

# Multi-Objective Optimization Framework for Reliable Safety Stock Decisions with Intermittent Demand Forecasting

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**Abstract**—Safety stock (SS), encompassing reorder point (RP) and maximum stock (MS), is designed to minimize inventory cost while maintaining maintenance safety for manufacturing enterprises. In recent years, advanced computational techniques have been applied to forecast spare parts demand (SPD), enabling dynamic updates to SS settings. However, existing methods have often failed to produce reliable SS decisions when confronted with significant demand volatility and random failures. The reliability of SS decisions remains an open problem and is still in its early stages of investigation. To address this issue, in this paper, a reliable SS model with uncertainty evaluation of SPD is proposed in this paper. Initially, a basic setting of RP and MS is derived on a three-level warehousing architecture by simultaneously minimizing excess inventory cost and shortage cost. Building upon this foundation, a novel SS reliability metric is introduced by integrating static information (inventory coverage and emergency replenishment rate) with dynamic information (decision compactness ratio). To enhance the decision compactness ratio, a multivariate intermittent time series forecasting method based on an improved graph neural network is developed. Accurate forecasting with a confidence interval is achieved through bootstrap resampling. Finally, a reliable RP and MS configuration is obtained by incorporating the forecasting interval into the basic stock setting. Validation is conducted using an actual spare parts dataset from a large rail transit manufacturing enterprise in China. The experimental results demonstrate that the proposed model not only achieves higher SPD prediction accuracy but also improves inventory turnover and coverage while significantly enhancing reliability.

**Index Terms**—Multi-objective optimization, Safety stock, Demand forecasting, Intermittent time series, Reliability, Graph neural networks.

## I. INTRODUCTION

**I**NVENTORY management is critical for ensuring after-sales service and controlling cost in manufacturing enterprises. As the most vital component of inventory management, safety stock (SS) is established to minimize inventory cost while maintaining maintenance safety [1]. A well-determined SS plays a substantial role in strengthening whole-lifecycle management of manufacturing enterprises and enhancing

maintenance efficiency [2]. Traditional SS models generally adopt a static inventory strategy, such as the  $(s, S)$  policy [3], where  $s$  denotes the reorder point (RP) and  $S$  represents the maximum stock (MS). Such decisions perform well for continuous and stable spare parts demand (SPD) data, which are common in retail fields [4]. In manufacturing enterprises, however, SPD is often sporadic, resulting in intermittent work order data from site warehouses, i.e., zero or near-zero SPD over certain periods. This intermittent pattern is significantly different from continuous demand patterns, thereby impeding the application of current SS models. Moreover, SPD frequently exhibits considerable fluctuations in the after-sales services of manufacturing enterprises. Seasonal variations in failure rates and inherent differences in spare parts lifecycles render static SS decisions ineffective for such demand patterns, often resulting in either excess inventory or frequent replenishment. For example, in rail transit and vehicle manufacturing enterprises, SPD is often irregular due to fluctuating failure rates and maintenance schedules. Such demand patterns may lead to frequent emergency replenishment during peak periods and excessive inventory during low-demand periods. These cases show that traditional static SS decisions are difficult to apply when SPD is intermittent and volatile. Therefore, a reliable and effective SS decision that can accommodate intermittent and volatile SPD is essential for manufacturing enterprises to reduce costs and enhance efficiency.

According to the literature review (see details in Section II), various optimization methods, such as genetic algorithms and particle swarm optimization, have been applied to inventory management [5]. However, these methods have remained confined to static SS models and have failed to provide reasonable SS decisions when faced with uncertain conditions, such as significant demand volatility and random failures. In recent years, advanced computational techniques have been applied to inventory management, primarily focusing on SPD forecasting [6]. Nevertheless, the application of such approaches to SS remains limited due to the intermittent nature of SPD in manufacturing enterprises. We have noticed that there is a pioneering study about dynamic SS model incorporated with SPD forecasting [7]. Through a dynamic fusion mechanism, that study simultaneously improved inventory turnover rate and coverage in a three-level warehousing architecture. Despite satisfactory results, the method exhibited limitations when addressing significant demand volatility because the SPD forecasting relied on a basic LightGBM model. LightGBM was initially employed to capture inter-sequence structural information and shared demand fluctuations across multiple spare parts. However, its forecasting capability became weakened when processing highly volatile SPD data. Consequently, the

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reliability of the SS decision (i.e., its capability to guarantee service levels under SPD fluctuations) was reduced. In general, current research on dynamic SS has primarily concentrated on optimizing inventory levels (i.e., RP and MS) and costs, while insufficient attention has been directed toward establishing and evaluating SS decisions in real-world after-sales scenarios characterized by high demand volatility.

In light of the aforementioned concern, this paper introduces a new open problem: while SS is designed to enhance the reliability of spare parts supply, what is the reliability of the SS decision itself? Unlike existing studies that mainly focus on inventory level optimization or ex-post service performance, this work explicitly investigates whether a given safety stock decision can maintain satisfactory supply performance under intermittent and volatile demand. Here, the reliability of an SS decision is defined as its capability to fulfill its intended functions, namely, ensuring customer satisfaction under inventory uncertainty. Clarifying this problem allows the effectiveness of the SS strategy to be assessed and the most critical factors influencing SS to be identified. To address this problem, as well as the concerns mentioned above, SS reliability is defined in this paper as the capability to simultaneously minimize the risks of excess inventory and shortage inventory under uncertain conditions [8]. As demonstrated by Fan et al. [7], MS ensures service levels under SPD fluctuations, while RP regulates inventory cost and excess inventory risk. When demand increases, the RP value should be raised accordingly to avoid shortages; conversely, the MS value should be reduced to mitigate excess inventory. From this perspective, a reliable SS decision (i.e., a reasonable configuration of MS and RP) is capable of reducing the occurrence of emergency replenishment while minimizing excess inventory cost. Consequently, SS reliability is designed here as a quantitative metric for evaluating service performance relative to inventory demand.

To clarify the problem setting, this study considers a three-level warehousing architecture consisting of one central warehouse, multiple regional warehouses, and multiple site warehouses. The inventory review cycle is monthly, and the replenishment process follows the classical  $(s, S)$  policy. The proposed model is built on historical work order data with intermittent SPD. In this framework, the key decision variables are RP ( $s$ ) and MS ( $S$ ), and the reliability is evaluated based on inventory coverage, emergency replenishment rate, and decision compactness ratio.

The overall flowchart of the proposed model is shown in Fig.1. Building upon the definition of SS reliability, a new SS reliability metric is proposed by combining static information (inventory coverage and emergency replenishment rate) with dynamic information (decision compactness ratio). Calculated using work order data, this metric not only concretizes the definition of reliability but also provides an empirical evaluation for the obtained SS setting. Furthermore, since the static information is determined once the work order data are collected, the improvement of the decision compactness ratio, which is considered vital in the SS reliability metric, is prioritized. To this end, a multivariate intermittent time series forecasting method based on a graph neural network (GNN) is proposed. In this method, each series is treated as a

graph node, and the series weights are dynamically adjusted through a graph attention mechanism. By incorporating a linear decay correction technique, commonly employed for handling intermittent time series, the method achieves SPD forecasting with a confidence interval via bootstrap resampling to quantify inventory uncertainty. Finally, a reliable RP and MS configuration is obtained by integrating the forecasting interval into the basic SS setting derived from multi-objective optimization on a three-level warehousing architecture. Validation is conducted using an actual after-sales spare parts dataset from a large rail transit manufacturing enterprise in China.

The main contributions of this paper can be summarized as follows.

- 1) The concept of SS reliability is proposed for the first time. SS reliability is formally defined as the capability to simultaneously minimize the risks of shortage inventory and excess inventory. Based on this definition, an SS reliability metric is developed by integrating both static and dynamic information from SPD data. Unlike current SS decisions, which are evaluated only after SPD occurs, this metric enables a preliminary assessment of SS decision effectiveness before demand realization and serves as a quantifiable indicator for empirical evaluation. To the best of our knowledge, this study represents the first attempt to explore SS reliability.
- 2) A novel multivariate intermittent time series forecasting method is introduced. By employing a graph attention mechanism and linear decay correction, the proposed method effectively exploits the structured relationships among sequences as well as the temporal evolution within each sequence. Distinct from most existing forecasting methods, this approach not only achieves an effective fusion of “vertical” and “horizontal” information but also generates prediction results with confidence intervals. This capability enables robust SPD forecasting in practical scenarios.

The remainder of this paper is organized as follows. Section II presents a brief literature review on intermittent time series forecasting and dynamic SS decision. In Section III, a static SS decision model with multi-objective optimization is developed on a three-level warehousing architecture, thereby providing a basic configuration of MS and RP. Section IV introduces the definition and formulation of the SS reliability metric. To enhance the decision compactness ratio in the SS reliability metric, Section V proposes a GNN-based multivariate intermittent time series forecasting method, which is followed by a trend information fusion mechanism in Section VI. Section VII presents a comprehensive set of experimental results based on real-world SPD data. Finally, the conclusion and potential research directions are summarized in the last section.

## II. RELATED WORKS

Effective SS decision is critical for large manufacturing enterprise when facing SPD fluctuation and inventory uncertainty [9]. As a pioneer study, the  $(s, S)$  policy has proven promising under the constraints of hold cost and shortage cost [10]. This policy was extended to incorporate practical

constraints including zero lead time, storage capacity, and service level requirements, demonstrating its generalization capability across domains [11]. In recent years, the inventory strategy on continuous characteristic data is starting to be developed. Multi-objective optimization algorithms, such as genetic algorithms [12], simulation optimization [13] and evolutionary algorithm [14] have been applied to seek the trade-off between diverse objectives including revenue benefits from shorter delivery time and inventory operation costs [15], ordering costs and holding costs [16], etc. In addition to average cost criteria, discounted cost models have also been studied in inventory management such as Babaveisi et al. [17], Basten and van Houtum [18], and Benshimol and Barron [19], which investigate spare parts planning and stock-out policy under stochastic demand and discounted cost settings. With promising results under the online retailing setting, these methods predominantly focus on stable and frequent SPD data, rather than fluctuating and intermittent demands. The obtained SS decision is usually hard to apply to SPD fluctuations, resulting in emergency replenishment or excess inventory.

