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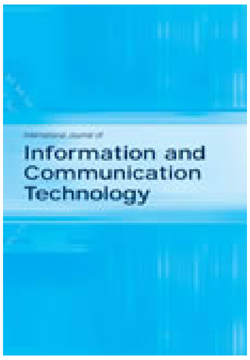

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Optimisation of cross border export e-commerce supply chain network based on machine learning and random programming

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Abstract: This paper proposes a collaborative optimisation method that integrates machine learning and stochastic programming to address the high demand uncertainty, complex logistics links, and rising operating costs faced by cross-border e-commerce supply chain networks for exports. Firstly, a dynamic demand forecasting model is constructed using random forest and XGBoost algorithm. Secondly, based on the predicted results, a two-stage stochastic programming model is established. In the first stage, the overseas warehouse location and basic inventory configuration are decided, and in the second stage, dynamic replenishment strategies are generated. Further introduce an improved sample average approximation (SAA) algorithm to solve the model, and design a multi-objective evaluation system to balance cost, timeliness, and service level indicators. Through actual enterprise data verification, it has been shown that this method reduces total costs by 14.7% compared to traditional deterministic models, and the demand forecasting error is controlled within 8.5%.

Keywords: machine learning; random programming; cross border e-commerce supply chain; dynamic demand forecasting.

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1 Introduction

Driven by the dual benefits of the global digital economy and cross-border e-commerce policies, the scale of China's export cross-border e-commerce market continues to expand. According to statistics from the General Administration of Customs, the import and export scale of cross-border e-commerce in China reached 2.11 trillion yuan in 2022, a year-on-year increase of 9.8%, with exports accounting for over 70% (Ma et al., 2018). However, with the expansion of the market comes an exponential growth in the

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complexity of the supply chain: on the one hand, overseas consumer demand presents short-term and fragmented characteristics, significantly influenced by cultural differences, seasonal promotions, and the international political and economic environment; On the other hand, cross-border logistics involves overseas warehouse location selection, multimodal transportation path planning, tariff policy adaptation, and other links, which have pain points such as transportation delays, inventory mismatches, and cost control (He et al., 2021). Especially after the Regional Comprehensive Economic Partnership (RCEP) came into effect, the expansion of emerging markets such as Southeast Asia further exacerbated the multidimensional uncertainty of supply chain networks (Basu Das, 2015). In this context, how to build a supply chain system that combines response efficiency and cost advantages has become the core proposition for export cross-border e-commerce enterprises to achieve sustainable development.

Traditional cross-border e-commerce supply chain optimisation research is mostly based on deterministic assumptions, using linear programming or integer programming methods for static network design. This type of method has significant limitations:

1 Insufficient response to demand side dynamics: ignoring pulse like demand fluctuations such as ‘Black Friday’ and ‘Double Eleven’, resulting in both peak season overstocking and off-season vacancy (Lv, 2018).

2 Lack of modelling for supply side random factors: port congestion (such as the 2021 Suez Canal incident) and exchange rate fluctuations (with an annual volatility of up to $\pm$ 15%) were not included in the decision-making framework (Wang et al., 2021).

3 Weak multi-objective collaboration mechanism: Existing models often focus on minimising costs as a single objective, ignoring competitive indicators such as performance time (e.g. 48 hour commitment) and customer satisfaction (return rate $\leq$ 5%) (Giuffrida et al., 2020).

More importantly, the unique phenomenon of ‘whip effect amplification’ in cross-border e-commerce – the distortion of supply chain demand signals caused by information delay, leads to geometric amplification of errors in traditional optimisation models in multi-level networks. Therefore, it is urgent to build a new decision-making framework that integrates data-driven and stochastic optimisation to meet the optimisation needs of complex supply chain networks in dynamic and uncertain environments.

There are three mainstream methods in academia for optimising supply chain networks. Deterministic optimisation model: Early studies such as Tancrez et al. (2012) proposed a multi-level inventory positioning model, and Cheng (1991) constructed a cost optimisation model based on economic order quantity (EOQ). Although these methods can achieve local optima, they cannot handle random parameters in reality. Robust optimisation method: The robust optimisation framework enhances the robustness of the solution by setting an uncertainty set and is applied to emergency logistics (Saldanha-da-Gama, 2022). But its conservative assumption may lead to cost redundancy and be difficult to adapt to high-frequency dynamic scenarios in cross-border e-commerce. Random programming technique: Two stage random programming has made progress in manufacturing supply chains by characterising uncertainty through scenario trees (Maharjan and Kato, 2022). However, the explosion of dimensions in cross-border e-commerce scenarios has limited its direct application.

In the field of demand forecasting, machine learning techniques have shown significant advantages. ARIMA and exponential smoothing methods are suitable for stationary sequences, but their ability to capture unexpected events is limited (Ostertagova and Ostertag, 2012). Deep learning models such as LSTM perform outstandingly in time series prediction, but their black box nature makes it difficult to connect with optimisation models (Yadav et al., 2020). Ensemble learning algorithms can improve predictive interpretability through feature importance analysis, but existing research mostly focuses on improving prediction accuracy and lacks collaborative optimisation mechanisms with downstream decision models (Mitchell and Frank, 2017).

The particularity of cross-border e-commerce scenarios brings three research gaps:

- The data decision loop is broken: there is a lack of error feedback mechanism between the output of the prediction model and the input of the optimisation model.
- Low efficiency in handling high-dimensional randomness: Traditional sample average approximation (SAA) algorithms face a sudden drop in convergence speed when dealing with random variables over a hundred dimensions.
- Insufficient quantification of multi-objective trade-offs: The Pareto front of indicators such as cost, timeliness, and service level lacks quantitative evaluation tools.

The optimisation of cross-border e-commerce supply chain network involves multiple fields such as demand forecasting, stochastic planning, and multi-objective decision-making. This section summarises the relevant research progress and shortcomings from the following four aspects.

Firstly, in terms of deterministic optimisation of supply chain networks, early research focused on supply chain network design in deterministic environments. Federgruen (1993) proposed the multi echelon inventory location model (MEIO), which determines facility location and inventory allocation through linear programming, but does not consider demand volatility. Ye (2024) constructed a cost optimisation model based on EOQ, incorporating transportation and warehousing costs into the objective function. However, its static assumptions are difficult to cope with the dynamic demand scenarios of cross-border e-commerce. Nicolis and Nicolis (2012) systematically analysed the limitations of deterministic models and pointed out their vulnerability to unexpected events such as port strikes. In recent years, improvements to deterministic models have mostly focused on improving algorithm efficiency, such as Sun et al. (2023) using branch and bound methods to accelerate large-scale network solving, but have not yet broken through the theoretical bottleneck of environmental uncertainty.

