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Predictive Modeling of Queue Lengths and Waiting Times in E-Commerce Platforms: A Statistical Approach

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The ever growing e-commerce sectors have posed new problems to do with how to control for the number of customers as well as the waiting times especially during peak sales periods affecting customer loyalty. The purpose of this current research work is to construct predictive models for forecasting queue dimensions that occur in e-business environments in order to improve operations functioning. This research applies multiple modeling techniques ARIMA, Linear Regression model, Neural Network model, employed the hybrid modeling technique to compare the performance of different models in variance in digital traffic patterns. Log files of our platform were analyzed using data from six months, data was preprocessed and model was assessed by Mean Absolute Error (MAE), Mean Squared Error (MSE) and Co-efficient of-determination (R2). The statistics show that the best results are obtained by the Neural Network model, whose R-squared is 0.85 during heavy traffic as well. We found that ARIMA achieved steady results for off-peak periods and that Linear Regression could be a decent benchmark. This paper's conclusions indicate that it is possible to apply and implement adaptive predictive models that can help e-commerce queue management to improve the given situation more effectively and optimize customers' waiting time. This study provides a systematic method for real-time traffic prediction of e-commerce which should open up directions for further

examination in mixture and real-time evaluation models.
Keywords: Predictive modeling, queue management, waiting time prediction, e-commerce platforms, ARIMA model, neural networks, customer satisfaction.

1. Introduction

The trend towards increased growth of e-commerce has changed the nature of global outreach through purchase and sell by means of real time purchase almost from anywhere in the world. As more consumers turn to e-commerce to buy goods and services, the congestion complexities of running an e-commerce facility increase especially with regards to the queue length and waiting time during periods of congestion. Managing queues is a significant factor in improving both the user interface and server productivity because long waits could significantly discourage users about the application, resulting in fewer visits in the future (Smith et al., 2021). Therefore, the concerned attempts at systemic overviews of queue lengths and waiting times have become a significant research focus in the sphere of e-commerce, devoted to predicting system breakdowns and offering preventative measures for improving the platform's performance.

Prior research in queue theory has adopted statistical solutions to conventional consumer and service sectors, with specific models concerning physical queues or customer service facilities (Kleinrock, 2020). However, applying these models in digital queues in e-commerce platforms seeking to manage consumers' flows has its challenges majorly because; digital traffic is highly volatile and consumers are not synchronous. These platforms usually experience high fluctuation demands often during the promotional period or during the holiday seasons, and such periods exert extra pressure on the system resources thus contributing to high abandonments (Zhou & Lee, 2019). Modern research focuses on the flexible and prognostic capabilities of such conditions as opportunistic, Responsive organisations and environments; self-adaptive; environment-adaptive; and providing insights into possible solutions toward optimising infrastructure and enhancing customer satisfaction (Perez & Wang, 2023).

The relevance of this research is that the ideas presented can fill the gap which exists between basic queue management and advanced e-commerce applications. In this study, the new statistical model has been proposed for estimating queue lengths and waiting times of e-commerce systems and this research adds valuable insight to scientific findings and e-commerce practises. Forecasting models should be viewed as useful instruments for operations managers – they help to implement early actions that may prevent possible queueing delays and provide high service levels. Also, planning for the precise amount of utilization of the system, e-commerce platforms are capable of efficient resource allocation hence lowering general costs and system expansion throughout demand surges.

This study aims to address the following research question: In what ways can predictive statistical models be utilised to manage fight forecasts on the queue length and waiting time on e-commerce firms, and their impacts on other efficiency and customer satisfaction? Based on this question, a detailed study of different statistical methods such as regression, time series modelling, and machine learning to design the model suitable to dynamic and complex e-commerce settings.

2. Literature Review

Previous theoretical and empirical studies of queue management have been primarily concerned with internal environments within outlets and other call centers where statistical models have been used to estimate queue length and waiting time (Gross & Harris, 2020). However, due to increased e-commerce, these conventional models have been developed to incorporate the aspect of digital queues in recent years. However, e-commence patterns cause difficulties because the traffic rates are highly variable and users are not simultaneous, which results in changing performance issues during high traffic peaks (Choudhary & Gupta, 2021).

Predictive Modeling Approaches in E-Commerce

Some previous works have described different approaches on using predictive modeling methods for controlling requests and response times of queues, but the dynamic and information-intensive characteristics of e-commerce environments suggest for models that can address these features adequately. For instance, predictability of high traffic periods has been well demonstrated by machine learning models thereby enabling organizations to prepare adequately (Kim et al., 2022). In its interaction with these concepts, linear regression and time series models are still traditional since ARIMA models are effective in stable environments but less efficient when faced with increased demand rates characteristic of e-shops (Patel & Ramasamy, 2021). In addition, neural networks have also been used for modeling in e-commerce, while their high demand on resources may limit their application in actual timely more business environments (Zhu & Chen, 2022).

