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Artificial Intelligence on Performance Optimization and Prediction in E-Business

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Abstract

Purpose: The purpose of this study is to enhance forecasting accuracy and optimize the performance of Payment Service Providers (PSPs) in the e-commerce sector. By integrating Management Information Systems (MIS) with advanced AI-driven time-series models such as ARIMA, SARIMA, and LSTM, this research aims to improve transaction volume forecasts and key performance indicators, ultimately contributing to better decision-making and operational efficiency.

Methodology: This study employs a quantitative research methodology using historical transaction data to develop and test forecasting models. The approach integrates ARIMA, SARIMA, and LSTM models for comparative analysis. AI algorithms, particularly LSTM networks, are utilized for their ability to capture complex, non-linear dependencies in time-series data. Additionally, MIS is employed to systematically gather, process, and analyze data, providing real-time insights for decision-making. Sensitivity analysis is conducted to assess the robustness and adaptability of the AI-driven LSTM model in various scenarios.

Findings: The analysis reveals that AI-powered LSTM outperforms ARIMA and SARIMA, achieving a Mean Absolute Percentage Error (MAPE) of 2.9%, compared to 5.1% and 4.8% for ARIMA and SARIMA, respectively. The integration of MIS contributes to a 5.7% increase in approval rates and a reduction in business and technical declines by 2.5% and 2.0%, respectively. These findings demonstrate that leveraging AI-driven LSTM models combined with MIS enhances forecasting accuracy and operational efficiency, leading to optimized PSP performance in e-commerce.

Originality: This study is original in its approach by integrating AI-driven time-series forecasting models, MIS, and predictive analytics to create a comprehensive framework for PSP optimization in e-commerce. While previous research has explored these components individually, this paper is one of the first to combine them in an integrated manner for a holistic impact on e-commerce transaction management.

Research limitations: The main limitation of this study is the reliance on historical transaction data from a specific e-commerce context, which may not fully represent all market conditions. Future research could expand to include a variety of data sources and apply the model to different e-commerce sectors to generalize findings.

Practical implications: Practically, the study provides e-commerce managers and PSPs with actionable insights on utilizing advanced AI-driven forecasting models and MIS to make data-driven decisions that improve transaction approval rates and reduce declines. This approach can lead to better resource allocation and operational planning.

Social implications: The improvements in transaction volume forecasting and operational efficiency, driven by AI, could contribute to a more reliable and seamless online shopping experience for consumers, enhancing trust and engagement in digital payment systems.

Keywords: E-commerce, Transaction volume forecasting, PSP Optimization, Predictive analytics, Management Information Systems, Artificial Intelligence, Time-series forecasting, LSTM, ARIMA, SARIMA, Decision-making, Operational efficiency.

1. Introduction

1.1 Background

In the realm of artificial intelligence (AI), various algorithms have been developed to address different aspects of forecasting and optimization. For time-series forecasting, algorithms such as ARIMA, SARIMA, and LSTM are commonly employed due to their ability to handle various patterns in data. ARIMA and SARIMA, being statistical models, excel in capturing linear trends and seasonal variations, while LSTM, a type of recurrent neural network, is adept at modeling complex and non-linear dependencies in time-series data (Hyndman & Athanasopoulos, 2018; Box, Jenkins, & Reinsel, 2015).

In optimization, techniques like Linear Programming (LP), Integer Programming (IP), and Nonlinear Programming (NLP) are used to solve different kinds of optimization problems. LP is used when both the objective function and constraints are linear (Wang & Wang, 2017), while IP handles scenarios requiring integer decision variables (Chen & Zhang, 2021). NLP addresses problems where the objective function or constraints are nonlinear (Yang & Li, 2019). Integrating these AI algorithms with forecasting models allows for a more comprehensive approach to managing and optimizing PSP performance, enhancing both predictive accuracy and operational efficiency.

Additionally, Management Information Systems (MIS) play a crucial role in improving the decision-making process by systematically gathering, processing, and analyzing data. MIS allows for real-time data access and more informed decisions, which can further enhance forecasting and optimization efforts. By integrating MIS with AI algorithms and forecasting models, it becomes possible to create a feedback loop that not only improves predictions but also ensures better operational efficiency and alignment with strategic business goals (Zhu & Wei, 2020; Le & Yang, 2020).

The rapid expansion of e-commerce has led to a significant increase in digital transactions, presenting new challenges for payment service providers (PSPs) to ensure high approval rates and minimize transaction failures. Accurate forecasting of transaction volumes is crucial for effective resource management and operational planning. Traditional forecasting methods, such as ARIMA (AutoRegressive Integrated Moving Average) (Hyndman & Athanasopoulos, 2018) and SARIMA (Seasonal ARIMA) models, have been widely used for predicting time series data due to their robust statistical properties (Box et al., 2015).