For manufacturing enterprise, SPD data often exhibits lumpy or intermittent pattern, characterized by periods of zero or near-zero demand for spare parts. The intermittent distribution characteristic of SPD data brings heavy block to demand forecasting [20]. As an early work, Croston et al. [21] achieved effective forecasting of intermittent demand by recognizing the importance of separating demand size and the inter-demand interval. Since then, several variants of Croston's method, such as SBA [22], TSB [23] and ESLD [24], were proposed. Among these methods, ESLD implemented linear decay correction for demand interval smoothing during zero-demand periods, thereby enhancing the extraction of evolution information from SPD sequences. In the past decade, machine learning techniques like support vector regression [25] and random forest [26] have delivered good results in intermittent time

series forecasting [28]. Deep learning methods, e.g., stacked LSTM [27], attention mechanism [29] and convolutional neural network [30], have also been used for demand prediction [31]. Also, due to the intermittent characteristic, these methods cannot guarantee to learn the internal trend information from intermittent sequences. Astonishingly, proven by Kiefer et al. [32], Croston's method still has comparative advantages than the deep learning methods in forecasting intermittent time series, particularly for the inventory cost-oriented metric.

There are some studies about dynamical setting of RP and MS in SS decision. Most studies calculate RP as the standard deviation of point forecasts, specifically by simple exponential smoothing (SES) [33] and autoregressive moving average [34]. These studies mainly aim to get a trustworthy RP, but inadequately analyze the impact of MS. Even that Kozodoi et al. [35] introduced GNN to calculate RP and MS in a probabilistic, the approach primarily applies to continuous demand pattern observed in retail business. For manufacturing enterprise, Fan et al. [7], regarded as state-of-the-arts, was proposed to achieve dynamic SS decision by integrating the forecasting results of intermittent SPD sequences. This method first calculated the static MS and RP via a multi-object genetic algorithm, and then adjusted the MS value and the RP value with point forecast and static statistic respectively, also named dynamic information fusion mechanism. However, this mechanism will become ineffective in scenarios characterized by high demand volatility. More importantly, existing methods only evaluate the effectiveness of SS decision with real SPD data, but fail to assess the effect of SS decision before SPD occurs [36]. The latter, i.e., the reliability of SS decision itself, is precisely what maintenance engineers are most concerned about when making decisions [37].

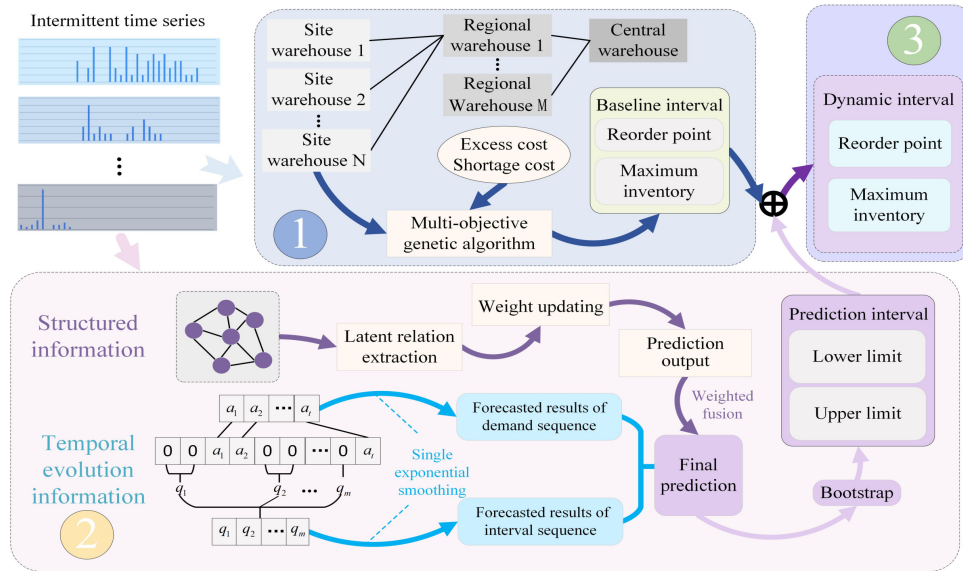


Fig. 1: Overall framework of the proposed model with three main parts: (1) multi-objective SS optimization, (2) multivariate intermittent time series forecasting, and (3) dynamic information fusion.

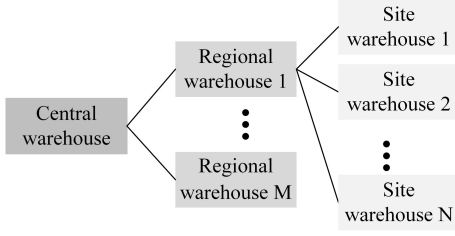


Fig. 2: Diagram of three-level warehousing architecture.

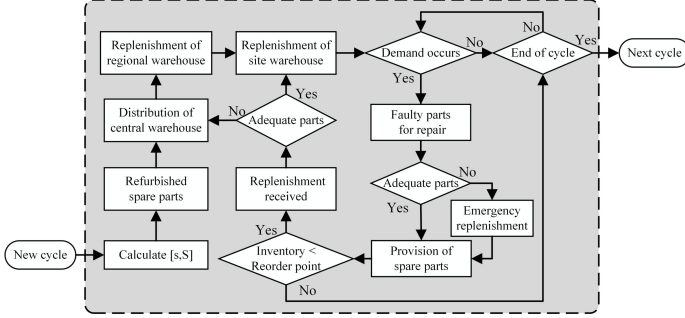


Fig. 3: Logic diagram of inventory management for large manufacturing enterprise.

### III. MULTI-OBJECTIVE SAFETY STOCK OPTIMIZATION MODEL

To obtain the basic RP and MS values, we first build a multi-objective safety stock optimization model in this section. The resulted  $(s, S)$  setting serves as the basic SS decision. Demand uncertainty learned from historical SPD over past inventory cycles will be integrated into the obtained  $(s, S)$ , rather than through an explicit parametric stochastic formulation. Without loss of generality, this model runs on a three-level warehousing architecture comprising a central warehouse, regional warehouses, and site warehouses, as illustrated in Fig. 2. Each level plays different roles, elaborated as follows:

- 1) Central warehouse: maintains the widest variety and highest quantity of spare parts within the inventory model. It manages all procurement and distribution of spare parts. Regarding of re-manufacturing, repairable parts are refurbished and returned to central warehouse.
- 2) Regional warehouse: receives spare parts from central warehouse and distributes parts to site warehouses. Every regional warehouse along with its  $N$  subordinate site warehouses forms a region. Each of regional warehouse merely caches a small number of spare parts.
- 3) Site warehouse: generates demand in the whole maintenance process. It holds a certain number of spare parts to meet demands and can be replenished from regional warehouse or adjacent site warehouses when an urgent demand occurs.

The whole inventory management process is illustrated in Fig. 3. The used definitions are as follows:

- Inventory cycle: is set to one month in this study, denoted by  $t$ . Also, denote the total number of cycles as  $T$ . The procurement lead time is set to 10 days.

- Default distribution time: is set 3 days from central warehouse to regional warehouse, 2 days from regional warehouse to site warehouse, and 1 day for urgent replenishment.
- Refurbishment cycle: indicates the time for repairable spare parts refurbished at the central warehouse, denoted by  $t_r$ . The repaired parts return to central warehouse.
- Replenishment: occurs to raise inventory in site warehouse up to  $S$  when the inventory level falls to or below  $s$ . Otherwise, no order is initiated. Here the classical  $(s, S)$  strategy is adopted.  $s$  and  $S$  set inventory interval. The replenishment order of a site warehouse is only linked to its adjacent site warehouse and regional warehouse.

The above time-related settings are based on the actual operational practices of actual manufacturing enterprise. According to the key target of SS decision, this model minimizes excess inventory cost and shortage cost simultaneously. The calculation of these two objectives includes the following steps:

#### 1) Calculation of RP

RP for the  $i$ -th site warehouse in the  $t$ -th inventory cycle is defined as:

$$s_i^t = Q \cdot \sqrt{t_b} \cdot \delta \quad (1)$$

where  $i \in \{1, 2, \dots, N\}$ ,  $Q$  denotes the safety factor for customer satisfaction. The value of  $Q$  1.65 corresponds to 95% satisfaction.  $\delta$  represents the per-cycle SPD standard deviation. In (1), the RP intuitively serves as a safety buffer to hedge against shortage risk during the replenishment lead time, so the RP value increases when the lead time becomes longer or the demand becomes more uncertain.

#### 2) Faulty spare parts refurbishment

Faulty spare parts from site warehouses undergo centralized transfer to the central warehouse for refurbishment. The quantity of repaired parts is calculated as:

$$Fp_i^{t+1} = dam_i^t \times RR \quad (2)$$

where  $Fp_i^{t+1}$  and  $dam_i^t$  denote the quantity of repaired and faulty parts, respectively, at the  $i$ -th site warehouse in  $(t+1)$ -th inventory cycle.  $RR$  corresponds to the successful refurbishment rate.

