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Optimizing Inventory Management In Retail With Hybrid Genetic Algorithms And LSTM

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Abstract

In the fast-changing retail industry, maintaining a balance between reducing operating expenses and meeting service demands is essential to effective inventory management. The traditional models are not as efficient as resolving the non-linear behavior of contemporary consumer demands. In this work, a Hybrid GA-LSTM model is proposed as an integrated model that utilizes an LSTM neural network for high-accuracy demand forecasting and Genetic Algorithms (GA) for multi-objective inventory optimization. The proposed model was compared to the conventional models, such as Economic Order Quantity (EOQ) and standalone LSTM models. The empirical result shows that the Hybrid GA-LSTM approach can effectively improve the performance of these benchmarks by reducing total inventory costs by 37.53%, maintaining 95% service level, and minimizing the stockout rate to 5%. The results indicate that using machine learning to improve the prediction and evolutionary algorithms for decision-making can better match the inventory to the real market. In practice, this study offers a flexible and efficient data-driven approach for retailers to deal with seasonality and promotions. Although it may have limitations in terms of computational requirements and the need for a vast database of historical data, the model could be expanded to incorporate more data and other factors, thereby improving its accuracy and applicability as time goes on. The study is important to the field because it shows the efficacy of the hybrid optimization, and it has implications beyond the narrow scope of the study, such as the healthcare and manufacturing industries. To further validate the effectiveness of the long-term solution, future studies could increase scalability and investigate the integration of other optimization methods, like reinforcement learning, in real operational settings.

Keywords: Inventory optimization, demand forecasting, LSTM, Genetic Algorithm, retail analytics, hybrid optimization, inventory management.

1. Introduction

In retail, inventory management is a key factor that can directly impact profitability, customer satisfaction, and operational efficiency. A retailer's challenge is to maintain a balance between having enough stock in their stores and not too much, so they can keep their customers happy and reduce the costs from overstocking and stockouts [1]. Some traditional inventory management methods like Economic Order Quantity (EOQ) and Reorder Point (ROP) are not able to handle the volatility and unpredictability of demand [2][3]. This creates challenges for retailers to keep their stocks in balance and prevents them from having enough items on hand, or selling items they have too much of, thus limiting their sales and customer satisfaction. One of the biggest hurdles is the ability to predict customer demand and the factors that impact it, including seasonal variations, sales events, and unpredictable events. Stockout and overstock scenarios cost companies money; fluctuating demand creates a challenge in determining the optimal levels of stock. Moreover, conventional forecasting techniques are not adept at handling the wealth of increasingly complex data available, and they are not as effective at providing accurate and timely forecasts. The solutions required for these challenges are advanced and better suited for the changing demand patterns and real-time inventory decisions. The inventory management solutions have been discussed in previous studies, either using the traditional method or machine learning (ML) [4]. The traditional models, such as EOQ and ROP, have been widely adopted, but they are not very effective in responding to demand fluctuations. In recent years, a variety of ML algorithms have been used for demand forecasting, such as ARIMA, support vector machines (SVM), and recurrent neural networks (RNN). Most of these models, however, do not optimize the decision-making process, or they do not consider the combined forecasting and inventory optimization problem. Although ML models have been found to be good at predicting demand, they may not include optimization for inventory management [5]. To fill this gap, this research suggests a hybrid model that fuses the prediction ability of the LSTM network with the optimization ability of GA. GA+LSTM gives the capability of forecasting not just the demand but also optimizing reorder points & quantities to reduce costs and enhance service levels.

Objectives:

- Design a hybrid GA-LSTM model for Retail Inventory Management.
- Analyze the effectiveness of the model for forecasting demand and optimizing inventory.
- Compare the hybrid model and traditional inventory management systems.
- Examine how the hybrid model affects relevant KPIs like inventory costs, stock-outs, and service levels.

The aim of this research is to see if the use of LSTM and GA can yield more accurate predictions of demand and more efficient inventory management, which can be a comprehensive solution to the modern retail problems.

