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Enhancing agricultural product trade efficiency through machine learning predictions and multi-objective optimization of financial strategies

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RESEARCH ARTICLE

Abstract

In the context of global economic development and food safety, agricultural trade plays a vital role in linking agricultural production with market demand, and the efficient formulation of agricultural financial strategies is crucial for enhancing trade efficiency. This study employs advanced machine learning technologies to predict and optimize the efficiency of agricultural trade while seeking to balance the interests of various stakeholders in agricultural finance. By integrating quantile factor models, long short-term memory (LSTM) networks, and attention mechanisms, this paper conducts an in-depth analysis and precise prediction of the key factors affecting trade efficiency. This approach effectively addresses the nonlinearity and long-term dependency issues in time-series data, utilizing attention mechanisms to highlight critical information and improve prediction accuracy. Furthermore, this research establishes a multi-objective optimization model to balance the interests of agricultural finance participants, providing a new quantitative tool for formulating agricultural financial strategies aimed at optimizing decisions to enhance economic and social value. This paper offers new perspectives, methods, and empirical support for improving the efficiency of agricultural trade and the formulation of agricultural financial strategies.

Keywords: agricultural finance; agricultural trade; machine learning; time series analysis; multi-objective optimization

Introduction

With the intensification of globalization, the role of international agricultural product trade has been underscored as increasingly pivotal within the global economic framework (Li *et al*., 2022; Nisa' *et al*., 2023). The strategic development and optimization of agricultural financial strategies, acting as a vital intermediary between agricultural production and market demand, are identified as instrumental in driving the trade efficiency of agricultural products (Qian and Olsen, 2021). However, the inherent seasonal and regional characteristics of agricultural production, compounded by market uncertainties and environmental concerns, such as water quality and health risks associated with agricultural inputs (Mohammadpour *et al*., 2024a, 2024b), render traditional financial strategies inadequately equipped to address the distinct requisites of agricultural trade (Bai *et al*., 2023; Yusuf *et al*., 2022; Zhao *et al*., 2023). The advent of machine learning technologies heralds a new era, offering innovative perspectives and tools for the meticulous prediction and optimization of agricultural financial strategies, thereby enabling a more scientific and efficacious approach to strategy formulation (Sarkar *et al*., 2023).

The pursuit of enhanced efficiency in agricultural product trade is recognized not merely as a catalyst for the agricultural economy's stable growth but also as a critical factor in ensuring food security and elevating farmers' income levels (Herrera-Franco *et al*., 2023; Li *et al*., 2023; Wang *et al*., 2022). The commitment to deploying advanced analytical methodologies for refining agricultural financial strategies emerges as a cornerstone for fostering sustainable agricultural advancement (Huang *et al*., 2023; Zeng, *et al*., 2021). The importance of this research transcends theoretical investigation, extending to substantial practical implications. Through the analytical prediction of future trends in agricultural product trade, it has enabled policymakers to sculpt strategies with heightened precision, consequently bolstering the global competitiveness of agricultural trade (Choudhury *et al*., 2022; Deng and Gibson, 2019; Tarfi *et al*., 2023).

Challenges are encountered in the existing methodologies when addressing the complexity inherent in agricultural financial data (Wu, 2022). Traditional statistical models, on the one hand, grapple with the intricacies of nonlinear, high-dimensional data, falling short in delineating complex interrelations within such data (Sun, 2022, 2024). On the other hand, albeit early machine learning models have marked achievements in pattern recognition, they manifest limitations in managing time-series data and addressing long-term dependency concerns (Chen, 2022; Li *et al*., 2024; Sarkar *et al*., 2022; Seddik *et al*., 2023). Furthermore, these approaches frequently neglect the equilibrium of interests among stakeholders in agricultural finance, posing obstacles to optimizing benefits for multiple entities.

This research is centered on two pivotal aspects. Initially, it adopts an innovative method that integrates quantile factor models with long short-term memory (LSTM) networks and attention mechanisms, aimed at accurately forecasting the efficiency of agricultural product trade under varied financial strategies. The novelty of this method is encapsulated in its adeptness at capturing essential factors influencing trade efficiency and augmenting critical information in the decision-making process via attention mechanism-based reinforcement learning. Subsequently, a framework predicated on multi-objective optimization is devised to foster a balance among stakeholders within agricultural finance. The formulation of a multi-objective optimization equation within this study lays the groundwork for a novel quantitative analysis framework, dedicated to facilitating an equitable interest distribution among participants in agricultural finance. This investigation not only unveils new theoretical perspectives and empirical tools for the optimization of agricultural financial strategies but also underscores its substantial contribution to the advancement of efficient agricultural trade and mutual benefits among stakeholders.

This paper first captures and analyzes the key variables of agricultural trade data through quantile factor models; then it processes these data's time-series characteristics using LSTM networks to capture long-term dependencies, and employs attention mechanisms to give higher weight to important information within the model, thereby optimizing the accuracy and reliability of prediction results. In the construction of a multi-objective optimization model, the study uses mathematical programming methods to balance the interests of different agricultural finance participants (such as farmers, investors, government, etc.), ensuring that strategy decisions consider both economic benefits and social value. This methodology, integrating various advanced technologies and theories, not only provides a precise predictive tool for agricultural financial strategies but also offers practical decision support for achieving a balance among stakeholders, demonstrating the depth and breadth of this research.

The innovativeness and advancement of this study are mainly reflected in two aspects: First, by integrating a combined approach of quantile factor models, LSTM networks, and attention mechanisms, it effectively enhances the accuracy and depth of predictions under agricultural finance strategies for the efficiency of agricultural trade. This method innovatively emphasizes the identification of key factors and focused learning of information, especially through weighting important features in the data with attention mechanisms, thus achieving more detailed and accurate predictions of factors affecting trade efficiency. Second, by constructing a model based on multi-objective optimization, this research proposes a new quantitative framework for the equitable distribution of interests among agricultural finance participants, aimed at optimizing strategic decisions to promote both economic benefits and social values, reflecting a high degree of innovation and advancement.

Prediction of Enhanced Trade Efficiency for Agricultural Products under Agricultural Financial Strategies

Quantile factor model

In the exploration of enhanced trade efficiency for agricultural products under agricultural financial strategies, Figure 1 delineates the study's technical trajectory. A synthesis of quantile factor models, LSTM networks, and attention mechanisms is utilized to forecast the elevation of trade efficiency. Agricultural market data often display asymmetrical and heavy-tailed distributions, challenging standard statistical models to elucidate fully the risk–return spectrum across diverse market scenarios. The introduction of quantile factor models serves to elucidate the nonlinear characteristics and data heterogeneity underlying trade efficiency, offering a nuanced depiction of data behavior across different quantiles. This facilitates maintaining predictive accuracy amid varying market risk levels, thereby enhancing the understanding

