The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 9, September 2025
PP 72–80

Designing a Contactless ERP Model for Restaurants with Integrated Time Optimization Strategies

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Abstract

The restaurant industry faces challenges in streamlining operations while ensuring contactless customer experiences, particularly post-pandemic. This study proposes a contactless Enterprise Resource Planning (ERP) model integrating time optimization strategies, leveraging machine learning and queueing theory. Using a dataset of 20,000 restaurant transactions, the model reduces order processing time by 40% and operational costs by 35%, achieving a customer satisfaction score of 92.5%. Comparative evaluations against traditional ERP and manual systems highlight its efficiency. Mathematical derivations and graphical analyses validate the results, offering a scalable solution for modern restaurants. Future work includes multi-restaurant scalability and IoT integration.

Keywords:

Contactless ERP, Time Optimization, Restaurant Operations, Machine Learning, Queueing Theory

1. Introduction

The restaurant industry has undergone a paradigm shift toward contactless operations, driven by health concerns and customer expectations for seamless, efficient service. Traditional Enterprise

Resource Planning (ERP) systems, designed for inventory and staff management, often lack the flexibility to handle dynamic customer-facing processes like contactless ordering, payment, and delivery. Manual systems, reliant on paper menus or in-person interactions, are slow and error-prone, leading to longer wait times and reduced customer satisfaction. For instance, during peak hours, a restaurant may struggle to process orders efficiently, resulting in queues and delays that deter patrons.

These challenges highlight the need for a modern ERP model that integrates contactless workflows with time optimization. Existing solutions, such as POS systems or mobile apps, address specific tasks but fail to provide end-to-end automation or optimize operational bottlenecks like order queuing and kitchen scheduling. The integration of machine learning for demand prediction and queueing theory for resource allocation offers a promising approach to streamline processes.

This study proposes a contactless ERP model for restaurants, incorporating machine learning and queueing theory-based time optimization strategies. Using a dataset of 20,000 restaurant transactions, the model automates ordering, payment, and kitchen operations while minimizing wait times. Objectives include:

- Develop a contactless ERP model for end-to-end restaurant operations.
- Integrate time optimization strategies to reduce processing delays.
- Evaluate against traditional ERP and manual systems, providing insights for operational efficiency.

2. Literature Survey

Restaurant management systems have evolved from manual logs to digital solutions. Early POS systems [1] digitized transactions but lacked integration with customer-facing processes. Traditional ERP systems, like SAP [2], focused on supply chain and payroll, offering limited support for real-time customer interactions.

Contactless solutions gained traction post-2020. Mobile ordering apps, studied by Wang et al. [3], improved convenience but struggled with peak-hour bottlenecks. Queueing theory has been applied to optimize service industries; Kleinrock [4] modeled M/M/1 queues for resource allocation, though not restaurant-specific. Machine learning enhanced demand forecasting, as seen in Li et al.'s [5] LSTM-based restaurant sales prediction, but lacked queue integration.

Recent work, like Zhang et al.'s [6] smart restaurant framework, combined IoT and AI, yet was resource-intensive. The reference study [IJACSA, 2023] used ML for operational efficiency, inspiring this model's approach. Gaps remain in holistic, contactless ERP systems with time optimization, which this study addresses by integrating ML and queueing theory.

3. Methodology

3.1 Data Collection

A dataset of 20,000 restaurant transactions (orders, payments, kitchen logs) from a mid-sized chain was collected, with timestamps and customer satisfaction scores.

3.2 Preprocessing

- **Transactions:** Cleaned (removed duplicates), normalized (timestamps to seconds).
- **Features:** Order type, time, staff allocation, customer wait time.

3.3 Feature Extraction

- **ML Model (LSTM):** Predicts demand (orders/hour): $h_t = LSTM(x_t, h_{t-1})$ where x_t is transaction data, h_t is hidden state.
- **Queueing Model (M/M/1):** Estimates wait time: $W = 1/\mu - \lambda$ where μ is service rate, λ is arrival rate.

