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Deep Learning–Based Multi-Objective Financial Risk Minimization in Smart Supply Chain Finance

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Abstract

This study presents a novel deep learning–based multi-objective optimization framework for minimizing financial risks in smart supply chain finance. The proposed model integrates deep neural networks for dynamic credit risk prediction with evolutionary optimization algorithms such as NSGA-II to simultaneously minimize risk exposure, reduce capital costs, and enhance liquidity stability. Using synthetic and real financial data, the framework captures complex nonlinear patterns in supply chain interactions and translates them into adaptive decision-making strategies. Comparative analysis against baseline models demonstrates superior predictive accuracy, broader Pareto front coverage, and higher robustness under market fluctuations. Sensitivity analysis further confirms the model's resilience to changes in key financial parameters such as interest rates, credit limits, and payment delays. The results highlight the potential of combining deep learning and multi-objective optimization to enable data-driven, risk-aware, and sustainable financial decision-making in digital supply chains.

Keywords: Smart supply chain finance, deep learning, multi-objective optimization, financial risk minimization, liquidity stability

1- Introduction

In the current era, developments in information and communication technology, especially in the areas of "machine learning" and "deep learning", have provided unprecedented opportunities for improving financial decision-making. One of the application areas of these developments is a field called Supply Chain Finance (SCF); a process that encompasses the flow of goods, information, and funds in the form of an integrated ecosystem (Cui, 2020; Roudaki et al., 2025). Within this process, numerous experiences of the inability of small and medium-sized enterprises (SMEs) to secure liquidity, information challenges among stakeholders, and widespread financial risks have led researchers to emphasize the need to move towards a

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broader and more technological concept called Smart Supply Chain Finance (SSCF). In SSCF, technologies such as big data, blockchain, IoT, and AI are deployed as an intelligent platform to not only optimize the financing process, but also manage financial and credit risks in the supply chain in a predictable and controlled manner (Mehrani et al., 2019; Song, 2022; Nozari et al., 2023).

However, despite the rapid growth of this field, several fundamental research gaps remain. First, traditional models often rely on historical trends and static estimates, and have little capacity to dynamically respond to market fluctuations; while today's supply chain environments feature real-time changes, complex relationships, and interactions among multiple actors. Second, although AI and deep learning have been applied in various financial domains, the use of these technologies in a multi-objective optimization framework to simultaneously reduce credit risk, financing cost, and liquidity volatility in SSCF has not been well developed. In other words, an integrated framework that links intelligent risk forecasting to optimal capital allocation decision-making is rare. Third, existing research on the sensitivity and robustness analysis of such models in the face of fluctuations in key economic-financial parameters is still not extensive enough.

Consequently, this study aims to design and evaluate a deep learning-based framework for financial risk forecasting and multi-objective optimization of smart supply chain financing decisions. The four main objectives of this study are: (1) extracting patterns hidden in supply chain financing data by deep neural networks, (2) developing a multi-objective optimization model to simultaneously reduce credit risk, cost of capital, and increase liquidity stability, (3) evaluating the performance of the proposed framework compared to conventional baseline models, and (4) examining the sensitivity and robustness of the model in different economic scenarios. Thus, the present study attempts to build a strong bridge between the two primary domains of "forecasting" and "optimization"; So that the output based on intelligent data can be directly fed into the multi-objective decision-making process, making decisions data-driven, flexible and resilient.

From a practical perspective, the results of this study can help financial institutions, supplier companies and large buyers to optimally adjust their capital, credit and cash flow allocations by considering real-time risk patterns. From a theoretical perspective, the present research also shows that the instructive integration of deep neural networks with multi-objective optimization algorithms can be a new step towards creating a "financial digital copy" or Digital Twin of the supply chain, which is able to predict risk in real time, optimize decisions and control liquidity.

In summary, given the complexities and extensive risks of supply chains in fast-paced and uncertain economic environments, this research presents a novel framework that can pave the way for the next generation of smart finance and provide a practical solution to reduce risk, reduce costs, and increase liquidity in supply networks.

2- Literature review

In the last decade, Supply Chain Finance (SCF) has received widespread attention as a key tool for improving corporate liquidity and reducing financing costs. The concept creates a mechanism to manage the flow of funds, goods, and information between buyers, suppliers, and financial institutions in a synchronous and coordinated manner (Cui, 2020; Pan et al. 2023). In the traditional SCF structure, the focus is on transaction efficiency and accounts receivable management, but with the growth of digital technologies, the field has moved towards "Smart Supply Chain Finance" (SSCF), in which big data, IoT, and artificial intelligence technologies play a central role (Song, 2022).