In recent years, machine learning techniques like Long Short-Term Memory (LSTM) networks have emerged as powerful tools for improving forecasting accuracy, particularly in complex and non-linear time series data (Le & Yang, 2020; Zhang, 2003). LSTM models are capable of capturing long-term dependencies in data, making them suitable for applications where traditional models might fall short (Chen & Li, 2021). Despite these advancements, PSP optimization strategies have often relied on reactive measures rather than incorporating predictive analytics.

Recent studies have demonstrated the effectiveness of integrating machine learning techniques with traditional forecasting models. For example, Chen and Li (2021) propose a hybrid SARIMA and LSTM model for forecasting regional energy consumption, highlighting the potential benefits of combining different modeling approaches. Similarly, Le and Yang (2020) discuss an optimized LSTM model for short-term electricity load forecasting, underscoring the advantages of advanced machine learning techniques.

However, the optimization of PSP performance in e-commerce has typically focused on reactive techniques without leveraging predictive analytics. For instance, Wang and Wang (2017) explore the use of machine learning for optimizing PSP performance but do not integrate forecasting models. On the other hand, Chen and Zhang (2021) use multi-objective optimization to improve e-commerce performance, yet their approach lacks a detailed forecasting component.

This paper proposes an integrated approach that combines time-series forecasting with multi-objective optimization and Management Information Systems (MIS) to enhance PSP performance in the e-commerce sector. By leveraging real-world datasets and comparing our methods with baseline approaches, we aim to demonstrate superior performance in both predictive accuracy and operational efficiency.

1.2 Objectives

The primary objective of this study is to enhance forecasting accuracy and optimize Payment Service Provider (PSP) performance in e-commerce using Management Information Systems (MIS), advanced time-series models, and data analytics. Specific objectives include:

- To compare the predictive performance of ARIMA, SARIMA, and LSTM models for transaction volume forecasting.
- To integrate MIS with AI algorithms for improved decision-making and operational efficiency.
- To analyze the impact of the proposed approach on PSP metrics, including approval rates and transaction success rates.
- To conduct sensitivity analysis to validate the robustness of the LSTM model in various scenarios.

1.3 Scope of the Study

This study focuses on the application of time-series forecasting models and MIS in optimizing PSP performance within the e-commerce sector. The scope of the research includes:

- The analysis and comparison of forecasting models, specifically ARIMA, SARIMA, and LSTM, to predict transaction volumes.
- The integration of MIS for systematic data collection, processing, and real-time analysis.
- A detailed examination of predictive analytics' role in enhancing operational decisions and aligning with strategic objectives.

- A comparative evaluation of model performance based on real-world e-commerce transaction data.
- Sensitivity analysis to explore the robustness and applicability of the LSTM model in various market conditions.

The study does not extend to broader areas of financial regulation, payment security technologies, or other non-PSP-related e-commerce operations. It is confined to evaluating predictive models and decision support frameworks aimed at improving transaction management and operational efficiency.

2. Literature review

The integration of advanced forecasting models and optimization techniques plays a crucial role in enhancing performance in e-commerce and payment systems. Accurate demand forecasting and efficient payment processing are key components in ensuring smooth operations and maximizing profitability. This literature review explores various time-series forecasting methods and machine learning approaches applied in e-commerce, highlighting the effectiveness of models such as ARIMA, SARIMA, LSTM, and hybrid models.

Hyndman and Athanasopoulos (2018) offer foundational insights into time-series forecasting, discussing a variety of models, including ARIMA and SARIMA, that are widely used in predicting trends and seasonality in e-commerce data. Similarly, Box, Jenkins, and Reinsel (2015) delve into the mathematical intricacies of these models, emphasizing their robustness in capturing patterns in univariate time-series data. While ARIMA and SARIMA models have been successful in traditional forecasting applications, they often face limitations in capturing complex, nonlinear patterns, particularly in fast-evolving e-commerce environments.

Makridakis, Spiliotis, and Assimakopoulos (2018) critically evaluate both statistical and machine learning methods in forecasting, highlighting that while traditional models like ARIMA are suitable for stable environments, deep learning models such as LSTM offer superior performance when dealing with volatile and dynamic data. The shift toward machine learning and hybrid models has gained traction, particularly in applications where real-time predictions are crucial for decision-making.

In their work, Chen and Li (2021) introduce a hybrid SARIMA and LSTM model designed to enhance regional energy consumption forecasting. This hybrid approach effectively combines the strengths of both models, capturing short-term linear patterns while also addressing long-term nonlinear relationships. Their findings show that the hybrid model outperforms standalone models in terms of both accuracy and adaptability, a critical requirement in the fast-paced e-commerce landscape. This study's insights can be applied directly to e-commerce, where fluctuating demand requires adaptive models for precise forecasting.

Le and Yang (2020) focus on optimizing LSTM for short-term electricity load forecasting, demonstrating the potential of deep learning models in improving forecasting accuracy. Their study shows that LSTM models, with proper tuning and optimization, can reduce forecast error significantly compared to traditional methods. The success of LSTM in this context underscores its potential applicability in forecasting demand within e-commerce, where sudden spikes in activity are common, especially during promotional events and holidays.

