construct a heterogeneous spatial-temporal knowledge graph to represent resource allocation information. This graph structure incorporates various nodes and edges, where nodes represent distinct PL resources and sites, and edges signify the transfer records among nodes. The knowledge within this graph is categorized into three main types: resource knowledge, allocation knowledge, and site knowledge.

Resource knowledge includes entities like raw materials, work-in-progress (WIP), components, and finished products, each defined by properties such as ID, location, and material standards for traceability. Allocation knowledge records resource transfers, noting details like timestamps, operator and vehicle information, and source/destination locations. Site knowledge refers to logistics buffers and operational stations, with a status property indicating whether a site is 'In service' (ready for resource handling) or 'Out of service' (due to unavailable personnel or equipment).

The construction of the spatial-temporal knowledge graph is depicted in Fig. 1 and proceeds as follows: First, entity recognition is performed using an ontology-based approach, identifying nodes representing specific entities in the graph, primarily those associated with resources and site knowledge, such as raw materials, components, and various stations. Next, directed edges are established between nodes based on historical transportation records, with each edge storing critical details like transport duration and quantity moved. Finally, real-time updates from IoT devices dynamically refresh each PL resource's spatial and temporal attributes, including position coordinates and remaining quantities. This

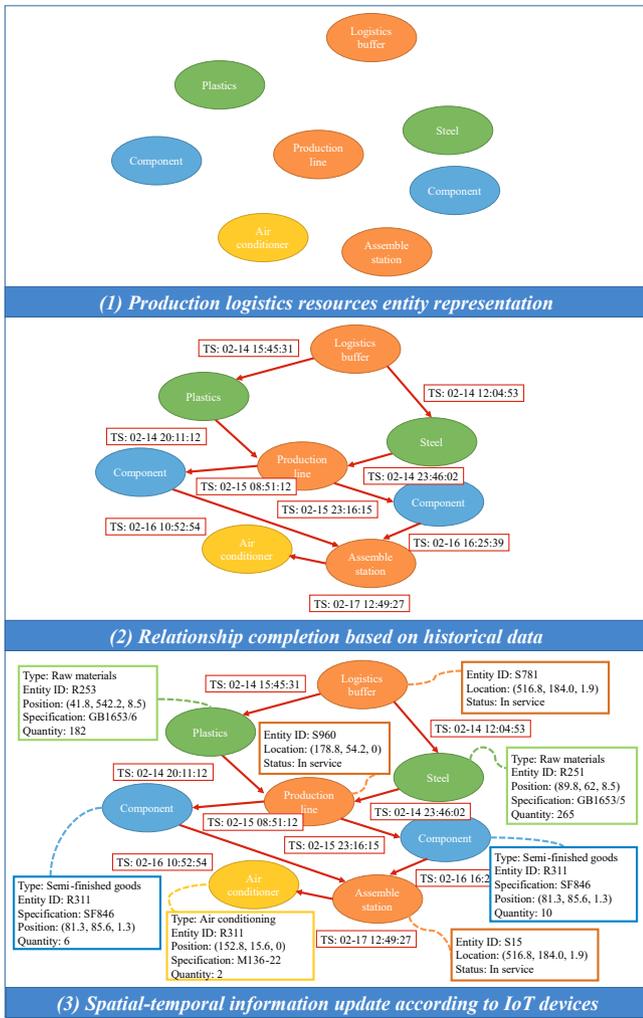


Figure 1. The construction steps of resource spatial-temporal knowledge graph

continuous update records entities' movement paths, enabling a dynamic knowledge graph that maintains consistency between physical resources in the industrial environment and their digital representations in cyberspace.

By following these steps, we have established the resource spatial-temporal knowledge graph (RSTKG) capable of accurately mirroring the status and interactions of PL resources. This model provides a robust foundation for further data-driven decision-making, allowing real-time insights into resource allocation and movement trajectories.

#### 4. RESOURCE RECOMMENDATIONS BASED ON 'LOOK-AROUND' REASONING MECHANISM

##### 4.1 'Look-around' reasoning mechanism

To leverage the embedded knowledge within RSTKG, we propose a 'look-around' reasoning mechanism designed to analyze, interpret, and forecast the interactions and coordination of PL resources. The concept of 'look-around' reasoning reflects a cognitive approach to deducing insights from spatial-temporal links among various objects or events. As depicted in Fig. 2, this mechanism utilizes a heterogeneous RSTKG that captures resource flow records alongside their respective timestamps, enabling us to apply 'look-around' reasoning to uncover underlying patterns and relationships in space and time.