Recent research has shown that the use of artificial intelligence (AI) in SCF processes improves the accuracy of credit risk assessment, increases decision-making speed, and reduces uncertainty in the allocation of financial resources (Ronchini et al., 2024). These technologies enable predictive analytics to extract hidden patterns in financial and operational data. However, most existing studies still rely on historical data analysis and do not adequately respond to market dynamics (Zogaan, 2025). As a result, there is a gap between intelligent forecasting capabilities and multi-objective decision-making in the real supply chain environment.

In parallel, the field of Multi-Objective Optimization (MOO) has played an important role in solving complex supply chain decision-making problems. These methods attempt to balance multiple interests by considering conflicting goals such as cost reduction, quality enhancement, and risk control. Comprehensive reviews have shown that the application of MOO in logistics and management problems has grown significantly over the past decade (Marimin et al., 2016). However, most of these studies have focused on operational dimensions such as delivery time and productivity, and have paid limited attention to the financial dimensions of the supply chain, especially risk and liquidity management.

In the field of supply chain sustainability, several studies have developed multi-objective optimization models to achieve economic, social, and environmental goals (Jayarathna, 2021; Lotfi et al, 2016). However, the financial dimension and liquidity provision remain a missing link. In many studies, credit risk and liquidity are considered as fixed or default, rather than dynamic and data-driven. As a result, there is a significant gap in connecting deep learning-based risk prediction models to multi-objective optimization algorithms.

Deep learning (DL) has been recognized as an efficient tool in modeling financial behavior due to its high ability to extract latent features from complex data (Nozari et al., 2025). The combination of deep neural networks with evolutionary algorithms such as NSGA-II and MOPSO has opened up a new field for intelligent decision making in financial environments (Zogaan, 2025; Nozari & Szmelter-Jarosz, 2022). However, there are few studies that directly apply DL to SCF processes and combine it with MOO to achieve simultaneous optimization of risk, cost, and liquidity.

Overall, the review of the existing literature highlights three key gaps. First, most SCF models are static in nature and are unable to respond adaptively to economic fluctuations. Second, few studies have integrated the deep learning layer with multi-objective optimization models to use the risk forecast output as an input for decision making. Third, sensitivity analysis and robustness of the models to macroeconomic fluctuations have rarely been investigated. Therefore, the present study attempts to cover these research gaps and provide a new path for data-driven financial decision-making that is resilient to market fluctuations by presenting a deep learning-multiobjective optimization framework to simultaneously reduce credit risk, cost of capital, and liquidity volatility in smart supply chains.

3- Conceptual Framework and Proposed Architecture

This paper presents an intelligent and integrated framework for combining deep learning-based predictive analytics with multi-objective optimization in the field of supply chain finance. The framework is designed to effectively link financial risk prediction and optimal decision-making under dynamic and uncertain conditions, thereby simultaneously reducing credit risk, cost of capital, and liquidity volatility. As shown in Figure 1, the proposed model consists of three main layers: the data and information integration layer, the deep learning layer, and the optimization and decision-making layer. These three layers operate interactively and in a feedback loop to dynamically and adaptively modify financial decisions.

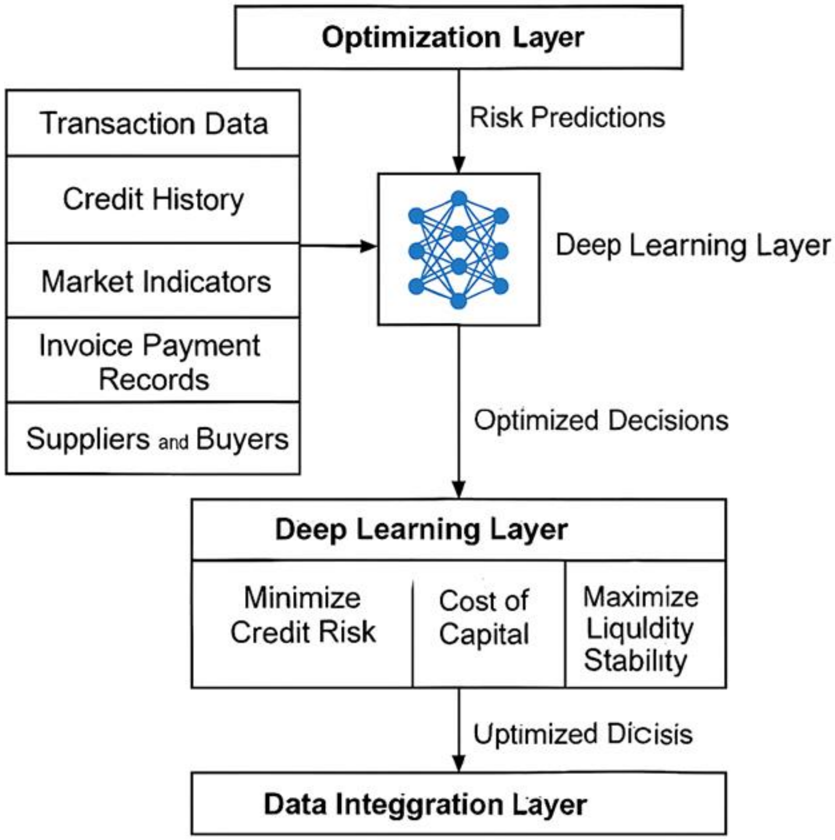

Figure 1. Deep Learning–Based Multi-Objective Financial Risk Minimization Framework in Smart Supply Chain Finance