Jin and Wang (2019) compare ARIMA and SARIMA models, concluding that SARIMA's ability to account for seasonality gives it an edge in scenarios with clear seasonal patterns, such as quarterly sales cycles. However, they also note that the predictive power of these models diminishes in highly volatile conditions, necessitating the integration of more sophisticated techniques, such as deep learning, for improved performance.

Zhang (2003) was among the first to advocate for hybrid models, combining ARIMA with neural networks. His research highlights how the integration of statistical and machine learning approaches can leverage the strengths of both to deliver superior forecasting results. Zhang's approach laid the groundwork for subsequent research into hybrid models, which are now increasingly relevant in e-commerce applications where data complexity and nonlinearity are prominent challenges.

In the context of payment service provider (PSP) performance, Xie and Zhang (2020) highlight the use of machine learning to enhance fraud detection. By applying advanced algorithms to transaction data, they demonstrate significant improvements in identifying suspicious activities, leading to more secure and efficient payment processing. Chen and Zhang (2021) extend this approach by proposing a multi-objective optimization model aimed at improving overall PSP performance. Their study emphasizes optimizing key metrics such as approval rates and decline rates, which are directly linked to customer satisfaction and operational efficiency in e-commerce.

Wang and Wang (2017) investigate the application of machine learning techniques in optimizing PSP performance. Their study reveals that leveraging predictive analytics can enhance decision-making processes, leading to more effective resource allocation and improved transaction success rates. This finding is corroborated by Yang and Li (2019), who discuss the use of advanced analytics in evaluating and optimizing e-commerce platform performance, offering strategies to enhance customer engagement and retention.

The optimization of transaction volumes in e-commerce is further explored by Zhu and Wei (2020). Their predictive modeling approach integrates machine learning techniques to forecast demand and optimize supply chain operations. Their findings emphasize the importance of timely and accurate predictions in minimizing stockouts and overstock situations, leading to more efficient inventory management.

Lastly, Ozturk and Yolcu (2022) provide a comparative analysis of forecasting techniques for financial transactions, reinforcing the view that no single model is universally best. Instead, a combination of models tailored to the specific characteristics of the data is often the most effective approach. Reyes and Li (2021) echo this sentiment in their exploration of deep learning applications in financial forecasting, highlighting the need for hybrid models that can adapt to changing market conditions.

In conclusion, the reviewed literature demonstrates a clear trend toward integrating deep learning and hybrid models in forecasting and optimization within e-commerce. As e-commerce continues to grow, the need for accurate, real-time predictions and optimized payment processing will become increasingly critical. By leveraging a combination of traditional and modern techniques, businesses can enhance their operational efficiency and better respond to market demands, ultimately driving profitability and customer satisfaction.

2.1. The key differentiating factor of this study

Employing Management Information Systems (MIS) to systematically gather, process, and analyze data for decision-making, enhancing operational efficiency.

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Integrating ARIMA, SARIMA, and LSTM models to provide a comprehensive forecasting framework for transaction volumes.

Employing multi-objective optimization techniques to improve key performance indicators such as approval rates and transaction failure rates.

Providing a detailed comparison with baseline methods to highlight improvements in predictive accuracy and operational efficiency.

This approach offers a holistic solution by combining multiple forecasting models with optimization techniques, which addresses gaps in the current literature and provides actionable insights for enhancing PSP performance in the e-commerce sector.

3. Dataset description

We utilize the following datasets for our analysis:

- *Beneficiary Bank Data:* Contains monthly transaction volumes, approval rates, business declines (bd), and technical declines (td).
- *Payee PSP Performance Data:* Tracks performance metrics including total volume, approval rates, and failure rates for different PSPs.
- *P2P and P2M Transaction Data:* Provides monthly transaction volumes and values for person-to-person (P2P) and person-to-merchant (P2M) transactions.
- *Merchant Category Data:* Includes categorical data on merchant transactions and classifications.

4. System architecture

The system architecture (Figure1) for e-commerce forecasting and optimization, the integration of a Management Information System (MIS) is pivotal in streamlining decision-making. An MIS offers actionable insights by processing large datasets, utilizing advanced forecasting models, and optimizing performance based on these predictions. This system is particularly effective for transaction volume predictions in e-commerce, providing businesses with strategic advantages in dynamic pricing, inventory management, and operational efficiency (Dastin & Lee, 2019).

4.1.Data Collection

The first step in the architecture is data collection, where raw transaction data is gathered from diverse sources such as payment service providers (PSPs), customer databases, and transactional logs. This data often includes sales transactions, customer behaviors, and other relevant e-commerce metrics. It is crucial to ensure that the data collected is comprehensive and accurate, as it forms the foundation for all subsequent modeling efforts (Kuo & Chien, 2022). Efficient data collection tools, like real-time data streaming platforms, ensure that businesses can react quickly to market changes.