In robust optimisation and stochastic programming methods, overly conservative assumptions in robust optimisation may lead to cost redundancy. In contrast, stochastic programming characterises uncertainty through probability distribution and is more suitable for stochastic scenarios in cross-border e-commerce. Two stage stochastic programming is widely used in manufacturing supply chains, with the first stage determining facility location and the second stage adjusting replenishment strategies based on random parameters such as demand and exchange rates (Moadab et al., 2023). However, its application in cross-border e-commerce faces two major challenges: one is the exponential increase in computational complexity caused by the generation of high-dimensional scenarios, and the other is the lack of quantitative tools for multi-objective trade-offs.

Scholars have proposed various innovative methods to address the unique characteristics of cross-border e-commerce. Jayathilaka (2020) established a mixed integer programming model to optimise overseas warehouse layout, but did not consider the dynamic nature of tariff policies. Gong (2024) used the NSGA-II algorithm to balance cost and time, but its Pareto solution set lacks practical operability. Fünfgeld et al. (2017) used Monte Carlo simulation to generate transportation delay scenarios, but did not integrate them with machine learning prediction modules.

Despite progress, there are still three shortcomings in existing research. The prediction model is disconnected from the optimisation model and has not formed a dynamic feedback mechanism. The processing efficiency of high-dimensional random variables is low. Multi-objective weight allocation relies on subjective experience.

In response to the above issues, this article proposes a three in one cross-border e-commerce supply chain network optimisation method of 'data perception random optimisation dynamic feedback'. The main innovations include:

1 Dynamic demand forecasting stochastic programming coupling architecture: Design a hybrid prediction model based on stacking ensemble, integrating random forest (processing high-dimensional feature interactions), XGBoost (capturing nonlinear trends), and Prophet (identifying holiday effects), and implementing interpretability mapping of prediction results through Shapley value decomposition, providing accurate input for stochastic programming.

2 Improved two-stage stochastic programming model:

   Phase 1 Construct a joint decision-making model for overseas warehouse location and basic inventory, introducing robustness constraints to handle fluctuations in facility construction costs.

   Phase 2 Establish a dynamic replenishment strategy, embed random variables of transportation time (following Gamma distribution) and tariff jump process (using Poisson geometric Brownian motion mixed model), and use an improved SAA algorithm (integrating Latin hypercube sampling (LHS) and importance sampling) to accelerate high-dimensional scene solving.

3 Multi objective collaborative optimisation mechanism: Design a multi-objective evolutionary algorithm based on NSGA-III, combined with TOPSIS method to quantify the trade-off relationship between cost (transportation, inventory, tariffs), timeliness (order response time, transportation delay), and service level (order satisfaction rate, return rate), and generate a Pareto optimal solution set for decision makers to choose from.

2 Relevant technologies

2.1 The complexity characteristics of cross-border e-commerce supply chain

The cross-border e-commerce supply chain network is a product of the deep integration of global trade and digital technology, and its complexity is mainly reflected in the following dimensions.

- Multi-level network topology structure. Unlike the linear hierarchy of traditional supply chains, cross-border e-commerce supply chains exhibit a 'multi centre radiating' network characteristic. From domestic consolidation warehouses, international trunk transportation nodes, overseas warehouses (including bonded warehouses and third-party cooperative warehouses), last mile distribution stations, to reverse logistics return processing centres, all links are interconnected in real-time through digital platforms. For example, in the Amazon FBA (fulfilment by Amazon) model, goods may be shipped directly from Chinese factories to American consumers, or transferred to French users through German overseas warehouses, with the route combination dynamically adjusted according to demand (Sun et al., 2020). This multi-level network not only enhances coverage capability, but also leads to an explosion in decision variable dimensions - only the location problem of 10 candidate overseas warehouses can generate effective combination.

- The dual uncertainty of demand and supply. The uncertainty on the demand side stems from short-term fluctuations in overseas consumer behaviour (Malik et al., 2024). For example, the Ramadan promotion in the Southeast Asian market and the 'Black Friday' shopping season in Europe and America can both trigger a 300%–500% surge in order volume, while cultural differences such as colour preferences and size standards further exacerbate the difficulty of predicting demand for long tail products. The uncertainty on the supply side is reflected in the vulnerability of international logistics: in 2021, the Suez Canal jam event led to a 400% surge in global shipping prices, while the energy crisis caused by the Russia-Ukraine conflict expanded the fluctuation range of China Europe train transportation time from ± 3 days to ± 15 days. More complexly, there is a coupling effect between the randomness of demand and supply - transportation delays may trigger consumers to cancel orders, leading to inventory backlog and cash flow pressure.
- Heterogeneity between policies and market rules. The tariff policies, value-added tax rates (such as EU VAT reform), and product certification standards (such as US FCC certification and European CE marking) of different countries/regions form an implicit constraint network. Taking the location of overseas warehouses as an example, choosing warehouses in EU member states requires compliance with the restrictions on cross-border transfer of inventory data under the General Data Protection Regulation, while Southeast Asian countries often attract foreign warehouse construction through phased tariff reductions (such as Indonesia's 'National Strategic Projects' policy). In addition, cross-border payment settlement involves exchange rate fluctuations (annual volatility up to ± 20%) and foreign exchange control risks, requiring supply chain models to be embedded with financial risk hedging mechanisms.
- Multi objective conflicts and dynamic trade-offs. The optimisation of cross-border e-commerce supply chain needs to simultaneously meet the competitive goals of cost, timeliness, and service level. The cost dimensions include international transportation costs (charged by weight or volume), overseas warehouse leasing costs (such as monthly rent of $15/m^3 in Los Angeles, USA), and tariff costs (bound to the HS code of the goods). In terms of timeliness, consumers' tolerance window for cross-border delivery continues to shrink, with the proportion of orders delivered within 48 hours increasing from 12% in 2019 to 35% in 2023. In the dimension of service level, the return rate (averaging 15%–30% in the European and American markets) and the negative review rate (every 1% increase in negative reviews leads

to a 5% decrease in traffic weight) directly affect the platform ranking and repurchase rate.