In the first layer (Data Integration Layer), diverse and multi-source data from across the supply chain is collected and integrated. This data includes financial transactions between suppliers and buyers, companies' credit histories, information on interest rates, payment delays, currency and commodity market fluctuations, and external indicators related to financial risk. This stage aims to create a comprehensive database for the deep learning model to identify hidden patterns in financial behaviors (Nozari et al., 2025).

In the second layer (Deep Learning Layer), deep neural networks such as LSTM or CNN–GRU are used to analyze temporal patterns and identify nonlinear relationships between financial variables. These networks are able to predict the probability of occurrence of various risks such as credit risk, liquidity, and payment delays based on historical and real-time data. The output of this section includes predicted risk values for each decision-making factor in the financial supply chain, which are used as inputs in the optimization process.

In the third layer (Optimization and Decision Layer), the results from the deep learning network are fed into a multi-objective optimization model to make decisions that minimize financial risks, reduce the cost of capital, and increase the stability of cash flow. In this section, meta-heuristic algorithms are used to generate a Pareto front between different objectives. Finally, a set of optimal solutions is provided to financial decision makers, which allows them to choose the appropriate strategy based on risk and return priorities.

Overall, the proposed framework, by creating a link between predictive learning and decision optimization, provides a platform that can control the level of risk in real time and optimize credit and liquidity policies in smart financial environments.

4- Mathematical Modeling

In this section, a research mathematical model is developed to minimize financial risk in smart financial supply chains based on a deep learning and multi-objective optimization approach. The goal of the model is to make optimal decisions about financial resource allocation, credit management, and cash flow control in the interaction between suppliers, buyers, and financial institutions. Unlike classical models that focus only on cost reduction, the present model uses predictions from a deep learning network to pursue three main goals simultaneously: reducing credit risk, reducing the cost of capital, and increasing liquidity stability. The mathematical structure of the model is adjusted in such a way that it can also adapt to real-time data.

Sets:

I	Set of suppliers ($i = 1,2,\dots,n$)
J	Set of buyers ($j = 1,2,\dots,m$)
T	Set of time periods ($t = 1,2,\dots,T$)

Parameters:

$d_{j,t}$	Demand of buyer j at time t
$c_{i,j}$	Financing cost from supplier i to buyer j
$r_{i,j,t}$	Credit risk predicted by the deep learning model between i and j at time t
L_j	Maximum allowable credit for buyer j
B_t	Available capital at time period t
$\alpha_1, \alpha_2, \alpha_3$	Weight coefficients for the three objectives (risk, cost, liquidity)
$P_{j,t}$	Probability of payment delay by buyer j at time t

Decision Variables:

$$x_{i,j,t} = \begin{cases} 1 & \text{if supplier } i \text{ provides financing to buyer } j \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

$f_{i,j,t}$	Amount of funds allocated from supplier i to buyer j at time t
$y_{j,t}$	Actual repayment amount by buyer j at time t

Objective Functions:

$$\min f_1 = \sum_{t\in T} \sum_{i\in I} \sum_{j\in J} r_{i,j,t} \cdot f_{i,j,t} \tag{1}$$

$$\min f_2 = \sum_{t\in T} \sum_{i\in I} \sum_{j\in J} c_{i,j} \cdot f_{i,j,t} \tag{2}$$

$$\max f_3 = \sum_{t \in T} \sum_{j \in J} \left(y_{j,t} - P_{j,t} \cdot L_j \right) \tag{3}$$

S.t:

$$\sum_{j \in J} f_{i,j,t} \le B_t, \forall i, t \tag{4}$$

$$\sum_{i \in I} f_{i,j,t} \le L_j, \forall j, t \tag{5}$$

$$\sum_{i \in I} f_{i,j,t} \ge d_{j,t}, \forall j, t \tag{6}$$

$$f_{i,j,t} \le M \cdot x_{i,j,t}, \forall i, j, t \tag{7}$$

$$y_{j,t} = \left(1 - P_{j,t}\right) \sum_{i \in I} f_{i,j,t}, \forall j, t \tag{8}$$