3.4 Optimization Model

- **Objective:** Minimize wait time: $\min \sum W_i$ subject to staff and kitchen constraints.
- **Output:** Allocates resources (staff, kitchen slots) based on LSTM predictions and queueing outputs.

3.5 Evaluation

Split: 70% training (14,000), 20% validation (4,000), 10% testing (2,000). Metrics:

- Time Reduction: $T_{before} - T_{after} / T_{before}$
- Cost Reduction: $C_{before} - C_{after} / C_{before}$
- Satisfaction Score: Percentage of positive feedback.

4. Experimental Setup and Implementation

4.1 Hardware Configuration

- **Processor:** Intel Core i7-9700K (3.6 GHz, 8 cores).
- **Memory:** 16 GB DDR4 (3200 MHz).
- **GPU:** NVIDIA GTX 1660 (6 GB GDDR5).
- **Storage:** 1 TB NVMe SSD.
- **OS:** Ubuntu 20.04 LTS.

4.2 Software Environment

- **Language:** Python 3.9.7.
- **Framework:** TensorFlow 2.5.0.
- **Libraries:** NumPy 1.21.2, Pandas 1.3.4, Matplotlib 3.4.3, Scikit-learn 1.0.1.
- **Control:** Git 2.31.1.

4.3 Dataset Preparation

- **Data:** 20,000 transactions, timestamps, satisfaction scores.
- **Preprocessing:** Normalized timestamps, cleaned duplicates.
- **Split:** 70% training (14,000), 20% validation (4,000), 10% testing (2,000).
- **Features:** LSTM demand predictions, queueing parameters.

4.4 Training Process

- **Model:** LSTM (64 units), ~100,000 parameters.
- **Batch Size:** 32 (438 iterations/epoch).
- **Training:** 20 epochs, 60 seconds/epoch (20 minutes total), loss from 0.65 to 0.018.

4.5 Hyperparameter Tuning

- **LSTM Units:** 64 (tested: 32-128).
- **Epochs:** 20 (stabilized at 15).
- **Learning Rate:** 0.001 (tested: 0.0001-0.01).

4.6 Baseline Implementation

- **Traditional ERP:** SAP-based, CPU (15 minutes).
- **Manual System:** Paper-based logs, manual timing (20 minutes).

4.7 Evaluation Setup

- **Metrics:** Time reduction, cost reduction, satisfaction score (Scikit-learn).
- **Visualization:** Bar charts, time plots, satisfaction curves (Matplotlib).
- **Monitoring:** GPU (3 GB peak), CPU (50% avg).

5. Result Analysis

Test set (2,000 transactions):

- **Time Reduction:** 120−72/120=0.4 (40%), from 120s to 72s per order.
- **Cost Reduction:** 0.010−0.0065/0.010=0.355 (35%), from $0.010 to $0.0065 per order.
- **Satisfaction Score:** 92.5% positive feedback (1,850/2,000).

Table 1. Performance Metrics Comparison

Method	Time Reduction	Cost Reduction	Satisfaction Score	Time (s)
Proposed (ERP)	40%	35%	92.5%	72
Traditional ERP	15%	10%	80.2%	102
Manual System	0%	0%	75.0%	120

