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RESEARCH ARTICLE

A IoT-Based Framework for Cross-Border E-Commerce Supply Chain Using Machine Learning and Optimization

WEI WANG
Anhui Business and Technology College, Hefei, Anhui 231131, China
e-mail: 18019562153@163.com

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ABSTRACT With the expansion of communication technologies and their impact on trade patterns, e-commerce strategies have also undergone significant changes. Adapting to these changes necessitates the utilization of artificial intelligence techniques to automate a wide range of processes and further develop e-commerce. This article employs a combination of machine learning techniques and multi-objective optimization to enhance the supply chain performance in Cross-Border E-Commerce (CBEC). To achieve this, a framework for intelligent CBEC based on Internet of Things (IoT) technology is proposed. By deploying machine learning models within this framework, efforts are made to improve supply chain performance through demand volume prediction. The predictive model used in the proposed method is an ensemble system based on Adaptive Neuro-Fuzzy Inference System (ANFIS), which employs weighted averaging to predict demand volume for each retail unit. The configuration of this prediction model is done at two levels, utilizing Particle Swarm Optimization. At the first level, the hyperparameters of each ANFIS model are optimized, and at the second level, the weight values of each learning component are optimized using this algorithm. The performance of this predictive model in enhancing the CBEC supply chain structure is evaluated using real-world data. Based on the results, the proposed predictive model achieves an average absolute error of 2.54 in demand volume prediction, showcasing a minimum reduction of 8.58% compared to previous research. Moreover, the improvement in supply chain performance through this model will lead to reduced delays and increased efficiency in CBEC, demonstrating the effectiveness of the proposed model.

INDEX TERMS E-commerce, Internet of Things, machine learning, multi-objective optimization.

I. INTRODUCTION

In recent years, the continuous advancement of communication and information technologies has driven a significant shift towards virtualization in many business transactions. These technologies have eliminated many geographical constraints in today's world, creating new opportunities for governments and cross-border commerce stakeholders [1]. These transformations in e-commerce serve as a catalyst for small companies to engage in international trade, enabling them to compete with larger counterparts and expand their businesses.

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The emergence of e-commerce has led to profound changes in various aspects, including the creation of new business models and opportunities [2]. E-commerce refers to any form of business activity conducted through electronic means. Depending on the nature of the exchange, e-commerce can encompass any combination between companies, governments, or consumers [3].

Today, businesses must become part of the e-commerce ecosystem; otherwise, they risk losing their competitive edge. In the global market, the presence of e-commerce as a leading form of commerce has opened new doors of opportunities for various companies, brands, and investors. However, the evolution of business models in e-commerce is an ongoing

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necessity, and e-commerce operators always require more efficient models that align with the dynamic conditions of the business world [4]. This need is particularly pronounced in the realm of Cross-Border E-Commerce (CBEC) due to its complexity, dynamism, and the vast amount of information that results from the integration of multiple businesses [5]. Therefore, recent research has attempted to provide frameworks for adapting CBEC to emerging communication technologies, such as the Internet of Things (IoT) [6]. Nevertheless, several research gaps exist in integrating these technologies with CBEC, motivating the current research. Tracking product information in the IoT environment requires a decentralized model, which needs redefinition based on the CBEC architecture. Additionally, efficiently managing the vast volume of data generated in the supply chain requires an architecture capable of intelligent utilization, allowing for the definition of business control strategies at different levels. In this research, a new and efficient framework based on IoT architecture for CBEC supply chain management is presented, based on which the mentioned challenges can be solved. In this framework, the combination of machine learning techniques has been used in order to improve the performance of the supply chain. The innovative contributions of this article include:

- In this article, a novel framework based on the IoT structure has been proposed for the deployment of CBEC and addressing the associated challenges in supply chain management. This framework utilizes a decentralized and hierarchical architecture to manage the big data of the supply chain.
- In this article, a new hybrid model based on Adaptive Neuro-Fuzzy Inference System (ANFIS) has been introduced for demand prediction and supply chain enhancement. This model employs the Particle Swarm Optimization (PSO) algorithm for optimizing the model parameters at both local levels (adjusting hyperparameters of each ANFIS model) and global levels (tuning the weight vectors of the ensemble model).

The continued structure of this article is as follows: In section II, some relevant research in the field is reviewed. Section III provides an explanation of the proposed model and the processes involved in its formation. Section IV delves into the discussion of research results and compares the performance of the proposed method with previous approaches. Lastly, section V presents the conclusions drawn from the study.

II. LITERATURE REVIEW

In [7] a model for predicting customer repurchase in an e-commerce platform based on machine learning. This research first analyzes the limitations and challenges of traditional online purchase behavior prediction methods and then proposes an analysis and prediction system for online purchase behavior. The approach combines logistic regression, a linear model, and the XGBoost model based on decision trees for prediction. It employs a model blending algorithm to combine the prediction results of individual prediction models to prevent overfitting.

In [8] focuses on the application of recommendation systems in e-commerce. In this study, a probabilistic unsupervised machine learning approach for an image similarity-based recommendation system in e-commerce is proposed. This method applies feature reduction using Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) on the data. Then, it utilizes the K-Means++ clustering approach to identify clusters of similar products. The Manhattan distance metric is employed to retrieve similar products in this method.

Leung et al. [9] have proposed a machine learning-based model for demand prediction in e-commerce applications. This research introduces a novel machine learning-based prediction method by merging time series data features to develop an ANFIS system. The results indicate that the ANFIS model can accurately predict three-hour demand in supply chains and can be used as a real-time order demand predictor.

Wijaya et al. [10] have employed machine learning methods for the analysis of big data in e-commerce. Their goal was to propose a framework for estimating poverty rates based on e-commerce data using machine learning algorithms. They suggest that e-commerce data can reflect actual household expenditures, which align better with actual poverty line calculations compared to other computational models.

Fraud detection is one of the applications of machine learning and big data in e-commerce. Nanduri et al. [11] discuss Microsoft's approach to reducing fraud in e-commerce. Their Fraud Management System (FMS) maintains the features used in machine learning risk models using archive data, dynamic risk tables, and knowledge-updated graphs. FMS utilizes customized long and short-term sequential machine learning models to identify fraud patterns. It also makes real-time and rapid decisions using a dynamic programming approach to optimize long-term profits while considering multi-dimensional decisions.

Rai and Dwivedi's [12], proposed a method for credit card fraud detection using unsupervised learning based on neural networks. The results show that their proposed method outperforms existing approaches such as Autoencoder (AE), Local Outlier Factor (LOF), Isolation Forest (IF), and K-Means clustering.