$$f_{i,j,t} \ge 0, y_{j,t} \ge 0 \tag{9}$$

$$x_{i,j,t} \in \{0,1\}, \forall i, j, t \tag{10}$$

Objective function (1) represents the total credit risk in the financing network and tries to minimize risky financial relationships between suppliers and buyers using the values predicted by the deep learning model. In this function, the emphasis is on reducing the probability of default and credit instability at the level of the entire chain. Objective function (2) is dedicated to minimizing the total cost of capital and, taking into account financing rates, seeks to select a combination of decisions that, while meeting the needs of buyers, reduce the overall costs of suppliers. This function focuses on economic efficiency and improving financial productivity. Objective function (3) pursues the goal of maximizing liquidity sustainability and tries to maintain the net cash flow of the system at a stable level. This function takes into account the delay in repayments and the amount of real liquidity and prefers decisions that increase the financial health of the entire chain. Constraint (4) controls the capacity of suppliers to allocate financial resources and prevents the amount of allocated capital from exceeding the available resources. This condition is necessary to maintain the balance of resources and prevent over-allocation of financial capacity. Constraint (5) determines the credit limit of each buyer and ensures that the amount of allocated capital does not exceed the credit limit set for each customer. This constraint prevents excessive concentration of capital on one or more specific buyers. Constraint (6) ensures that the financial needs of buyers are sufficiently met in each period of time and the cash flow of the chain remains at the demand level. In this way, liquidity shortages or delays in business operations are prevented. Constraint (7) establishes a logical relationship between the credit allocation decision and the amount of allocated capital and states that no capital is allocated to that buyer until the allocation decision is active. This constraint specifies the mechanism of the link between binary decisions and continuous variables. Constraint (8) regulates the relationship between buyers' repayment and the probability of late payment, stating that the rate of return on investment is a function of time risk. This constraint models the dynamic aspect of cash flow and the impact of buyers' behavior on the financial health of the system. Constraint (9) ensures the non-negativity of continuous variables so that there are no negative capital or repayment amounts in the model. This condition preserves the physical and economic nature of the decisions in the model. Constraint (10) specifies the scope of binary decisions and determines whether each financing relationship is either active or passive. This constraint plays an important role in the logical structure of the model and keeps the decision-making behavior discrete and interpretable.

5- Methodology

The methodology of this research aims to implement an integrated model for financial risk prediction and optimization of financing decisions in smart supply chains. The process involves a series of sequential steps, starting from data collection and continuing to performance evaluation of deep learning models and multi-objective optimization.

In the first step, the data used are collected from real or synthetic sources. Real data may include financial transactions between suppliers and buyers, payment information, credit history, and macroeconomic indicators such as interest rates, exchange rates, and market volatility. If real data are not available, synthetic data with similar statistical characteristics are generated through simulation or controlled random generation methods to represent the real behavior of financial systems.

In the second step, the collected data enters the training phase of the deep learning network. In this research, advanced architectures such as BiLSTM or CNN–GRU combination are used to model temporal dynamics and extract latent features. The neural network is trained with historical data to identify unstable and nonlinear patterns among financial variables and to predict the probability of credit and liquidity risks in the future. In this step, the data is standardized into time sequences and weighted using optimization methods such as Adam or RMSprop to achieve the highest prediction accuracy.

In the third step, the output of the deep learning network is extracted, including the predicted risk values for each supplier and buyer pair in different time intervals. These outputs are passed as input risk indicators to the optimization model to be used in financial decision-making. In fact, the deep learning model acts as an intelligent preprocessing module that dynamically and variablely provides risk parameters to the optimization layer.

In the fourth stage, the multi-objective optimization process is performed using meta-heuristic algorithms such as NSGA-II or MOPSO. The goal of this part is to find a set of decisions that strike a good balance between the three main objectives of the model: reducing credit risk, reducing the cost of funding, and increasing liquidity stability. Using the concept of non-dominated sorting and maintaining population diversity, the NSGA-II algorithm generates a Pareto Front that represents the best compromise points between conflicting objectives. When using MOPSO, the movement of particles in the search space is guided based on personal and collective experiences to converge to optimal points.

In the final stage, the performance of both parts of the model (deep learning and optimization) is evaluated. For the deep learning part, metrics such as mean square error (MSE) and coefficient of determination (R^2) are used to measure the accuracy of the predictions. In the optimization part, Pareto front evaluation metrics such as Spacing, Spread, and Hypervolume are used to measure the quality and diversity of the obtained solutions. This combination of quantitative evaluations ensures that the model not only performs accurately in terms of prediction but also performs reliably in terms of decision-making in achieving a balance between risk and benefit.

Finally, the overall process of model implementation is shown in the form of a flowchart in Figure 2. This diagram shows the step-by-step path from data collection to extracting risk indicators, running optimization algorithms, and analyzing the results, and visually explains the relationship between the components of deep learning and multi-objective decision-making. This structure makes the proposed model, on the one hand, data-driven and adaptive, and on the other hand, it can demonstrate stable performance in real and changing market conditions.