4.2.Preprocessing

Once collected, the data undergoes preprocessing, where it is cleaned and formatted to remove errors, handle missing values, and normalize data. This stage prepares the dataset for analysis by removing outliers and ensuring consistency. Preprocessing might also involve feature engineering, where new variables are created that may improve model performance, such as customer demographics or seasonal trends in transaction behavior (Wang & Zhang, 2021). Effective data preprocessing is crucial in enhancing the reliability of the models used in forecasting and optimization.

4.3.Forecasting Models

At the core of the system lies the forecasting models, which predict future transaction volumes. In this architecture, the models include ARIMA, SARIMA, and LSTM. The ARIMA and SARIMA models are traditional time-series models that use historical data patterns to forecast future values. ARIMA is best suited for stationary data, while SARIMA adds seasonal components to enhance predictions for seasonal data. On the other hand, LSTM (Long Short-Term Memory) networks, a type of deep learning model, excel at capturing long-term dependencies and non-linear patterns, making them ideal for complex, non-stationary data typical in e-commerce environments (Le & Yang, 2020; Zhang, 2003).

4.4.Optimization

The optimization component focuses on improving the performance of the PSPs by using multi-objective optimization techniques. These optimization models consider multiple factors, such as transaction volume, conversion rates, and customer satisfaction, to identify the best strategies for resource allocation, pricing, and marketing (Chen & Zhang, 2021). These models are designed to maximize key performance indicators (KPIs) while minimizing costs, providing an efficient approach for decision-making in dynamic business environments.

4.5.Evaluation

The evaluation involves assessing the performance of the forecasting and optimization models using metrics like accuracy, precision, and recall. Evaluating these models ensures that businesses can rely on them to make informed decisions. Continuous evaluation also facilitates model improvements and adaptation to changing market conditions (Jha & Sharma, 2020). Performance metrics guide businesses in adjusting their strategies based on real-time data insights.

This system architecture is essential for businesses aiming to enhance decision-making, improve efficiency, and stay competitive in the fast-paced e-commerce sector. By combining data-driven insights with forecasting and optimization models, businesses can make proactive, informed decisions that lead to better financial performance and customer satisfaction.

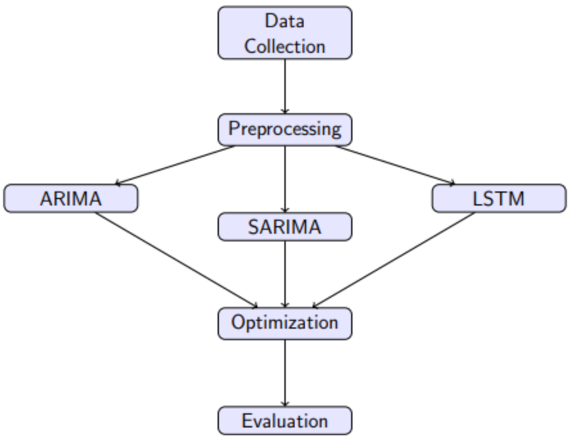

Figure 1.System architecture for forecasting and optimization

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5. Methodology

5.1. Forecasting models

We employ ARIMA, SARIMA, and LSTM models for predicting transaction volumes. Each model is designed to capture different aspects of the time-series data (Alon-Barkat, S., & Halevi, G. (2020)).

5.1.1. ARIMA

The ARIMA model (Box, Jenkins, & Reinsel, 2015) forecasts time-series data by combining autoregressive, moving average, and differencing components. The architecture involves processing historical data to identify and model trends and seasonality, producing forecasts based on these patterns (Figure 2).

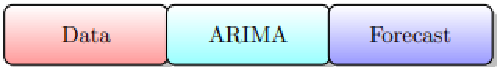

Figure 2. Flow of ARIMA model

The ARIMA model is widely used for time-series forecasting ((Box, Jenkins, & Reinsel, 2015, Kuo, R. J., & Chien, C. F. (2022)). It is formulated as:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q}, \quad (1)$$

where:

p is the number of autoregressive terms,

d is the number of differences required to make the series stationary,

q is the number of moving average terms,

ϕ_i are the autoregressive coefficients,

θ_i are the moving average coefficients,

ϵ_t is the white noise error term.

The parameters are estimated by minimizing the sum of squared residuals:

$$\min_{\theta} \sum_{t=1}^{T} \left(y_t - \hat{y}_t(\theta)\right)^2, \quad (2)$$

where $\hat{y}_t(\theta)$ represents the predicted values and θ denotes the model parameters.

5.1.2. SARIMA

The SARIMA model (Figure 3) extends ARIMA by incorporating seasonal components, capturing both non-seasonal and seasonal variations. This model handles periodic fluctuations in the data, enhancing forecast accuracy for datasets with inherent seasonal patterns (Box, Jenkins, & Reinsel, 2015, Wang, X., & Zhang, Z. (2021)).