Machine learning can also be employed for sentiment analysis and customer satisfaction evaluation in e-commerce. For example, Chatterjee et al. [13] have used text mining and machine learning techniques to investigate satisfaction with health care/health product services in e-commerce. They utilize text mining, machine learning, and econometrics to understand which aspects of primary and augmented service features and which sentiments in which service domains are more critical in terms of customer satisfaction feedback and prediction. This model can assist e-commerce managers in designing and delivering better healthcare/health product services.

Zhao et al. [14] have presented a sentiment analysis model based on machine learning for examining opinions related to products sold online. This approach employs a weighting and feature selection technique. The sentiment analysis method consists of four main stages: firstly, customer opinions regarding products are collected. In the next step, preprocessing is performed on the extracted data. Then, the data preprocessed in the previous step undergoes weighting and feature selection operations through Long Term Frequency-based Modified Inverse Class Frequency (LTF-MICF). Finally, sentiments embedded in customer opinions are classified into positive, negative, and neutral categories.

Demircan et al. [15] have proposed a sentiment analysis model using machine learning techniques for e-commerce data. In this research, several models for sentiment prediction from provided texts are described. These sentiment analysis models are constructed using machine learning classifiers such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), Logistic Regression, and k-Nearest Neighbors (KNN). In all these models, sentiments are classified as positive, negative, or neutral.

Anita and Kalaiarasu in [16] have suggested a machine learning-based collaborative filtering recommendation system for use in e-commerce. This recommendation system consists of two stages: in the first stage, an SVM classifier is used to classify entities based on positive and negative feedback. Then, an SVM-IACO collaborative filtering model is constructed, and recommendations are provided solely based on positive feedback from entities.

Capalbo et al. [17] have examined the role of optimization and machine learning techniques in e-commerce logistics for the year 2030. Xu et al. [18] have introduced a perspective on embedding products and presented a comprehensive theoretical view from both the representation learning and learning theory perspectives. Arab [19] has proposed an approach for predicting customer quality in e-commerce social networks based on big data techniques and machine learning. In this research, a graph-based social network analysis framework is utilized to detect communities, and customer quality is predicted based on the discovered communities.

Guan [20] has suggested an intelligent e-commerce logistics construction model based on big data analysis. Cui et al. [21], have proposed an intelligent optimization method for e-commerce product marketing. This article constructs an e-commerce product marketing model based on SVM classifiers. In this study, the Q-Learning strategy has been improved to utilize e-commerce data, and the standardization of averages is used to reduce the impact of noise on the reward signal derived from the fixed time interval between decision points. Cai et al. [22], have presented a multi-modal model for predicting product demand volume in e-commerce using deep learning techniques. In this model, three categories of features are evaluated simultaneously: order history, customer reviews, and user profile information. Each of these features is processed by biLSTM models, and feature vectors extracted from them are processed by convolutional layers. Finally, predictions are made based on the integration of this feature set.

III. RESEARCH METHODOLOGY

In this research, a framework based on the IoT architecture is presented to improve supply chain performance in CBEC. Machine learning techniques are employed as a strategy for order volume prediction and supply chain management adjustment based on it. In this section, after explaining the data structure used in the research, the proposed architecture is presented.

A. DATA

The research data is collected over a one-month period from the sales records of six active retailers in the CBEC domain. All retailers are active in cross-border selling of physical products, meaning that all products purchased by customers must be shipped via one of the ground, air, or sea shipping methods. Each retailer uses a minimum of three online sales platforms. The collected dataset for each retailer includes 550 data records, which specify the wholesale order histories for each retailer. The minimum and maximum volume of wholesale product sales in each data record are 4 and 28, respectively. We employed a multi-pronged approach to gather data from the chosen retailers' online sales platforms. Direct data extraction from each platform's API ensured the accuracy and consistency of the collected data. Additionally, we complemented this method with web scraping techniques to capture any additional relevant information not readily accessible through API integration. The retrieved data underwent a rigorous preprocessing phase to ensure its quality and suitability for analysis. This included handling missing values, data cleaning, and data normalization to ensure consistency across different datasets. We also extracted relevant features from the unprocessed data, focusing on 23 specific variables that were deemed critical for modeling retailer sales patterns:

- Order registration time
- Day of order registration
- Month of order registration
- Method of order registration (type of platform used)
- Order volume
- Destination of the order
- Product type
- Shipping method
- Retailer's inventory level
- History of product dispatch delay by the retailers in the last 7 transactions
- History of product order volume in the last seven days, each of which is described by numerical vectors with a length of 7.

B. PROPOSED FRAMEWORK

In this research, a cross-border e-commerce structure with the supply chain of physical products is considered, which is managed through multiple platforms and retailers. The research focuses on the supply chain of physical products in CBEC and utilizes the Internet of Things architecture to improve the supply chain's performance. Figure 1, illustrates the proposed framework for this structure. This framework comprises four main components:

- Retailers
- Common sales platform
- Product warehouse
- Supply center

The CBEC model assumed in this research consists of N independent retailers, each of whom can engage in marketing and selling one or more products. Each retailer has at least one warehouse for storing their supplied products. Additionally, each retailer can use multiple online web sales platforms to introduce and sell their products. Online customers register their desired product orders through these sales platforms. The registered orders through the platform are then sent to the retailer who holds the product. By doing this, the receiving retailer organizes the sales form and sends it to the data center located in the supply center. In conventional CBEC approaches, the supply of resources is reactive, leading to delays in order processing, which can result in customer dissatisfaction and potential customer loss. In the proposed framework, this process is proactive. Machine learning techniques are used to predict the future order volume of each retailer in upcoming time intervals, and resources are supplied to the warehouses of each retailer based on the prediction results.

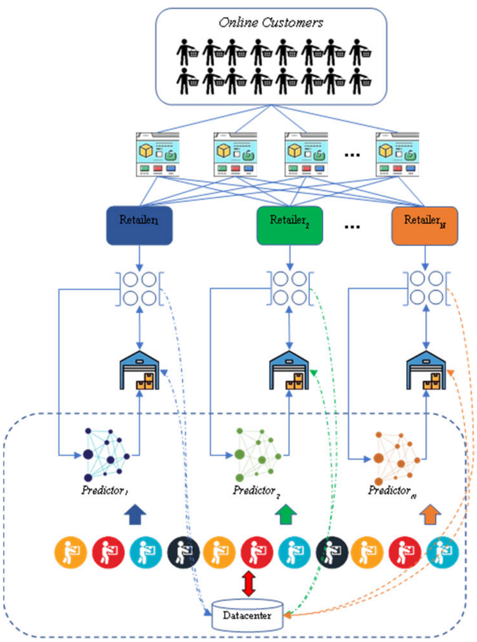

FIGURE 1. Proposed framework for supply chain management based on iot and machine learning.