This paper is organized in the following way: In Section 2, traditional inventory management techniques, such as Economic Order Quantity (EOQ) and Reorder Point (ROP), are reviewed, and the application of machine learning models in inventory optimization, particularly Long Short-Term Memory (LSTM) networks and Genetic Algorithms (GA), is discussed. The methodology consists of a qualitative and quantitative approach, which is outlined in section 3. The quantitative aspect includes modeling of the hybrid GA-LSTM model for demand forecasting and inventory optimization, and the qualitative aspect involves comparing this model with the traditional models. Section 4 discusses the test of the hybrid model on real-world retail data, its performance on demand forecasting and inventory optimization, and compares it with the traditional methods. Section 5 ends with a summary of key findings, implications for retail inventory management, and recommendations for future research, including scaling and adapting the model to other retail settings.

2. Literature Review

Inventory management has been one of the main concerns of Operations Research, and it is the classic inventory control models, such as the Economic Order Quantity (EOQ) and the Reorder Point (ROP), that have served as the basis for modern practices [6][9]. EOQ aims to minimize total inventory costs, balancing the cost of ordering and holding inventory. ROP also seeks to establish the best time to place new orders to prevent stock-outs. These techniques work well in very stable environments with predictable demand; however, they are not suitable for the complexity and diversity of today's retail environment. Predicting future demand in inventory management is of great importance, and time series forecasting is a very popular approach to predicting future demand from historical data [7][8]. Recurrent neural networks (RNNs) are specifically useful for capturing long-range dependencies and trends in time series data, making them particularly effective for these types of problems. Long Short-Term Memory (LSTM) networks, which are a type of recurrent neural network (RNN), have been found to be particularly effective for time series data modeling, owing to their capacity to handle long-term dependency and trends. LSTM models have the ability to capture the complex, nonlinear relationships in demand data, which is suitable for use in retail inventory management, where demand can be affected by seasonality, promotions, and other changing factors [12].

Optimization methods such as Genetic Algorithms (GA) contribute optimization support toward complex problems, including but not limited to inventory management [10][13]. Because the types of optimization tasks that GAs are well suited for include non-linear objectives from very large solution (search) spaces, such as optimal reorder points, order quantities, and inventory policies in very large solution spaces, GAs can be very useful. Many of these problems can be solved through the process of mimicking natural evolution, wherein GAs evolves a population of potential solutions over several generations, including through mutation, crossover, and selection. GAs are also utilized in combination with others (hybrid optimization approaches) as demonstrated in applications to supply chain management, manufacturing, and health care [15][17]. In inventory management, a promising approach is the application of hybrid models that combine machine learning techniques (LSTM) with metaheuristic optimization techniques (GA) in order to increase demand, forecast accuracy, and optimally manage inventory [11]. Hybrid approaches combine the forecasting capabilities of LSTMs and optimization capabilities of GAs to develop solutions that will be more robust and adaptable to the complex and dynamic nature of retail inventory management [18].