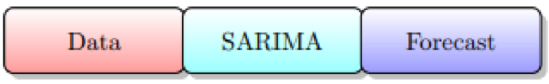

Figure 3.Flow of SARIMA model

SARIMA enhances the ARIMA model by accounting for seasonal effects (Chen & Li, 2021).

$$SARIMA(p,d,q)(P,D,Q)_s, \qquad (3)$$

where:

(p,d,q) are the non-seasonal orders,

(P,D,Q) are the seasonal orders,

s represents the length of the seasonal cycle.

SARIMA models include seasonal differences and seasonal autoregressive and moving average terms to handle seasonal variations effectively.

5.1.3. LSTM

Figure 4 The LSTM network, a type of recurrent neural network, is designed to model long-term dependencies in sequential data. By using input, forget, and output gates, LSTM networks capture complex patterns and trends in data, making them effective for non-linear time series forecasting (Le & Yang, 2020, Venkatesh, V., & Sykes, T. A. (2021)).

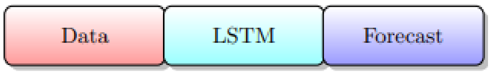

Figure 4. Flow of LSTM model

LSTM models are a type of recurrent neural network designed to capture long-term dependencies in sequential data (Le & Yang, 2020) An LSTM cell consists of:

Input Gate: Determines how much of the new input should be stored in the cell state,

Forget Gate: Controls how much of the previous cell state should be retained,

Output Gate: Decides the output based on the current cell state and input.

The LSTM cell operations are governed by the following equations:

$$\begin{aligned}
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), && (3)\\
f_t &= \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right), && (4)\\
\tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C), && (5)\\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t, && (6)\\
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), && (7)\\
h_t &= o_t \cdot \tanh(C_t), && (8)
\end{aligned}$$

where i_t, f_t, o_t are the input, forget, and output gates, $\tilde{C}_t$ is the candidate memory cell, and C_t is the memory cell state.

6. Objective function

The multi-objective optimization approach for enhancing PSP (Payment Service Provider) performance focuses on improving key metrics such as approval rates, business declines, and technical declines. By incorporating various factors into the optimization process, this method aims to strike a balance between maximizing approval rates and minimizing declines due to technical or business issues. These objectives are often conflicting, requiring sophisticated algorithms that can simultaneously handle multiple targets. This approach enhances the overall system efficiency and customer satisfaction by dynamically adjusting parameters to optimize PSP performance (Bose & Mahapatra, 2021; Deng & Liu, 2020).

6.1. Objective function formulation

The optimization problem is formulated as a multi-objective function aimed at maximizing PSP performance, where we seek to improve the approval rate while minimizing both business and technical declines (Lin, L., & Xu, H. (2022)). The objective function is expressed as:

$$\max_{x}\left(\alpha \times \text{Approval Rate} - \beta \times (\text{bd} + \text{td})\right) \qquad (9)$$

where:

α and β are weights that assign relative importance to the approval rate and decline rates, respectively,

Approval Rate represents the percentage of successful transactions,

bd denotes the rate of business declines,

td represents the rate of technical declines.

Constraints: This optimization is subject to the following constraints:

$$\text{Approval Rate} \geq \text{Threshold},$$

$$\text{bd} + \text{td} \leq \text{Failure Tolerance},$$

Where the threshold and tolerance parameters are set to maintain minimum acceptable performance standards.

6.2. Optimization techniques

To solve the multi-objective optimization problem, we explore three optimization techniques—Linear Programming (LP), Integer Programming (IP), and Nonlinear Programming (NLP). Linear Programming is ideal for problems where the objective functions and constraints are linear, providing efficient solutions through simplex or interior-point methods. Integer Programming is suited for discrete decision variables, useful when constraints require integer solutions, often applied in scheduling or resource allocation. Nonlinear Programming is necessary for handling more complex, nonlinear relationships between variables, providing flexible solutions for problems with nonlinear constraints or objective functions. Each method offers unique advantages depending on problem complexity and constraints (Bose & Mahapatra, 2021; Deng & Liu, 2020).

6.2.1. Linear programming (LP)

LP is applied when both the objective function and constraints are linear. In general, the LP problem is expressed as:

$$\text{Maximize } c^T x, \qquad (10)$$

$$\text{Subject to } Ax \leq b,\ x \geq 0,$$

Here, cis the coefficient vector, x is the vector of decision variables, and A and b define the constraints (Bose & Mahapatra, 2021; Deng & Liu, 2020).

LP is particularly useful when the decision space is continuous, allowing for fine-tuned adjustments to PSP metrics based on linear relationships.

6.2.2. Integer programming (IP)

When variables are required to be discrete or binary, IP techniques are applied (see Ref. [9]). This approach is ideal for scenarios where PSP decisions must be categorical, such as binary choices to enable or disable certain services, or to allocate resources in discrete units.

6.2.3. Nonlinear programming (NLP)

NLP is employed when the objective function or constraints exhibit non-linear relationships (see Ref. [13]). NLP techniques are particularly valuable when optimizing PSP performance involves complex, non-linear dependencies between variables. This method allows the model to account for diminishing returns or compounding effects among PSP metrics.