In the proposed framework, after an agent submits a sales form to the data center, the inventory of that agent at the data center is updated. Using a machine learning-based model, the projected number of orders for that product by the retailer is predicted. Subsequently, based on the prediction results, the necessary resources for the retailer are provided by the supply center. This process leads to a reduction in the processing time for orders and a decrease in the likelihood of inventory depletion. As previously mentioned, this framework leverages IoT architecture to enhance supply chain performance. For this purpose, Radio Frequency IDentification (RFID) technology is employed for supply management. In the proposed model, each product is identified using an RFID tag. Passive RFID tags are utilized in the proposed model to reduce the implementation cost. These electronic tags in the framework act as automated data carriers for the asset management system based on RFID technology. The architecture of this system employs passive RFID tags that operate in the UHF band.

Furthermore, each retailer's product warehouse is equipped with a tag reader gateway, through which the entry and exit of products can be monitored. In the proposed model, when a product enters or exits, the unique identification information stored in the RFID tags is first extracted via the tag reader. This identification information is then transmitted to a controller connected to the tag reader node. The controller sends the unique product ID to the data center in the form of a query to retrieve information about the product, including its authorization for entry or exit. If the process is authorized, the controller sends a storage command to record the product's movement in the data center, updating the inventory of the corresponding product for the retailer.

1) INTEGRATION OF IOT AND RFID IN THE PROPOSED ARCHITECTURE

The proposed IoT-based architecture for CBEC supply chain management leverages RFID technology to track product movement and supply center-based machine learning to predict future demand. This integration of RFID and IoT technologies enables real-time inventory monitoring, proactive resource supply, and automated decision-making, leading to improved supply chain efficiency, reduced costs, and enhanced customer satisfaction.

RFID technology plays a crucial role in the proposed IoT-based architecture for CBEC supply chain management. RFID tags are embedded into products, enabling their identification and tracking throughout the supply chain. This process is facilitated by RFID reader gateways installed within each retailer's warehouse. When a product enters or exits the warehouse, the RFID tag's unique identifier is captured by the reader gateway and transmitted to a controller. The controller then sends a query to the data center located in the supply center to retrieve information about the product, including its authorization for movement. Upon authorization, the controller updates the product's inventory status in the data center, providing real-time visibility into the warehouse's inventory levels. The integration of RFID technology offers several key benefits for optimizing supply chain performance:

1. Real-time Inventory Tracking
2. Enhanced Order Processing Efficiency
3. Automated Replenishment

On the other hand, the proposed IoT architecture serves as the backbone for integrating RFID technology into the CBEC supply chain. The architecture consists of a network of connected devices, including RFID readers, controllers, and data center, that collect, transmit, and analyze real-time data. This interconnected network enables the seamless flow of information throughout the supply chain, facilitating data-driven decision-making and optimizing operations.

The integration of RFID and IoT technologies within the proposed framework creates a powerful synergy that significantly enhances supply chain performance. RFID technology provides the mechanisms for real-time product tracking and identification, while the IoT architecture enables centralized data collection, analysis, and automated decision-making. This combination results in a more efficient, responsive, and data-driven supply chain that can adapt to changing market conditions and customer demands.

2) PREDICTING ORDER VOLUMES BASED ON MACHINE LEARNING AND OPTIMIZATION

In the proposed framework, a weighted ensemble model is used to predict future order volumes for each retailer. The number of prediction models used in the proposed framework is equal to the number of retailers in the CBEC system. Each prediction model attempts to predict the volume of customer orders for the corresponding retailer in future time intervals based on the estimates provided by the learning models deployed within them. This allows for the necessary products for each retailer to be supplied by the supplier based on these predictions, reducing the delay caused by reactive product supply in a proactive manner.

The task of predicting order volumes for each retailer is assigned to ANFIS models. The ANFIS models used in the proposed framework are trained on historical sales data, demographic information, and market trends (the 23 features listed in section III-A), obtained through common sales platform, retailers and RFID-based supply management system (see Fig. 1). This data provides the model with insights into the factors that influence demand for specific products or services. The model then uses this information to generate forecasts of future sales figures.

The demand forecasts generated by the ANFIS models are integrated into the supply chain management models, which use these forecasts to optimize inventory management and production planning.

The proposed weighted ensemble model for predicting order volumes for each retailer consists of three ANFIS models. Each of these models is trained based on the input order patterns of the corresponding retailer. Although the ensemble learning technique can be effective in improving prediction accuracy in machine learning systems, there are two key considerations for its effectiveness:

- Each learning component within an ensemble system must exhibit an acceptable performance to reduce the overall prediction error through their output combinations. This necessitates the use of learning models with optimal configurations, ensuring that each learning model can maintain its desirable performance in processing various data patterns.
- In most practical scenarios of ensemble systems, the learning components forming the system do not have the same prediction error. Some learning models have higher error rates, while others have lower error rates in predicting the target variable. Contrary to the approach used in conventional ensemble systems, where equal value predictions are often assumed for the output of each component, in the proposed framework, it is not possible to predict the same value for each component's output.

To address these challenges, a strategy of weighting the outputs of each learning component is employed, resulting in the formation of a weighted ensemble system. In this case, determining the optimal weight for each learning component in the ensemble is a challenging task and needs to be dynamic. In the proposed method, particle swarm optimization is used to solve this problem. PSO dynamically determines the optimal weights for each learning component within the ensemble system. The overall functioning of the proposed weighted ensemble model for predicting order volumes is represented as shown in Figure 2(a).

As depicted in Figure 2(a), the proposed weighted ensemble model consists of three prediction components based on the ANFIS structure. These components collaborate to predict the volume of orders for a retailer. Each of these prediction models is trained based on a subset of sales history data specific to its corresponding retailer (the 23 features listed in section III-A). The basic structure of each ANFIS model is illustrated in Figure 2(b). According to this structure, each ANFIS model takes features as input through its input layer and processes them through four subsequent layers to predict the future order volume for the corresponding retailer. The details of this model are explained in the following section.

In the proposed method, each ANFIS model is configured using the PSO algorithm. It is important to note that the configuration of each ANFIS model is independent of the other two models. This allows for the expedited configuration and training of each model using parallel processing techniques. The PSO algorithm, during the configuration process of each ANFIS model, attempts to determine the values of fuzzy set radii in a way that minimizes the mean squared error criterion. This mechanism ensures that a set of learning models with optimal configurations can be obtained, guaranteeing the satisfactory performance of each individual component.