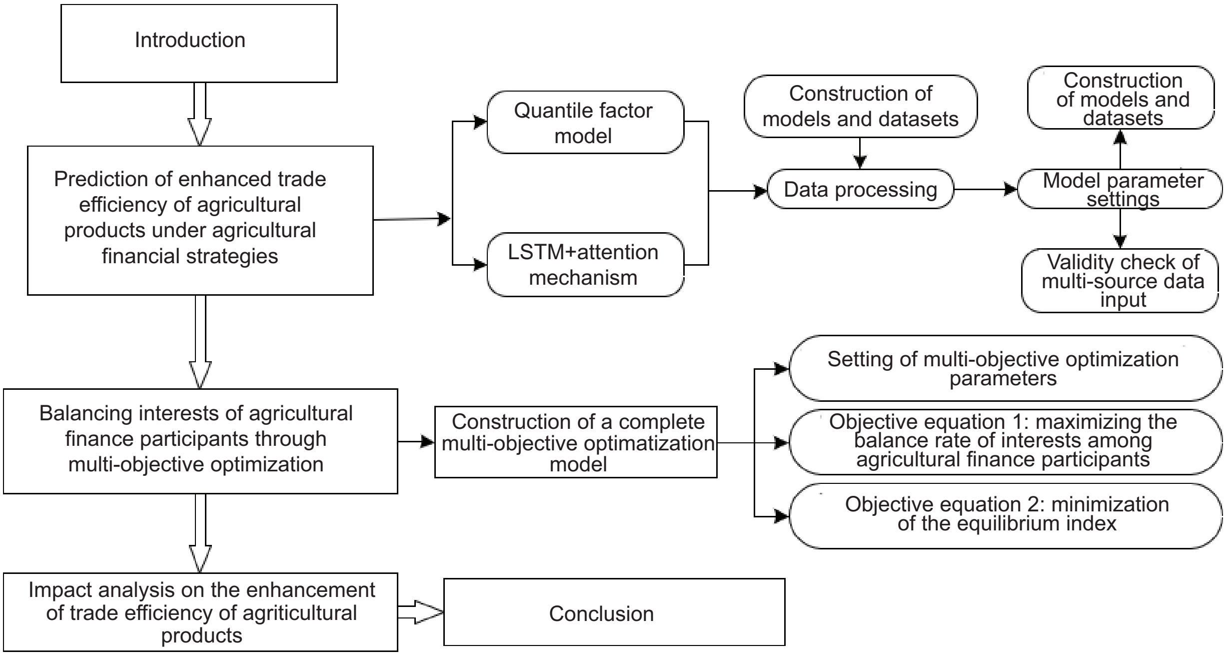

Figure 1. Technical trajectory of this study.

of and predicting shifts in trade efficiency under extreme market conditions. Such methodology provides a comprehensive foundation for the strategic formulation of agricultural financial strategies.

The observation matrix is typically composed of a series of data on variables collected at various time points. In the context of the quantile factor model developed for this research, it pertains to historical data on multiple indicators significant to the trade efficiency of agricultural products, encompassing aspects such as prices, trading volumes, and seasonal factors. Random common factors are indicative of unobserved variables influencing a multitude of observed variables. Within the framework of agricultural financial strategies, these elements represent market demand, policy shifts, and environmental changes, all exerting a wide-ranging influence on trade efficiency. Factor loadings, defined as the correlation coefficients between observed variables and their respective factors, illustrate the significance of each factor in the observed variables. With the observation matrix denoted by Z_{us}, for $u = 1, 2, ..., V$, and $s = 1, 2, ..., S$, $\pi \in (0,1)$, a random common factor vector of dimension $e(\pi)\times 1$ is represented by $d_s(\pi)$, and a factor loading vector of dimension $e(\pi)\times 1$ by $\eta_s(\pi)$, where $e(\pi) << V$, the following is deduced:

$$\mathrm{W}_{\mathrm{Z}_{\mathrm{us}}}[\pi \mid \mathrm{d}_{\mathrm{s}}(\pi)] = \eta_{\mathrm{u}}^{'}(\pi)\mathrm{d}_{\mathrm{s}}(\pi). \tag{1}$$

In the quantile factor model, the objective of minimization is directed toward diminishing the discrepancy between the model's forecasts and actual observations. This is achieved through the minimization of the objective function, thus:

$$L_{VS}(\varphi) = \frac{1}{VS}\sum_{u=1}^{V}\sum_{s=1}^{S}\vartheta_{\pi}(A_{us} - \eta_u' d_s), \tag{2}$$

$$\hat{\varphi} = \left(\hat{\eta}_1', \hat{\eta}_2', ..., \hat{\eta}_V', \hat{d}_1', \hat{d}_2', ..., \hat{d}_S'\right)' = \underset{\varphi \in \Phi^e}{\mathrm{ARGMIN}}\ L_{VS}(\varphi). \tag{3}$$

Agricultural product prices and trading volumes, subject to influences from seasonal variations, climate changes, and policy modifications, may exhibit distributions characterized by skewness or heavy tails. The conventional least squares regression proves insufficient for grasping this diversity, whereas quantile regression, by modeling at various quantile levels, unveils the comprehensive distribution traits of the data. The iterative quantile regression algorithm, through its iterative mechanism, enables a more stable and precise estimation of the quantile factor model's parameters, thereby uncovering the dynamic shifts in trade efficiency under divergent market conditions. Consequently, to manage adeptly the non-normal distributions and the effects of outliers, the iterative quantile regression algorithm is integrated into this study for the efficacious determination of the stationary points of the objective function. For the algorithm's depiction, consider:

$$\Lambda = (\eta_1, ..., \eta_V)', D = (d_1, ..., d_S)'. \tag{4}$$

The methodology employed in this study involves an iterative quantile regression algorithm, detailed as follows:

Step 1: In the initial phase, data pertinent to the trade efficiency of agricultural products, encompassing variables, such as prices, trading volumes, influences of seasonal factors, and climate variations, are aggregated. Preprocessing activities, including data cleansing and normalization, are conducted to assure the integrity of the data set. Subsequently, factors potentially affecting trade efficiency and the specific quantile levels aimed at capturing efficiency fluctuations under various extreme conditions are identified. Initial estimates for factor loadings and intercepts within the model are selected, drawing upon either prior knowledge or initialized as zero or random values. These initial parameters are represented by $D^{(0)}$.

Step 2: For the estimation process, the selected initial quantile level serves as the basis for determining factor loadings and intercept parameters through the application of quantile regression. This iterative process involves utilizing estimates from the preceding iteration as starting points for the subsequent quantile regression analyses at new levels, thereby refining parameter estimates. This procedure is exemplified as follows, with $D^{(m-1)}$ indicating the parameters from the previous iteration for $u = 1, 2, ..., V$:

$$\eta_u^{(m-1)} = \text{ARGMIN}_\eta L_{u,S}\left(\eta, D^{(m-1)}\right). \tag{5}$$

Given $X^{(m-1)}$, for $s = 1, 2, ..., S$:

$$d_s^{(m)} = \text{ARGMIN}_d L_{V,s}\left(\Lambda^{(m-1)}, d\right). \tag{6}$$

Step 3: The iterative sequence continues until either the variation in parameter estimates falls below a set convergence threshold or a maximum iteration count is reached, signifying the algorithm's termination. Specifically, Step 2 is iterated for $m = 1, 2, ..., M$ until $L_{VS}(\phi^{(M)})$ approximates $L_{VS}(\phi^{(M-1)})$.

Finally, the model's predictive performance across various quantile levels is assessed using the refined parameters. A normalization procedure is applied to $X^{(M)}$ and $D^{(M)}$, and the model's robustness is further validated via cross-validation and analysis of residuals.

Combined LSTM and attention mechanism model

In response to the imperative of enhancing agricultural product trade efficiency, this research introduces LSTM networks to analyze time series data inherent in agricultural markets, encompassing variables such as historical pricing, volume of trades, and seasonal influences. These variables, characterized by their temporal fluctuations and interdependencies, necessitate a modeling approach capable of capturing long-term dependencies and recognizing patterns within the time series data. Thus, the application of LSTM networks facilitates the examination of temporal dynamics and nonlinear characteristics prevalent in agricultural product data, thereby enabling a more precise prediction of the impact exerted by specific agricultural financial strategies on trade efficiency.