Customer Behavior and Service Expectations

Understanding customer behavior is integral to effective queue management, as perceived wait times can directly influence customer satisfaction and retention (Anderson et al., 2020). Studies on customer expectations in digital environments indicate that prolonged wait times often lead to increased cart abandonment, thus affecting sales and customer loyalty (Smith et al., 2021). Nevertheless, there is a lack of predictive models specifically designed to accommodate the fluctuating patterns of customer behavior and the variance in digital traffic caused by promotional events or holiday seasons (Johnson & Lee, 2019).

Identified Research Gaps

However, various issues remain open in the prediction research area even after the significant development of a machine learning algorithm. First, most current research uses models with fixed parameters that cannot automatically scale during busy periods, which is crucial for real-time systems (Patel & Ramasamy, 2021). Moreover, although machine learning models provide accuracy, the models are not portable across other platforms; there are few studies that examine the application of the models in large–scale cloud systems acceptable for e-commerce environments (Zhu & Chen, 2022). Two such gaps are First, there is a dearth of studies that address different kinds of hybrid models, which blend conventional statistical methods with machine learning to enhance the reliability of demand predictions for various demand conditions (Choudhary & Gupta, 2021).

Addressing the Research Gaps

These gaps this research intends to fill by proposing the development of a new comprehensive model based on the Assistance of Machine Learning with Statistical Techniques (AMIST) for higher adaptability and scalability for operation in various e-commerce domains. As a result, this research will be able to identify suitable approaches including ARIMA, neural networks and other hybrid techniques so as to develop a framework for learning the dynamics of the demand patterns during this period by adding a dynamic element to change in line with changes in the unknown demand patterns. In addition, this research aims to advance knowledge within the area by identifying resource management approaches that enhance customer waiting time and decrease time to;/ wait. Unlike previous studies, this research will focus on system performance in real-time which has been missing in previous models; also, the solution developed here is scalable and more adaptable to the actuality of digital queues in e-commerce especially under high traffic conditions.

3. Methodology

3.1 Research Design

The current research adopt a quantitative, predictive research approach that seeks to model and predict the lengths of queues as well as waiting times for business on the e-business platforms. A two-state analysis technique that combines more conventional analytical statistical methods with machine learning techniques in order to improve the accuracy of the predictions as well as to allow them to be more flexible to alterations in the signals. This design is perfect for the fluidity in e-commerce traffic and that it can capture frequent oscillations in customer traffic (Choudhary & Gupta, 2021).

3.2 Data Collection Methods

For this study, data was gathered from the logs of a widely used e-commerce trading floor's queue data and user behavior analysis over a period of six months. This information includes the total concurrent user, average line, delay and time of hour. In this context, the first phase of data preprocessing involved cleaning in an attempt to eliminate records with missing values and normalization of data in an effort to harmonize the ranges of variable input data for models (Patel & Ramasamy, 2021).

Data Collection Process:

1. Identification of Relevant Metrics: Key performance indicators (KPIs) such as average queue length, waiting time, and server resource utilization.

2. Data Cleaning and Preprocessing: Removal of outliers, normalization of data, and handling missing values.

3. Segmentation by Demand Peaks: Data is segmented into peak and off-peak hours to study different traffic patterns.

3.3 Sample Selection

Its element contains data of records from six months of the operation of an e-commerce platform. To obtain a model applicable for various every day situations, random sampling is used for both peak and off-peak demand segments. After pre-processing, the last set of data comprises nearly 100,000 instances that allow covering the sufficient amount of data for training, validation, and testing (Anderson et al., 2020).

3.4 Analysis Techniques

The analysis includes three main steps: exploratory data analysis (EDA), model selection, and performance evaluation.

1. Exploratory Data Analysis (EDA): EDA is done with the aim of exploring data, describe the nature and assess the data for possible outliers. To observe changes in queue length and time waiting in queue descriptive analytics, and data visualization that differentiate the time segments are used (Gross & Harris, 2020).

2. Model Selection and Training: The study employs multiple predictive models, including:

- ARIMA for short-term, seasonal time series prediction.
- Linear Regression to establish relationships between independent variables (such as traffic volume) and waiting times.
- Neural Networks (NNs) to capture complex, nonlinear relationships in queue data.

Each model is trained on 70% of the dataset, with hyperparameter tuning conducted using grid search to optimize performance. Cross-validation with a 5-fold split is used to ensure model robustness (Zhu & Chen, 2022).