#### 3) Central warehouse procurement and distribution

The central warehouse tackles replenishment orders from regional warehouses and subsequently allocates parts to the regional warehouses raising request. The quantity of procured parts is denoted by:

$$Pu^t = \sum_{i=1}^M Rp_i^t - Fp^{t-1} \quad (3)$$

where  $Fp^t$  represents the quantity of repaired spare parts in the last inventory cycle,  $Rp_i^t$  denotes the replenishment quantity for the  $i$ -th regional warehouse in the  $t$ -th inventory cycle, as:

$$\begin{cases} Rp_i^t = 0, & \text{if } RI_i^t > \overline{SI}^t \\ Rp_i^t = \overline{SI}^t - RI_i^t, & \text{if } RI_i^t < \overline{SI}^t \end{cases} \quad (4)$$

where  $RI_i^t$  denotes the actual inventory quantity of the  $i$ -th regional warehouse in the  $t$ -th inventory cycle,  $\overline{SI}^t$  represents the average inventory quantity across subordinate site warehouses, as:

$$\overline{SI}^t = \frac{1}{N} \sum_{i=1}^N SI_i^t \quad (5)$$

where  $SI_i^t$  denotes the actual inventory quantity at  $i$ -th site warehouse in the  $t$ -th inventory cycle. The replenishment quantity  $Rp_i^t$  is zero if the regional warehouse does not raise demand.

#### 4) Site warehouses replenishment

When inventory quantity of site warehouse falls below  $s_i^t$ , replenishment to  $S_i^t$  occurs from either the regional warehouse or adjacent warehouses.  $S_i^t$  is denoted as the MS value of the  $i$ -th site warehouse in the  $t$ -th inventory cycle. The replenishment quantity  $Sp_i^t$  is calculated as:

$$\begin{cases} Sp_i^t = 0, & \text{if } SI_i^t > s_i^t \\ Sp_i^t = S_i^t - SI_i^t, & \text{if } SI_i^t < s_i^t \end{cases} \quad (6)$$

The excess inventory cost  $EC^t$  across regional and site warehouses in the  $t$ -th inventory cycle is then given by:

$$\begin{aligned} EC^t(s_i^t, S_i^t) = & \left( \sum_{i=1}^M (RI_i^t + Rp_i^t - Rec_i^t) \right. \\ & \left. + \sum_{j=1}^M \sum_{i=1}^N (SI_i^t + Sp_i^t - De_i^t) \right) \\ & \times U_{holding} \end{aligned} \quad (7)$$

where  $Rec_i^t$  denotes the actual consumption quantity at the  $i$ -th regional warehouse in the  $t$ -th inventory cycle, and  $U_{holding}$  represents the unit cost of part holding that includes fixed inventory cost, inventory management cost, and depreciation cost.

#### 5) Emergency replenishment of site warehouses

Emergency replenishment will be triggered when site warehouse inventory quantity cannot accommodate unexpected demand. High shortage cost is then raised. The shortage cost  $SC_i^t$  is calculated as:

$$SC_i^t(s_i^t, S_i^t) = \sum_{j=1}^M \sum_{i=1}^N (Erq_i^t * Ert_i^t) * U_{c_{shortage}} \quad (8)$$

where  $U_{c_{shortage}}$  denotes the shortage cost per unit of parts that involves emergency transportation cost, project delay, and customer loss cost.  $Erq_i^t$  and  $Ert_i^t$  represent the emergency replenishment quantity and occurrence times, respectively, at the  $i$ -th site warehouse in the  $t$ -th inventory cycle.

Based on (7) and (8), the static SS optimization model is to solve the following minimization problem:

$$\begin{aligned} \min Cost_i(s_i^{T+1}, S_i^{T+1}) = & \left\{ \sum_{t=1}^T EC^t(s_i^t, S_i^t), \sum_{t=1}^T SC_i^t(s_i^t, S_i^t) \right\} \\ \text{s.t. } & s_i^{T+1}, S_i^{T+1}, \\ & RR = 0.9, \\ & Erq_i^t, Ert_i^t, Rp_i^t, Sp_i^t, RI_i^t, \\ & Fp_i^t, dam_i^t, SI_i^t, De_i^t, Rec_i^t \in N \end{aligned} \quad (9)$$

In (9), the MS value should always be greater than the RP value. The actual demand quantity  $De_i^t$ , replenishment quantity  $Sp_i^t$ , emergency replenishment times  $Ert_i^t$ , etc. are required to be positive integer in the cost calculation, while the successful refurbishment rate  $RR$  is set a default value of 0.9. As determined by (6),  $s_i^{T+1}$  and  $S_i^{T+1}$  are the optimization variables for the next inventory cycle, representing the RP and MS values, respectively.

This study employs multi-objective genetic algorithm [38] to solve (9). Specifically, the optimization variables  $s_i^{T+1}$  and  $S_i^{T+1}$  are integer-encoded. After crossover and mutation, infeasible solutions are repaired to satisfy the non-negativity constraints and the ordering constraint  $S_i^{T+1} > s_i^{T+1}$ . Specifically, the RP and MS are first rounded to integers and clipped to non-negative values. If the ordering constraint is violated, the two values are reordered, and MS is increased by one unit when necessary to ensure  $S_i^{T+1} > s_i^{T+1}$ . The resulting optimal RP and MS values constitute the basic SS decision for the subsequent dynamic fusion. In the optimization process, the cost calculation is based on the historical SPD observations. No realized future demand is used in this stage. Future demand uncertainty is incorporated only through the forecasting interval and the subsequent dynamic fusion with the basic  $(s, S)$  decision. In this way, the proposed SS model essentially belongs to ex-ante optimization.

## IV. SS RELIABILITY METRIC

From Section III, it is clear that the obtained setting of  $(s, S)$  is optimized to enhance customer satisfaction with excess inventory reduced as much as possible. Essentially, the SS decision should be reliable for inventory management in face of uncertain cases, e.g., SPD fluctuates to some extent. Specifically, RP is expected to initiate replenishment in advance to reduce inventory shortage risk, whereas MS is expected to constrain excessive inventory. We believe that SS reliability can be explained as the capability of simultaneously minimizing the risk of excess inventory and shortage inventory. There is a concept closely related to reliability, namely, robustness that emphasizes resistance to uncertainty-induced disturbances. Since reliability in this paper emphasizes whether a given SS decision can fulfill its intended inventory management goal under uncertainty, the concept of reliability is formally adopted.

Following the understanding, a new SS reliability metric is proposed for quantitative evaluation, as shown in (10). The proposed metric is inspired by system reliability theory [39], in which overall performance is jointly determined by multiple

indispensable components. The multiplicative form is adopted to reflect the weak-link effect that unsatisfactory performance in any single component should reduce the overall reliability. Unlike an additive form, a low component directly suppresses the product and cannot be fully offset by high values of the other components.

$$\mathcal{R}^t = (IC^t)^{w_1} (\widetilde{W}^t)^{w_2} (1 - P^t)^{w_3} \quad (10)$$

In (10), the subscript  $t$  indicates the  $t$ -th inventory cycle, while  $IC^t$ ,  $\widetilde{W}^t$  and  $P^t$  indicate inventory coverage, decision compactness ratio, and emergency replenishment rate, respectively. These three parts evaluate the SS reliability from two perspectives of service level and inventory cost, as elaborated below:

- 1) Inventory coverage: demonstrates the extent to which the available inventory satisfies the overall demand fulfillment, as shown in (11).

$$IC^t = \sum_{i=1}^N IC_i^t \quad (11)$$

$$IC_i^t = \begin{cases} 1, & \overline{De}_i \leq SI_i^t \\ 1 - \frac{\overline{De}_i - SI_i^t}{\overline{De}_i}, & \overline{De}_i > SI_i^t \end{cases}$$

where  $IC_i^t$  is inventory coverage in the  $t$ -th inventory cycle,  $\overline{De}_i$  is the average demand from the  $i$ -th site warehouse in each inventory cycle. A higher inventory coverage value indicates greater resilience to supply.

- 2) Emergency replenishment rate: represents the frequency of emergency replenishment in a cycle in the case that actual SPD exceeds available inventory quantity, as shown in (12).

$$P^T = \frac{1}{N} \sum_{i=1}^N P_i^t \quad (12)$$

$$P_i^t = \frac{1}{T} \sum_{t=1}^T \mathbb{I}(De_i^t > SI_i^t)$$

where  $P^T$  is the emergency replenishment rate in the  $T$ -th inventory cycle. Compared to (11), emergency replenishment rate shows the shortage frequency of individual spare part. From (11) and (12), inventory coverage and emergency replenishment rate are directly calculated by means of SPD data, that means, these two ones are essentially of static information and jointly represent service level after the current inventory cycle ends.

- 3) Decision compactness ratio: is designed to quantify the appropriateness of SS decision, as shown in (13). As introduced in Section II, RP is the threshold to trigger replenishment, while MS sets the maximum inventory to fulfill demand. Thus, the interval between RP and MS reflects how tightly the SS decision is set and further affects the trade-off between the risks of excess inventory and shortage before real SPD occurs.

$$\widetilde{W}^t = \frac{1}{N} \sum_{i=1}^N \min \left( 1 - \frac{W_i^t}{W_i^{max}}, 1 \right) \quad (13)$$

$$W_i^t = (S_i^t - s_i^t)$$

where  $\widetilde{W}^t$  indicates decision compactness ratio in the  $t$ -th inventory cycle, and  $W_i^{max}$  represents the maximum decision interval from the  $i$ -th site warehouse in historical inventory cycle. A more compact decision interval, corresponding to a larger  $\widetilde{W}^t$ , generally indicates a lower excess inventory, and vice versa. Since the decision interval can determine the inventory cost in the next inventory cycle before the current inventory cycle ends, decision compactness ratio is essentially of dynamic information. The practical effect on SS reliability is further examined through a sensitivity analysis in Section VII.