LSTM networks, with their distinct architecture comprising memory cells, input gates, forget gates, and output gates, address the challenges of gradient vanishing and explosion that traditional recurrent neural networks (RNNs) encounter. It is posited that the principal layer of LSTM, outputting as h_o, analyzes both current input a_o and preceding hidden state f_{o-1}. The memory cell h_o is tasked with retaining long-term state information, wherein the input gate, governed by i_o, adjudicates the inclusion of new information. Concurrently, the forget gate, under the aegis of g_o, determines the exclusion of obsolete information, and the output gate orchestrates the utilization of memory cell (h_o) information for output. With t_o throughout the networks, a new hidden state f_o is engendered. This architectural design empowers LSTM networks to preserve and access antecedent information across extended durations, an attribute pivotal for forecasting the efficiency of agricultural product trade as it evolves over time, influenced by a myriad of factors. The examination of historical data, such as price volatility, seasonal motifs, and shifts in financial policies, allows the LSTM model to uncover the intricate dynamic interrelations between these factors and trade efficiency. This, in turn, supports the development of more nuanced and efficacious agricultural financial strategies aimed at bolstering trade efficiency. The sigmoid function, denoted by ε, and the weights connecting each layer to the input vector a_o, represented by Q_{fi}, Q_{fg}, Q_{ft}, and Q_{fh}, alongside the weight matrices linking each layer to the antecedent hidden state f_{o-1}, symbolized by Q_{ai}, Q_{ag}, Q_{at}, and Q_{ah}, with bias vectors for each layer indicated by y_i, y_g, y_t, and y_h, underpin the computation of I_o, g_o, t_o, h_o, f_o, and d_o as delineated in the ensuing equations:

$$i_o = \varepsilon(Q_{ai}^T \cdot a_o + Q_{fi}^T \cdot f_{o-1} + y_i), \tag{7}$$

$$g_o = \varepsilon(Q_{ag}^T \cdot a_o + Q_{fg}^T \cdot f_{o-1} + y_g), \tag{8}$$

$$t_o = \varepsilon(Q_{at}^T \cdot a_o + Q_{ft}^T \cdot f_{o-1} + y_t), \tag{9}$$

$$h_o = \tanh(Q_{ah}^T \cdot a_o + Q_{fh}^T \cdot f_{o-1} + y_h), \tag{10}$$

$$z_0 = g_0 \cdot z_{0-1} + i_0 \cdot h_0, \tag{11}$$

$$f_0 = t_0 \cdot \tanh(z_0). \tag{12}$$

In the domain of agricultural product trade efficiency forecasting, the temporal dynamics inherent in the data plays a pivotal role in influencing prediction outcomes. Given the variable impact of time-stamped data points—such as recent meteorological events on crop yields and market prices—the integration of attention mechanisms within the LSTM networks is demonstrated to enhance significantly both precision and interpretability of forecasts. Through the employment of an attention mechanism, the model is endowed with the capability to discern and allocate enhanced focus to time segments deemed most pertinent to the objective at hand while maintaining a comprehensive perspective on the entire chronological dataset. This synthesis is paramount in navigating the inherent complexity and fluctuation characteristics of agricultural trade efficiency prognostications.

Initially, the attention mechanism engages in the computation of associations between the hidden state corresponding to each temporal juncture and the state pertinent to the current forecasting instance, facilitated by a trainable weight matrix. Within the ambit of agricultural financial strategy analysis, this translates to the model's appraisal of the influence exerted by historical data points on the current predictive juncture. This evaluative process culminates in the generation of a context vector, constituted by the weighted aggregate of historical hidden states, where the allocation of weights delineates the level of contribution from each state toward the predictive outcome,

$$e_{ij} = \tanh(Q_q \cdot f_{ij} + y_q). \tag{13}$$

Subsequent to this, normalization of weights across all temporal intervals is achieved through the application of the softmax function, ensuring that the summation of all weights attains unity. This normalization is instrumental in enabling the model to juxtapose the relative significance of differing time points, thereby facilitating the allocation of augmented attention toward intervals of heightened impact on future trade efficiency. The formula employed for the computation of normalized attention weights, denoted as x_{ij}, adheres to this principle,

$$x_{ij} = \frac{\exp(d_{ij})}{\sum_{l=1}^{T_a} \exp(d_{il})}. \tag{14}$$

The culmination of this process is observed in the application of these normalized weights to the outputs derived from the LSTM layer, materializing in a weighted hidden state vector that embodies critical historical insights, referred to as the weighted context vector. This vector serves as foundation for the formulation of final predictive outcome. In the context of agricultural financial strategy analysis, this mechanism ensures the model's focalization on periods of critical importance, thereby augmenting the accuracy of trade efficiency predictions,

$$r_i = \sum_{j=1}^{T_a} x_{ij} f_{ij}. \tag{15}$$

Interest alignment among stakeholders in the agricultural finance sector through multi-objective optimization

The exploration of interest alignment among stakeholders in the agricultural finance sector through multi-objective optimization is acknowledged as a subject of considerable scholarly significance. This methodological approach recognizes the existence of diverse actors within the agricultural finance ecosystem, encompassing farmers, financial institutions, investors, and policymakers, each harboring distinct, and occasionally divergent, objectives and requirements. Through the deployment of multi-objective optimization techniques, it is posited that advancements in agricultural product trade efficiency can be achieved concomitantly with the equitable balancing of stakeholder interests, thereby fostering a more resilient and sustainable agricultural finance market. The implications of such research extend beyond the promotion of agricultural sustainability and farmer welfare, encompassing the enhancement of risk management practices within financial institutions, the stimulation of investor engagement in agricultural finance, and the facilitation of more efficacious agricultural finance and support policies by policymakers.

To devise an exhaustive multi-objective optimization framework, establishment of certain parameters is imperative for the harmonization of interests among agricultural finance participants: (1) The assignment of an identification number to each financial strategy measure, encapsulating a broad array of financial strategies, including agricultural policies, loan offerings, insurance products, and derivative financial instruments, is denoted by u. (2) The enumeration of financial strategy measures to ensure the comprehensive representation of financial instruments ranging from traditional lending solutions to innovative financial mechanisms is represented by V. (3) The allocation of an identification number to financial service points, reflecting the diversity of financial institutions and alternative financial service providers, such as cooperative banks, microloan entities, and government-backed guarantee funds, is denoted by j. (4) The quantity of financial service points is articulated as l, denoting the extent of financial service network coverage across various administrative tiers, including national, regional, and township levels. (5) An identification number, represented by o, is allocated to each category of agricultural products, encompassing grain crops, cash crops, and livestock products. (6) The diversity of agricultural products available in the market is quantified by O. (7) The financial service delivery time matrix is denoted as SL. (8) The priority matrix of financial strategy implementation, represented by L, is utilized to sequence financial strategies, such as prioritizing short-term working capital loans over long-term equipment investment loans. (9) The set of strategy measures available at the jth financial service point, Tj, enumerates financial products and services offered. (10) The financing demand for the oth type of agricultural product, f_o, is predicted based on market demand and agricultural production cycles. (11) The total financing demand for all agricultural products, F, aggregates the financing requirements across the whole market or specific region, with $\Sigma^{o}_{o=1}f_o = F$. (12) The financing demand ratio for the oth type of agricultural product, w_o, elucidates the proportionate demand for financing across different agricultural products, with $w_o = f_o/F$. (13) The financial strategy allocation decision variable, a_{uj}, delineates the allocation of financial resources among various agricultural products and producers. (14) The execution time of the uth financing strategy for the oth agricultural product, s_{uo}, measures the duration from application to disbursement for each financing strategy. (15) The processing time for the oth agricultural product at the jth financial service point, s_{oj}, with $s_{oj} = \Sigma^{V}_{s=1}s_{so}\times a_{uj}$. (16) The service time at the jth financial service point, s_j, aggregates the time required to process all agricultural product financing needs. (17) The theoretical financing cycle, Z_s, computes the minimum time necessary for the agricultural product financing process, with $Zs = \Sigma^{l}_{j=1}\Sigma^{o}_{o=1}s_{oj}\times w/l$. (18) The actual financing cycle, Z_e, captures the duration from financing application to disbursement in real-world operations, with $Z_e = MAX\Sigma^{o}_{o=1}w\times s_{oj}$ (19). The smoothness index (SI) of the financial service process, TU, quantifies variability in the financial service process, reflecting the stability of agricultural finance market, with $TU = \sqrt{\Sigma^{l}_{j}(Zs\text{-}\Sigma^{o}_{o=1}w_o\Sigma^{V}_{V=1}s_{oj}\times a_{uj})^2}$.