3. Performance Evaluation: Model performance is evaluated by Mean Absolute Error (MAE) Mean Squared Error (MSE) and R-squared values. Further, the results of a comparative analysis of the models are presented to identify the advantages and disadvantages of each model in terms of accuracy and computational complexity.

Methodology Flowchart

The following flowchart outlines the step-by-step process used in this study.

Flowchart:

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Data Collection ──► Data Preprocessing ──► EDA ──► Model Selection ──► Model Training and Tuning ──► Performance Evaluation ──► Result Interpretation

4. Results

The following part discusses the queuing analysis and prediction applied to the queue length or waiting time of the e-commerce platform. The similarity and difference in ARIMA, Linear Regression and Neural Network model in predicting the queue metrics are discussed and major patterns that have been identified have been discussed.

4.1 Descriptive Statistics and Exploratory Analysis

Using descriptive statistics, the distribution of queue lengths and waiting times across the different time segments implied by the real-life situation were found out during EDA. An average of 45.3 users were waiting in the queue on an average during the peak hours and took 3.4 minutes to be served. On the other hand, there was a considerably low number in the other four hours at an average of 15.2 users and a wait time of 1.1 minute.

Table 1: Descriptive Statistics of Queue Length and Waiting Time

Metric	Peak Hours	Off-Peak Hours
Average Queue Length	45.3	15.2
Average Waiting Time (minutes)	3.4	1.1
Standard Deviation (Queue Length)	5.7	2.3
Standard Deviation (Waiting Time)	1.2	0.5

To analyse the hourly distribution of this queue's length and the time people spent waiting, I included in Figure 1 a graph of the monthly variation. It was also revealed that traffic flow significantly rose in for the whole day 6-9 PM which falls in the category of promotions and shopping.

4.2 Model Performance and Accuracy

Each model's predictive accuracy was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared values. Table 2 provides a summary of the performance metrics for each model.

Table 2: Model Performance Metrics

Model	MAE	MSE	R-Squared
ARIMA	0.57	0.76	0.72
Linear Regression	0.65	0.82	0.68
Neural Network	0.42	0.54	0.85

The Neural Network model produced the lowest MAE and MSE values; in addition, it had the highest R squared of .85 showing the NN model has the ability to predict complex non-linear trends. However, during stable demand periods, short-term prediction accuracies of the ARIMA model were almost the same as those of the ARIMA whilst the Linear Regression yielded baseline predictions with fairly acceptable levels of accuracy.

4.3 Comparative Analysis of Prediction Trends

Figure 2 provides the actual and predicted queue length of each tested model in the course of high traffic periods. The Neural Network model best matches the actual queue data especially during the time of high traffic, and the degree of disparity is very small. However, during the periods of high increment in demand, ARIMA predictions are slightly slower than the actual data, whereas, during low demand, it is strikingly consistent.

Table 3: Predictive Accuracy by Demand Segment

Model	Peak Hours MAE	Off-Peak Hours MAE
ARIMA	0.71	0.44
Linear Regression	0.78	0.50
Neural Network	0.48	0.36

During peak hours, the Neural Network model demonstrated the lowest MAE (0.48), underscoring its ability to adapt to sudden increases in traffic more effectively than the other models.

4.4 Significant Patterns and Trends

The findings revealed that:

- Peak Hour Trends: Demand surges between 6-9 PM significantly impact queue lengths and waiting times, with higher fluctuations in model accuracy during these intervals.
- Model Suitability by Traffic Level: The Neural Network model is best suited for high-traffic, dynamic demand conditions due to its ability to capture non-linear patterns, while ARIMA is more effective in stable demand scenarios.
- Customer Impact: Prolonged waiting times correlate with peak traffic, indicating potential periods for targeted resource allocation to reduce abandonment rates.

5. Conclusion

The models of queue length and wait time prediction constructed for the e commerce platforms in this study were ARIMA, Linear regression and Neural network. Some of the findings show that the Neural Network performs better than the other models especially during high activity periods, because of its benefit on nonlinear data. ARIMA was suitable for small fluctuations and short-range prediction but failed to handle sharp traffic increase, whereas Linear regression exhibited mediocre predictive performance as a benchmark model.

The relevance of these findings concerns the improvement of customer attitudes and organization at e-business sites, as long waiting times are counterproductive to cart retention and user engagement. This work helps to enhance knowledge of queue management in digital contexts by finding the best models for performance and offering a highly reliable base for traffic prediction in emergent, highly populated e-commerce environments.

In a practical sense, these models can be used by the e-commerce platforms for better utilization of resources and for better handling of the high trafficked periods consequently leading to better user experience and customer loyalty. In the future, more investigations can use hybrid models or employing real-time data streams to enhance the optimisation of the prediction accuracy and first in context of scalability in situations with dynamic evolution of the demand.

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