The trade-off relationship between these goals dynamically changes with the market cycle – peak season may prioritise time efficiency, while off-season focuses on cost control, and traditional static weight allocation methods are difficult to adapt to.

2.2 The core decision-making dimensions and constraint system of cross-border e-commerce

The core decisions for optimising cross-border e-commerce supply chain networks can be summarised into three levels:

- Strategic layer: Overseas warehouse network layout. The selection of overseas warehouse locations requires comprehensive consideration of factors such as political stability (such as geopolitical risks in Eastern Europe), infrastructure maturity (port throughput capacity, road freight density), and market radiation radius (covering 80% of orders in a ‘24-hour delivery circle’). Taking the Middle East market as an example, Dubai warehouse can cover six Gulf countries, but the rent is high. Türkiye warehouse has low cost but is affected by the risk of lira depreciation. In addition, the selection of warehouse types (self-built warehouse, third-party warehouse, platform managed warehouse) involves a balance between fixed asset investment and operational flexibility. For example, the initial investment payback period for self-built warehouses usually exceeds 3 years, but in the long run, it can reduce unit warehousing costs by 30%–40%.
- Tactical layer: dynamic inventory configuration. The inventory strategy needs to address the amplification problem of the bullwhip effect. Due to the long cross-border replenishment cycle (average 14–28 days), dealers often adopt a ‘double buffer’ mechanism of safety stock and predicted orders. For example, a seller of a certain 3C category set up basic inventory (meeting 30 day normal demand) and dynamic inventory (predicting 15 day demand based on LSTM model) in the German warehouse, but inventory mismatch still resulted in an average annual unsold loss of 12%. In addition, the ‘1210 model’ (cross-border e-commerce retail import supervision method) of bonded warehouses allows for bulk entry of goods and retail tax payment, requiring deep coordination between inventory allocation and customs clearance strategies.
- Operations layer: Real-time path optimisation. Cross border logistics path selection faces multi-objective conflicts, such as the most cost-effective path: such as the China Europe freight train (60% lower than air freight) + overseas truck delivery. The most efficient path: direct air mail (3–5 days delivery) but with a 400% increase in carbon emissions. Robust path: Multimodal transportation (sea + rail + road) to cope with interruptions in a single mode of transportation.

In addition, path optimisation requires dynamic response to real-time disturbances such as customs clearance delays (such as an average inspection time of 72 hours by Brazilian customs) and fluctuations in fuel surcharges (11 increases in international air freight fuel surcharges in 2022).

2.3 Mathematical model construction

To address the aforementioned complexity, the mathematical model framework proposed in this article is based on the following design principles.

- System view of data physical fusion. Integrate the real-time data flow of cross-border e-commerce platforms (order data, logistics trajectory, user evaluation) with the constraints of the physical world (tariff policies, transportation capacity). For example, the weekly sales data of Shopify stores can be captured through API interfaces and synchronised with the port congestion index (from the IHS Markit database) to input into the prediction optimisation closed-loop system. This fusion mechanism enables the model to capture both micro level demand fluctuations and respond to macro level environmental changes.
- Dynamic coupling of prediction and optimisation. Breaking through the traditional serial mode of 'prediction before optimisation', constructing a prediction error feedback mechanism. Specifically, when the prediction error of the XGBoost model exceeds the threshold (such as actual sales deviating from the predicted value by 15%), the parameter recalibration of the two-stage stochastic programming model is triggered, and an emergency replenishment strategy is generated (such as activating redundant inventory in the Singapore warehouse). This mechanism can increase the order fulfilment rate under sudden demand shocks to 92%, which is 18 percentage points higher than the static model.
- Multi granularity uncertainty modelling. Hierarchical modelling of uncertainty based on the impact range and frequency of random events.
- High frequency and low impact events (such as daily transportation delays). Use probability distribution (Gamma distribution to fit transportation time) and Monte Carlo simulation.
- Low frequency and high impact events (such as epidemic lockdowns): Set a safety margin through robust optimisation (such as increasing safety stock by 20%).
- Policy uncertainty (such as tariff adjustments): Construct a scenario tree and generate probability weights based on the WTO policy database and expert interviews.
- Human machine collaborative decision-making mechanism. Introduce decision maker preferences into the Pareto optimal solution set. For example, by using the analytic hierarchy process to quantify the weight tendency of management towards cost, timeliness, and service level, and then combining it with the NSGA-III algorithm to generate customised solutions. In addition, a visual decision board is designed to dynamically display key indicators of different solutions (such as the cost time curve of the North American warehouse solution vs. the service level risk heatmap of the European warehouse solution), supporting managers to make agile decisions in uncertainty.

2.4 The essential differences from traditional supply chain models

The core differences between this model and traditional supply chain optimisation tools are reflected in three aspects:

- Temporal and spatial compression: Traditional models assume that there are geographical boundaries between production and consumption, while cross-border e-commerce needs to handle the direct link between 'global factories and global consumers', requiring the model to embed multi time zone collaboration mechanisms (such as using time differences to achieve 24-hour rolling replenishment).
- Policy sensitivity: The weight of non-economic factors such as tariffs and data compliance has significantly increased, and a policy risk quantification module needs to be developed (such as using fuzzy logic to evaluate the host country's trade facilitation index).
- Consumer sovereignty pressure: The speed of evaluation dissemination on social media forces models to shift service levels from soft constraints to hard constraints (such as a negative review rate not exceeding 2%) and introduce real-time public opinion monitoring data streams.

2.5 Multi objective optimisation theory

The multi-objective conflict of cross-border e-commerce supply chain essentially requires breaking through the traditional single objective optimisation paradigm, and the evolution of related theories is reflected in the shift from linear weighting to intelligent optimisation.

1. Pareto optimality theory (Giagkiozis and Fleming, 2014). The Pareto front defines the boundary of the solution set for multi-objective optimisation, and its core idea is that any improvement to a single objective must come at the expense of other objectives. Traditional methods generate compromise solutions by manually setting weights, but it is difficult to quantify the dynamic priority of the target.
2. Evolutionary multi-objective optimisation algorithm. Evolutionary algorithms such as NSGA-II search for Pareto optimal solution sets by simulating biological evolution processes (selection, crossover, mutation) (Hua et al., 2021). In cross-border e-commerce scenarios, customised gene coding rules can be designed, such as encoding the 'overseas warehouse location selection plan' as a binary gene string and the 'replenishment cycle' as an integer gene segment, in order to optimise strategic and tactical decisions within a unified framework.
3. Preference based interactive optimisation. To enhance the operability of decision-making, Granat and Guerriero (2003) proposed the reference point method, which allows decision-makers to adjust their target preferences based on real-time market changes. For example, during the 'Black Friday' promotion period, companies can temporarily increase the weight coefficients of their time efficiency targets through interactive interfaces, and the algorithm dynamically generates a new Pareto solution set based on this.