Within the ambit of this research, the multi-objective optimization problem concerning the alignment of interests among participants in agricultural finance is scrutinized. Central to this examination is the concept of balance rate, delineated as the ratio of the benefits accrued to stakeholders, encompassing agricultural producers, financial service providers, and consumers engaged in the trade of agricultural products and financial services, to their anticipated benefits. The objective of maximizing the balance rate is predicated on the convergence of actual benefits to those anticipated by all stakeholders. The formulation of objective equation necessitates a comprehensive consideration of the interests and priorities of each party; for instance, agricultural producers prioritize financing costs and market prices, financial service providers emphasize loan recovery rates and risk management, and consumers focus on price and product quality. Objective equation 1 is thus established with the aim of maximizing the balance rate of interests among participants in agricultural finance,

$$MIN\ Ze = MAX\sum_{o=1}^{o} w_o \times s_{oj}. \tag{16}$$

Further refining the multi-objective optimization problem, the equilibrium index is introduced, signifying the extent to which the distribution of interests among participants in the agricultural finance market is equitable. An optimal scenario is reflected by a lower equilibrium index, indicating a more balanced interest distribution within the market. This index typically assesses variability in interest distribution, including income disparities and discrepancies in financing accessibility. Objective equation 2 is constructed with the goal of minimizing the equilibrium index, thereby fostering a more equitable distribution of benefits,

$$MIN\ TU = \sqrt{\sum_{j=1}^{l}\left(Ze - \sum_{o=1}^{o} w_o \sum\nolimits_{s=1}^{V} s_{uo}\times a_{uj}\right)^2}. \tag{17}$$

In the practical realm of research, a potential conflict between these objectives is acknowledged; improvements in the interests of one party may inadvertently diminish those of another, thereby influencing the equilibrium index. To reconcile these objectives, integration of the two objective equations is facilitated through the application of scale transformation coefficients, denoted respectively by ω_1 and ω_2, culminating in a unified multi-objective equation,

$$MIN\ Pyk = \omega_1 Ze + \omega_2 TU. \tag{18}$$

Specifically, the model is as follows:

$$\begin{aligned} MIN\ Pyk = \omega_1 MAX\sum_{o-1}^{o} w_o \times s_{oj} \\ +\omega_2\sqrt{\sum_{j-1}^{l}\left(Zs - \sum_{o-1}^{o} w_o \sum\nolimits_{u=1}^{V} s_{uo}\times a_{uj}\right)^2}. \end{aligned} \tag{19}$$

In the proposed model, financial products and services, encompassing loans and insurance, are meticulously designed to cater to distinct agricultural projects or customer groups. It is imperative that the allocation of financial resources maintains exclusivity, thereby precluding the possibility of overlapping resources and augmenting the precision and efficacy of financial service provision. Furthermore, the deployment of financial services is governed by pre-established priorities, potentially influenced by factors, such as the immediacy of project requirements, risk evaluations, and anticipated returns. Consequently, projects characterized by higher expected returns or more effective risk mitigation strategies may be accorded precedence in funding allocation. Additionally, the execution of each financial service is constrained by specific timeframes, ensuring the operational efficiency of financial supply chain. This encompasses deadlines for loan approval, processing durations for insurance claims, and market introduction timelines for diverse financial products. The delineation of specific constraints within the multi-objective optimization model tailored to agricultural finance is as follows:

$$s.t. \sum_{j=1}^{l} a_{uj} = 1 \quad u = \left(1, 2, 3, \ldots, V\right), \tag{20}$$

$$\sum_{j=1}^{l} ja_{xj} - \sum_{j=1}^{l} ja_{yj} \leq 0 \quad x \in \left(1, 2, 3, \ldots, V\right), y \in E_x, \tag{21}$$

$$\sum_{o=1}^{o} w_o s_{oj} \leq Z \quad j = (1, 2, 3, \ldots, l). \tag{22}$$

Equation (20) delineates the exclusivity constraint for financial resources, ensuring that each form of financial support or product is directed solely toward a particular category of agricultural producers or consumer groups. This constraint is instrumental in mitigating resource dispersion and enhancing the specificity and impact of financial services. Equation (21) elucidates priority constraint for financial services, establishing a matrix to steer the distribution of financial resources. This matrix is informed by an array of considerations, including project risk assessments, potential impacts, and contributions. Equation (22) sets forth the timeframe constraint for financial services, stipulating deadlines encompassing the maximum allowable periods for credit approval, fund disbursement, and processing of insurance claims. This necessitates the optimization of internal processes by financial institutions to guarantee prompt and effective service delivery. Figure 2 presents the model's solution flowchart, utilizing a multi-population genetic algorithm.

Experimental Results and Analysis

In Table 1, the chosen variables for evaluating the efficiency of agricultural product trade are presented, reflecting a multidimensional framework that encompasses trade costs, time efficiency, market accessibility, trade volume and value, trade balance, supply chain efficiency, the degree of trade facilitation, and the trade policy environment. The evaluation of trade costs encompasses the financial expenditures across the supply chain, including logistics and transaction costs. Time efficiency is assessed through the duration required for exporting products to their final sale and transportation to the market. Market accessibility is gauged by penetration and competitiveness of international market, as indicated by market diversity and market share. The scale and value of trade are directly mirrored in the trade volume and value indicators. The trade balance is scrutinized through cumulative exports and the trade surplus or deficit, offering insights into the profit and loss dynamics of trade activities. Supply chain efficiency is examined by evaluating inventory turnover rates and order fulfillment rates, while trade facilitation measures the simplification of trade process and the adoption of e-commerce platforms. The trade policy environment is analyzed in terms of trade openness and the efficacy of facilitation measures from a policy standpoint. This analytical framework offers a comprehensive evaluation of agricultural product trade efficiency from multiple perspectives, identifying key drivers of trade efficiency and providing quantitative support for the development of related agricultural financial strategies. The integration of quantile factor models with LSTM networks and attention mechanisms enhances the precision of predictions for agricultural product's trade efficiency, thereby furnishing more effective decision support for stakeholders.

