A Multi-Stack LSTM-Assisted Inventory Management for the Manufacturing Execution System

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***Abstract*—The rapid progress of artificial intelligence (AI) promotes the development of numerous critical, intelligent systems like the manufacturing execution system (MES). The inventory management (IM) of the MES is a crucial study direction in the smart factory as a core aspect of the MES's entire control process. This study proposed a multi-stack deep learning-assisted inventory management based on the LSTM. MSIM, in particular, converts the statistical issue into a supervised learning task and trains it using the sequential pattern of propagation with many tiers, allowing the training process to be efficiently optimized. The experimental results demonstrate that MSIM has the highest inventory demand forecast accuracy of 93% with the lowest error loss of 0.05 compared to other state-of-the-art methodologies.**

***Index Terms*—AI, Inventory Management, Multi-stack LSTM, Manufacturing Execution System**

I. Introduction

Manufacturing revolves around productivity. The problem is that increased production with fewer resources is imperative for efficiency. Therefore, the industrial productivity outcome is only as good as the method of its operation. The introduction of artificial intelligence (AI) [1], [2] and other innovations, in addition to the accelerated advancement in the performance of information communication technology [3], has exerted a profound impact on the Smart factory [1]. Implementing the manufacturing execution system (MES) has notably enabled this improvement [1], [4].

The growth of research awareness in the MES has significantly influenced the effectiveness of supply chain technology. Connecting and collecting data from machinery and terminals on the production line supervises changing raw materials into completed goods. When used correctly, it assures the efficient implementation of manufacturing procedures while also improving production efficiency. Inventory management (IM) [4], [5], as a crucial component of supply chain management, plays a critical role in lowering total supply chain management costs [1].

The rapid growth of AI capabilities notably enables the intelligent management of various decision-making components of the supply chain process, including inventory management [1], [6]. Although most studies state that implementing AI improves manufacturing processes, the non-experimentation of these AI techniques for actual prediction inhibits their use in efficiently handling the inventory management problem [1], [5]. Hence, this claim is difficult to substantiate. In view of this assumption, this study proposes an AI-assisted inventory management system based on a multi-stack Long short-term memory algorithm (LSTM) [1], [6], and MSIM. MSIM intends to forecast consumer demand for efficient inventory management decisions.

This study aims to guide and optimize product inventory management by leveraging a publicly available inventory dataset to predict product back-order [7]. As a preliminary investigation, this study specifically focuses on the following:

1) This study utilizes the multi-stack LSTM to predict product demand in a supply chain and inventory management problem.
2) To assess and ascertain the applicability of AI in the MES inventory management system.
3) Compared the proposed approach's performance with other deep learning models for reliability tests.

Section I is followed by section II, which illustrates the proposed system model. Section III is the evaluation of the proposed AI technique. Section IV concludes.

II. System Methodology

A. MES Inventory Management (IM)

Present MES regulates resources via inventory management (IM), starting with acquiring unique commodity identification, potentially separately for critical sub-assemblies and components. Then produces and manages logistical duties for resource handlers, such as designating storage areas and distributing products around the factory. Through efficient AI prediction, practical IM minimizes material shortages, ensuring that a resource deficiency never disrupts production.

B. Proposed Methodology

The standard LSTM model consists of one concealed LSTM tier preceded by a conventional feed-forward output node. The stacked LSTM is a concept improvement that features many obscured LSTM tiers, each comprising various memory cells. Concisely, multi-stack LSTM consists of various layers, depending on the developers' needs. The proposed multi-stack LSTM (MSIM) is for predicting product back-order in the

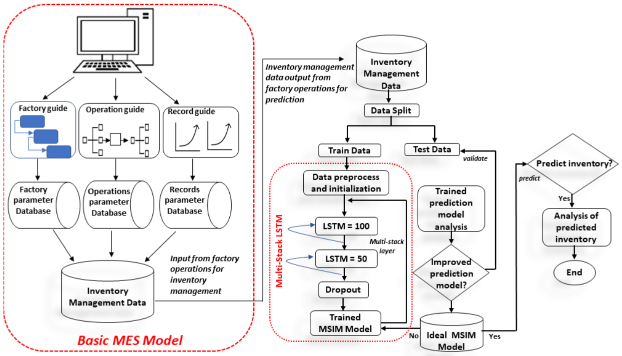

Fig. 1. Architecture of the Proposed System Model for the Manufacturing Execution System Inventory Management

MES inventory management. Fig. 1 illustrates a three-phased workflow and system model of the proposed MSIM.

The three-phased architecture comprises data acquisition and preprocessing, model training, testing, and validation. Preprocessing removes duplicated and inconsistent data (nan, inf), eliminating superfluous data identification features. One-hot encoder, label-encoding transforms the residual non-numeric categorical data into numeric values (0,1); while the Min-Max algorithm scales the data features. Finally, divide the residual inventory dataset data into the train (60%), test (25%) batches, and 15% from the train set for validation. The first LSTM tier with 100 neurons receives the train set as input, forwarding a range of values to the next tier with 50 neurons rather than a single value. Each outcome per intake time step, instead of one outcome input sequence for all input epochs. The test batch validates the performance of the model training. The performance indicators govern the best model selection based on the specified performance metrics such as accuracy, precision, recall, and f-score.

C. Dataset Description

A consumer demand not yet executed is known as back-order, signifying that consumer demand exceeds the industry supply capacity. Product back-orders occur due to exceptional sales performance, often causing friction between suppliers and consumers, resulting in low client dependability. Generation of the product back-orders dataset [7] was to mitigate the challenge emanating from back-orders. The dataset is from Kaggle's *"Can You Predict Product Back-orders"* dataset [7], consisting of records for eight weeks preceding the week unpredicted. The data is weekly samples at the beginning of each week. The variable that went on back-order represents the target (or response).

III. Performance Evaluation

This study proposed MSIM for MES inventory management prediction in a preliminary investigation, leveraging the product back-orders prediction dataset. The simulation result with python on google collaboratory demonstrates the applicability of AI in MES inventory management for prediction. The comparison focuses on the parameter metrics regarding model precision, prediction accuracy, recall, loss, and f-score. Demonstrating the suitability of AI for prediction in the MES inventory management, the conventional LSTM and Bi-directional LSTM (Bi-LSTM) were also analyzed for the reliability of the performance of the proposed MSIM. The experimental results demonstrate that the proposed MSIM was significant, as shown in Table I, outclassing other compared models with 93.27% accuracy, 94.29% precision, 93.20% f-score, 92.13% recall, and a minor loss of 0.05 at the 14th epoch.

TABLE I
Performance Comparison of the Proposed Approach with other State-of-the-Art Techniques

Parameter Metrics	Proposed MSIM	LSTM	Bi-LSTM
Prediction Accuracy (%)	93.27	91.49	50.35
Precision (%)	94.29	90.81	50.01
Recall (%)	92.13	92.33	52.05
F-score (%)	93.20	91.56	50.40
Loss (#)	0.05	10	0.2500
Epoch (#)	14	17	17

IV. Conclusion

This study proposed a multi-stack (MSIM) deep learning-assisted inventory management for MES. The MSIM demonstrates its applicability in a preliminary result in implementing AI in MES inventory management. In the future, this study seeks to improve the models' prediction accuracy and extend the comparison with more recent inventory management datasets.

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