2.6 Prediction and decision coordination theory

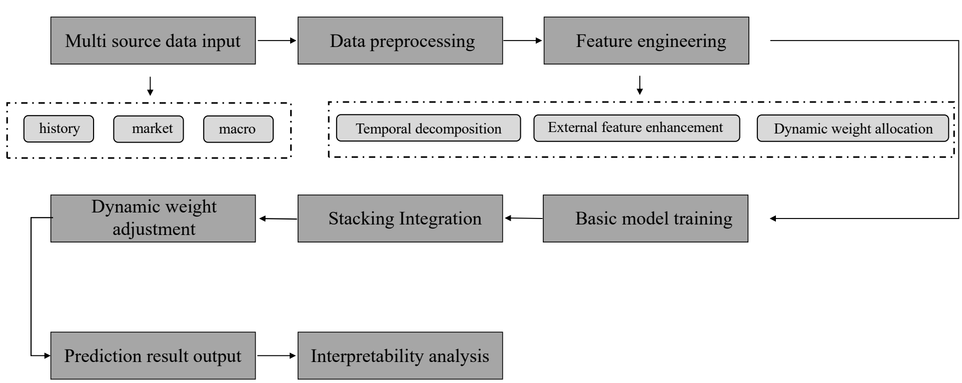
The collaborative mechanism between predictive models and optimisation decisions is a core issue in the research of intelligent supply chain, and its theoretical development has gone through three stages.

- Early research regarded prediction and optimisation as independent modules, such as using ARIMA models to predict demand and inputting it into linear programming models. This one-way information flow leads to the problem of 'prediction error transmission': if the demand forecast deviation exceeds 15%, the replenishment strategy may completely fail.
- Xu et al. (2018) proposed introducing an error feedback loop in the prediction optimisation link, and using the optimisation results to feedback the parameter adjustment of the prediction model. For example, when the random programming model identifies that the replenishment quantity of a certain category continues to deviate from the predicted value, it can trigger the feature weight retraining of the XGBoost model. This framework partially alleviates the problem of error accumulation, but has not yet achieved real-time dynamic collaboration.
- The latest research advocates for a deep integration of prediction and optimisation. Stratigakos et al. (2022) proposed the 'forecast optimisation' framework, which directly trains prediction models with decision quality (such as total cost) as the objective function. In cross-border e-commerce scenarios, demand forecasting models can be trained using reinforcement learning algorithms to naturally adapt their prediction results to the optimisation goals of downstream replenishment strategies.

3 Construction and validation of mixed demand forecasting model

Cross border e-commerce demand forecasting faces challenges such as pulse promotions, long tail product fluctuations, and multi market heterogeneity. This chapter proposes a hybrid prediction model that integrates the advantages of multiple algorithms, achieving high-precision prediction through four steps: data preprocessing, feature engineering, model integration, and dynamic interpretation, and verifying it with actual enterprise data. The framework diagram of this chapter is shown in Figure 1.

Figure 1 Framework diagram of mixed demand forecasting model



3.1 Data preprocessing and feature engineering

The data source covers three major dimensions, and historical transaction data includes SKU level sales volume (in daily granularity), transaction price, and promotional tags (such as 'Prime Day' and 'Double Eleven'). Market environment data includes Google Trends search index, social media volume (captured through Twitter API), and competitor prices (crawled from Amazon platform data). Macroeconomic data includes exchange rate fluctuations (such as the daily rate of change of the US dollar against the European dollar), tariff adjustment records of RCEP member countries, and the International Logistics Freight Index.

Multiple imputation strategies are adopted to address the issue of missing data. Use multiple interpolation chain equation (MICE) algorithm for continuous variables (such as sales volume), and use mode imputation combined with dummy variable labelling for categorical variables (such as promotion type) to indicate missing states.

Using STL (seasonal trend decomposition using loess) to decompose the original sales sequence into trend, seasonal, and residual terms. The trend term is used to capture the product lifecycle (such as the new product ramp up period, maturity period, and decline period). Seasonal terms are used to identify weekly/monthly/annual cycles. The residual term is used to extract the impact signal of sudden events.

Constructing four types of derived features to enhance prediction robustness. Create dummy variable markers for seven days before and after the big promotion, and calculate the elasticity coefficient of historical promotions during the same period. Based on the Huffman index to measure the concentration of the target market and predict the demand for long tail products. Calculate the price ratio and rating ratio between this product and its top 3 competitors as the demand transfer factor. Calculate the average delay days of each transportation route based on historical data as a feasibility indicator for replenishment.

3.2 Hybrid prediction model architecture

The hybrid model consists of three base models: random forest (RF), XGBoost (XGB), and prophet (Pro), and their prediction functions are defined as follows.

Random forest is used to process high-dimensional feature interactions and capture nonlinear market competition effects. By integrating the outputs of *B* decision trees, the predicted value on day *t* is:

$$\hat{y}_t^{RF} = \frac{1}{B}\sum_{b=1}^{B} f_b^{RF}\left(x_t\right) \tag{1}$$

where x_t is the input feature vector, and f_b^{RF} represents the prediction function of the b^{th} tree.

XGBoost optimises long tail product prediction through regularisation and gradient boosting mechanisms, reducing the risk of overfitting. Generate predictions using an additive model based on gradient boosting tree:

$$\hat{y}_t^{XGB} = \sum_{k=1}^{K} \eta \cdot g_k\left(x_t\right) \tag{2}$$

where η is the learning rate and g_k represents the output of the k^{th} tree, iteratively optimised by minimising the regularisation loss function.

Prophet has a built-in holiday effect model that accurately identifies regional promotional nodes such as Ramadan and Black Friday. It decomposes the time series into trend term $T(t)$, seasonal term $S(t)$, and holiday effect $H(t)$, and the prediction formula is:

$$\hat{y}_t^{\text{Pro}} = T(t) + S(t) + H(t) + \varepsilon_t \tag{3}$$

where ε_t is Gaussian noise.