The reasoning framework can be divided into three key sub-modules: (1) 'Look-backward' reasoning, which examines historical data to understand past interactions. (2) 'Look-present' reasoning, focusing on the current state and dynamics of resources. (3) 'Look-forward' reasoning, which anticipates potential future developments and trends. Each of these submodules is discussed in further detail in the following sections. This comprehensive framework provides a holistic view of PL resources, aiding in identifying meaningful spatial-temporal patterns for informed decision-making.

##### 4.1.1 'Look backward' reasoning

'Look backward' reasoning is an essential component of the 'look-around' reasoning mechanism. When a resource flow event takes place, it updates the features of the entities involved based on specific event details. The RSTKG, defined as  $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$ , includes nodes  $\mathcal{V} = \{v_1, \dots, v_n\}$  and edges  $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ . Each node  $v_i$  has two main attributes:  $m_i(t)$  and

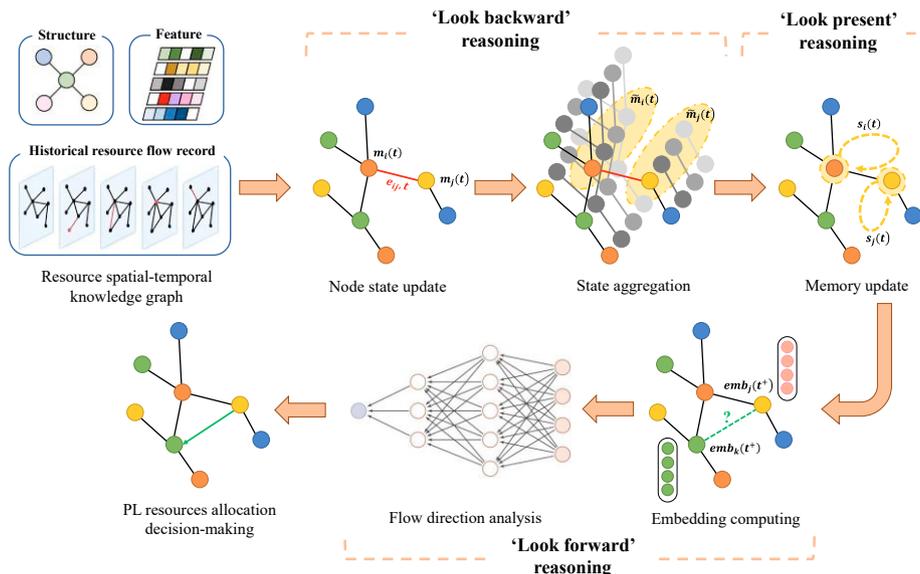


Figure 2. The framework of 'look-around' reasoning mechanism

memory  $s_i(t)$ . During each resource allocation event  $e_{ij}(t)$  from source node  $i$  to target node  $j$ , the message states of the nodes are updated based on Eq. (1) and Eq. (2):

$$m_i(t) = \text{encoder}(s_i(t^-), s_j(t^-), \Delta t, e_{ij}(t)) \quad (1)$$

$$m_j(t) = \text{encoder}(s_j(t^-), s_i(t^-), \Delta t, e_{ij}(t)) \quad (2)$$

where  $s_i(t^-)$  and  $s_j(t^-)$  denote the nodes' memory states prior to time  $t$ ,  $\Delta t$  represents the time interval since the previous interaction, and the *encoder* function integrates these inputs to form a new embedding.

In RSTKG, resource allocation events are illustrated as edges, and over time, nodes become connected to numerous others as records of resource flow accumulate. To improve the propagation and learning of information, the 'look backward' reasoning uses graph neural network (GNN) aggregation functions. These functions merge local node data with global data from adjacent nodes, removing distance dependencies within the graph and bolstering reasoning robustness (Rossi et al. 2020). The aggregation operation is defined as:

$$\bar{m}_i(t) = \text{agg}(m_i(t_1), m_i(t_2), \dots, m_i(t)), t_1 \leq t_2 \leq \dots \leq t(3)$$

where *agg* is the aggregation function. In GNN, different types of aggregation exist: the most recent aggregator retains only the latest value for a node, the maximum aggregator selects the highest value, and the average aggregator computes the mean across values. To capture recent resource flow trends, the 'look backward' reasoning adopts the mean aggregator as the implementation of the *agg* function.