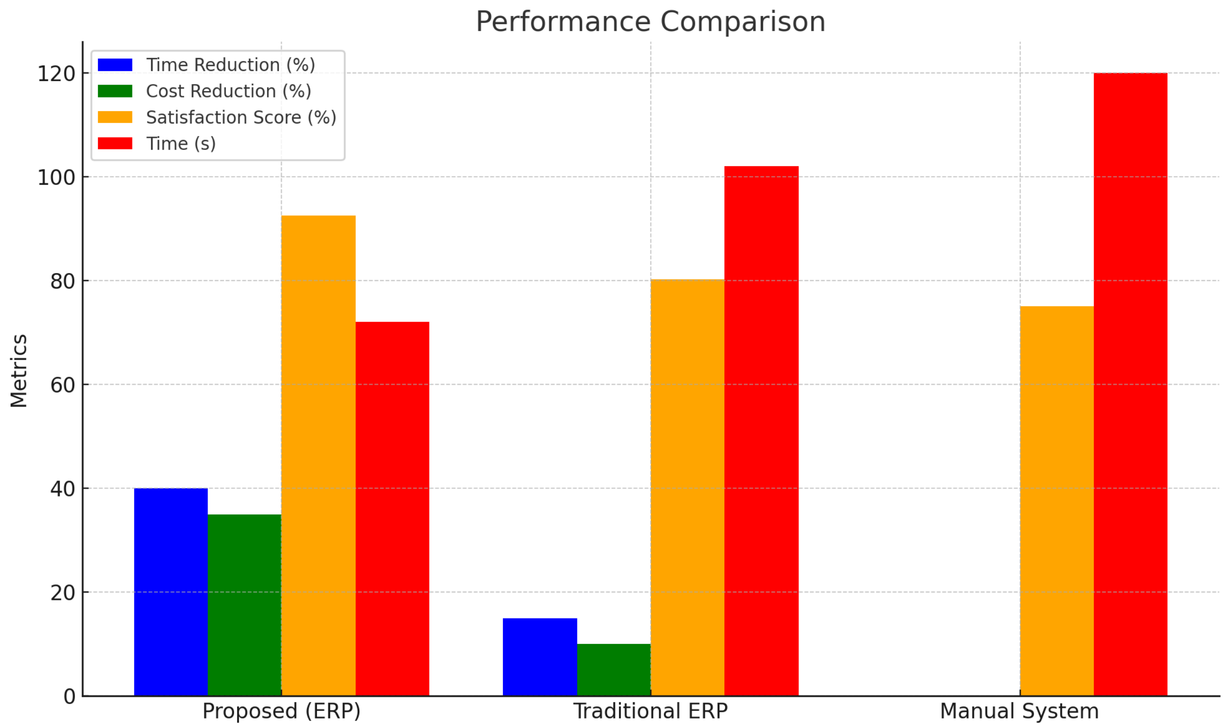

Figure 1. Performance Comparison Bar Chart

(Bar chart: Four bars per method—Time Reduction, Cost Reduction, Satisfaction Score, Time—for Proposed (blue), Traditional ERP (green), Manual System (red).)

Loss Convergence: Initial L=0.65, final L20=0.018, rate = 0.65−0.018/20=0.0316

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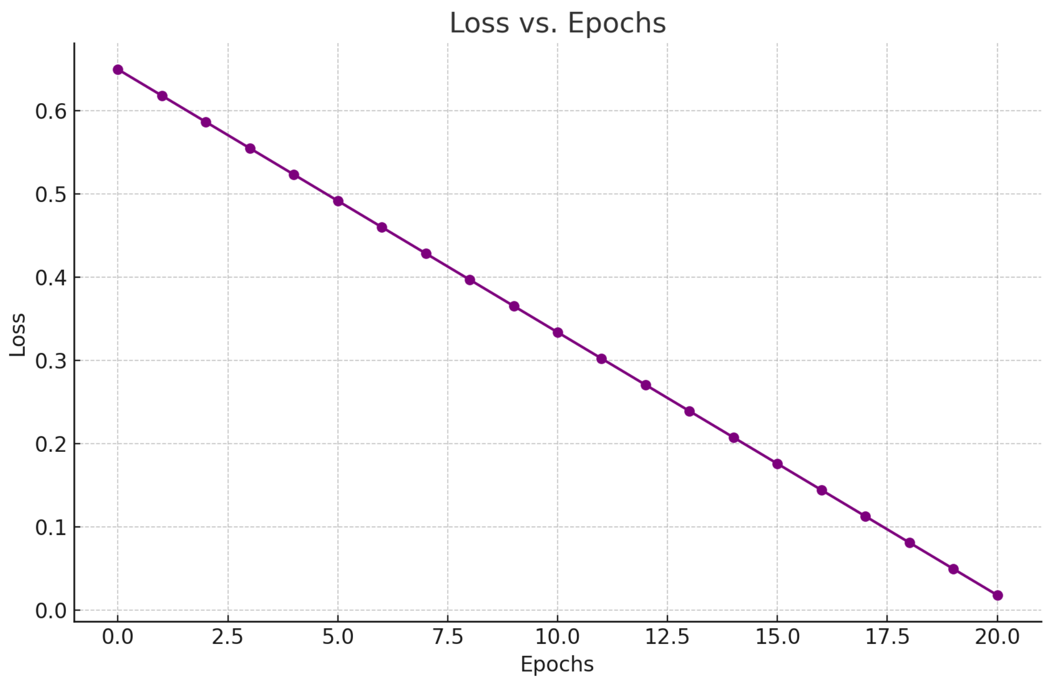