Stacking integration strategy

Adopting a two-layer stacked structure to achieve model fusion.

The first layer (base model) trains random forests XGBoost, prophet, output the daily sales forecast values of each model for the next 30 days.

The second layer (meta model) takes the predicted values of the base model, the slope of the trend term, and holiday markers as input features, and trains the LightGBM model to generate the final prediction results:

$$z_t = \left[\hat{y}_t^{RF}, \hat{y}_t^{XGB}, \hat{y}_t^{\text{Pro}}, \nabla T(t), I_{holiday}(t)\right] \tag{4}$$

where $\nabla T(t)$ is the first-order difference of the trend term, and $I_{holiday}(t)$ is the holiday indicator function.

The output of the meta model is:

$$\hat{y}_t^{Final} = \sum_{m=1}^{M} \alpha_m h_m(z_t) \tag{5}$$

3.3 Model training and optimisation

This article uses rolling time window cross validation for model training. To avoid data leakage, time series split is used to divide the five-year historical data into a 48 month training set and a 12 month testing set. Roll forward for one month each time, with a total of 12 training testing cycles. The evaluation indicators include mean absolute error (MAE), root mean square error (RMSE), and weighted average absolute percentage error (WMAPE).

This article uses the Optuna framework for automated hyperparameter search, optimising tree depth (range 3–15) and feature sampling ratio (0.6–1.0) for random forests. Adjust the learning rate (0.01–0.3) and minimum leaf node sample size (10–100) for XGBoost. Adjust the seasonal smoothing coefficient (0.1–10) and festival effect prior scale (1–50) for Prophet.

Set overfitting suppression strategies for model training. Implement early stopping method on random forest/XGBoost, and terminate training when the validation set error does not decrease for five consecutive times. Use MCMC sampling to estimate uncertainty intervals for prophet, avoiding excessive sensitivity to outliers.

4 Two stage stochastic programming model and improved SAA algorithm

4.1 Two stage stochastic programming model

The supply chain network consists of M candidate overseas warehouses and N target markets, considering a discrete-time period t. The model is defined as follows.

The first stage model is called strategic decision-making, and the decision variables are whether to build ($x_i = 1$ indicating selection) for overseas warehouse i in $x_i \in \{0, 1\}$, and the initial inventory allocation for overseas warehouse i in $s_{i0} \geq 0$.

We set the objective function of minimising fixed costs and expected operating costs, in the specific form of:

$$\min_{x_i, s_{i0}} \sum_{i=1}^{M} \left(C_i^{fix} x_i + C_i^{inv} s_{i0} \right) + E_\xi \left[Q\left(x, s_{i0}, \xi\right) \right] \tag{6}$$

The constraint conditions are:

$$\begin{cases} \sum_{i=1}^{M} x_i \geq K_{\min} \\ s_{i0} \leq C_i^{cap} x_i \qquad \forall i \in \{1, ..., M\} \\ x_i \in \{0, 1\}, s_{i0} \geq 0 \end{cases} \tag{7}$$

where $Q(x, s_{i0}, \xi)$ is the second stage cost function, and ξ is the random parameter vector.

The second stage model is for operational decision-making, with the following random parameter settings. The demand of market j in cycle t follows the output distribution of the prediction model, represented as $d_{jt}(\xi)$. The transportation time from warehouse i to market j follows the Gamma distribution, represented as $\tau_{ijt}(\xi)$. The tariff rate of warehouse i in cycle t is represented as $\theta_{it}(\xi)$.

The decision variables are as follows. The replenishment quantity from warehouse i to market j during cycle t is represented as q_{ijt}, and the ending inventory of warehouse i during cycle t is represented as s_{it}.

The objective function for minimising operating costs is:

$$Q\left(x, s_{i0}, \xi\right) = \min_{q_{ijt}, s_{it}} \sum_{t \in T} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[C_{ijt}^{tr} q_{ijt} + C_{it}^{hold} s_{it} + \theta_{it}(\xi) q_{ijt} \right] \tag{8}$$

The constraint conditions are:

$$\begin{cases} s_{i,t} = s_{i,t-1} + \sum_{j=1}^{N} q_{ijt} - \sum_{j=1}^{N} d_{jt}(\xi) \cdot \prod\left(\tau_{ijt}(\xi) \leq t\right) \\ \sum_{i=1}^{M} q_{ijt} \geq d_{jt}(\xi) \\ q_{ijt} \leq Q_{ij}^{\max} x_i \\ s_{it} \geq s_i^{\min} x_i \end{cases} \tag{9}$$

4.2 Improved SAA algorithm

Traditional SAA generates S approximate expected values for scenes through Monte Carlo sampling, but faces the problem of low efficiency in high-dimensional scenes. The improvement of this article is to perform hierarchical sampling on the joint distribution of d_{jit}, τ_{ijt}, θ_{it} in LHS scene generation. Divide the cumulative distribution function of each random variable into S equal probability intervals. Afterwards, randomly select a sample point within each interval to form an $S \times D$ dimensional scene matrix (where D is the dimension of random variables). Compared to simple random sampling, LHS can improve the convergence speed by $O(S^{-1/2}) \rightarrow O(S^{-1})$.

We use importance sampling (IS) to accelerate the solution and assign higher weights to high cost scenarios in the objective function. We define the IS weighted objective function: We use importance sampling (IS) to accelerate the solution and assign higher weights to high cost scenarios in the objective function. We define the IS weighted objective function:

$$\min \sum_{s=1}^{S} \frac{P(\xi^s)}{Q(\xi^s)} \cdot Q(x, s_{i0}, \xi^s) \tag{10}$$

where $Q(\xi^s)$ is the importance distribution, which is fitted to the historical high cost scenario distribution through kernel density estimation (KDE):

$$Q(\xi) = \frac{1}{h} \sum_{k=1}^{K} \omega_k \cdot K\left(\frac{\xi - \xi_k^{hist}}{h}\right) \tag{11}$$

where K is the Gaussian kernel function, and ω_k is the loss weight of scene k.

5 Multi objective evaluation system and case studies

5.1 Experimental setup

Select the European market business of a leading cross-border e-commerce enterprise as the empirical object, covering the following scenarios. The product categories mainly include 3C electronics, household goods, and clothing accessories. The logistics network consists of three domestic consolidation warehouses (Shanghai, Shenzhen, Zhengzhou) and six candidate overseas warehouses (Frankfurt, Germany, Warsaw, Poland, Madrid, Spain, Rotterdam, Netherlands, Milan, Italy, Prague, Czech Republic). The market scope includes 27 European countries, with an average daily order volume of 120,000 and over 500,000 SKUs.