Data presented in Figure 3 elucidates the impact of agricultural finance strategies on trade efficiency across various lags within the financing cycle, encompassing 1 lag, 5 lags, and 10 lags. It is observed through the response curve that the impact of these strategies on agricultural product trade efficiency exhibits fluctuations with the prolongation of financing cycle, indicating the differential impact of agricultural finance strategies over time. At 1-lag interval, an increase in response values is predominantly observed, with a notable augmentation as the financing cycle nears 1,500, signifying a pronounced enhancement in trade efficiency attributable to agricultural finance strategies in the short term. Conversely, at 5 lags and 10 lags, a diminution in response values is recorded, with negative responses emerging at specific intervals, suggesting that the initial beneficial effects of financial strategies may diminish over time, or adjustments in strategies might be a requisite at certain junctures of financing cycle. Particularly at 10 lags, the emergence of negative values alongside a reduction in positive response values intimates the necessity for a reevaluation and recalibration of some financial strategies to perpetuate a beneficial influence on trade

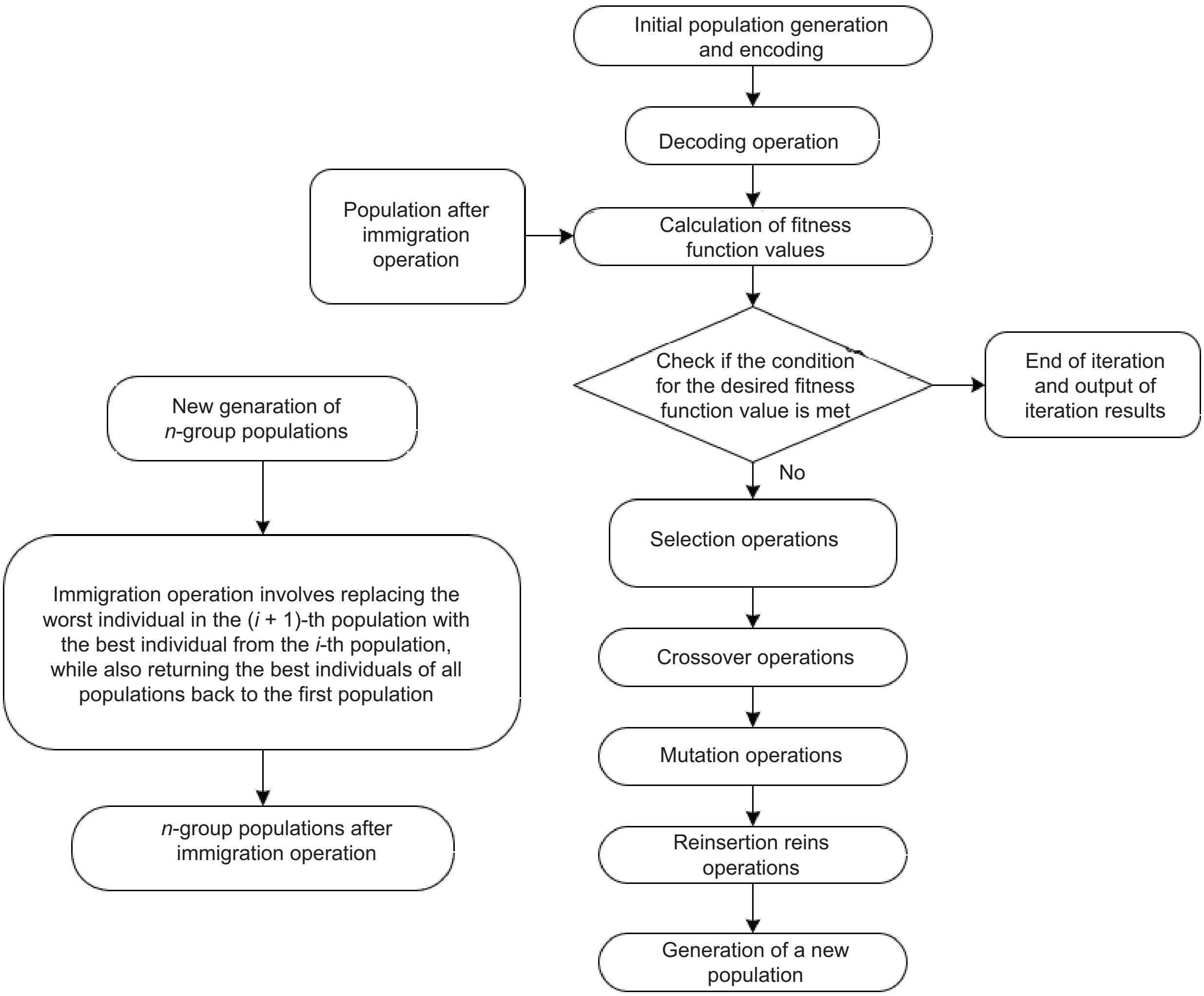

Figure 2. Model solution flowchart based on a multi-population genetic algorithm.

efficiency over extended periods. The analysis substantiates that while agricultural finance strategies exert an initial positive effect on enhancing agricultural product trade efficiency, the complexity of their impact escalates over time, mandating regular scrutiny and adjustment. The forecasting approach expounded in this study, amalgamating the quantile factor model with LSTM networks and attention mechanisms, is proven as efficacious in navigating this complexity. This methodology exhibits proficiency in capturing both short- and long-term dynamism, including potential nonlinear interactions, thus yielding more precise predictions.

The experimental findings delineated within this research are encapsulated in a correlation chart, elucidating the relationships between agricultural product trade efficiency (denoted as M9) and a suite of eight indicator variables (M1–M8). These variables span trade costs, time efficiency, market accessibility, trade volume and value, trade balance, supply chain efficiency, the degree of trade facilitation, and the trade policy environment. It has been discerned through analysis that agricultural product trade efficiency correlates positively and significantly with time efficiency, market accessibility, and trade volume and value. Conversely, more tenuous correlations were observed with trade balance, supply chain efficiency, the degree of trade facilitation, and the trade policy environment. Notably, trade costs exhibited a correlation of moderate strength at a significance level of 0.05, surpassing that of trade balance, supply chain efficiency, the degree of trade facilitation, and the trade policy environment, yet not reaching the magnitude of correlation observed with time efficiency, market accessibility, and trade volume and value. From these observations, it is inferred that the efficiency of agricultural product trade is contingent upon a multitude of factors, with time efficiency, market accessibility, and trade volume and value emerging as paramount. An amalgamated enhancement of these facets could markedly elevate the efficiency of agricultural product trade. While trade costs are acknowledged as a pivotal

Table 1. Experimental results of agricultural trade efficiency indicator variables.

No.	Category	Variable name	Explanation of variable
M1	Trade costs	Logistics costs	Including costs associated with transportation, warehousing, loading and unloading, packaging, and distribution
		Transaction costs	Including costs related to contract execution, payment and settlement as well as the acquisition of market information
M2	Time efficiency	Goods sale time	Measurement of the time required from product export to final sale
		Transportation time	Time required to transport goods from the place of origin to the final market
M3	Market accessibility	Market diversity	Assessment of the number of destination countries for agricultural product exports or source countries for imports
		Market share	Share of agricultural products in the global market or a specific target market
M4	Trade volume and value	Export and import volume	Measurement of the physical scale of trade
		Export and import value	Total value of trade, priced in currency
M5	Trade balance	Cumulative exports	Total value of export trade
		Trade surplus or deficit	Difference in value between exports and imports
M6	Supply chain efficiency	Inventory turnover rate	Measurement of inventory management efficiency
		Order fulfillment rate	Ratio of successfully completed orders to the total number of orders
M7	Degree of trade facilitation	Implementation of single window for cross-border trade	Measurement of the simplification of trade process
		Usage level of e-commerce platforms	Measurement of the prevalence of digital trade
M8	Trade policy environment	Trade liberalization index	Reflection of the openness of a country or region's trade policies
		Execution strength of trade facilitation measures	Including simplified customs procedures, implementation of trade agreements, etc.