#### 4.1.2 'Look present' reasoning

'Look present' reasoning focuses on temporal reasoning, using each node's previous memory state  $s_i(t^-)$  and the aggregated information state  $\bar{m}_i(t)$  from past events to infer its updated current memory state  $s_i(t)$ . The main objective of this module is to condense the history of each node into a compact form, enabling the reasoning mechanism to capture long-term dependencies for every node in the graph. This reasoning process can be expressed as follows:

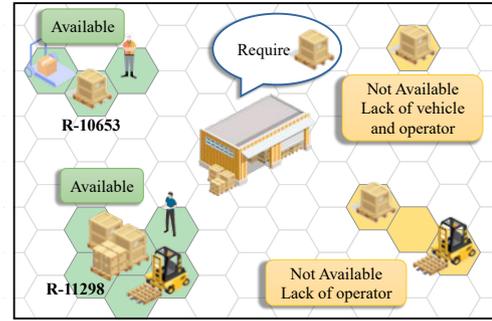
$$s_i(t) = \text{mem}(\bar{m}_i(t), s_i(t^-)) \quad (4)$$

A variety of memory update modules can be used for this task, including architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), both of which can maintain long-term dependencies in sequential data. In our approach, we ultimately chose GRU due to its computational efficiency and suitability for handling dynamic node updates within the graph.

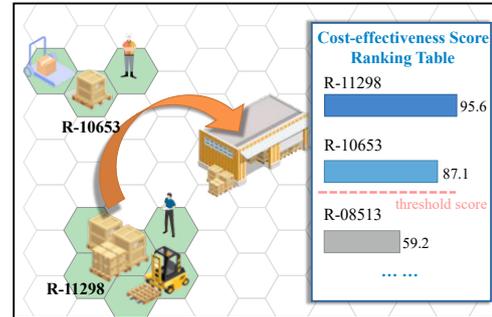
When a new node is introduced in a real-world scenario, its memory state is initially set to an empty vector. From this point, each interaction involving the node will update its memory state according to the expressions above, progressively building a richer historical context for the node.

#### 4.1.3 'Look forward' reasoning

'Look forward' reasoning aims to integrate environmental information surrounding resource nodes, exploring potential collaboration among multiple resource nodes. 'Look forward'



(1) Assess resource availability



(2) Resource allocation based on the result of reasoning

Figure 3. Recommendation-based resource allocation method

consists of many layers of multi-head attention (MHA) layer. Specifically, the input to the  $l$ -th layer is the node  $i$ 's representation  $h_i^{(l-1)}(t)$  and the features extracted by the multi-head attention block  $\tilde{h}_i^{(l)}(t)$ . As shown in Eq. (5),  $t$  represents the current timestamp, and  $\parallel$  is the concatenation operator.

$$h_i^{(l)}(t) = FC^{(l)}(h_i^{(l-1)}(t) \parallel \tilde{h}_i^{(l)}(t)) \quad (5)$$

The output of 'look forward' reasoning module can be succinctly summarized as follows:

$$\text{emb}_i(t) = h_i^{(L)}(t) \quad (6)$$

where  $L$  represents the number of total layers, and  $h_i^{(L)}(t)$  denotes the output of 'look forward' reasoning. Ultimately,  $\text{emb}_i(t)$  will be stored as feature vectors at each node, facilitating participation in subsequent resource recommendation and other processes. In this paper,  $L = 2$  and each MHA layer consists of two attention heads.

#### 4.2 Recommendation-based resource allocation method

Resource recommendations are generated dynamically based on 'look-around' reasoning and current PL resource demands. Initially, resources in the required category are assessed for availability, as illustrated in Fig. 3. If crucial personnel or vehicles are lacking nearby, the resource's status is marked as unavailable, excluding that node in the RSTKG from further reasoning and temporarily removing it from allocation.

Then, by conducting 'look-around' reasoning on RSTKG, each resource node  $i$  obtains a reasoning embedding  $\text{emb}_i(t)$ , and the cost-effectiveness score between resource node  $i$  and site node  $j$  is calculated using Eq. (7), which utilizes node

embeddings as inputs for the scoring model  $SC$ , which consists of many layers of feedforward neural network.

$$\text{Cost effectiveness score}(i, j) = SC \left( emb_i(t), emb_j(t) \right) \quad (7)$$

Higher scores indicate better allocation suitability, and resources are prioritized by score, from highest to lowest. Resources with scores below a set threshold are excluded to optimize production efficiency. If top-ranked nodes lack sufficient materials, the following highest-ranking nodes are selected to meet the deficit. Any unmet demand, after considering all nodes, will be deferred to the next round.