In (10), the metric takes into account the effect of the three indicators simultaneously. A decrease of any indicator will reduce the value of reliability even the other indicators' value increase. The three weights in (10) are adjustable to specific task requirement: to favor customer satisfaction, increase the value of  $w_1$ ; conversely, to focus on dead stock costs, increase the value of  $w_3 > 0$ . In this study, equal weights are set by default. Specifically, the equal-weight setting is fixed throughout all main experiments, while other weight settings are only used in the sensitivity analysis. Since all three components are normalized in  $[0, 1]$ ,  $\mathcal{R}^t$  is then bounded in  $[0, 1]$ , increasing monotonically with  $IC^t$  and  $\widetilde{W}^t$  while decreasing monotonically with  $P^t$ . From (11) to (13), the SS reliability metric in (10) combines static information (inventory coverage and emergency replenishment rate) with dynamic information (decision compactness ratio). Since the static information will be determined once SPD data are collected, decision compactness ratio is believed pivotal in the SS reliability metric. The effect of decision compactness ratio on SS reliability can be analyzed as follows.

- Widened inventory interval increases the maximum inventory quantity, thereby inducing excess inventory cost. In such case, lower decision compactness ratio will result in a decrease in (10), i.e., a reduction of SS reliability.
- Tightened inventory interval shows a higher decision compactness ratio in (10), but does not indicating that the overall SS decision is always preferable. Its effect needs to be interpreted under different demand scenarios. Please note that there are two special cases:

- 1) Zero demand. The SS interval tends to be set rather lower to minimize inventory quantity. The remaining spare parts are able to not only fulfill sporadic demand, but also avoid excessive inventory cost. In such case, tightened inventory interval can raise a high value of SS reliability.
- 2) Non-zero demand. SS interval needs to be set higher. A tightened inventory interval leads to excess inventory or frequent emergency replenishment. SS reliability will be reduced accordingly.

Furthermore, (10) can be applied in various cases: (1) Prospective reliability evaluation: To preliminary evaluation

of SS decision effect before real SPD occurs, one can utilize the average value of inventory coverage and emergency replenishment rate from the preceding cycles to approximate the corresponding values for the cycle. (2) Retrospective reliability evaluation: To assess the effectiveness of the SS decision within the current cycle, one can directly calculate the reliability using the actual SPD data and the predetermined SS decision. This operation provides a quantitative evaluation of the SS performance. In the experiment section of this paper, the latter approach is adopted as the performance metric for evaluating the proposed SS model.

From (10), one can identify the significant factors impacting SS decision. As mentioned above, the inventory coverage and emergency replenishment rate in (10) are of static information that is determined once real SPD data is collected. Only decision compactness ratio has space to optimize. More accurate value of decision compactness ratio, as well as SS reliability, will be obtained if SPD trend can be precisely predicted. This is just the key motivation of this study.

## V. MULTIVARIATE INTERMITTENT TIME SERIES FORECASTING METHOD

To optimize decision compactness ratio, this section proposes a new multivariate intermittent time series forecasting method based on GNN. Accordingly, this method is designed to simultaneously extract the structured information between multiple sequences and the temporal evolution information of each sequence itself. Different from existing GNN or graph attention models mainly designed for dense and continuous sequences, the proposed method is tailored for intermittent demand forecasting by explicitly emphasizing demand occurrence pattern under sparse conditions. This idea can be figuratively viewed as the fusion of two-directional information: one is horizontal and another one is vertical. Fig. 4 provides a diagrammatic representation of this fusion process.

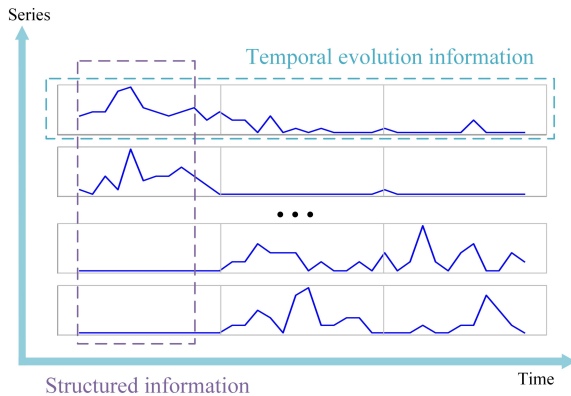


Fig. 4: Schematic diagram of the two-directional information fusion.

The implementation of the proposed forecasting method is summarized as follows. First, this method carries out joint forecasting of multiple sequences by an improved GNN. This method regards each series as a graph node, and dynamically adjusts inter-sequence weights through graph attention

mechanism. The structured information among multiple sequences can then be exploited. Moreover, this method learns temporal evolution information of each sequence using linear decay correction model [7]. By integrating the two-directional information, this method achieves precise SPD forecasting. Finally, to further quantify demand uncertainty, a confidence interval is also obtained plus the point forecast via bootstrap resampling. The overall structure of the proposed forecasting method is detailed in Fig. 5 and will be explained in the following subsections.

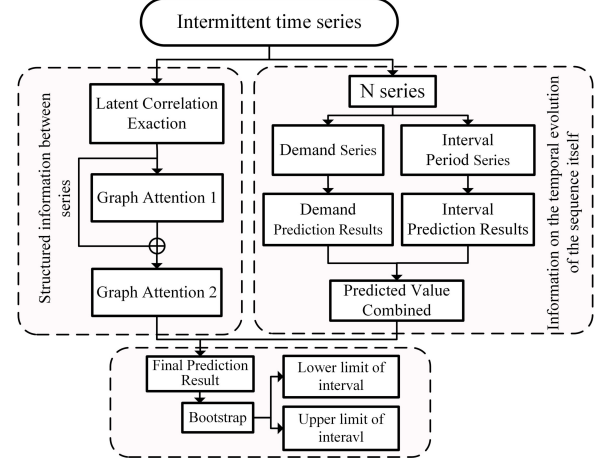


Fig. 5: Flowchart of the proposed forecasting method.

### A. Multi-layer graph neural network with attention mechanism

In the case of similar working condition or the same project schedule, the SPD sequences collected from the same or adjacent site warehouse could be intrinsically related. Since a single intermittent time series only can provide limited evolutionary information, a feasible solution is to borrow the structured information among different SPD sequences to improve the whole prediction performance. Different SPD sequences may exhibit correlated demand patterns under similar working conditions, project schedules, regional environments, and maintenance activities. Nevertheless, the relationship between different SPD sequences may vary significantly, and crucially, those with low relationship will decrease the forecasting accuracy. This section develops a multi-layer GNN model with attention mechanism that dynamically updates the inter-sequence weights for the joint forecasting. The technical workflow of this model is shown in Fig. 6. Compared with Transformer-based architectures, GNN is more applicable here in exploiting the structured information among different SPD sequences under sparse demand conditions.

Considering the scarcity of non-zero elements in intermittent time series, we implement the following improvements: (1) A demand occurrence matrix is designed by marking non-zero demand positions with 1 and zero demand with 0, enabling classical GNN to identify demand occurrence in SPD sequences via normalization. (2) Residual connection is implemented between consecutive layers in GNN to prevent

loss of demand occurrence information during the model training. These improvements can enhance the capability of classical GNN in handling intermittent time series. The details are elaborated below.

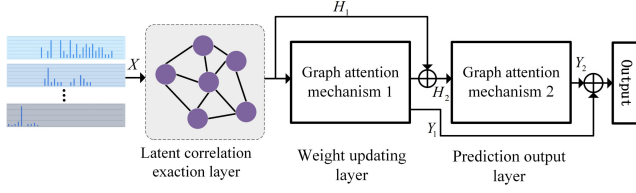


Fig. 6: Technical flowchart of the improved GNN model. The number of attention mechanism blocks is determined according to the actual requirement. Here we take a three-layer network architecture for illustration.

As illustrated in Fig. 6, the proposed model is composed of three core components:

- Latent correlation extraction layer: calculates the initial graph adjacency matrix using attention mechanism to capture inter-sequence structured information).
- Weight updating layer: dynamically updates the adjacency matrix by employing graph attention mechanism.
- Prediction output layer: utilizes graph convolution to calculate demand prediction for each graph node according to the adjacency matrix.

Denote the SPD Sequences by  $X = \{X_i\}_{i=1}^N$ , where  $X_i = (x_i^1, x_i^2, \dots, x_i^T)$ ,  $x_i^t$  is the value of the  $i$ -th SPD sequence at the  $t$ -th inventory cycle,  $N$  and  $T$  represent the total number of the SPD sequences and inventory cycles, respectively. The demand occurrence matrix, denoted by  $D \in \{0, 1\}^{N \times T}$ , is built by setting  $d_i^t = \begin{cases} 1, & \text{if } x_i^t > 0 \\ 0, & \text{if } x_i^t = 0 \end{cases}$ . Thus,  $d_i^t = 0$  explicitly indicates a zero-demand position. To reduce the distortion caused by prolonged zero-demand periods, normalization is conducted by integrating demand occurrence matrix to estimate the effective scale of each sequence rather than repeated zero values.

$$\bar{x}_i = \frac{\sum_{t=1}^T x_i^t}{\sum_{t=1}^T d_i^t} \quad (14)$$

$$\sigma_i = \sqrt{\frac{1}{\sum_{t=1}^T d_i^t} \sum_{t=1}^T (x_i^t - \bar{x}_i)^2} \quad (15)$$

where  $\bar{x}_i$  and  $\sigma_i$  indicate the mean and standard deviation of the  $i$ -th SPD sequence, respectively. In this way, long zero-demand periods are not overemphasized, while their temporal positions are preserved through the occurrence matrix  $D$ . This improves the stability of feature normalization for highly intermittent sequences. The normalized SPD data matrix  $\tilde{X}$  is then calculated with the element as:

$$\tilde{x}_i^t = \frac{x_i^t - \bar{x}_i}{\sigma_i} \quad (16)$$

where  $\tilde{x}_i^t$  is the normalized value of the  $i$ -th SPD sequence in the  $t$ -th inventory cycle.