3. Methodology

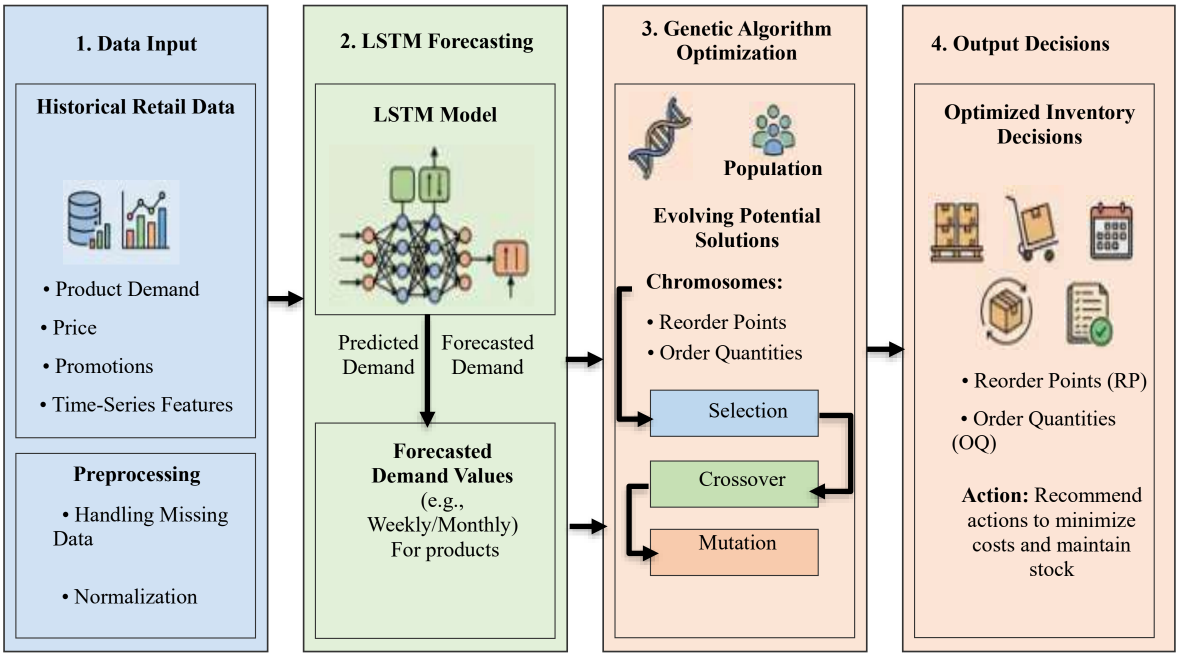

Figure 1. Architecture Diagram for Hybrid GA-LSTM Approach for Inventory Optimization

Figure 1 depicts the architecture diagram of the Hybrid GA-LSTM approach used to forecast the demand and optimize inventory. The process commences with the Data Input, where historical retail information (e.g., product demand, price, promotions) has been gathered and pre-processed (missing value handling and normalizing feature scaling). Pre-processed data are then provided to the LSTM Forecasting block, where LSTMs will predict the future demand flow based on previous trends and input variables. Predicted demand values are then used within the GA-Optimization block, where GAs will enhance the potential for inventory decisions by evolving chromosomes (representing the reorder point and order quantity) through operations such as selection, crossover and mutation. Therefore, GAs will help you optimize the inventory decision (total cost, i.e. holding cost, ordering cost and stockout cost). Finally, the output of the decision will provide you with improved inventory recommendations (i.e. reorder point and order quantity) to ensure your inventory levels are in line with the demand forecast with a minimized cost. The architecture also demonstrates combining the forecasting ability of LSTM and the optimizing ability of GA provides an effective solution for dynamic retail inventory management [16].

Dataset Description

Historical retail demand data were used for this study. Demand data were captured for each individual retail transaction (item sold for a given price) over two years (issue period) by product type and product variety across many retail locations, and in total there are 50,000 records of individual demand transactions in the data set. The demand data, source used to create the demand data and the key variables contained in each demand record (product id, date/time, demand quantity, selling price, location where demand occurred, demand promotional activity) will be discussed. Demand data will be cleaned (delete missing data, manage outliers, normalize numeric variables) so that they can be utilized for time series forecasting. The cleaned demand data set will be converted to a time series data set by summing demand for the entire week to represent total demand for the week, and the new data set will include 80 percent of the cleaned units for training and 20 percent for testing model performance.