## 5. CASE STUDY

### 5.1 Experimental details

A leading air conditioning manufacturer in the Greater Bay Area of China faces significant challenges in managing the complexity of PL resource allocation. As a prominent player in the discrete manufacturing sector, the company produces units of multiple distinct components, each requiring individualized assembly material. This production process leads to highly variable and intricate resource demands, underscoring the critical need for a well-coordinated resource allocation system.

To improve the situation, we implemented an intelligent PL resource tracing system incorporating related hardware devices and software algorithms. The system relies on real-time tracking data of mobile PL resources, workforce members, and vehicles, which are essential for dynamically assessing resource availability. IoT Bluetooth low-energy tags, equipped with Bluetooth chips, sensors, and batteries, are vital in this system. These tags are affixed to equipment and personnel and emit unique Bluetooth signals at predetermined intervals, enabling precise location and status tracking. The gateways installed on the ceiling monitor received signal strength indication to calculate distances to each tag, facilitating accurate real-time position tracking.

Three primary sites, including the logistics warehouse, the central air-conditioning plant, and the precision machining workshop, were monitored for two months. During this period, all resource requests and position information for equipment, personnel, and vehicles were recorded. This data provides comprehensive insights into logistical needs and patterns across the production environment. Among them, the first month's data was analyzed, and the optimal allocation plans, developed by several senior experts, served as the ground truth for training the 'look-around' reasoning mechanism model. The model was trained in 100 iterations. Subsequently, the second month's data was used to evaluate and compare the performance of the trained algorithm, providing insights into its practical effectiveness and adaptability.

### 5.2 Result analysis

To comprehensively assess the effectiveness of our proposed approach, we benchmarked against the company's previous allocation method. Resource coordination in PL follows a step-by-step process: an operator must locate and retrieve a forklift, gather materials, and transport them to the designated workshop. The company's previous allocation method relied

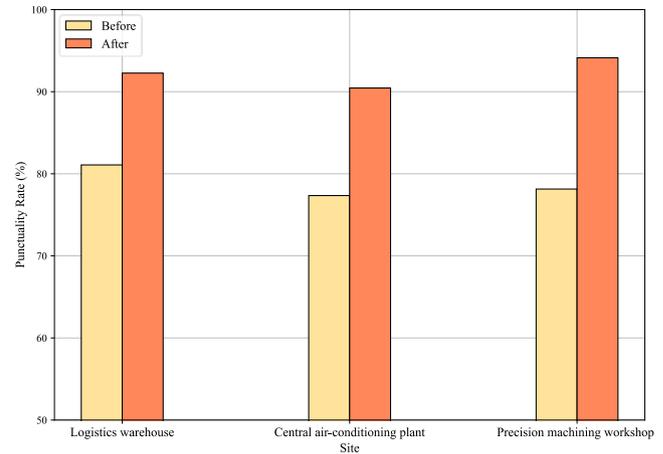


Figure 4. Punctuality rate for different methods

on a distance-based algorithm to minimize distances between critical points, from the operator to the vehicle, vehicle to material, and material to the resource demand location.

In PL, the punctuality rate is a vital indicator for evaluating how reliably resources like raw materials and components arrive on schedule. It is defined as the percentage of resources that reach their destinations on time compared to the total scheduled. Fig. 4 illustrates punctuality rates achieved by different methods, and the related results were averaged across five runs. It can be found that our resource allocation method based on the 'look-around' reasoning mechanism achieves a punctuality rate above 90% across all sites, outperforming the previous method. The primary reason is the absence of predictive capabilities in previous methods. Such approaches could only respond to resource demands as they occurred, without the ability to anticipate future needs based on recent resource movement trends. This limitation hindered the deployment of relevant resources in advance, resulting in a lower punctuality rate among all sites.

## 6. CONCLUSIONS

This paper proposes a PL resource allocation based on a 'look-around' reasoning mechanism. The 'look-around' reasoning mechanism contributes to extracting insights from seemingly unrelated spatial-temporal data. It can combine critical features such as historical information and flow trends to achieve personalized recommendations for each site node, thereby supporting the resilience of real-time decision-making. The proposed approach can be adopted by logistics coordinators, providing them with actionable insights for optimizing resource allocation in dynamic environments. Furthermore, it could be utilized by decision-makers within manufacturing companies to enhance operational efficiency through better-informed planning.

However, the current research has several limitations. As the volume of real-time data grows, the RSTKG will become a dense graph with a lot of nodes and edges, which will increase the inference time during the reasoning phase. In the future, we plan to employ sampling techniques to update the state of each node within the graph, thereby reducing the overall computational complexity.

## ACKNOWLEDGEMENTS

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