Furthermore, each sequence is regarded as a graph node. The input feature matrix  $H^{(0)}$  of the whole network is calculated by:

$$H^{(0)} = \tilde{X} \odot D \quad (17)$$

After the normalization operation,  $H^{(0)}$  will encode the positions of demand occurrence while reducing the influence of zero-demand. Zero-demand periods are not removed from the sequence, but are prevented from dominating the feature magnitude, while their occurrence structure is preserved through  $D$ . This helps the network extract evolutionary information from  $H^{(0)}$ . In this study, the initial graph is set as fully connected, without relying on prior knowledge. The graph attention mechanism then adaptively learns the attention weight of each edge, so the inter-sequence relationships are modeled as fully connected edges with learned attention weights. We then initialize the adjacency matrix  $A^{N \times N}$  for  $H^{(0)}$ , which allows each node to integrate structural information from its graph context. Without loss of generality, the adjacency matrix  $A^{(l)}$  at the  $l$ -th layer will be updated by means of graph attention mechanism, where the matrix element is just the attention weight, is:

$$\alpha_{i,j} = \frac{\exp(\text{LeakyReLU}(a^\top [Wh_i \parallel Wh_j]))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(a^\top [Wh_i \parallel Wh_k]))} \quad (18)$$

where  $i$  and  $k \in \mathcal{N}(i)$  are the index of target node and its neighbor nodes,  $W$  and  $a$  are the learnable weight matrix and coefficient vector,  $\alpha_{i,j}$  represents the edge weight from node  $i$  to node  $j$ ,  $h_i$  corresponds to the feature vector of node  $i$ .

The feature vector of node  $i$  at the  $(l+1)$ -th layer can be represented by aggregating the adjacency matrix  $A^{(l)}$ , as:

$$h_i^{(l+1)} = \phi \left( \sum_{j \in \mathcal{N}(i)} \alpha_{i,j}^{(l)} h_j^{(l)} \right) \quad (19)$$

where  $\alpha_{i,j}^{(l)}$  is the attention weight from node  $i$  to neighbor  $j$  at the  $l$ -th layer,  $\phi(\cdot)$  represents the activation function,  $h_i^{(l+1)}$  corresponds to the updated feature vector of node  $i$  at the  $(l+1)$ -th layer. The output feature matrix of this layer is  $H^{(l+1)} = [h_1^{(l+1)}, \dots, h_N^{(l+1)}]^T$ .

Moreover, to preserve the original feature information, a residual connection is incorporated between the first layer and the last layer, as:

$$H^{(L)} = \phi(A^{(L-1)} H^{(L-1)}) + H^{(1)} \quad (20)$$

where  $L$  is the index of the last layer,  $A^{(L-1)}$  and  $H^{(L-1)}$  are the attention weight matrix and feature matrix at the  $L-1$ -th layer. Finally, the network output is obtained by (21).

$$\hat{y} = \gamma y^{(1)} + (1 - \gamma) y^{(L)} \quad (21)$$

where  $y^{(1)}$  and  $y^{(L)}$  are the prediction vector from the first layer and the last layer, respectively, and  $\gamma$  is the tradeoff coefficient.

### B. Fusion with linear decay correction

Besides capturing inter-sequence structured information, we have also employed a classical variant of the Croston's method, the linear decay correction model [7], to extract temporal evolution information of each sequence itself. Due to space limitation, we will not provide the implementation details of the linear decay correction model here. With these two models, we perform a weighted fusion of structured information and temporal evolution information. The process is as follows.

The mean absolute error  $MAE$  between the real value  $y_i$  and the predicted value  $\hat{y}_i$  of the  $i$ -th sequence is calculated by (22) and (23). The weight coefficient of each model is determined by (24).

$$MAE_i^{m1} = \frac{1}{T} \sum_{t=1}^T |\hat{y}_i^t - y_i^t|_{m1} \quad (22)$$

$$MAE_i^{m2} = \frac{1}{T} \sum_{t=1}^T |\hat{y}_i^t - y_i^t|_{m2} \quad (23)$$

$$\begin{aligned} \text{Weight}_i^{m1} &= \frac{MAE_i^{m2}}{MAE_i^{m1} + MAE_i^{m2}} \\ \text{Weight}_i^{m2} &= \frac{MAE_i^{m1}}{MAE_i^{m1} + MAE_i^{m2}} \end{aligned} \quad (24)$$

where  $m_1$  and  $m_2$  indicates the improved GNN model and the linear decay correction model, respectively.  $\text{Weight}_i^{m1}$  and  $\text{Weight}_i^{m2}$  are the weight coefficient of  $m_1$  and  $m_2$ .

The final forecasting result, essentially being point forecast, is obtained by multiplying the forecasting result of each model with its corresponding model weight, as:

$$y_i^{T+1} = \hat{y}_i^{T+1(m1)} \times \text{Weight}_i^{m1} + \hat{y}_i^{T+1(m2)} \times \text{Weight}_i^{m2} \quad (25)$$

where  $y_i^{T+1}$  is the point forecast,  $\hat{y}_i^{T+1(m1)}$  and  $\hat{y}_i^{T+1(m2)}$  are the predictions of  $m_1$  and  $m_2$ , respectively. Here the subscript  $i$  and the superscript  $T+1$  means the  $i$ -th SPD sequence and the  $T+1$ -th inventory cycle.

### C. Bootstrap-based interval prediction

Although some operations have been applied in Section V-B to tackle the intermittent characteristics of SPD data, there is still a certain degree of uncertainty in the obtained point forecast, since perfectly accurate predictions are rarely achievable for real-world data. On the contrary, for maintenance engineers, they would prefer to obtain a confidence interval for the forecasting result so that for them to make a flexible decision within a certain range. This section therefore introduces the bootstrap method to quantify demand uncertainty. We first calculate prediction error values from the training phase of the forecasting model proposed in Section V-B. Subsequently, the bootstrap method performs multiple resampling operations on these prediction error values and plus them onto the point prediction to generate an ensemble of values. Finally, point forecast is extended to forecasting interval using the quantile method. The details are elaborated as follows.

The prediction error value  $\varepsilon_i^t$  of the  $i$ -th SPD sequence in the  $t$ -th inventory cycle is calculated by  $\varepsilon_i^t = y_i^t - \hat{y}_i^t$ , where  $y_i^t$  and  $\hat{y}_i^t$  represent the real value and the prediction value, respectively. During the training of the proposed forecasting model, we employ a sliding window approach with window size  $K$  to process the SPD data. The prediction error sequence is then expressed as  $\{\varepsilon_i^t\}_{t=K+1}^T$ , where  $T$  is the total number of the inventory cycles.

To preserve the temporal characteristics of the prediction error sequence, we divide the sequence into a set of overlapping blocks  $\{B_i^t\}_{t=K+1}^T$ , where each block  $B_i^t = (\varepsilon_i^t, \dots, \varepsilon_i^{t+L-1})$  contains  $L$  prediction error values. Assuming that the iteration of resampling is  $R$ , each iteration generates a new residual sequence  $\{\varepsilon_i^{f,(r)}\}_{f=1}^F$ , where  $r = 1, 2, \dots, R$ . Here,  $f$  indexes the prediction error values in the new prediction error sequence,  $F$  equals the number of point forecasts. For the sake of better explanation, we set  $F = 1$ , which means that only the prediction value for one inventory cycle can be obtained. Therefore,  $\{\varepsilon_i^{f,(r)}\}_{f=1}^F$  is simplified as  $\varepsilon_i^{(r)}$ . Subsequently,  $\varepsilon_i^{(r)}$  is superimposed onto the point forecast to generate a prediction value  $\hat{y}_i^{T+1,(r)} = \hat{y}_i^{T+1} + \varepsilon_i^{(r)}$ .

By sorting  $R$  values of  $\hat{y}_i^{T+1,(r)}$ , the  $q$ -th quantile is given by  $Q_i^{T+1}(q) = \text{Quantile}\left(\{\hat{y}_i^{T+1,(r)}\}_{r=1}^R, q\right)$  by getting the  $q$ -th quantile from the sorted  $\{\hat{y}_i^{T+1,(r)}\}_{r=1}^R$ , which means that the probability of demand being less than or equal to  $Q_i^{T+1}(q)$  is  $q\%$ . We choose the 0.1-th and 0.9-th quantiles as the lower and upper bounds of the prediction interval, that is,  $[Q_i^{T+1}(0.1), Q_i^{T+1}(0.9)]$ .

## VI. DYNAMIC SAFETY STOCK DECISION WITH DEMAND FORECASTING

In practical inventory management, adjustment mechanisms are often expected to be simple, stable, and easy to implement. Accordingly, a dynamic SS decision is established by fusing the obtained forecasting interval into the basic SS decision (i.e., the RP and MS) from Section III. The forecasting interval represents future demand uncertainty estimated from historical SPD data, rather than realized future demand. The fusion operation is straightforward and effective. We directly adjust RP and MS using  $Q_i^{T+1}(0.1)$  and  $Q_i^{T+1}(0.9)$ , both of which are calculated with the SPD forecasting results. As a result, the static SS decision can be coupled with dynamic information well. Meanwhile, the adopted proportional weighting scheme does not introduce additional learnable parameters.