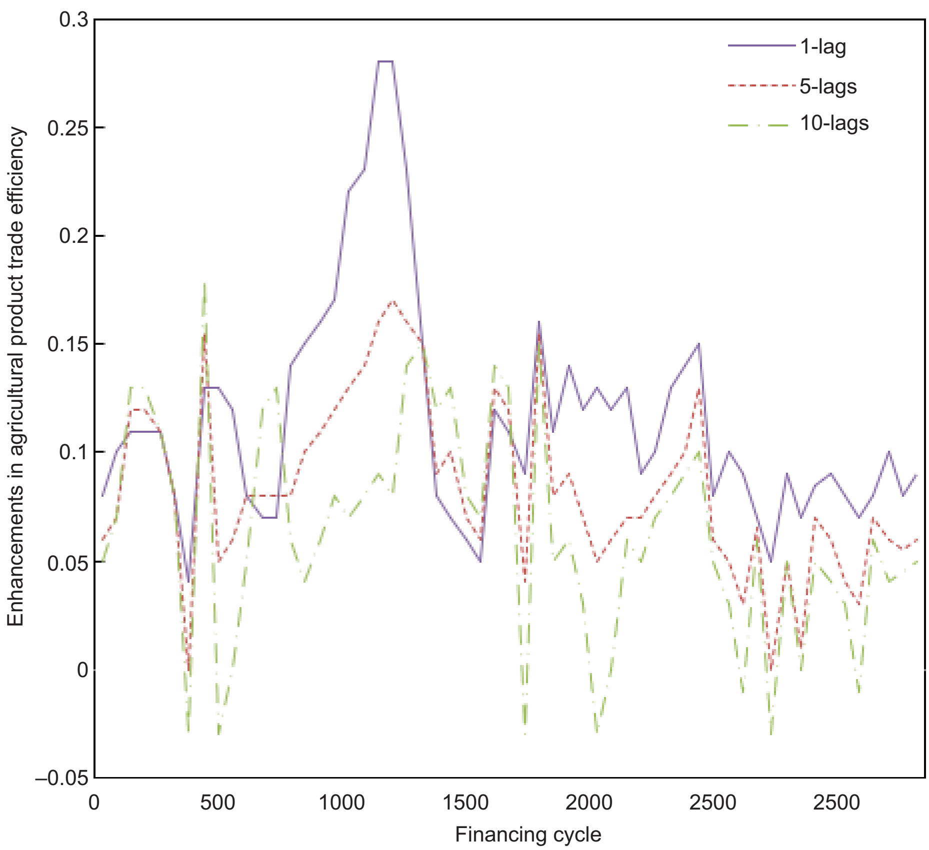

Figure 3. Response curve of agricultural finance strategies to enhancements in agricultural product trade efficiency.

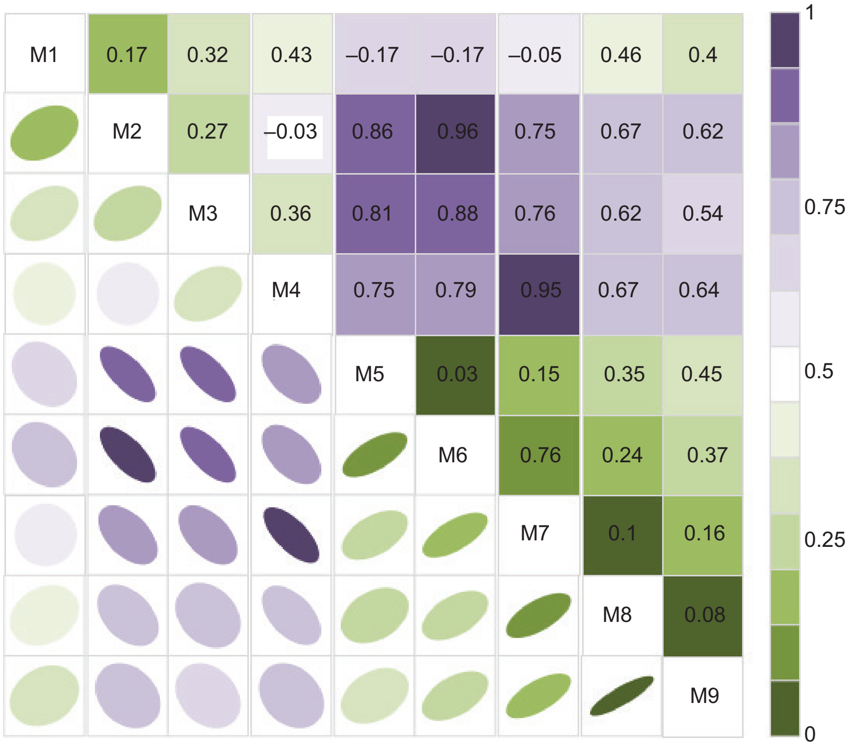

Figure 4. Correlation chart between agricultural product trade efficiency and efficiency indicator variables.

element, their influence on efficiency amplification is comparatively less pronounced than that of the aforementioned factors. Such insights are invaluable for the formulation and refinement of agricultural product trade strategies, providing policymakers, trade organizations, and agricultural enterprises with empirical evidence to inform more efficacious measures aimed at augmenting the overall efficiency of agricultural product trade.

Within the scope of this study, 18 agricultural finance strategies, denoted as CL1–CL18, were examined, encompassing a diverse range of financial instruments and models. These include microcredit services, agricultural loan guarantee programs, value chain financing, cooperative credit systems, agricultural insurance products, land banking systems, producer payment mechanisms, agricultural trust funds, agricultural development banks, public–private partnership (PPP) financing models, agricultural credit cooperatives, government subsidy programs, crowd-funding and crowd-sourcing, agricultural futures and options markets, agricultural venture capital investment, income share agreements (ISA), non-traditional collateral financing, and agricultural leasing services.

The analysis presented in Figure 5 outlines the trends of significantly positive correlated indicators, transportation time, market diversity, cumulative exports, and inventory turnover rate across the aforementioned financial strategies. It was observed that these indicators consistently exhibit positive trends, suggesting a homogenous impact of financial strategies on the aspects of agricultural supply chain and market performance. Notably, these strategies collectively appear to exert a beneficial influence on the agricultural sector, enhancing supply chain management, market expansion, export support, and inventory management. Such improvements are pivotal for the robust development of agricultural financial ecosystem. Further, a complementary effect among the diverse financial strategies was identified, with each contributing to advancements in key performance indicators. This synergy among financial strategies underscores their collective capacity to bolster the efficiency of agricultural supply chain, expand market diversity, enhance export capabilities, and optimize inventory management. The data compiled in Table 2 compare experimental results under various scale transformation coefficients across a spectrum of financial service points. This comparison elucidates the nuanced effects of different financial strategies on the balance rate and SI across multiple scenarios, reinforcing the notion that a comprehensive application of various financial tools and strategies can significantly improve agricultural production and trade efficiency from multiple dimensions.

Table 2 elucidates the interplay between the proliferation of financial service points and both balance rate and SI under varied scale transformation coefficient scenarios.