After the configuration of each ANFIS component in the proposed ensemble system, the process of determining weights for the outputs of each prediction component takes place. Once again, the PSO algorithm is employed for this

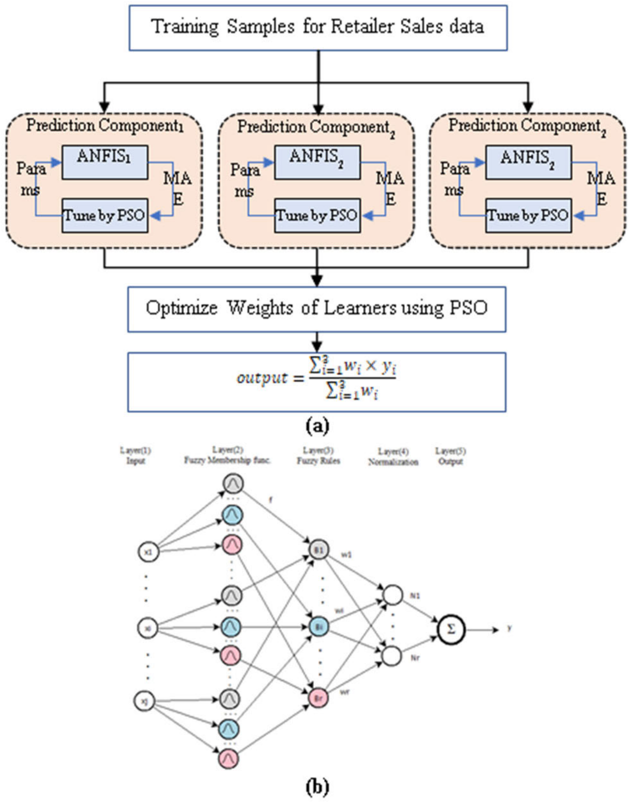

FIGURE 2. **(a) Functionality of the proposed weighted ensemble model for predicting order volumes and (b) ANFIS model structure in the ensemble model.**

purpose. In this phase, the PSO algorithm strives to adjust the output values of each learning model in proportion to its performance. After optimizing the weight values using the PSO algorithm, the configured and weighted models can be used for predicting order volumes in new samples.

In the testing phase, each of the prediction components, ANFIS1, ANFIS2, and ANFIS3, is fed with input features, and the final output of the proposed weighted model is determined as the weighted average of the outputs of these models.

This approach enables the creation of a robust prediction system where each component is optimally configured, and the weightings of their outputs are dynamically adjusted to ensure accurate order volume predictions for retailers in the CBEC system.

a: PSO-BASED CONFIGURATION OF ANFIS MODEL

In the proposed ensemble model, ANFIS models based on the Sugeno fuzzy inference system are utilized to forecast the future order volumes for each retailer. Each ANFIS model employed in the suggested prediction system consists of five layers: input, fuzzy membership functions, fuzzy rules, normalization, and output. Initially, each input record is applied to the neurons in the input layer. This layer handles the input data in its raw form. Subsequently, based on the values of each input feature, corresponding fuzzy membership functions are activated. These membership functions help convert the precise input values into fuzzy values that can be processed further. Once the fuzzy membership functions are activated, fuzzy rules are executed based on the fuzzy input values. These rules determine the fuzzy output values. The weight values derived from the execution of fuzzy rules are normalized in the fourth layer of the ANFIS model. Normalization ensures that the output values fall within a consistent range, allowing for effective combination. Finally, by combining these features, the output of the ANFIS model is computed in the fifth layer. The output value is determined as [23]:

$$y_i = \sum_{i=1}^{N} N_i f_i = \frac{\sum_{i=1}^{N} w_i f_i}{\sum_{i=1}^{N} w_i} \tag{1}$$

In this context, N_i represents the output of the normalization layer, $w_i$signifies the weight obtained from executing the fuzzy rules in the third layer of the ANFIS model, and f_i denotes the output of a first-order polynomial function applied as an activation function in the fifth layer of the ANFIS model based on the weight values.

Despite utilizing neural network structures for determining the weight values in ANFIS, this model still requires the configuration of some parameters to achieve desirable performance. One of the most significant configurable parameters in the ANFIS model is the radii of the clusters [23]. The radius of each cluster in the ANFIS model specifies the range of influence of the center of each cluster on each of the data dimensions (assuming that the data is located in a unit-hyperbox with unit dimensions).

Larger cluster radii values lead to a reduction in the number of fuzzy rules and a decrease in detection accuracy. On the other hand, using smaller radius values can increase the complexity of the model and may lead to overfitting. Therefore, configuring these parameters should be done carefully. In the proposed method, the PSO algorithm is employed to optimize each ANFIS model based on these parameters. It's worth noting that each ANFIS model in the proposed ensemble system performs the cluster creation process using the differential clustering strategy.

First, it's necessary to describe the structure of each particle and how its fitness is evaluated in the PSO algorithm for configuring each ANFIS model. The radius values, which determine the effective range of each cluster's center for each dimension, are represented as real numbers in the range [0, 1]. Each training record has 23 input features (as mentioned in section III-I) and one output variable (the forecasted order volume). Therefore, the set of cluster radius parameters in the ANFIS model is described by a real vector with a length of 24. Based on this, each particle in the PSO algorithm in this phase is represented by a real vector with a length of 24, where each element corresponds to one of the radius values of the ANFIS model being configured. The search range for each parameter of the particle is set within the interval [0, 1].

The evaluation of fitness for each particle to configure the parameters of an ANFIS model is done based on the mean absolute error of validation. To do this, the radius values determined by a particle are applied to the ANFIS model, and the configured model is trained based on 25% of the samples from the training dataset. Then, the fitness of the particle is evaluated based on the remaining training samples, as follows:

$$fitness = \frac{1}{N_v} \sum_{i=1}^{N_v} |T_i - output_i| \tag{2}$$

In the above equation, N_v represents the number of validation samples, T_i denotes the actual target value for the i-th validation sample, and $output_i$ describes the predicted value by the trained model for this sample. The objective of the PSO algorithm in the configuration phase of the ANFIS model is to determine an optimal configuration through a particle that can minimize Equation 10. To achieve this, the search for each particle is performed in the following steps:

Step 1: The parameters for the PSO are determined as P=100 (population size) and G=300 (the number of algorithm iterations).

Step 2: The initial population of particles and their velocities are randomly assigned.

Step 3: The fitness of each particle is calculated based on Equation 2.

Step 4: The values of the individual best (pbest) and global best (gbest) particles are determined within the population.

Step 5: The velocity of each particle is updated based on the following equation [24]:

$$v_i^{t+1} = v_i^t + c_1 r_1 \left(pbest_i^t - p_i^t\right) + c_2 r_2 \left(gbest_i^t - p_i^t\right) \tag{3}$$

Step 6: With the updated velocity of each particle, the position of each particle is updated based on the following equation [24]:

$$p_i^{t+1} = p_i^t + v_i^{t+1} \tag{4}$$

Step 7: If the fitting (fitting error) has reached zero or the number of algorithm iterations is equal to G, then Step 8 will be executed. Otherwise, the algorithm returns to Step 3 and repeats.