Specifically, fusing the basic RP with  $Q_i^{T+1}(0.1)$  is promising to maintain stable inventory quantity for reducing the risk of excess inventory. The weight coefficients for the basic RP  $s_i^{T+1}$  and  $Q_i^{T+1}(0.1)$  are shown in (26). The final RP value  $\hat{s}_i^{T+1}$  at the  $i$ -th warehouse in the  $(T+1)$ -th inventory cycle can be obtained by (27).

$$\begin{cases} w_{s1} = \frac{s_i^{T+1}}{s_i^{T+1} + Q_i^{T+1}(0.1)} \\ w_{s2} = \frac{Q_i^{T+1}(0.1)}{s_i^{T+1} + Q_i^{T+1}(0.1)} \end{cases} \quad (26)$$

$$\hat{s}_i^{T+1} = w_{s1}s_i^{T+1} + w_{s2}Q_i^{T+1}(0.1) \quad (27)$$

Fusing the basic MS with  $Q_i^{T+1}(0.9)$  ensures that warehouse maintains sufficient inventory quantity for reducing the

risk of shortage inventory. The weight coefficients for the basic MS  $S_i^{T+1}$  and  $Q_i^{T+1}(0.9)$  are shown in (28). The final MS value  $\hat{S}_i^{T+1}$  at the  $i$ -th warehouse in the  $(T+1)$ -th inventory cycle can be obtained by (29).

$$\begin{cases} \mathcal{W}_{s1} = \frac{S_i^{T+1}}{S_i^{T+1} + Q_i^{T+1}(0.9)} \\ \mathcal{W}_{s2} = \frac{Q_i^{T+1}(0.9)}{S_i^{T+1} + Q_i^{T+1}(0.9)} \end{cases} \quad (28)$$

$$\hat{S}_i^{T+1} = \mathcal{W}_{s1} S_i^{T+1} + \mathcal{W}_{s2} Q_i^{T+1}(0.9) \quad (29)$$

Finally, the dynamic SS interval  $[\hat{s}_i^{T+1}, \hat{S}_i^{T+1}]$  is obtained according to (27) and (29). The effectiveness of the proposed fusion operation, as well as its comparison with alternative fusion schemes, will be further examined in Section VII.

## VII. EXPERIMENTAL RESULTS

### A. Data description

This paper employs a dataset of actual after-sales SPD data from a large railway transportation manufacturing enterprise in China. The dataset provides 517 types of after-sales parts from January 2020 to December 2022, a total of 36 months of historical faulty parts data contains twelve features, including: spare parts number, monthly failure quantity, monthly repaired quantity, and price, etc. To secure the confidentiality of the enterprise's information, the SPD data has been anonymized by the enterprise. The part indicators shown in the dataset have no real meaning.

For better understanding of this dataset, Fig. 7 shows the actual demand data for the four parts (NO.90, No.96, No.189 and NO.516) over 36 months. The SPD sequences in Fig. 7 show an obvious intermittent distribution. Two commonly-used evaluation indicators, average demand interval ( $ADI$ ) and coefficient of variation ( $CV^2$ ) [40], are also introduced to quantify the intermittent characteristics. In terms of these two indicators, the SPD sequences can be categorized into four types with the threshold  $ADI = 1.32$  and  $CV^2 = 0.94$ . The categorization results are shown in Fig. 8. Obviously, this dataset exhibits clear lumpy and intermittent distribution.

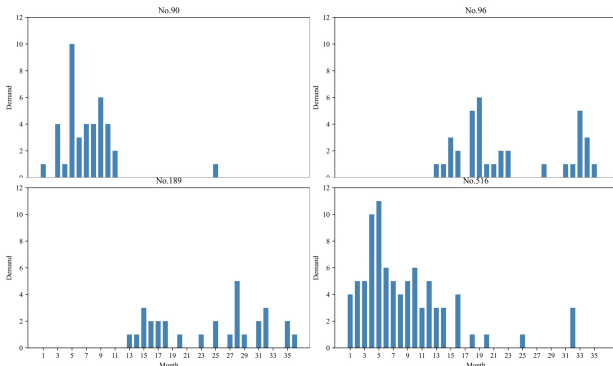


Fig. 7: SPD sequences of four actual spare parts in the employed dataset.

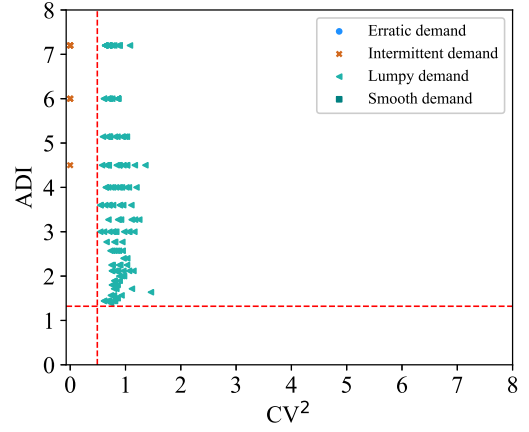


Fig. 8: Intermittent distribution characteristic of the used SPD data. The two dashed lines indicate  $ADI = 1.32$  and  $CV^2 = 0.94$ .

### B. Results of SS optimization

A popular multi-objective optimization method, NSGA-II [38], is utilized to solve (2). Fig. 9 illustrates the obtained Pareto solutions that are trade-off between excess inventory cost and shortage cost. when excess inventory cost remains below 3000 monetary units, shortage cost decrease significantly as excess inventory cost increase. Beyond this threshold, further increases in excess inventory cost yield only marginal reduction in shortage cost. Given this study's priority of shortage avoidance, the optimal solution, indicated by the red data point in Fig. 9, was selected for subsequent experiments. This solution is just the basic safety stock decision.

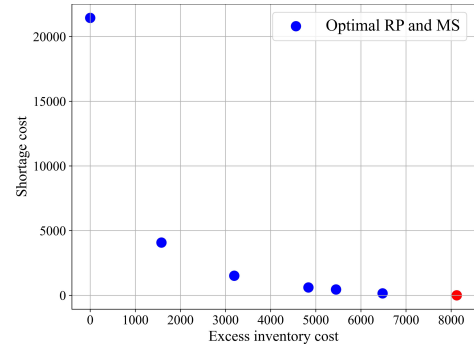


Fig. 9: Pareto solutions obtained by NSGA-II in solving (2).

### C. Results of intermittent time series forecasting

The demand data of the starting 24 months in the SPD sequences are chosen as the initial training set, while the demand of the 25th month (January 2022) is first used for forecasting. For reproducibility, the hyperparameter settings of the proposed forecasting model are summarized in Table I.

A rolling-origin forecasting scheme is adopted, in which multiple one-step-ahead predictions are generated by progressively shifting the forecasting origin along the time axis. The training window is shifted forward by one month at each step (e.g., the data from the 2nd to the 25th month are used to

predict the 26th month), and this process is repeated until the end of the 36-month sequence. The final forecasting performance is evaluated by averaging the error metrics across all rolling forecasting instances. For straightforward comparison, we randomly choose four SPD sequences from the dataset for illustration, as shown by Fig. 10. From the rolling-origin forecasting results over the last 12 months, the point forecasts by the proposed method follow the actual SPD variations well, while the forecasting intervals provide a reasonable description of the demand uncertainty.

TABLE I: Hyperparameter settings of the proposed forecasting method.

| Hyperparameter            | Value              |
|---------------------------|--------------------|
| Number of GNN layers      | 3                  |
| Hidden dimension          | 32                 |
| Number of attention heads | 4                  |
| Learning rate             | $1 \times 10^{-4}$ |
| Batch size                | 32                 |
| Epochs                    | 60                 |
| Forecast horizon          | 1                  |
| Dropout rate              | 0.5                |

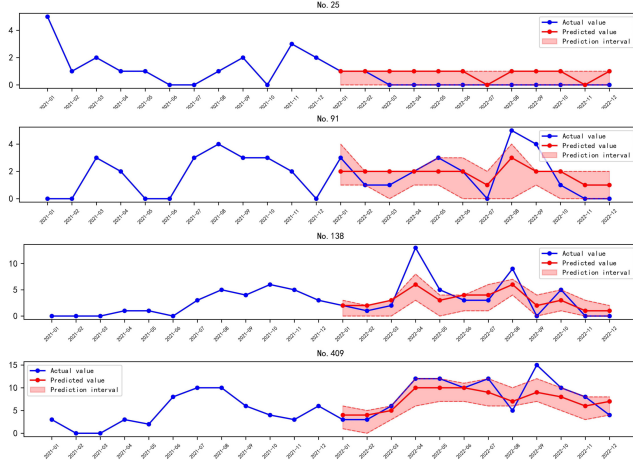


Fig. 10: Rolling-origin one-step-ahead forecasting results over the last 12 months on four spare parts.

To verify the effectiveness of the proposed forecasting algorithm, we introduce eleven representative demand forecasting methods, including statistical models (SBA [22], TSB [23], ESLD [24], ARIMA [41] and Prophet [42]), shallow machine learning methods (SVR [43] and BHT-ARIMA [44]), and deep learning methods (Fedformer [45], Temporal Fusion Transformer (TFT) [46], LSTM [47] and LightGBM [48]). Fig. 11 illustrates the forecasting performance of all twelve methods. The method whose forecast matches the actual demand (red line) is the best.

In Fig. 11, despite some methods (TSB, ESLD, BHT-ARIMA) match the actual demand on specific sequence, the proposed algorithm still gets the best forecasting performance on all the four SPD sequences. We also observe that SVR always gets the worst prediction results, which indicates traditional shallow-model machine learning method is unsuitable

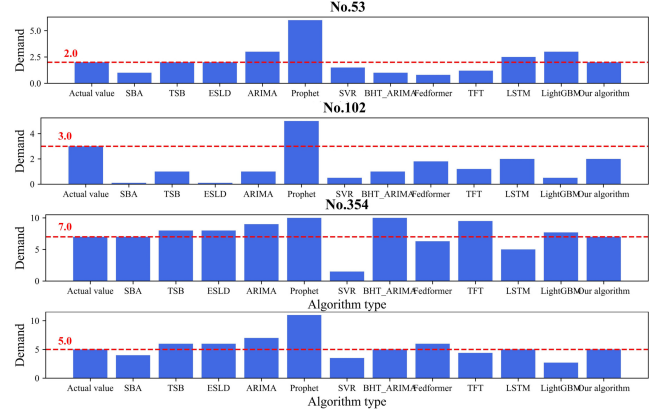


Fig. 11: Comparison of forecasting results by all 12 methods.

to intermittent time series. Conversely, the two Transformer-based methods do not show clear improvement on the employed SPD dataset, possibly because the SPD sequences are highly sparse and short in length.