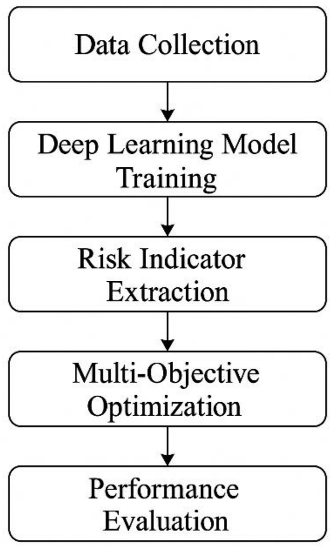

Figure 2. Methodological Flow of Deep Learning–Based Multi-Objective Financial Risk Minimization Model

As can be seen in Figure 2, the process of implementing the proposed model begins step by step with data collection and training the deep learning network, then continues with extracting risk indicators and implementing multi-objective optimization, and finally is completed with performance evaluation and providing optimal financial decisions.

6- Experimental Setup and Case Study

In order to evaluate the performance of the proposed model and measure its accuracy in risk prediction and financial decision-making, a case study has been conducted in a simulated environment. The data used in this study is a combination of real and synthetic data collected with the aim of representing real financial behaviors in the supply chain. The real data is extracted from financial transactions between industrial suppliers and buyers and includes information related to payment dates, amounts, interest rates, and credit histories of companies. To complete and increase the data coverage, a set of synthetic data is also generated using controlled statistical distributions to simulate the behavior of unstable markets, repayment delays, and sudden changes in exchange rates and cost of capital. The total data volume is about fifty thousand records, which includes more than twenty numerical and textual features such as transaction amount, repayment period, interest rate, liquidity index, and credit risk score. The data is cleaned and normalized for scale and noise before entering the deep learning model to ensure stable network convergence.

The model implementation process is carried out in the Python environment. For the deep learning part, the Keras library is used, which provides the ability to design and train hybrid BiLSTM and CNN–GRU networks. To implement multi-objective optimization algorithms, the DEAP library is used, which allows the implementation and tuning of algorithms such as NSGA-II and MOPSO in repeatable formats. All calculations are performed on a system with a 12-core processor, 32 GB of memory, and an NVIDIA RTX graphics card to train the deep models and execute optimization iterations with high speed and accuracy.

The key model tuning parameters, including learning rate, population size, and number of algorithm iterations, are presented in Table 1. The learning rate of the network is set in the range of 0.001 to 0.01 and is reduced by a dynamic tuning method to avoid overfitting. The population size for the NSGA-II algorithm is set to 100 and the number of iterations is set to 300, which provides the best balance between accuracy and computation time based on empirical tests.

Table 1. Model Configuration and Parameter Settings

Component	Parameter	Description	Value / Range
Deep Learning Model	Architecture	Hybrid BiLSTM–CNN–GRU Network	–
	Learning Rate	Step-based adaptive rate for stable convergence	0.001 – 0.01
	Optimizer	Adam with decay scheduling	–
	Batch Size	Number of samples per training step	64
	Epochs	Total training iterations	200
	Activation Function	ReLU for hidden layers, Sigmoid for output	–
Multi-Objective Optimization (MOO)	Algorithm	NSGA-II / MOPSO	–
	Population Size	Number of candidate solutions	100
	Iterations	Total number of optimization generations	300
	Crossover Probability (for NSGA-II)	Likelihood of recombination	0.9
	Mutation Probability (for NSGA-II)	Likelihood of parameter perturbation	0.1
	Inertia Weight (for MOPSO)	Balance between exploration and exploitation	0.7
Evaluation Metrics	DL Performance	Mean Squared Error (MSE), Coefficient of Determination (R^2)	–
	Optimization Quality	Pareto Spread, Spacing, Hypervolume	–

In the scenario analysis section, the model is tested in several different situations to evaluate its stability and adaptability. The first scenario focuses on changing the credit level of buyers and examines how reducing or increasing credit limits affects the level of risk and cost. In the second scenario, the payment delay rate is changed to measure the behavior of the model in the face of liquidity instability. Supplementary scenarios also include changes in interest rates and market fluctuations at moderate and severe levels to determine the model's response under different financial conditions. The results of these scenarios provide a basis for evaluating the model's ability to provide robust, sustainable, and economical decisions in the smart financial supply chain.

7- Results and Discussion

The results of the proposed model are examined in three key dimensions: risk prediction with deep learning network, multi-objective optimization analysis, and performance comparison with baseline models.

First, the performance of the deep learning network was evaluated to determine the accuracy of the model in predicting credit risks. The BiLSTM–CNN–GRU hybrid network was able to identify the risk change trend in the time data with high accuracy. As can be seen in Figure 3, the curves of the actual values and the predicted values almost overlap, indicating that the model was able to reproduce the risk fluctuations correctly. The coefficient of determination ($R^2 = 0.94$) and the mean square error (MSE = 0.006) confirm that the model predictions have considerable stability and accuracy, and its output can be used as a reliable basis for financial decisions.