Step 8: The particle *gbest* is returned as the optimal solution.

After completing the aforementioned steps, the determined radius values from the optimal particle are applied to the ANFIS model, and this configured model is trained using all the samples. The resulting trained model is then used for predicting order volumes in the proposed ensemble model.

b: PSO-BASED WEIGHTING OF THE ENSEMBLE MODEL

After configuring and training each prediction component, the PSO algorithm is used again to assign optimal weights to each of these components. The optimal weight assignment refers to determining the importance coefficient of the output of each of the ANFIS1, ANFIS2, and ANFIS3 prediction components in the final output of the proposed ensemble system. In this case, the optimization variables in the PSO algorithm consist of the optimal set of coefficients for the three estimation components used in the proposed ensemble model. In other words, each particle in the PSO algorithm has a length equal to 3, where the first to third elements represent the weight coefficients assigned to the outputs of ANFIS1, ANFIS2, and ANFIS3, respectively, in the calculation of the ensemble model's output. The search range for each optimization variable is a real number in the range [0, 1]. Given the explanation of the computational steps of the PSO algorithm in the previous section, in this section, we will only provide the fittness function used.

The fitness function used in the PSO algorithm to assign weights to the learning components based on the mean absolute error criterion is described by the following equation:

$$fitness = \frac{1}{n} \sum_{i=1}^{n} T_i - \frac{\sum_{j=1}^{3} w_j \times y_j^i}{\sum_{j=1}^{3} w_j} \tag{5}$$

In the above equation, T_i represents the actual target value for sample i. Additionally, y_j^i denotes the estimated output predicted by ANFIS model j for training sample i, and w_j specifies the weight assigned to ANFIS model j through the solution vector. Finally, n describes the number of training samples.

This algorithm determines a weight coefficient in the range [0, 1] for each learning component, which defines its impact on the final output of the ensemble model. It's worth noting that the weighting phase for learning components occurs only once and after the configuration and training operations.

After determining the optimal weight values for each learning component using the PSO algorithm, the trained models and the specified weight values are used to predict future order volumes. In this case, the proposed weighted ensemble model, following the determination of the predicted output for all three ANFIS models within it, estimates the number of future orders as follows:

$$output = \frac{\sum_{i=1}^{3} w_i \times y_i}{\sum_{i=1}^{3} w_i} \tag{6}$$

In the equation above, w_i represents the weight assigned to ANFIS model i, and y_i indicates the predicted value of this model for the input sample. Finally, the future requirements of the retailer are fulfilled based on the predictions made by this ensemble model.

IV. RESULTS AND DISCUSSIONS

For the implementation of the proposed model, MATLAB 2020a software was used. To evaluate the effectiveness of the proposed model in improving CBEC efficiency and the accuracy of the recommended ensemble model in predicting order volumes were examined. These experiments were conducted using data collected from six active retailers in the CBEC sector over a one-month period. All these sellers exclusively deal with the sale of physical goods. Each retailer has used at least three platforms for selling their products. To study the impact of the proposed model on improving the efficiency of these retailers, the average time for order delivery was compared between the cases of using and not using the proposed method. These results are presented in Figure 3.

In Figure 3, the horizontal axis represents the studied retailers, and the vertical axis indicates the average time spent on fulfilling an order. This time interval represents the period from order reception to order delivery to the customer. As the results presented in Figure 3 show, the use of the proposed strategy has led to a reduction in the order fulfillment time for all the studied retailers. This reduction is more pronounced in sellers who initially had a longer order fulfillment time, indicating that these sellers were using inefficient and traditional sales mechanisms.

The results shown in Figure 3 reveal that, before implementing the proposed approach, the average order fulfillment time for all retailers was 14.02 hours, which decreased to 11.74 hours after the implementation of the proposed model. Thus, the proposed approach can reduce the average order fulfillment time by 16.26%. This reduction implies increased customer satisfaction and improved efficiency for retailers active in the CBEC field. The improvement achieved after using the proposed model can be attributed to the performance of the learning model in predicting future order volumes. This model can predict the volume of orders for each retailer in future time intervals, determine the necessary products for each retailer, and thereby improve the supply chain's performance.

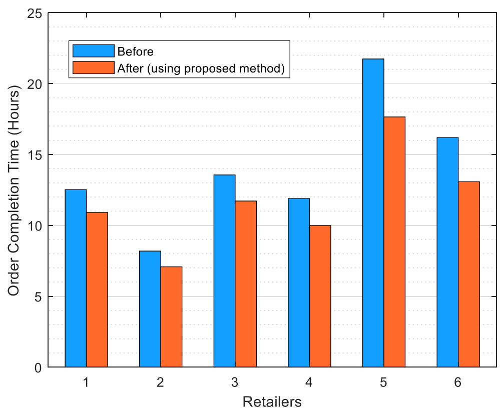

FIGURE 3. **The impact of the proposed model on the efficiency of CBEC in terms of order fulfillment time.**

Continuing with this section, the performance of the proposed model in predicting the order volumes of CBEC sellers is assessed. To achieve this, a cross-validation technique with 10 repetitions is employed. In this technique, the data samples are divided into 10 subsets, and the training and testing processes are repeated using these data subsets. In each iteration, one subset is used for testing the model, while the remaining data is used for training. After obtaining the model's predictions, the predicted order volume is compared to the actual volume. Based on this comparison, the prediction accuracy is evaluated using metrics such as RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), NRMSE (Normalized RMSE) and accuracy. This cross-validation approach helps assess how well the proposed model generalizes to unseen data and provides insights into its prediction accuracy and reliability.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2} \tag{8}$$

$$Accuracy = 100 - \frac{100 \times MAE}{\max(y) - \min(y)} \tag{9}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{|y_i - \hat{y}_i|}{y_i} \tag{10}$$

$$NRMSE = \frac{RMSE}{\frac{1}{N}\sum_{i=1}^{N} y_i} \tag{11}$$

In the above equations, y_i represents the actual value of the target variable (number of product orders) for test sample i, and $\hat{y}_i$represents the predicted value by the learning model for that sample. Additionally, max and min describe maximum and minimum functions, respectively. It is evident that the desirable state for an effective prediction model is to maximize accuracy and minimize the MAE, MAPE, RMSE and NRMSE metrics.