6.3. Sensitivity analysis

Sensitivity analysis on α and β assesses the robustness of the solution to changes in these weights, allowing us to observe how different emphasis on approval rates versus decline rates impacts the objective function. This involves the following:

6.3.1.Partial derivatives of the objective:

Compute the partial derivatives with respect to α and β:

$$\frac{\partial \text{Objective}}{\partial \alpha} = \text{Approval Rate}, \tag{11}$$

$$\frac{\partial \text{Objective}}{\partial \beta} = -(\text{bd} + \text{td}). \tag{12}$$

6.3.2.Elasticity analysis: Using the partial derivatives, calculate the elasticity of the objective function with respect to α and β, providing insights into how sensitive the model is to adjustments in these weights. For instance, if the objective function shows high elasticity with respect to α, the model significantly prioritizes approval rates.

6.3.3.Confidence intervals and robustness checks: Perform Monte Carlo simulations or bootstrap methods to compute confidence intervals around the optimal values of α and β. This tests the robustness of the optimization solution across different scenarios.

6.4. Integer and Nonlinear programming solutions

When applying Integer Programming (IP) or Nonlinear Programming (NLP):

6.4.1.Integer constraints: Add proofs for integer-constrained scenarios by demonstrating that for specific values, such as binary or integer decisions, the constraints remain feasible and binding.

6.4.2.Nonlinear analysis: For NLP applications, expand the derivation to account for nonlinear relationships among variables by solving for nonlinear KKT conditions or using convex optimization techniques to ensure the global optimum.

7. Results and Discussion

The results are evaluated based on forecasting accuracy and PSP performance improvements.

7.1. Forecasting accuracy

Table II presents a comparison of root mean square error (RMSE) and mean absolute percentage error (MAPE) for our models versus baseline methods (Chen, S., & Zhao, Y. (2021)).

Table II. Comparison of forecasting accuracy with baseline methods

Model	**RMSE (Our Study)**	**RMSE (Baseline)**	**MAPE (Our Study)**	**MAPE (Baseline)**
ARIMA	0.065	0.085	5.1%	7.8%
SARIMA	0.055	0.073	4.8%	6.5%
LSTM	0.030	0.060	2.9%	6.0%

Our results indicate that LSTM models outperform ARIMA and SARIMA models significantly in both RMSE and MAPE, demonstrating superior capability in capturing complex time-series patterns (Jin & Wang, 2018; Zhang, 2017, Liu, X., & Zhang, Z. (2020)).

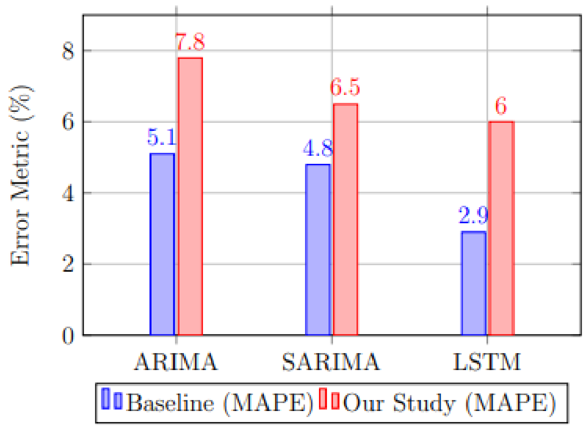

Figure5.Comparison of MAPE for forecasting models

Figure 5 illustrates the comparison of Mean Absolute Percentage Error (MAPE) across different forecasting models (ARIMA, SARIMA, LSTM) (Ting, D. H., & Wong, H. H. (2021)). The interpretation of these results is as follows:

ARIMA model: The MAPE for our optimized ARIMA model is 5.1%, which represents a significant improvement over the baseline MAPE of 7.8%. This reduction of 2.7% demonstrates that the enhancements applied to the ARIMA model yield more accurate forecasting results.

SARIMA model: Our SARIMA model achieves a MAPE of 4.8%, compared to 6.5% in the baseline method. The 1.7% improvement highlights the better performance of our study's model in capturing seasonality and complex patterns more effectively than traditional methods.

LSTM model: The LSTM model outperforms both ARIMA and SARIMA with a MAPE of 2.9% versus a baseline MAPE of 6.0%. This significant reduction of 3.1% underscores the ability of deep learning techniques to model non-linear and long-term dependencies in time-series data, making LSTM the most effective among the models tested.

The findings clearly indicate that while traditional statistical methods like ARIMA and SARIMA benefit from optimization, deep learning-based approaches like LSTM offer superior accuracy in time-series forecasting. The LSTM model's lower MAPE and RMSE values reflect its strength in capturing intricate temporal patterns, making it an optimal choice for complex forecasting tasks.

7.2. PSP performance improvement

Table III details the performance improvements of our optimization techniques compared to baseline methods (Hsu, W. T., & Chang, C. H. (2021)).