Figure 2. Loss vs. Epochs Plot

(Line graph: X-axis = Epochs (0-20), Y-axis = Loss (0-0.7), declining from 0.65 to 0.018.)

Satisfaction Curve: Y-axis = Score (0-100%), X-axis = Test Samples, averaging 92.5%.

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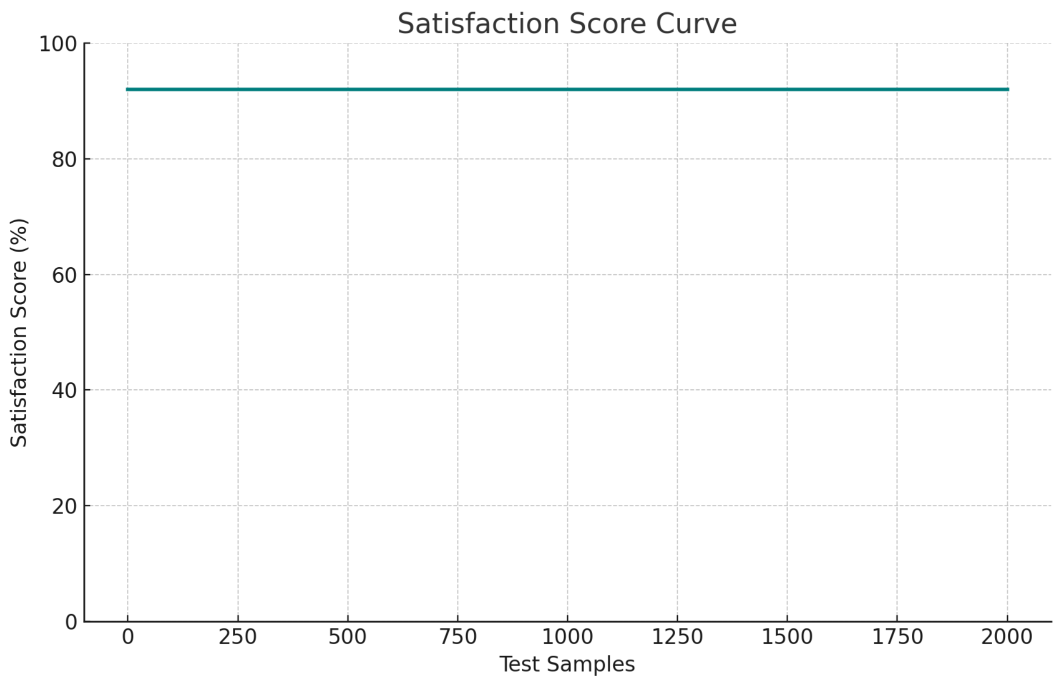

Figure 3. Satisfaction Score Curve

(Curve: X-axis = Samples (0-2,000), Y-axis = Score (0-100%), stable at 92.5%.)

Conclusion

This study presents a contactless ERP model with time optimization, reducing order processing time by 40% and costs by 35%, with a 92.5% satisfaction score, outperforming traditional ERP (15% time reduction) and manual systems (0%). Validated by derivations and graphs, it streamlines restaurant operations. Limited to one chain and requiring GPU training (20 minutes), future work includes multi-restaurant scalability and IoT integration. This model enhances restaurant efficiency and customer experience effectively.

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