To assess the effectiveness of each technique used in the proposed model, its performance in predicting the order volumes for each seller in the database has been compared in the following scenarios:

- Proposed (without PSO): This scenario refers to cases where the optimization step of ANFIS models by the PSO algorithm is ignored, and a weighted combination of base ANFIS models is used for predicting the order volumes for each seller. This scenario can demonstrate the impact of ANFIS model configuration strategy on improving prediction accuracy in the proposed method.
- Conventional Ensemble: In this case, the weighting step of the ensemble components by PSO is disregarded. In other words, the weights for all prediction components in the proposed ensemble system are considered equal to 1. By comparing this scenario with the proposed method, it can be determined how the weighted ensemble strategy affects the increase in prediction accuracy.
- Single ANFIS: In this scenario, instead of using the proposed ensemble model for predicting order volumes, a single ANFIS model is used. Comparing this scenario with the proposed method can highlight the impact of the set of techniques used in the proposed method (weighted ensemble and configuration of each ANFIS model) on increasing prediction accuracy.

In Figure 4, the number of orders recorded by customers is plotted against the predicted values for the number of orders by the proposed method and other scenarios for 50 test samples. Figure 4 shows that the predicted values by the proposed method have less deviation from the actual number of customer orders compared to other scenarios. These results indicate that each of the weighted ensemble techniques and the fuzzy neural network configuration by the PSO algorithm have contributed to the formation of a more accurate prediction model. To further evaluate the performance of the proposed model in predicting customer order volumes, error metrics can be used.

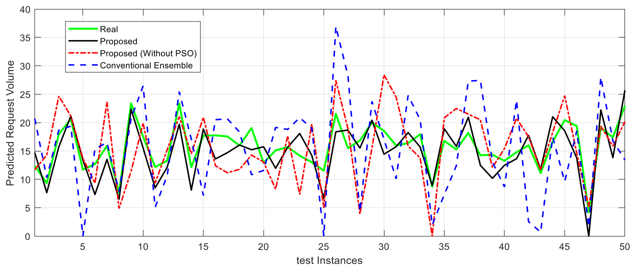

FIGURE 4. Number of orders recorded vs. predicted values by the proposed method and other scenarios for 50 test samples.

In Figure 5, the results of evaluating the performance of the proposed method in predicting customer order volumes over 10 repeated experiments are presented based on the MAE. The results of the proposed method are compared with methods [9] and [22], which are machine learning-based order volume prediction models. It's important to note that all models were trained and tested on the same dataset. In Figure 5a, the changes in the MAE values for each method during the 10 repeated evaluations are shown. In contrast, Figure 5b visualizes the changes in MAE values for each method in the form of a box plot.

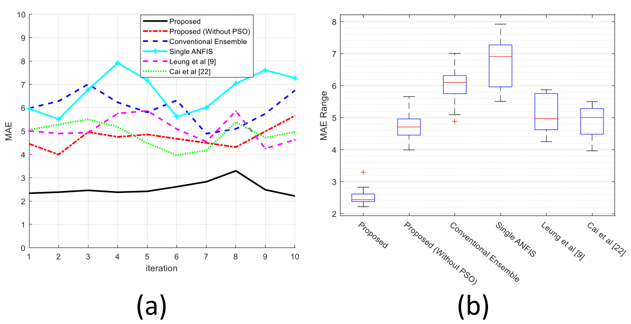

FIGURE 5. Prediction error based on MAE (a) Error in each cross-validation iteration (b) Box plot of error for each method.

Based on the results presented in Figure 5a, the proposed method can predict customer order volumes with a lower Mean Absolute Error. The results shown in this figure indicate that the proposed method, in addition to having higher average accuracy, has a narrower range of variation for MAE over different iterations. The limitation on the range of error variations in an algorithm is considered an advantage. By narrowing the range of error changes, the reliability of the algorithm also increases.

In Figure 5b, the range represented by the whiskers of each box indicates the upper and lower bounds of the error variations of the algorithm in different iterations. Each box signifies the range where at least 50% of the experiments produced errors within that range. The middle line of each box indicates the median of the Mean Absolute Error of the algorithm over all iterations. By examining the performance of the proposed method compared to other scenarios, three main conclusions can be drawn:

- First, comparing the proposed method to a scenario where weighted ensemble of base ANFIS models (without PSO optimization) is used shows that the configuration strategy of ANFIS models can reduce the estimation error in all iterations. Thus, the configuration strategy of ANFIS models by PSO in the proposed method is an effective technique in reducing the error, resulting in an average error reduction of 7.99%.
- Second, comparing the proposed weighted ensemble model to the conventional ensemble scenario demonstrates that using optimal weights to determine the effectiveness of each learning model on the final output can be effective in reducing the error. Based on the obtained results, in this scenario, the proposed method can reduce the Mean Absolute Error by an average of 12.76%.
- Third, if the proposed weighted ensemble model is replaced with a single base ANFIS model, the average Mean Absolute Error will be 7.32, which is an increase of 15.28% compared to the average Mean Absolute Error of the proposed method (3.09). Based on these results, each of the techniques used in the proposed method can be effective in reducing prediction error.

The performance analysis of the proposed method based on the RMSE metric yields similar results. The results of this evaluation are presented in Figure 6. Examining the variations in RMSE during 10 repeated experiments and the box plot of RMSE variations confirms the research findings. According to this figure, the proposed method consistently achieves lower squared errors in all iterations. As the results of evaluating the proposed method and comparing its performance with other scenarios indicate, the proposed method can predict the volume of customer orders for different sellers with higher accuracy and achieve lower MAE and RMSE. The lower prediction error levels (Figures 5a and 6a) and the narrower range of error variations (Figures 5b and 6b) in the proposed method suggest that the output of the proposed method is more reliable than other scenarios.

Figures 5 and 6 show that even without configuring the ANFIS models and utilizing the weighted ensemble strategy, the prediction error is reduced compared to other methods [9] and [22]. Combining multiple learning models allows leveraging the capabilities of different models simultaneously, thus covering the partial errors of each learning model through collaboration with others. On the other hand, using the weighted ensemble strategy in the proposed method can enhance this process. The proposed method improves the performance of the ensemble model compared to each individual learning model, ensuring that the output of the ensemble model has a lower error than the base models.