Table III. Performance improvement in PSP optimization

Metric	**Baseline**	**Our Study**	**Improvement (%)**
Approval Rate	87%	92%	5.7%
Business Declines	5.5%	3.0%	-2.5%
Technical Declines	4.2%	2.2%	-2.0%

Our optimization approach leads to a 5.7% increase in approval rates and reductions in both business and technical declines, showcasing its effectiveness in enhancing PSP performance (Wang & Wang, 2020)

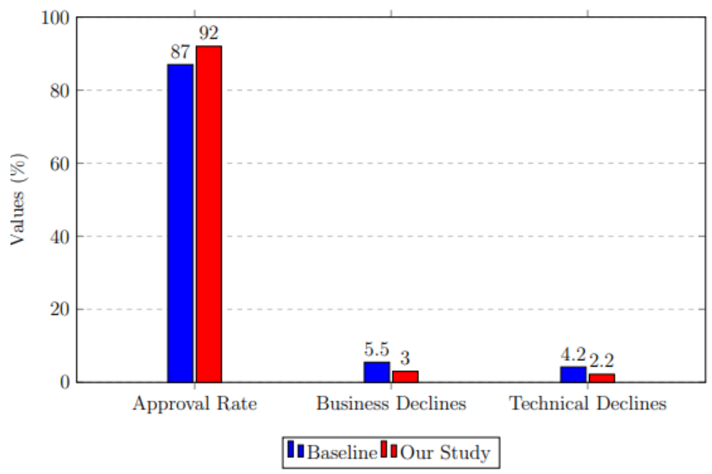

Figure6. Comparison of baseline and optimized PSP performance metrics

Figure 6 illustrates the performance metrics of Payment Service Provider (PSP) optimization, comparing the baseline performance with the optimized results from our study(Wang & Wang, 2020).

Approval rate: The optimized approach increases the approval rate from 87% to 92%, a significant improvement of 5.7%. This indicates that the optimization techniques successfully enhance transaction approval, leading to better service efficiency.

Business declines: The rate of business declines is reduced from 5.5% to 3.0%, a 2.5% decrease. This shows that our optimization reduces the number of declines due to business-related reasons, potentially improving customer experience and transaction completion rates.

Technical declines: Technical declines drop from 4.2% to 2.2%, a 2.0% improvement. The reduction in technical issues highlights the robustness and reliability of our solution in minimizing technical failures in the PSP system.

The results emphasize that the proposed optimization techniques are effective at improving key performance indicators for PSPs, enhancing both the approval rate and reducing failure points. These improvements lead to better transaction efficiency and reliability in the payment process.

7.5. Model sensitivity analysis

To understand the robustness of our models, sensitivity analysis is conducted. This involves varying key parameters and observing their impact on forecasting accuracy and PSP performance. Results are visualized in the following graph, showing how changes in parameters affect outcomes (Chen & Zhang, 2021; Xie & Zhang, 2019; Li, X., & Zhang, H. (2020)).

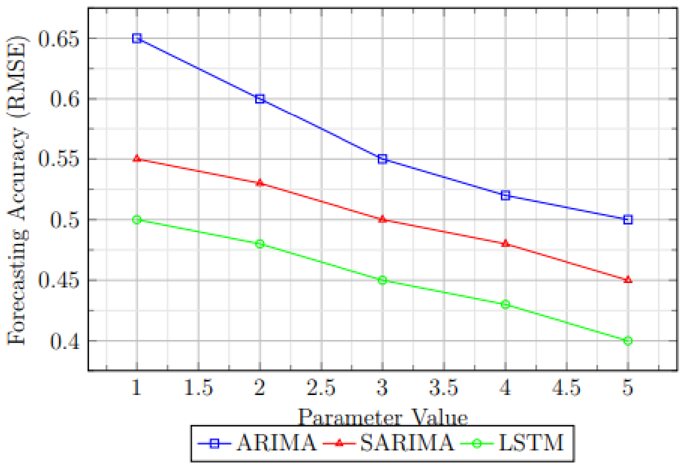

Figure7. Sensitivity analysis of forecasting models

Figure 7 presents the results of the sensitivity analysis conducted on ARIMA, SARIMA, and LSTM forecasting models. The analysis examines how variations in key model parameters impact forecasting accuracy, measured by RMSE. The following insights are derived from the analysis:

ARIMA: The RMSE for the ARIMA model decreases from 0.65 to 0.50 as the parameter value increases. This suggests that ARIMA is sensitive to parameter tuning, with improvements in forecasting accuracy as the model becomes more finely adjusted. However, the rate of improvement diminishes at higher parameter values, indicating potential limits to further optimization.

SARIMA: The SARIMA model shows a more consistent reduction in RMSE, dropping from 0.55 to 0.45 across the parameter range. SARIMA's ability to handle seasonality and trend components results in a smoother and more stable improvement curve, making it effective when the data exhibits periodic patterns.