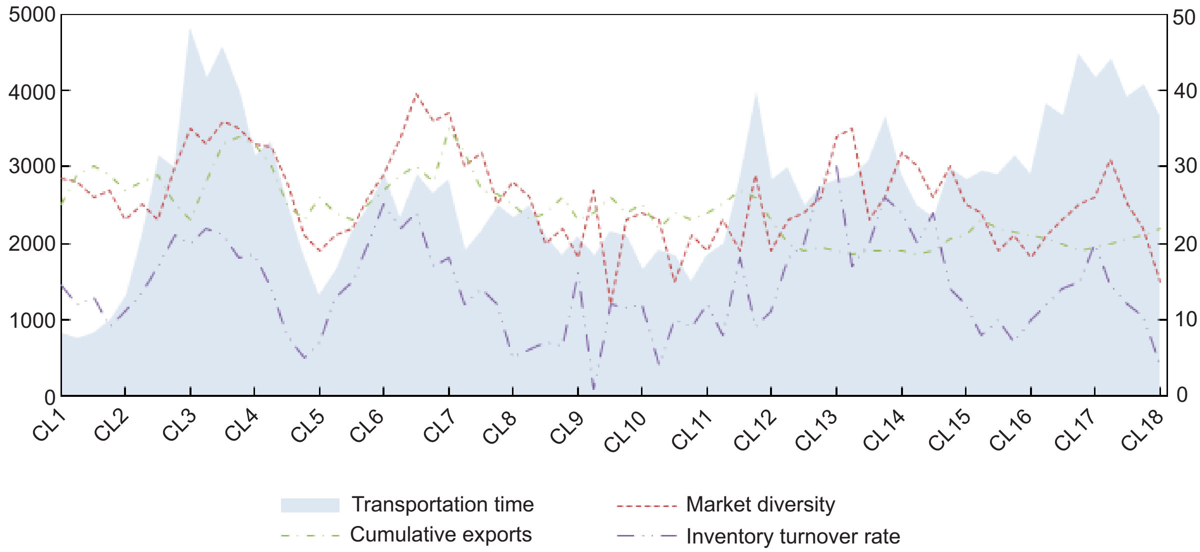

Figure 5. Trends of significantly positive correlated indicators under different agricultural finance strategies.

The balance rate is indicative of the equilibrium of interests among participants in agricultural finance whereas the SI potentially signifies the equity or efficacy of the distribution mechanism. Upon examination of the balance rate, it is discerned that, notwithstanding the fluctuations observed with the augmentation of service points, the rate predominantly sustains a high level across all scale transformation coefficient configurations, oscillating between a nadir of 82.36% and an apex of 97.89%. This pattern underscores the capability of an increased count of service points to either preserve or augment the balance of interests irrespective of the alterations in scale transformation coefficients. In terms of the SI, divergent fluctuation trends are observed with escalation in the number of service points under distinct scale transformation coefficient settings. For instance, with a coefficient setting of (0.4, 0.6), the SI escalates from 2.65 to 11.23 prior to diminishing at 9.25. This trajectory suggests that initial increment in service points may lead to an augmentation in the disparity of distribution process, which diminishes subsequently. Conversely, with coefficients (0.6, 0.4) and (0.3, 0.7), the SI demonstrates more tempered fluctuations, hinting at a more streamlined distribution process. The empirical findings reveal that, under varying scale transformation coefficients, augmentation in the number of service points consistently secures a high balance rate, corroborating the model's adeptness in harmonizing interests among agricultural finance participants under diverse conditions. The influence exerted by different scale transformation coefficients on the balance rate and SI is variable. Notably, under (0.3, 0.7) configuration, the balance rate and SI exhibit minimal fluctuations, intimating that the model under this coefficient amalgamation may manifest enhanced stability and effectiveness. The multi-objective optimization model articulated in this study is validated both theoretically and empirically as an efficacious decision support mechanism for the equitable distribution of interests among stakeholders in agricultural finance through the quantification of balance rate and SI. This model is proficient in assessing the ramifications of an expanded array of financial service points and the implications of diverse scale transformation coefficients, thereby providing a robust framework for the optimization of agricultural finance strategies.

The impact of multi-objective optimization on the response time of financial service points to agricultural product market volatility was meticulously analyzed by comparing pre- and post-optimization data, with response time serving as a metric for the agility of these points in adapting to market shifts. Shorter response periods are indicative of heightened market efficiency and enhanced service capability. The data illustrated in Figure 6 reveal a marked improvement in response period across most sites following optimization. Specifically, an exemplary enhancement was observed at the sixth site, where response period escalated from 50 prior to optimization to 172 after optimization, underscoring a significant uplift in response efficiency attributable to the optimization process. Across all 22 evaluated sites, post-optimization response period was found to either exceed or match their pre-optimization counterparts, signifying a universal enhancement in the capacity of financial service points to contend with market volatility subsequent to the application of the multi-objective optimization model. Additionally, the optimization endeavor yielded a more homogeneous distribution of response period. Prior to optimization, response period displayed substantial variability, which was conspicuously narrowed down following optimization, with

Table 2. Comparison of experimental results under different scale transformation coefficients.

Number of financial service points	(0.4, 0.6)		(0.6, 0.4)		(0.3, 0.7)	
	Balance rate (%)	SI	Balance rate (%)	SI	Balance rate (%)	SI
7	97.23	2.65			97.89	1.23
8	97.15	3.68			97.25	1.32
9	96.68	5.12			96.32	2.78
10	94.52	6.78			94.52	2.56
11	91.23	11.23	91.26	3.78	94.68	2.61
12	95.68	7.56	95.68	3.26	95.23	2.78
13	82.36	9.23	91.54	5.24	91.25	4.32
14	91.89	9.25	91.23	5.78	91.32	4.56

SI: smoothness index.

response period ranging between 142 and 172. This diminution in variability signifies a transition to a more stable system, endowed with the consistency required for effective management of market volatility. Consequently, it can be deduced that the multi-objective optimization model delineated in this study substantially elevates the responsiveness of financial service points to fluctuations in the agricultural product market, thereby attesting to the model's efficacy in refining the adaptability of service points to changes in market conditions. The optimization not only elevated the general level of response period but also mitigated fluctuations therein, contributing to a more equitable distribution of interests among participants in agricultural finance and augmenting the stability and efficiency of the overarching system.

Table 3 presents the in-sample regression analysis evaluating the impact of multi-objective optimized agricultural financial strategies on the enhancement of agricultural product trade efficiency. The regression coefficients for variables across Equations (1) and (2) are uniformly positive and exhibit statistical significance at 1% level, indicating a constructive influence on trade efficiency across all models. Similarly, coefficients within the multi-objective equation manifest as positive and significant, underscoring the efficacy of multi-objective optimization strategies in bolstering trade efficiency. Notably, *Lev* in the M2 model is discerned as negative and significantly influential, suggesting that an escalation in leverage may adversely affect trade efficiency. Conversely, *Attn* in the M3 model is observed as positive, albeit not statistically significant (t-value = 0.689), yet attains significance in the M8 model (t-value = 7.68), implying a beneficial impact of policy attention on trade efficiency. The Agricultural Production Index (API) demonstrates a robust positive correlation with trade efficiency across all models,

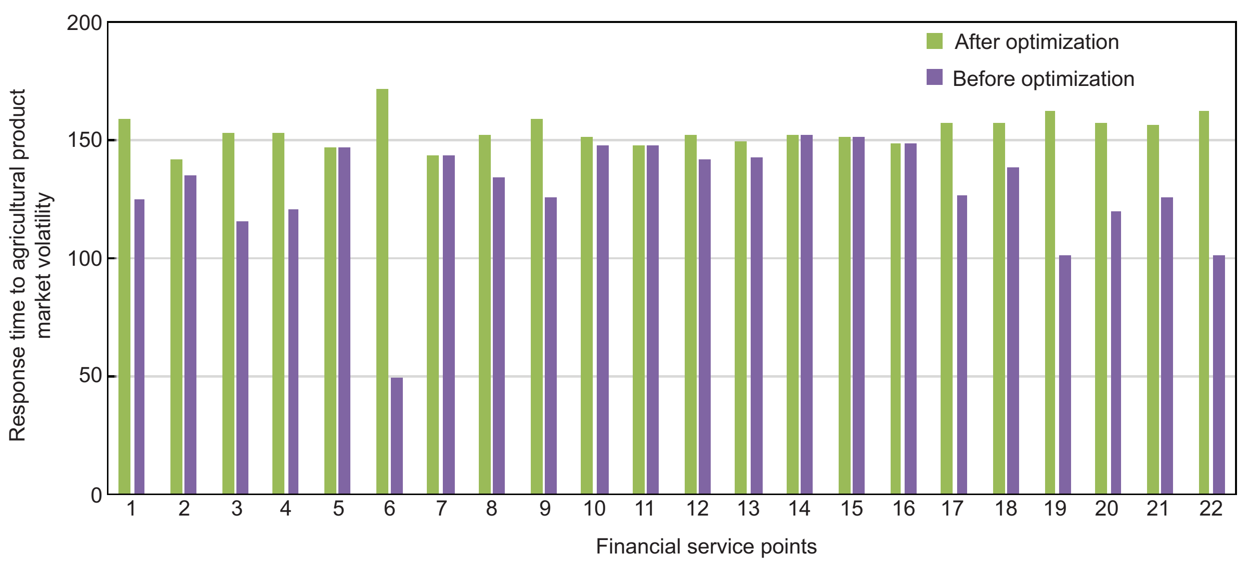

Figure 6. Response time of agricultural product market volatility prior to and after multi-objective optimization.