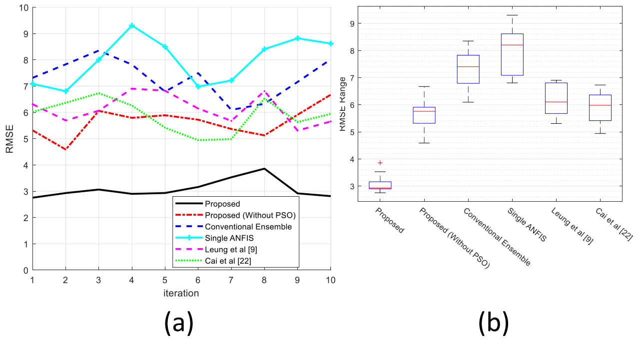

FIGURE 6. **Prediction Error of Order Volume Based on RMSE (A) Error at each cross-validation iteration (B) Box plot of error for each method.**

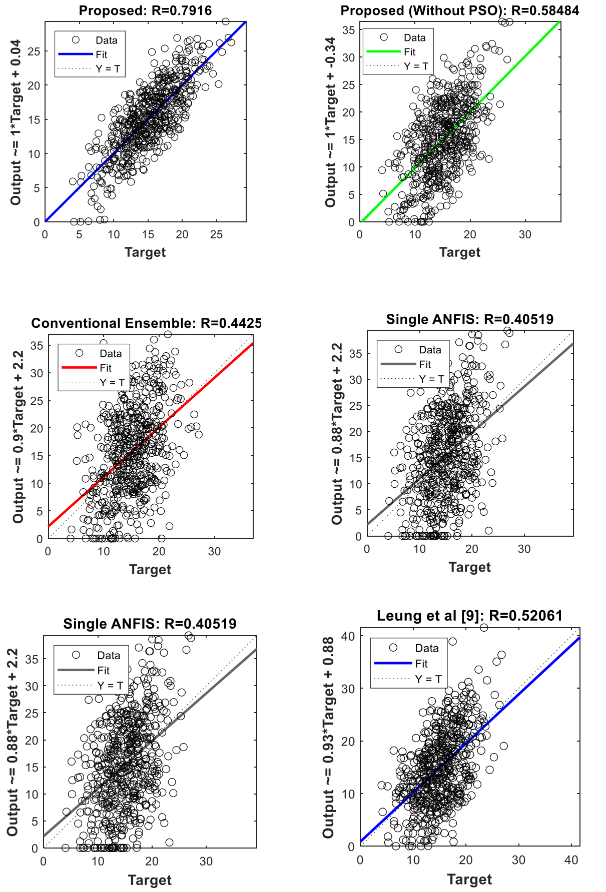

FIGURE 7. **Regression plots for various methods in predicting customer order volumes.**

In Figure 7, regression plots for the proposed method and other compared scenarios for predicting customer order volumes are presented. In these plots, actual volume values of customer orders are on the horizontal axis, and the predicted values by each method are on the vertical axis. Based on the results presented in this figure, an R value of 0.7916 in the proposed method indicates a higher correlation between the outputs of this method and the target variable. The regression points for the proposed method are concentrated around the Y=T axis.

Furthermore, the linear regression equation between the outputs of the proposed method and the target variable is Y=T+0.04, which, compared to the regression equations of other scenarios, has less displacement and a slope closer to 1. Therefore, it can be concluded that the outputs of the proposed method are more in line with the actual values. The reason for this lies in the improvement in accuracy due to the weighted ensemble of learning models, as well as the result of configuring the ANFIS component by the PSO algorithm. Both optimization objectives in PSO aim to increase the convergence between the prediction outputs and the target variable.

By examining the error frequency ranges, we can provide a more comprehensive perspective on the performance of order volume prediction methods. In Figure 8, the chart displays the frequency of errors for different methods in predicting customer order volume for test samples in the database.

In each chart of Figure 8, the horizontal axis represents error ranges in predicting customer order volume, and the vertical axis indicates the frequency of predictions falling within the respective error range. As shown in these charts, the proposed method has a narrower error range compared to the compared methods. The error bounds for the proposed method for all database samples are $[-7.9, +8.8]$. This means that in the worst case, the proposed method predicts the order volume for a seller with an error of 8 orders, which is lower compared to other methods. Furthermore, more than 75% of the prediction errors of the proposed method fall within the range of $[-1.7, +1.8]$. This indicates that the proposed method predicts the order volume with an error of less than 2 in more than three-quarters of the cases, demonstrating its effectiveness.

Figure 9 presents a Taylor diagram comparing the performance of various methods. The Taylor diagram can simultaneously compare the performance of prediction methods based on correlation, standard deviation, and RMSE metrics. Based on the results presented in Figure 9, the proposed method has lower RMSE and standard deviation compared to other methods. Additionally, the output of the proposed method exhibits a higher correlation with actual customer order volumes. These results indicate that the proposed method significantly outperforms other methods in terms of the mentioned criteria, highlighting the efficacy of the techniques employed in the proposed approach for enhancing prediction accuracy.

Figure 10, compares prediction algorithms in terms of MAE, RMSE, MAPE and NRMSE after 10 folds of cross-validations.

Based on Figure 10, the proposed method in addition to reducing prediction MAE and RMSE, can achieve lower NRMSE and MAPE which is the result of using the

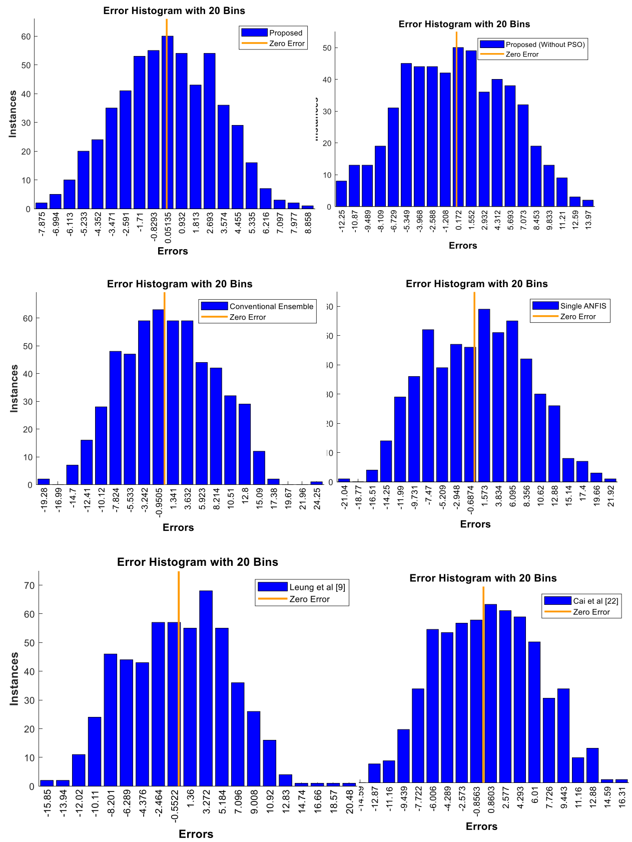

FIGURE 8. Frequency of error for different methods in customer order volume prediction.