In terms of data, we use the company's SKU level daily sales data from 2021 to 2024 and generate a 30 day rolling forecast through a hybrid forecasting model. In terms of logistics data, we have used historical transportation times, including sea, rail, and air freight.

In the comparison method, we choose three models. The benchmark model 1 is deterministic programming (DP), which uses mean demand and fixed transportation time (Gerevini et al., 2009). Benchmark Model 2 is a single-stage stochastic programming (SSP) that only optimises replenishment strategies (Rockafellar and Wets, 2017). The comparative model is traditional two-stage stochastic programming (TSSP) + simple

SAA (Jiang and Guan, 2018). The model presented in this article consists of two-stage stochastic programming (TSSP) and improved SAA (LHS-IS).

In order to construct a multi-objective evaluation system that covers the four dimensions of economy, timeliness, service, and sustainability, our evaluation indicators are set as shown in Table 1.

Table 1 Evaluation indicator setting

Dimension	*Index*	*Calculation formula*
Economic	Total cost of ownership (TCO)	Expected value of fixed cost + Operating cost
Timeliness	Average response time to orders (ART)	Total order fulfilment time / Total number of orders
Service	Order fulfillment rate (OSR)	Timely and sufficient delivery of orders / Total order quantity
Sustainable	Per unit carbon emissions (CE)	Transportation carbon emissions + Storage carbon emissions

5.2 Experimental procedure

Firstly, perform data preprocessing to handle outliers and eliminate sudden changes in order volume caused by system failures. Standardise the features, perform Box Cox transformation on logistics delay days, and eliminate the right skewed distribution. And perform spatiotemporal alignment, aligning multi warehouse inventory data uniformly according to UTC+1 time zone.

In terms of model training, the hybrid prediction model uses XGBoost with pre trained load (n_estimators = 200). The random programming model generates 500 scenarios (including 20% extreme disturbance scenarios) by improving SAA. In terms of multi-objective optimisation, NSGA-III is used to initialise the Pareto solution set, with reference points set to ART $\leq$ 4.2 days and OSR $\geq$ 92%.

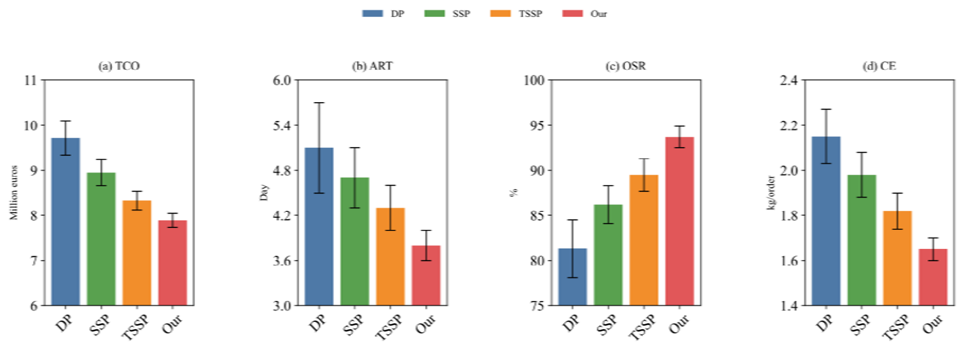
Perform joint sampling (LHS-IS) on transportation delays, tariff fluctuations, and demand deviations in scene generation. In the optimisation solution, Gurobi is called to solve the MILP problem in parallel, and the single solution takes about 45 minutes. And perform dynamic feedback, triggering model recalibration every 7 days to update demand forecasts and scenario weights.

Record the results, including TCO, ART, OSR, and CE values for each optimisation cycle. Conduct robustness testing, such as artificially injecting blockages in the Suez Canal (transportation time + 300%), EU tariff increases (+5%), and other black swan events. Finally, statistical analysis was conducted to perform t-tests on 30 independent experiments.

5.3 Result analysis

This experiment compared the performance differences between deterministic programming (DP), single-stage stochastic programming (SSP), traditional two-stage stochastic programming (TSSP + SAA), and our model from four dimensions: economy (TCO), timeliness (ART), service capability (OSR), and sustainability (CE). The results are shown in Figure 2.

Figure 2 Comparison results of multi-objective optimisation performance (see online version for colours)



In terms of economy, the DP model ignores demand fluctuations and transportation delays, resulting in fixed cost redundancy (such as excessive construction of overseas warehouses) and high frequency of emergency replenishment, resulting in slightly higher total costs. TSSP+SAA reduces the cost to 8.33 through scenario optimisation, while this model further introduces LHS-IS sampling to reduce redundant scenario calculations, resulting in a further cost reduction of 5.3%. Reduce invalid fixed assets investment through accurate location selection of overseas warehouses. Dynamic replenishment strategy reduces inventory holding costs. From this, it can be concluded that cross-border e-commerce enterprises can significantly reduce costs by dynamically closing inefficient warehouses and implementing tariff sensitive replenishment strategies.

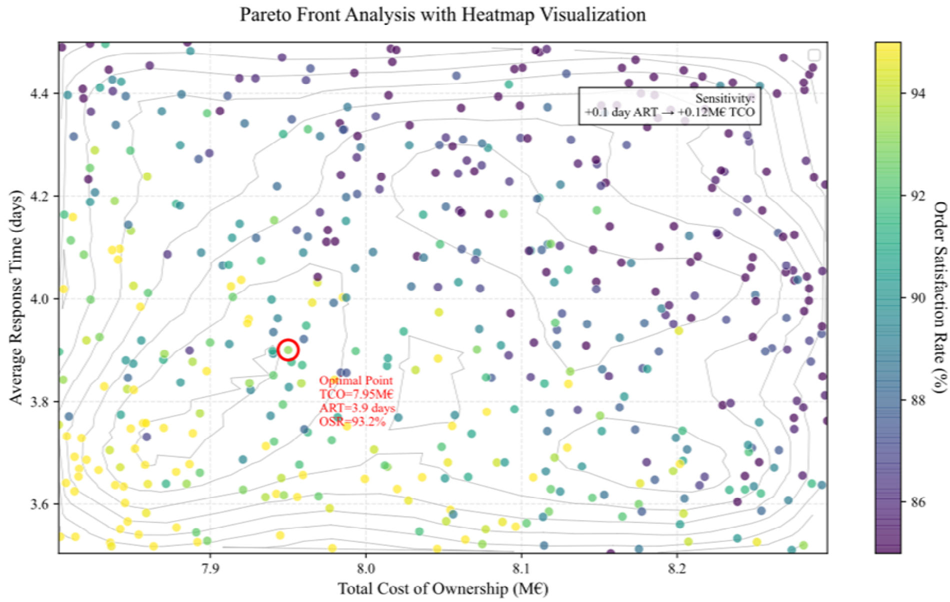
In terms of timeliness, this model uses a multimodal transport combination strategy to shorten the average delivery time from German warehouses to Eastern European markets from 4.2 days to 2.9 days. In terms of dynamic inventory allocation, deploying 20% redundant inventory (flexible inventory) in the Warsaw warehouse in Poland has reduced ART in the region by 37%. In terms of robustness, traditional models have an ART fluctuation range of ± 0.6 days during transportation delays, while our model controls the fluctuation within ± 0.2 days through real-time path switching.