The comparative evaluation on all 517 spare parts is listed in Table II. The proposed method achieves the lowest prediction errors. To assess the statistical significance of this improvement, the Wilcoxon signed-rank test is conducted. Specifically, for each spare part, the MAE and RMSE values are first averaged over all rolling forecasting instances. The test is then performed on the paired average errors of all spare parts. The p-values are summarized in Table III. The results show that the proposed method significantly outperforms all compared baselines under both MAE and RMSE.

To evaluate the contributions of different components in the proposed forecasting method, an ablation study is conducted by comparing three variants: (1) a GNN-only model (named GNN only), (2) a linear decay correction-only model (named GNN only), and (3) the proposed method combining both components. All variants are evaluated on the same dataset under the same rolling-origin setting, and the results are reported in Table IV. The proposed method outperforms the GNN-only and LDC-only variants in both MAE and RMSE, indicating the effectiveness of combining the two components.

#### D. Results of dynamic safety stock decision

We will examine the reliability of the proposed SS model on the SPD data with two cases: large fluctuation and smooth fluctuation. Here we employ the SPD data in 2022 for test. We also calculate the basic SS decision obtained in Section III for comparison.

Fig. 12 shows the effect of the proposed dynamic SS model on the two spare parts with highly fluctuating demand. For the parts No.409, the red frame on the left indicates an ascending demand trend from February to April. Correspondingly, the value of MS and RP increases to inventory quantity, while the shortage cost is simultaneously reduced. In this case, service level will be definitely ensured. The right red frame indicates a decrease in demand from August to September, coupled with a corresponding decrease of RP and MS. Significant cost savings can be achieved for excess inventory. The dynamic

TABLE II: Comparative evaluation of all the 12 methods under the rolling-origin evaluation scheme on all 517 spare parts. The reported error value is the mean value of repeated forecasting on the last 12 months. The smallest forecasting error is highlighted in bold.

|      | SBA    | TSB    | ESLD   | ARIMA  | Prophet | SVR    | BHT-ARIMA | Fedformer | TFT    | LSTM   | LightGBM | Our Algorithm |
|------|--------|--------|--------|--------|---------|--------|-----------|-----------|--------|--------|----------|---------------|
| MAE  | 0.5284 | 0.3361 | 0.3217 | 0.4389 | 0.3615  | 0.5012 | 0.3926    | 0.5718    | 0.6485 | 0.3482 | 0.3349   | <b>0.2614</b> |
| RMSE | 1.2638 | 0.9987 | 0.9316 | 1.6125 | 1.0982  | 1.5879 | 1.2048    | 1.1426    | 1.2647 | 0.9271 | 0.9783   | <b>0.8126</b> |

TABLE III: Wilcoxon signed-rank test results (p-values) between the proposed method and baseline methods under MAE and RMSE.

| Baseline  | MAE p-value | RMSE p-value |
|-----------|-------------|--------------|
| SBA       | < 0.0001    | < 0.0001     |
| TSB       | 0.0018      | 0.0036       |
| ESLD      | 0.0042      | 0.0069       |
| ARIMA     | < 0.0001    | < 0.0001     |
| Prophet   | 0.0003      | 0.0008       |
| SVR       | < 0.0001    | < 0.0001     |
| BHT-ARIMA | 0.0001      | 0.0004       |
| Fedformer | < 0.0001    | 0.0001       |
| TFT       | < 0.0001    | < 0.0001     |
| LSTM      | 0.0075      | 0.0113       |
| LightGBM  | 0.0051      | 0.0087       |

TABLE IV: Ablation study on the contributions of GNN and LDC.

| Model          | MAE           | RMSE          |
|----------------|---------------|---------------|
| GNN only       | 0.3742        | 0.8560        |
| LDC only       | 0.3954        | 0.9481        |
| Proposed model | <b>0.2614</b> | <b>0.8126</b> |

SS decision effectively ensures the basic supply of inventory and strengthen the reliability of SS decision as well. A similar pattern is also observed for part No.138.

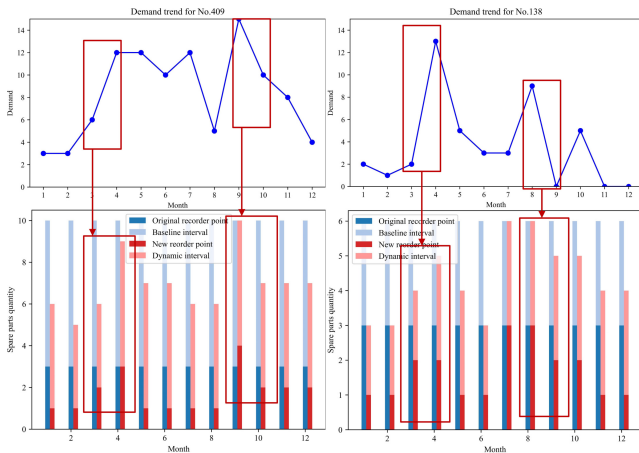


Fig. 12: Comparison of static and dynamic SS decision on the two spare parts No. 409 and No. 138 whose demand data involve large fluctuations.

Fig. 13 illustrates the effect of the proposed dynamic SS model on the two spare parts whose demand data exhibit smoother fluctuation. For the parts No.91, the demand sinks

into a trough in January-March and reaches the peak in July-August. It is clear that the obtained SS decision can decrease and increase accordingly. For the parts No.205 that has rather smoother fluctuation, the dynamic SS decision stabilizes at a minimal level during prolonged zero-demand periods. Crucially, the model successfully captures the demand decline in January-February and surge in July-August through adjusting the SS decision. These results collectively validate that the proposed dynamic SS model is able to forecast the onset of demand, leading to the values of RP and MS continuously adjusted to accommodate demand. The effect in Fig. 12 and Fig. 13 demonstrates significantly enhanced reliability of the dynamic SS decision compared to the static SS decision.

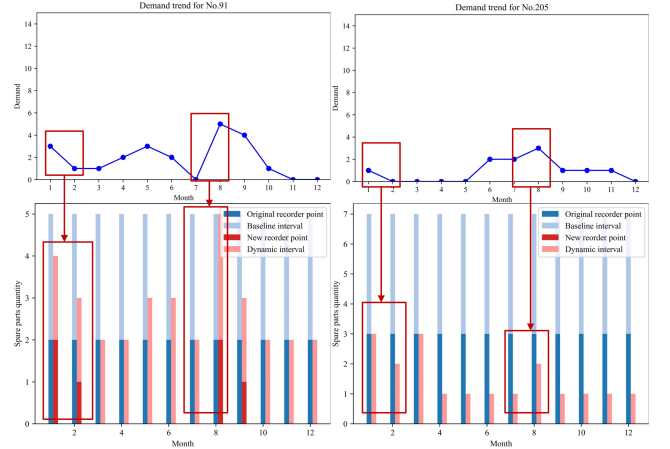


Fig. 13: Comparison of static and dynamic SS decision on the two spare parts No. 91 and No. 205 whose demand data involve smooth fluctuations.

For a rigorous comparison, all SS methods are implemented under identical experimental conditions, including the same SPD dataset, inventory cycle and inventory management process. Fan's method, as discussed in Section II, can be regarded as the state-of-the-art dynamic SS model that also integrated the forecasting results of intermittent time series into a static SS decision. The corresponding results are summarized in Table V. In addition, Fig. 14, Fig. 15, and Fig. 16 present numerical comparison of inventory coverage defined by (11), inventory turnover rate defined by (30), and SS reliability defined by (10), respectively. From (30), the inventory turnover rate  $ITR^t$  refers to the ratio of actual demand quantity  $De_i^t$  to average inventory quantity  $\overline{De}_i$ . The higher inventory turnover rate indicates the less inventory quantity.

$$ITR^t = \sum_{i=1}^N \frac{De_i^t}{\overline{De}_i} \quad (30)$$

TABLE V: Average performance comparison of different SS models over the 12 months under identical experimental conditions.

| Method           | Inventory coverage | Inventory turnover rate | SS reliability | Excess cost | Shortage cost |
|------------------|--------------------|-------------------------|----------------|-------------|---------------|
| Static method    | 0.859              | 0.303                   | 0.721          | 1896        | 1007          |
| Fan's method [7] | 0.934              | 0.346                   | 0.843          | 1582        | 1039          |
| Proposed method  | <b>0.940</b>       | <b>0.633</b>            | <b>0.883</b>   | <b>1372</b> | <b>924</b>    |

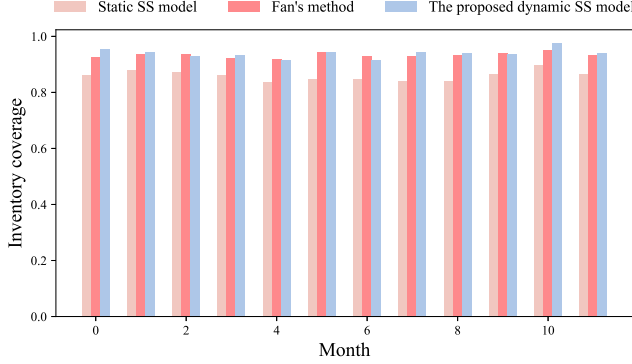


Fig. 14: Comparison of inventory coverage for different SS models.