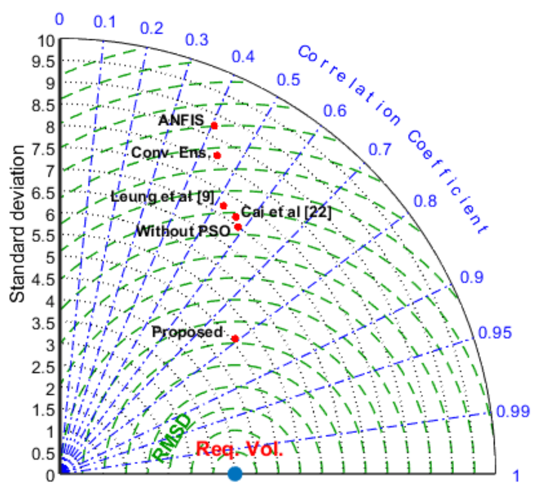

FIGURE 9. Taylor diagram resulting from the comparison of different methods.

techniques of ensemble learning and optimization of ANFIS models. Table 1 displays the average error values in predicting target variable for the proposed method and other methods. The values presented in this table represent the averages obtained from 10 repeated experiments. The table also compares the performance of the proposed method with some previous research.

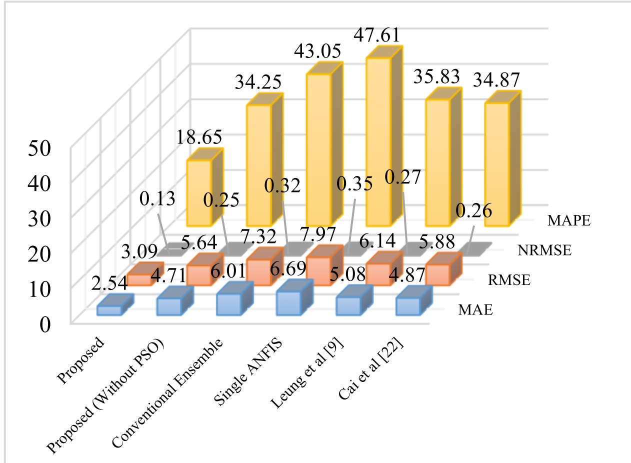

FIGURE 10. Comparison of MAE, RMSE, MAPE and NRMSE after 10 folds of cross-validations.

TABLE 1. Comparison of the performance of the proposed method and other methods.

Methods	RMSE	MAE	Accuracy (%)	R (correlation)	Std. dev.
Proposed	3.0866	2.5421	90.6335	0.7916	5.012
Proposed (without PSO)	5.6448	4.7125	82.6364	0.5848	6.984
Conventional Ensemble	7.3197	6.0078	77.8637	0.4426	8.083
Single ANFIS	7.9743	6.6893	75.3529	0.4052	8.749
Leung et al [9]	6.1398	5.0811	81.2782	0.5206	7.233
Cai et al [22]	5.8823	4.8699	82.0564	0.5647	7.210

As the results presented in Table 1 demonstrate, the proposed method can perform predictions with higher accuracy and lower error. The higher correlation in the proposed method indicates better alignment of its outputs with the target variable. Additionally, the smaller error range in the proposed method, compared to other methods, suggests that the outputs of this method have a higher level of confidence. This improved accuracy in the proposed method can be attributed to the effectiveness and flexibility of the weighted ensemble and ANFIS model configuration techniques in reducing prediction errors.

In general, the results obtained from these experiments showed that the proposed framework can have the following benefits in practical implementations of CBEC:

- *Enhanced demand forecasting accuracy*: The ANFIS model's ability to handle complex nonlinear relationships between input and output variables leads to more accurate demand predictions, which translates into improved inventory management and reduced stock-outs or overstocking.

- *Optimized inventory levels*: By leveraging precise demand forecasts, the supply chain management models can optimize inventory levels, ensuring that adequate stock is available to meet customer demand while minimizing storage costs and associated risks.
- *Efficient production planning*: The demand forecasts and optimized inventory levels guide the production planning process, enabling businesses to manufacture the right quantities of products at the appropriate times. This reduces production costs and ensures a smooth flow of goods through the supply chain.

However, there are several implementation challenges that should be addressed for deploying the proposed framework in real-world CBEC supply chain. These challenges include cost considerations, scalability requirements, and potential barriers such as data availability and integration with existing systems. Using RFID technology in the proposed architecture, can efficiently address the cost consideration concerns and at the same time, utilizing IoT-based architecture meets the scalability requirements for a wide range of real-world CBEC supply chains. The only concerning barrier in this case would be data availability and the possibility of unauthorized access to data which can be addressed by integrating a security protocol with IoT architecture.

V. CONCLUSION

The presented framework offers an efficient approach to enhance the performance of the supply chain and increase CBEC (Cross-Border E-Commerce) efficiency, addressing the requirements for aligning commerce with emerging communication technologies. In this research, a new IoT-based framework for the CBEC supply chain was introduced, aiming to tackle some of the challenges in this domain. In this framework, information tracking for products occurs in a decentralized and hierarchical manner, addressing scalability challenges. Furthermore, it efficiently manages the massive amount of data generated within the supply chain. This framework combines machine learning and optimization techniques to improve supply chain performance. A weighted combination of ANFIS models for demand prediction and supply chain management was proposed. The PSO algorithm was employed to optimize the hyperparameters of each ANFIS model and fine-tune the weight values of the prediction model. The investigations indicated that optimizing the model could effectively reduce prediction error by at least 7.99%. Based on the obtained results, the proposed learning model achieved an average absolute error of 2.54 in demand prediction, which is a reduction of at least 8.58% compared to previous research. Furthermore, improving supply chain performance using this model is expected to reduce delays and enhance efficiency in CBEC, demonstrating the effectiveness of the proposed model.

It's important to note that the proposed framework in this study focused solely on improving CBEC supply chain performance and management. Future research could extend this framework to address marketing, feedback assessment, and product recommendation strategies, which are vital for enhancing cross-border e-commerce trade. Also, deploying the proposed framework in a real-world Cross-Border E-Commerce supply chain in order to more accurately identify the obstacles for practical implementation and also provide strategies to overcome these challenges will be the subject of our future research. In conclusion, this research contributes to the advancement of cross-border e-commerce by offering an effective framework for supply chain enhancement and management. The combination of IoT, machine learning, and optimization techniques has the potential to significantly improve supply chain efficiency, leading to better customer service and overall business performance.

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WEI WANG was born in Anhui, China, in 1980. He received the bachelor's degree in management from Anhui University, in 2004, and the master's degree in management from the Hefei University of Technology, in 2014. Since 2004, he has been an Associate Professor with the Anhui Business and Technology College, mainly focusing on economic management, e-commerce, and cross-border e-commerce.