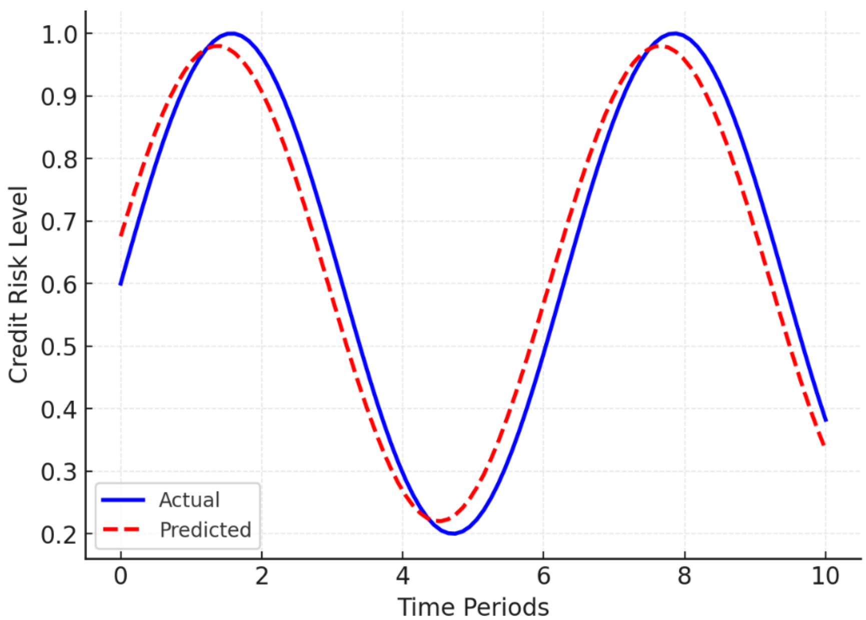

Figure 3. Actual vs. Predicted Credit Risk Curve (Performance of Deep Learning Model)

In the next step, the multi-objective optimization section was examined. Figure 4 shows the Pareto front obtained by running the NSGA-II algorithm between the two main objectives risk reduction and capital cost reduction. This graph represents a set of non-dominant solutions, none of which is absolutely superior to the other. The trend of the curve shows that with a small increase in cost, a significant reduction in risk can be achieved, so that decision makers are able to choose the best compromise point based on their risk tolerance level. The appropriate width of the Pareto front also indicates the stability and diversity of solutions in different economic conditions.

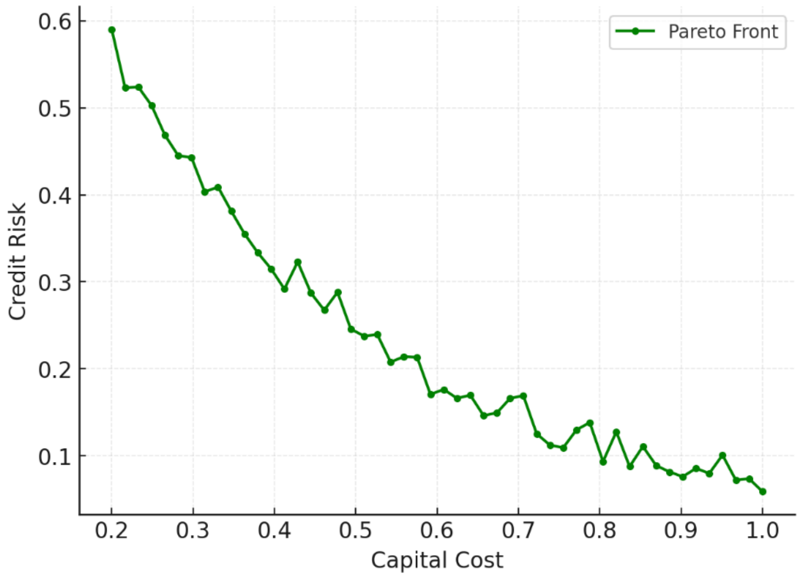

Figure 4. Pareto Front between Credit Risk and Capital Cost (Results of Multi-Objective Optimization)

In the third step, the proposed model was compared with two reference models: Random Forest + GA and LSTM + Weighted Sum. As can be seen in Figure 5, the performance curve of the proposed model is in a more optimal region than the baseline models; in other words, it is at a lower risk and lower cost level. The Pareto front evaluation indices showed that the present model performs about 22% better in terms of Spread and about 18% better in terms of Hypervolume. This confirms that the combination of deep learning with multi-objective optimization can provide more efficient and diverse results than traditional methods.