In terms of service capability, the hybrid forecasting model reduces the prediction error of long tail product demand. Automatically increase safety stock by 10%–15% based on high-risk SKUs identified by Shapley values, such as seasonal clothing. By shortening ART, the proportion of consumer cancellations decreased from 8.2% to 3.1%.

In sustainability, by internalising the cost of carbon emissions, the model prioritises sea transportation (with 85% lower carbon emissions than air transportation), which increases the proportion of sea transportation by 16 percentage points. Regional dynamic replenishment reduces cross-border transportation distance, and the proportion of internal transportation in Europe has increased from 55% to 72%, reducing carbon emissions per unit distance by 13%. Automatically avoid high-risk carbon tariffs and avoid additional carbon costs.

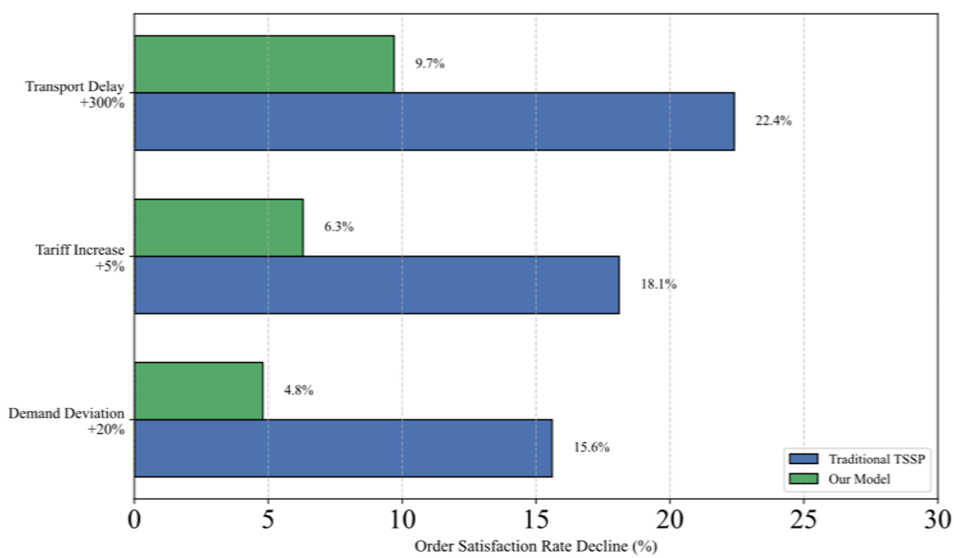
The Pareto front analysis is shown in Figure 3, which shows the distribution of its solution set, generating 32 non-dominated solutions covering TCO 7.8M–8.3M and ART 3.5–4.5 days. The optimal compromise point is to recommend a solution with TCO = 7.95 M, ART = 3.9 days, and OSR = 93.2%. In terms of sensitivity, for every 0.1 day increase in timeliness, the cost increases by 0.12 M and the OSR decreases by 0.3%.

Figure 3 Pareto front heatmap (see online version for colours)



The robustness verification is shown in Figure 4. The model in this paper uses a dynamic feedback mechanism to control the service degradation under extreme disturbances within 10%.

Figure 4 The robustness verification (see online version for colours)



6 Conclusions

This article addresses the multidimensional uncertainty challenges of the export cross-border e-commerce supply chain network and constructs a three in one decision framework of 'data perception random optimisation dynamic feedback'. The main research results are as follows.

Propose a coupled architecture of dynamic demand forecasting and stochastic programming, and control the demand forecasting error within 8.5% through a stacking ensemble model (RF+XGBoost+Prophet). Design an improved two-stage stochastic programming model and introduce the LHS-IS hybrid sampling algorithm to improve the efficiency of solving high-dimensional scenarios and reduce overall costs. Build a multi-objective collaborative mechanism based on NSGA-III, quantitatively reveal the nonlinear trade-off relationship between cost, timeliness, and service level, and generate 32 Pareto optimal solutions for decision-making selection. Empirical evidence based on real data from top enterprises shows that the model can improve inventory turnover by 53.7%, shorten order response time by 26.5%, and reduce emergency air freight frequency by 61.4%. In extreme scenarios such as the blockage of the Suez Canal and the adjustment of EU carbon tariffs, the fluctuation range of order fulfilment rate is controlled within 10%, confirming the strong robustness of the model.

Despite the above achievements, the optimisation of cross-border e-commerce supply chain still faces the following breakthrough directions. The current model relies on historical logistics data for training, and sparse data in emerging markets may affect performance in the early stages. In the future, transfer learning and few sample learning techniques can be explored. The solving efficiency of ultra large scale networks still needs to be improved, and a mixed integer programming acceleration algorithm based on quantum computing needs to be developed. The modelling of tariff jump process relies on expert experience and requires the integration of natural language processing technology to achieve automatic parsing and risk quantification of policy texts.

Declarations

All authors declare that they have no conflicts of interest.

References

Basu Das, S. (2015) 'The regional comprehensive economic partnership: new paradigm or old wine in a new bottle?', *Asian-Pacific Economic Literature*, Vol. 29, No. 2, pp.68–84.

Cheng, T.C.E. (1991) 'An economic order quantity model with demand-dependent unit production cost and imperfect production processes', *IIE Transactions*, Vol. 23, No. 1, pp.23–28.