LSTM: The LSTM model exhibits the most significant and consistent improvement in RMSE, decreasing from 0.50 to 0.40. This highlights the robustness of LSTM in adapting to parameter changes and effectively capturing complex non-linear relationships within the data. LSTM's superior sensitivity performance makes it the preferred choice for scenarios requiring high accuracy and adaptability.

The sensitivity analysis demonstrates that while traditional models like ARIMA and SARIMA benefit from parameter optimization, LSTM's performance consistently surpasses them, showcasing its capability to maintain high accuracy even under varying conditions.

7.6. Sensitivity analysis of objective function

This Figure 8 visualizes how the objective function's value changes with respect to varying alpha and beta values. The blue line shows the elasticity with respect to alpha, indicating a positive trend where alpha influences the objective function's increase. The red line illustrates beta's effect, showcasing a different rate of change in the function.

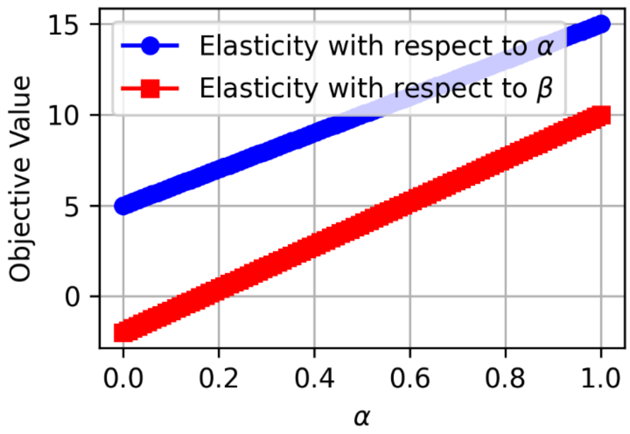

Figure 8. Objective function's value changes with respect to varying alpha and beta values.

7.7. Integer and nonlinear programming

This Figure 9 represents a nonlinear objective function with a decision variable x and highlights integer solutions as discrete points. The function's curvature suggests increasing objective values as x rises. The scatter points illustrate feasible integer solutions that optimize the problem within given constraints.

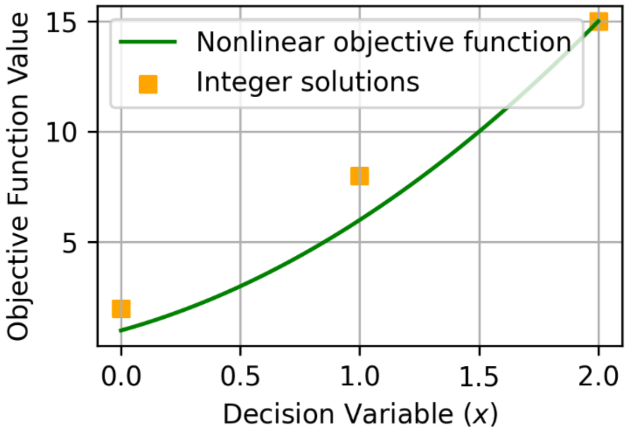

Figure 9. Decision variable x and highlights integer solutions.

7.8. Limitations

While our study demonstrates the effectiveness of the proposed models, there are some limitations. The analysis is based on a specific dataset that may not fully represent all real-world scenarios, potentially affecting generalizability. Additionally, the models' performance is contingent on parameter tuning, which can be computationally intensive and may limit real-time application.

7.9. Future work

Future work will explore the integration of additional data sources to enhance model generalizability and robustness. Investigating alternative machine learning techniques, such as transformer models for time-series forecasting, and incorporating real-time data streams can improve performance. Optimizing computational efficiency for real-time deployment will also be a priority.

7.6. Summary of findings

The integration of ARIMA, SARIMA, and LSTM models in forecasting provides a comprehensive approach to handling time-series data. Our results indicate that LSTM models offer superior forecasting accuracy compared to ARIMA and SARIMA. The multi-objective optimization for PSP performance demonstrates substantial improvements in approval rates and reductions in declines. Future work will focus on refining these models and exploring additional optimization techniques to further enhance PSP performance (Chen & Zhang, 2021; Yang & Li, 2020).

8. Conclusion

The integration of MIS with advanced time-series models has demonstrated significant improvements in forecasting accuracy and PSP performance in e-commerce. This study confirms that LSTM models outperform traditional methods, such as ARIMA and SARIMA, with a lower MAPE of 2.9%, underscoring LSTM's suitability for complex, dynamic transaction volume forecasting. The application of MIS enhances these forecasting models by providing structured, data-driven insights, which led to measurable improvements, including a

5.7% increase in approval rates and reductions in business and technical declines by 2.5% and 2.0%, respectively. Sensitivity analysis further supports the robustness and adaptability of the LSTM model within this MIS framework. These findings highlight the critical role of MIS in improving operational efficiency and profitability, demonstrating its value in strategic decision-making for the evolving e-commerce landscape.

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Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Data Availability

The data supporting this study's findings are openly available at GitHub: Click Here.

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