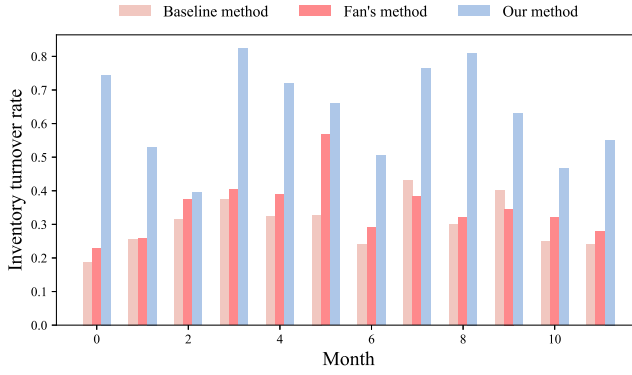


Fig. 15: Comparison of inventory turnover rate for different SS models.

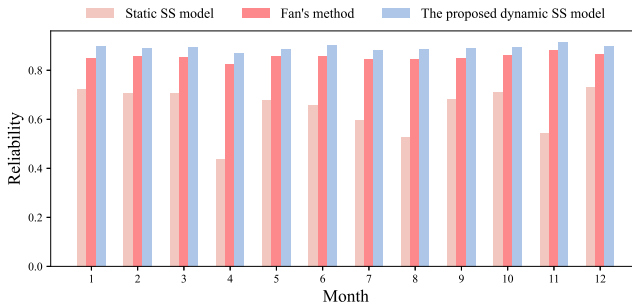


Fig. 16: Comparison of SS reliability for different SS models.

From the viewpoint of classical inventory management theory, inventory coverage and inventory turnover rate cannot increase at the same time. But, as shown in Fig. 14 and Fig. 15, the proposed SS model can promote these two metrics to be higher. This effect demonstrates that dynamic information is beneficial for boosting maintenance efficiency and safety, which also proves the rationality of the proposed SS reliability

metric. Obviously, the proposed dynamic SS model achieves the best value inventory turnover rate and SS reliability than the other models. Consistent with these observations, Table V shows that the proposed method outperforms both the static SS model and Fan's method in terms of SS reliability, while achieving lower excess and shortage costs. The proposed model is able to mitigate excess inventory without reducing service level, demonstrating particular effect in scenarios characterized by significant demand fluctuation.

To evaluate the proposed fusion operation, an ablation study is conducted. Specifically, four settings are considered: (1) the static SS decision without forecasting information (Static); (2) dynamic fusion operation based on point forecasts (Point Fusion); (3) dynamic fusion operation with equal weights (Interval-EW); and (4) the proposed proportional-weight dynamic fusion operation (Interval-PW). The results are summarized in Table VI. All the dynamic fusion operations achieve higher SS reliability than Static. Compared with Point Fusion, Interval-EW and Interval-PW achieve better cost performance under demand uncertainty. Among the four settings, Interval-PW achieves the highest SS reliability and the lowest excess inventory cost and shortage cost.

TABLE VI: Ablation results of different fusion operations.

| Method       | SS reliability | Excess cost | Shortage cost |
|--------------|----------------|-------------|---------------|
| Static       | 0.721          | 1896        | 1007          |
| Point Fusion | 0.844          | 1662        | 1089          |
| Interval-EW  | 0.858          | 1518        | 1146          |
| Interval-PW  | <b>0.883</b>   | <b>1372</b> | <b>924</b>    |

### E. Sensitivity analysis

To examine the sensitivity of the proposed method, this subsection conducts sensitivity analyses on inventory interval width  $S_i^t - s_i^t$  and the weight coefficients in (10). The forecasting quantiles used in interval prediction are also analyzed.

For the sensitivity analysis of inventory interval width, 20 representative spare parts from the testing set are selected, including 10 low-volatility parts and 10 high-volatility parts identified by the standard deviation of their historical SPD sequences. Specifically, all 517 spare parts are ranked by the standard deviation of historical SPD, and the 10 lowest and 10 highest ones are selected to represent demand variability.

Let  $(s_{i,0}^t, S_{i,0}^t)$  denote the original SS decision obtained by the proposed model, and let  $c_{i,0}^t = (s_{i,0}^t + S_{i,0}^t)/2$  be the corresponding interval center. Perturbed SS decisions are then constructed by symmetrically adjusting the interval width around the same center:

$$s_i^t = c_{i,0}^t - \frac{\lambda (S_{i,0}^t - s_{i,0}^t)}{2},$$

$$S_i^t = c_{i,0}^t + \frac{\lambda (S_{i,0}^t - s_{i,0}^t)}{2}, \quad (31)$$

where  $\lambda$  is the interval-width coefficient. Here,  $\lambda < 1$  tightens the interval and  $\lambda > 1$  widens it. In this study, we set  $\lambda \in \{0.6, 0.8, 1.0, 1.2, 1.4\}$ . All settings are evaluated under the same inventory cycle and inventory management process. The obtained evaluation results are reported in Tables VII and VIII.

TABLE VII: Sensitivity analysis of interval width for the low-volatility spare parts.

| $\lambda$ | SS reliability | Excess inventory cost | Shortage cost |
|-----------|----------------|-----------------------|---------------|
| 0.6       | 0.901          | 1216                  | 676           |
| 0.8       | 0.922          | 1468                  | 561           |
| 1.0       | 0.914          | 1735                  | 517           |
| 1.2       | 0.892          | 2011                  | 486           |
| 1.4       | 0.861          | 2328                  | 462           |

TABLE VIII: Sensitivity analysis of interval width for the high-volatility spare parts.

| $\lambda$ | SS reliability | Excess inventory cost | Shortage cost |
|-----------|----------------|-----------------------|---------------|
| 0.6       | 0.791          | 1084                  | 1572          |
| 0.8       | 0.841          | 1362                  | 1268          |
| 1.0       | 0.872          | 1649                  | 1043          |
| 1.2       | 0.889          | 2088                  | 917           |
| 1.4       | 0.878          | 2521                  | 861           |

The results indicate that the effect of the decision compactness ratio is scenario-dependent. For the low-volatility group, SS reliability reaches its maximum at  $\lambda = 0.8$ , indicating that a relatively compact interval is beneficial when demand is stable. For the high-volatility group, SS reliability increases from 0.791 at  $\lambda = 0.6$  to 0.889 at  $\lambda = 1.2$ , suggesting that a moderately wider interval is more suitable under fluctuating demand. These results provide empirical support for the decision compactness ratio in the proposed SS reliability metric.

In addition, the sensitivity of the weight coefficients in (10) and the quantile levels used in interval forecasting is examined. Starting from the equal-weight setting, several representative coefficient settings are tested by increasing one of the three coefficients. Different quantile settings are also examined, and the results are summarized in Tables IX and X.

TABLE IX: Sensitivity analysis of representative coefficient settings in the SS reliability metric.

| Weights     | SS reliability | Relative change |
|-------------|----------------|-----------------|
| (1, 1, 1)   | 0.883          | 0.00%           |
| (1.5, 1, 1) | 0.876          | -0.79%          |
| (1, 1.5, 1) | 0.891          | +0.91%          |
| (1, 1, 1.5) | 0.879          | -0.45%          |

As shown in Table IX, the average SS reliability changes slightly under different coefficient settings, indicating that the SS reliability metric is stable under moderate coefficient

TABLE X: Sensitivity analysis of quantile levels.

| Quantiles    | SS reliability | Excess cost | Shortage cost |
|--------------|----------------|-------------|---------------|
| (0.05, 0.95) | 0.887          | 1518        | 881           |
| (0.10, 0.90) | 0.883          | 1372        | 924           |
| (0.15, 0.85) | 0.876          | 1256        | 986           |
| (0.20, 0.80) | 0.868          | 1148        | 1079          |

variations. Thus, the main conclusions under the equal-weight setting remain relatively stable. Table X shows that wider quantile intervals reduce shortage cost but increase excess inventory cost, whereas narrower quantile intervals show the opposite trend. Among the examined settings, (0.10, 0.90) provides a favorable cost balance.

## VIII. CONCLUSION

This paper proposes a reliable dynamic SS model for manufacturing enterprise under significant demand volatility. In addressing the open problem of SS reliability, this paper identifies the critical factor, i.e., decision compactness ratio. To further optimize this factor, this paper proposes a multi-variate intermittent time series forecasting method based on an improved GNN. Subsequently, a reliable SS decision is obtained by integrating dynamic information with the basic SS decision. Validated using an actual after-sales spare parts dataset from a Chinese large rail transit manufacturing enterprise, the proposed dynamic SS model improves the value of inventory coverage and inventory turnover rate simultaneously, also significantly enhancing SS reliability. Specific conclusions can be drawn as follows:

- 1) Through effectively forecasting the intermittent SPD sequences, the proposed SS model adapts to the demand fluctuation in SPD data and improves inventory coverage as well as turnover rate. By integrating dynamic information provided by the forecasting interval, the proposed model enhances the SS reliability, that is, *change brings reliability*.
- 2) The proposed SS reliability metric enables a priori estimation based on historical statistics during planning phases, and serves as an ex-post evaluation of actual performance using completed-cycle inventory data. This versatility supports diverse enterprise operational requirements.
- 3) Using graph attention mechanism, the proposed forecasting method adaptively determines inter-sequence similarity, facilitating the extraction of structural information from different SPD sequences. The fusion of structured information and temporal evolution information effectively yields reliable prediction.

In the following work, we plan to investigate uncertainty quantification in intermittent time series forecasting. Actual SPD data exhibit substantial stochasticity, obscuring evolutionary patterns and inevitably introducing prediction uncertainty. Bayesian neural networks will be integrated to establish confidence interval for neuron-level feature representation, thereby mitigating demand uncertainty and enhancing prediction credibility. Furthermore, this study utilizes a simplified three-level

inventory model and excludes the business logic of lateral distribution. Our next work will develop a reliability-oriented SS optimization model within complex operational scenario.

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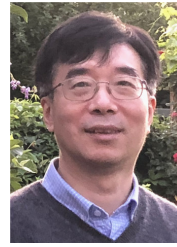
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