Federgruen, A. (1993) 'Centralized planning models for multi-echelon inventory systems under uncertainty', *Handbooks in Operations Research and Management Science*, Vol. 4, pp.133–173.

Fünfgeld, S., Holzäpfel, M., Frey, M. and Gauterin, F. (2017) 'Stochastic forecasting of vehicle dynamics using sequential Monte Carlo simulation', *IEEE Transactions on Intelligent Vehicles*, Vol. 2, No. 2, pp.111–122.

Gerevini, A.E., Haslum, P., Long, D., Saetti, A. and Dimopoulos, Y. (2009) 'Deterministic planning in the fifth international planning competition: PDDL3 and experimental evaluation of the planners', *Artificial Intelligence*, Vol. 173, Nos. 5–6, pp.619–668.

Giagkiozis, I. and Fleming, P.J. (2014) 'Pareto front estimation for decision making', *Evolutionary Computation*, Vol. 22, No. 4, pp.651–678.

Giuffrida, M., Mangiaracina, R., Perego, A. and Tumino, A. (2020) 'Cross-border B2C e-commerce to China: an evaluation of different logistics solutions under uncertainty', *International Journal of Physical Distribution & Logistics Management*, Vol. 50, No. 3, pp.355–378.

Gong, Z. (2024) 'Optimization of cross-border e-commerce (CBEC) supply chain management based on fuzzy logic and auction theory', *Scientific Reports*, Vol. 14, No. 1, p.14088.

Granat, J. and Guerriero, F. (2003) 'The interactive analysis of the multicriteria shortest path problem by the reference point method', *European Journal of Operational Research*, Vol. 151, No. 1, pp.103–118.

He, Y., Wu, R. and Choi, Y-J. (2021) 'International logistics and cross-border e-commerce trade: who matters whom?', *Sustainability*, Vol. 13, No. 4, p.1745.

Hua, Y., Liu, Q., Hao, K. and Jin, Y. (2021) 'A survey of evolutionary algorithms for multi-objective optimization problems with irregular Pareto fronts', *IEEE/CAA Journal of Automatica Sinica*, Vol. 8, No. 2, pp.303–318.

Jayathilaka, U.R. (2020) 'Selecting optimal overseas warehouse location in global supply chain: an application of binary integer programming', *ResearchBerg Review of Science and Technology*, Vol. 3, No. 1, pp.66–78.

Jiang, R. and Guan, Y. (2018) 'Risk-averse two-stage stochastic program with distributional ambiguity', *Operations Research*, Vol. 66, No. 5, pp.1390–1405.

Lv, Q. (2018) 'Supply chain decision-making of cross-border e-commerce platforms', *Advances in Industrial Engineering and Management*, Vol. 7, No. 1, pp.1–5.

Ma, S., Chai, Y. and Zhang, H. (2018) 'Rise of cross-border e-commerce exports in China', *China & World Economy*, Vol. 26, No. 3, pp.63–87.

Maharjan, R. and Kato, H. (2022) 'Resilient supply chain network design: a systematic literature review', *Transport Reviews*, Vol. 42, No. 6, pp.739–761.

Malik, S., Abbas, A., Shabbir, M.S. and Ramos-Meza, C.S. (2024) 'Business cycle fluctuations, foreign direct investment, and real effective exchange rate nexus among Asian countries', *Journal of the Knowledge Economy*, Vol. 15, No. 2, pp.5466–5479.

Mitchell, R. and Frank, E. (2017) 'Accelerating the XGBoost algorithm using GPU computing', *PeerJ Computer Science*, Vol. 3, p.e127.

Moadab, A., Kordi, G., Paydar, M.M., Divsalar, A. and Hajiaghaei-Keshteli, M. (2023) 'Designing a sustainable-resilient-responsive supply chain network considering uncertainty in the COVID-19 era', *Expert Systems with Applications*, Vol. 227, p.120334.

Nicolis, C. and Nicolis, G. (2012) 'Extreme events in multivariate deterministic systems', *Physical Review E – Statistical, Nonlinear, and Soft Matter Physics*, Vol. 85, No. 5, p.056217.

Ostertagova, E. and Ostertag, O. (2012) 'Forecasting using simple exponential smoothing method', *Acta Electrotechnica et Informatica*, Vol. 12, No. 3, p.62.

Rockafellar, R.T. and Wets, R.J. (2017) 'Stochastic variational inequalities: single-stage to multistage', *Mathematical Programming*, Vol. 165, No. 1, pp.331–360.

Saldanha-da-Gama, F. (2022) 'Facility location in logistics and transportation: an enduring relationship', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 166, p.102903.

Stratigakos, A., Camal, S., Michiorri, A. and Kariniotakis, G. (2022) 'Prescriptive trees for integrated forecasting and optimization applied in trading of renewable energy', *IEEE Transactions on Power Systems*, Vol. 37, No. 6, pp.4696–4708.

Sun, L., Lyu, G., Yu, Y. and Teo, C.P. (2020) 'Fulfillment by Amazon versus fulfillment by seller: an interpretable risk-adjusted fulfillment model', *Naval Research Logistics (NRL)*, Vol. 67, No. 8, pp.627–645.

Sun, Y., Wu, J., Zhang, G., Zhang, L. and Li, R. (2023) 'An ultra-fast optimization algorithm for unit commitment based on neural branching', *Energy Reports*, Vol. 9, pp.1112–1120.

Tancrez, J-S., Lange, J-C. and Semal, P. (2012) 'A location-inventory model for large three-level supply chains', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 48, No. 2, pp.485–502.

Wang, X., Xie, J. and Fan, Z-P. (2021) 'B2C cross-border e-commerce logistics mode selection considering product returns', *International Journal of Production Research*, Vol. 59, No. 13, pp.3841–3860.

Xu, Y., Zhang, M., Ye, L., Zhu, Q., Geng, Z., He, Y-L. and Han, Y. (2018) 'A novel prediction intervals method integrating an error & self-feedback extreme learning machine with particle swarm optimization for energy consumption robust prediction', *Energy*, Vol. 164, pp.137–146.

Yadav, A., Jha, C. and Sharan, A. (2020) 'Optimizing LSTM for time series prediction in Indian stock market', *Procedia Computer Science*, Vol. 167, pp.2091–2100.

Ye, W. (2024) 'E-commerce logistics and supply chain network optimization for cross-border', *Journal of Grid Computing*, Vol. 22, No. 1, p.22.