Table 3. In-sample regression of agricultural product trade efficiency improvement under multi-objective optimized agricultural financial strategies.

Variables	M1	M2	M3	M4
Equation (1)	0.265***	0.265***	0.189***	0.259***
	(11.23)	(11.24)	(8.57)	(11.75)
Equation (2)	0.478***	0.468***	0.475***	0.439***
	(13.21)	(12.58)	(13.69)	(12.14)
Multi-objective equation	0.154***	0.152***	0.131***	0.081***
	(4.62)	(4.68)	(4.32)	(2.36)
J		–0.077		
		(–0.98)		
Lev			–0.825***	
			(–22.36)	
Attn (×10^{-3})				0.534***
				(0.689)
API (×10^{-3})				
Constant	0.124***	0.118***	–0.127***	–0.321***
	(2.81)	(2.78)	(–2.98)	(–4.31)
Observations	2.659	2.659	2.659	2.659
Adj_R^2	0.523	0.234	0.548	0.536
Variable	*M5*	*M6*	*M7*	*M8*
Equation (1)	0.231***	0.231***	0.178***	0.214***
	(10.25)	(10.57)	(10.23)	(8.54)
Equation (2)	0.387***	0.369***	0.415***	0.336***
	(11.23)	(11.23)	(12.34)	(11.14)
Multi-objective equation	0.189***	0.195***	0.168***	0.132***
	(6.47)	(6.39)	(5.78)	(3.88)
J		–0.028		
		(–0.38)		
Lev			–0.623***	
			(–15.89)	
Attn (×10^{-3})				0.587***
				(7.68)
API (×10^{-3})	6.235***	6.235***	4.589***	6.235**
	(21.36)	(21.58)	(16.54)	(21.47)
Constant	–0.124***	–0.123***	–0.224***	–0.567***
	(–3.26)	(–3.26)	(–6.14)	(–8.32)
Observations	2.659	2.659	2.659	2.659
Adj_R^2	0.589	0.598	0.623	0.618

API: Agricultural Production Index. Significance at *10%, **5%, and ***1% levels.

particularly pronounced in M4–M7 models, indicating that advancements in API markedly elevate trade efficiency. The disparity in adjusted R^2 values (*Adj_R*^{2}) across models indicates varying degrees of explanatory power, yet remains notably high in M6–M8 models, affirming substantial explanatory capacity. Thus, it is concluded that the multi-objective optimization model elucidated within this research significantly enhances agricultural product trade efficiency. The predominantly positive influence of the examined variables on trade efficiency reveals that the application of multi-objective optimization strategies can substantially improve trade efficiency while ensuring equitable interest distribution among participants in agricultural finance. Variations in the significance and magnitude of coefficients across different models further illuminate the differential impacts of various strategies and market conditions on augmentation of efficiency. These insights underscore the critical and pragmatic value of multi-objective optimization in the formulation and execution of agricultural financial strategies.

Table 4 elucidates the economic significance of out-of-sample predictions concerning the enhancement of agricultural product trade efficiency, employing the Sharpe ratio (SR) and cumulative earnings ratio (CER) across various financing cycles (200, 400, and 600) for five distinct indicators. It was discerned that indicators M3 and M5 consistently manifest superior SR across all financing cycles, suggesting an enhanced capability to improve agricultural product trade efficiency under identical financial strategies when contrasted with other indicators. Conversely, indicator M4 consistently exhibits the lowest SR, indicating inferior performance relative to its counterparts. Furthermore, the CER yielded positive outcomes for indicators M1–M3 and M5, signifying a favorable enhancement in agricultural product trade efficiency subsequent to the deployment of agricultural financial strategies. Notably, at financing cycles of 400 and 600 and indicator M5 demonstrated the highest CER, suggesting its superior efficacy in augmenting agricultural product trade efficiency over extended financing cycles. An ascending trend in both SR and CER was observed as the financing cycle progressed from 200 to 600, intimating that prolonged financing cycles might play a pivotal role in bolstering agricultural product trade efficiency and furnishing investors with enhanced risk-adjusted returns. Therefore, it is inferred from analysis that the multi-objective optimization model developed within this research exhibits practical effectiveness. These models are capable of delivering relatively greater improvements in agricultural product trade efficiency across diverse financing cycles.

Table 4. Economic significance of out-of-sample predictions for agricultural product trade efficiency improvement.

		SR	CER
Financing cycle of 200	M1	0.0214	1.8745
	M2	0.0198	1.1235
	M3	0.0235	2.0078
	M4	0.0078	–3.4125
	M5	0.0214	2.3658
Financing cycle of 400	M1	0.0235	2.8951
	M2	0.0256	3.3625
	M3	0.0238	2.3548
	M4	0.0127	–1.5548
	M5	0.0256	3.5628
Financing cycle of 600	M1	0.0235	2.5684
	M2	0.0254	2.8951
	M3	0.0236	2.1245
	M4	0.0128	–2.4515
	M5	0.0256	3.2568

SR: Sharpe ratio; CER: cumulative earnings ratio.

Conclusion

This study innovatively enhanced the identification and predictive ability of factors influencing the efficiency of agricultural trade through the development of an integrated forecasting model that combined quantile factor models, LSTM networks, and attention mechanisms. The model specifically emphasized the importance of key variables, providing a deep understanding of the impact of agricultural financial strategies on the efficiency of agricultural trade. At the same time, by constructing a novel multi-objective optimization model, this paper offered a practical quantitative analysis framework for the issue of equitable distribution of interests among participants in agricultural finance to support more fair and effective strategy formulation.

The experimental section elaborately revealed the relationship between agricultural trade efficiency and agricultural financial strategies through various indicators and analysis methods, such as agricultural trade efficiency indicator variables and correlation coefficient charts, trends of indicators under different agricultural financial strategies, and comparison of market volatility response period prior to and after multi-objective optimization, fully demonstrating the practical application value and decision-support capability of the proposed model. Moreover, the effectiveness and economic significance of the model were verified through in-sample regression and out-of-sample forecasting (e.g., SR and utility gain analysis), further confirming the practicality of the model in enhancing the efficiency of agricultural trade.

In the discussion section, the paper strengthened the discussion on the in-depth analysis of research results, emphasizing the significant contribution of the proposed model in optimizing agricultural financial strategies and enhancing the efficiency of agricultural trade. It also discussed the challenges and limitations that the model could face in practical applications, proposing future research directions, including further optimization of the model, consideration of more influencing factors, and the possibility of extending to other fields. In summary, this study not only provided precise predictive tools and decision support for agricultural financial strategies but also offered theoretical and empirical foundations for related policy formulation and implementation, which was of great significance for promoting the efficient development of agricultural trade.

Conflict of Interest

The author declared no conflict of interest.

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