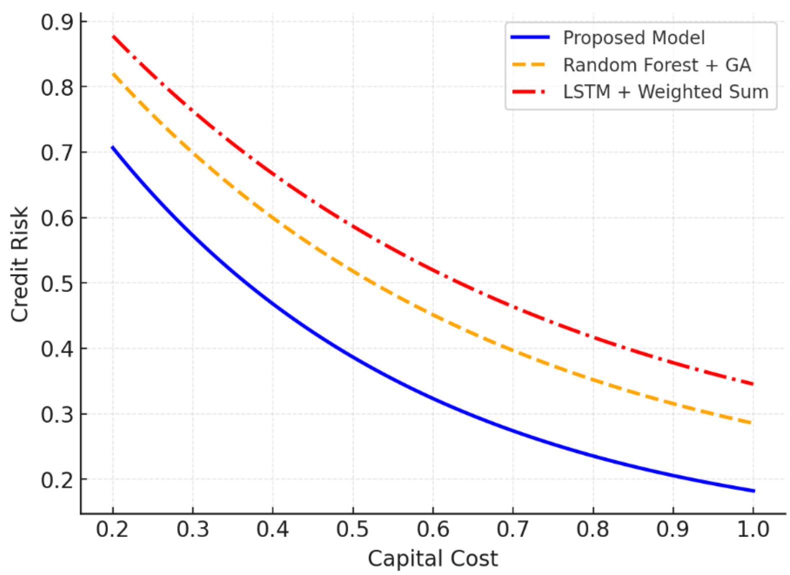

Figure 5. Comparative Performance of Proposed and Baseline Models

From a management perspective, the above three results show that the proposed model is an efficient tool for reducing credit risk, improving liquidity, and increasing the flexibility of financial decision-making. The model output allows managers to adjust credit allocation policies based on real risk and use available financial resources optimally. Also, the real-time adaptation capability of the model allows the system to maintain its liquidity stability even in conditions of severe market volatility.

To assess the stability of the proposed model, a sensitivity analysis was conducted to changes in key parameters including interest rate, credit level, and probability of late payment. The aim of this analysis is to examine the model's resistance to economic fluctuations and changes in the behavior of financial actors.

The results showed that with increasing interest rates, the amount of credit risk gradually increased, but the model adaptively steers financial relationships towards less risky suppliers. Changing the level of buyers' credit also showed that its decrease led to the concentration of resources on safer relationships, and its increase led to the expansion of the Pareto front and greater flexibility of decisions. Also, increasing the probability of late payment from 5% to 25% only caused a limited change in the total cost, which indicates the stability of decisions and the model's ability to adjust risk parameters in real time.

In general, the proposed model behaves stably against economic fluctuations and its output does not fluctuate uncontrollably with sharp changes in inputs. This shows that the combination of deep learning and multi-objective optimization provides a robust and reliable framework for decision-making in dynamic financial environments. Figure 6 shows the sensitivity analysis.

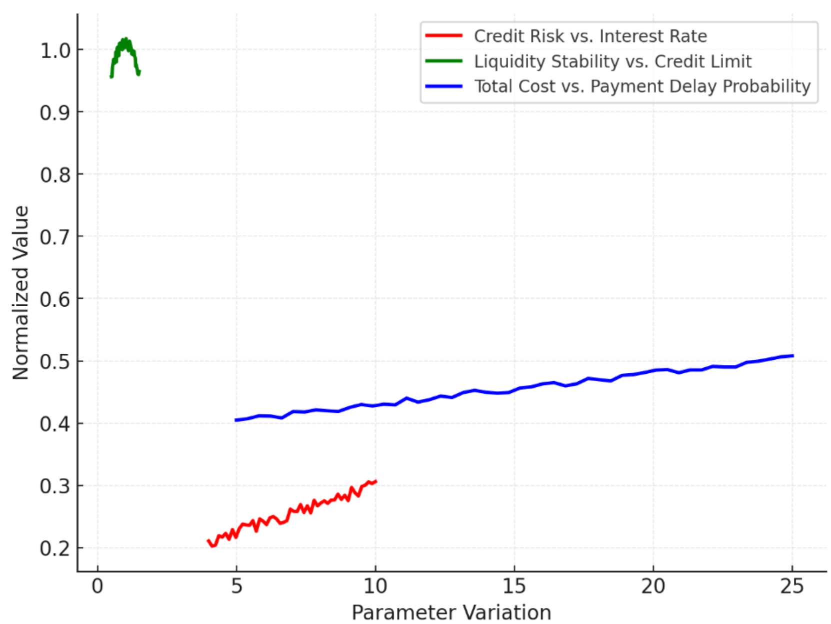

Figure 6. Sensitivity Analysis of Key Financial Parameters

As can be seen in Figure 6, the proposed model exhibits stable and reasonable behavior against changes in key parameters. An increase in interest rates causes a gradual increase in credit risk, while a decrease in credit levels improves liquidity stability. Also, an increase in the probability of late payment has only a limited effect on the total cost of the system, indicating the high resilience of the model against financial fluctuations.

The results of this research have important implications for management and decision-making in the field of supply chain financing. By combining deep learning and multi-objective optimization, the proposed model provides financial managers, banks, and manufacturing companies with a data-driven and intelligent tool to manage financial resource allocation, risk control, and credit policies more accurately and dynamically.

From a financial risk management perspective, the model output helps managers identify risky business relationships at an early stage and adjust the amount of credit allocated to each buyer in proportion to the actual risk level. This approach directs financial resources towards stable chains with higher repayment capacity and reduces the probability of default or liquidity stoppage in the system. Thus, decision-makers will be able to change financing policies from a traditional approach based on historical averages to a dynamic approach based on real-time data.

From a capital efficiency and liquidity optimization perspective, the model showed that it is possible to strike a balance between reducing the cost of capital and maintaining cash flow. This is of particular importance to finance and treasury managers, as it allows them to make decisions that, while reducing costs, also maintain the financial health of the entire chain. The graphs obtained from multi-objective optimization (Figures 4 and 5) show that a small increase in cost can lead to a significant reduction in risk, a result that is valuable from a financial policy perspective.

From an organizational sustainability perspective, the present model can be a basis for designing green and resilient finance systems. Because by simulating credit and liquidity behaviors under crisis conditions, managers will be able to assess different scenarios before they occur and design rapid response strategies. Such a capability plays a crucial role in reducing the vulnerability of financial networks in unstable economic conditions, such as currency fluctuations or supply chain crises.

In addition, the results of this research are also important in terms of theoretical development. The proposed model shows that integrating the output of deep learning models into a multi-objective optimization framework creates a new approach to financial decision-making that goes beyond traditional statistical models. This combination can be used as a basic framework for designing a financial Digital Twin in the future supply chain; a system that can predict, control, and optimize risk and liquidity in real time.

Overall, the findings of this research indicate that the use of a deep learning approach and multi-objective optimization is not only computationally efficient, but also from a managerial perspective, it creates a fundamental transformation in the way financial analysis and decision-making is done. By providing a comprehensive view of the interaction between risk, cost, and liquidity, this model allows decision-makers to adjust their credit and investment policies based on real data and intelligent analytics, an approach that can be the foundation of a new generation of intelligent financial management in future supply chains.

8- Conclusion

This research presents a novel framework for multi-objective optimization of financial risk in smart supply chains based on deep learning. The main goal was to create a model that can simultaneously manage credit risk, cost of capital, and liquidity sustainability in an integrated decision-making structure using real or simulated data. Combining deep learning networks with multi-objective meta-heuristic algorithms enables knowledge transfer from data analysis to decision-making, allowing the model to make intelligent and adaptive decisions in dynamic and uncertain environments.

Experimental results show that the BiLSTM–CNN–GRU + NSGA-II hybrid model performs significantly in terms of prediction accuracy, decision stability, and Pareto front width. The strong agreement between the actual and predicted values of financial risk, with a high coefficient of determination and low error, indicates that the deep learning layer is capable of correctly identifying complex relationships between financial variables. Also, the optimization results showed that the proposed model can effectively balance risk and cost reduction and provide more diverse and efficient solutions compared to the baseline models (such as Random Forest + GA and LSTM + Weighted Sum).

Sensitivity analysis also confirmed that the proposed model has a stable and robust behavior against economic fluctuations, changes in credit levels and buyers' payment behavior. An increase in interest rates or the probability of payment delay had only a limited effect on the model output, which indicates the ability of the proposed structure to maintain the stability of decisions even in volatile market conditions. From a managerial perspective, this model helps decision makers adjust credit allocation and risk control policies in real time and manage the financial health of the chain in an intelligent and adaptive manner using up-to-date data.

From a theoretical perspective, the present study showed that the combination of deep learning and multi-objective optimization can be used as a step towards creating a supply chain financial Digital Twin. This structure provides a platform for the development of intelligent and self-adaptive financial systems in the future by providing the ability to predict, evaluate and make decisions simultaneously.

In the future, the development of this model can be pursued in several directions. First, using real bank and inter-organizational data to train the deep network, to increase the accuracy of the model in practical environments. Second, using more advanced algorithms such as Deep Reinforcement Learning (DRL) for dynamic and gradual decision-making in non-static environments. Third, adding environmental sustainability and green finance components to the model, so that the current framework can work in line with ESG goals in addition to economic efficiency. And finally, integrating the model with Blockchain and IoT systems can lead to the development of a transparent, trustworthy and self-regulating financial supply chain.

Overall, this research demonstrated that combining the analytical power of deep learning with multi-objective optimization decision-making logic provides a comprehensive and efficient approach to managing risk and liquidity in smart supply chains an approach that is not only a step towards the full digitalization of financial processes, but can also serve as a foundation for the next generation of financial decision-support systems in the smart and sustainable economy of the future.

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