LSTM Modeling and Genetic Algorithm (GA) Hybrid Framework

Long Short-Term Memory (LSTM) networks offer a practical approach to predicting demand by learning from temporal relationships within time-series data. They can identify sequential patterns in the historical demand data, and can be broken down into 3 main layers: (1) input layer; (2) LSTM layer; (3) dense output layer. The input feature set includes the three components of demand: historical demand, price and sales promotion. All three variables must be standardised prior to being fed into the LSTM model. The LSTM model has 2 hidden layers, each with 64 hidden units. The two hidden layers allow the LSTM model to learn the temporal relationship of the demand dataset. The hidden layers use the ReLU activation function, whilst the output layer uses the linear activation function in order to provide a prediction of future demand.

The LSTM model is trained using the Adam optimisation algorithm with a learning rate of 0.001 and the Mean Squared Error (MSE) as its loss function. The training consists of 100 epochs with a batch size of 32 and early stopping based on overfitting. The MSE is defined in Equation (1):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{\mathrm{predicted},i} - y_{\mathrm{actual},i})^2 \quad (1)$$

where $y_{\mathrm{predicted},i}$ is the predicted demand for product i, and $y_{\mathrm{actual},i}$ is the actual demand.

In order to improve your inventory decision making process, It uses Genetic Algorithm (GA) and finds the optimal reorder point and the order quantity. Each individual "solution" in the GA population is represented as a vector of decision variables: reorder points and order quantities of each item in the population. The fitness function is used to evaluate how well each individual solution meets the needs of the business, by taking into account the total associated costs. These costs include the costs to hold the inventory on hand; to place an order; and penalties incurred due to stockouts. The objective is to minimize the total cost of all three of these components, while achieving the desired level of service (i.e. stock availability). The formulation of the fitness function is provided in equation (2):

$$\text{Fitness} = \text{Total Cost} = \text{Holding Costs} + \text{Ordering Costs} + \text{Stockout Penalties} \quad (2)$$

In GA operations, candidates are selected at random with a level of fitness using dynamic selection based on the genetic algorithm dynamic selection of individual candidates based upon the performance of an individual (fitness) will be utilized. A two-parent (or multi-parent) crossover operation occurs in order to create new individuals by swapping genes between parents; this is done as indicated by a single crossover point located on the chromosome. Findings the use of a mutation rate of 0.01 ensures that there remains sufficient diversity within the population, thereby preventing local optima.

In this case, prediction of weekly product demand is performed by the long short-term memory (LSTM) algorithm, which models all previous product demand and certain influences (price, promotion) on that demand to predict what future product demand will be. LSTM predictions are passed to the GA to determine optimal values for reorder point, and order quantity based on minimizing total costs while providing adequate levels of inventory in response to the forecasted product demand. LSTM prediction values will be passed as inputs to the GA when performing GA optimization. The combination of LSTM's forecasting ability with GA's optimization capabilities improves the efficiency of inventory management.

Algorithm for Hybrid GA-LSTM Approach

```
def train_LSTM(data):
  model = LSTM(input_shape=(timesteps, features), units=64, activation='relu')
  model.compile(optimizer='adam', loss='mean_squared_error')
  model.fit(data, epochs=100, batch_size=32, early_stopping=True)
  return model
def forecast_demand(model, future_data):
  return model.predict(future_data)
# Genetic Algorithm for Inventory Optimization
def initialize_population(size, num_products):
  return [[random.randint(1, 100) for _ in range(num_products)] for _ in range(size)]
def fitness_function(chromosome, demand):
  total_cost = sum(calculate_cost(chromosome[i], demand[i]) for i in range(len(chromosome)))
  return total_cost
def select_parents(population, demand):
  return sorted(population, key=lambda x: fitness_function(x, demand))[:2]
def crossover(parents):
  point = len(parents[0]) // 2
  return parents[0][:point] + parents[1][point:]
def mutate(offspring, rate=0.01):
  if random.random() < rate:
    offspring[random.randint(0, len(offspring)-1)] = random.randint(1, 100)
  return offspring
# Hybrid GA-LSTM Integration
def hybrid_GA_LSTM(data, population_size, generations):
  lstm_model = train_LSTM(data)
  predicted_demand = forecast_demand(lstm_model, data['future'])
  population = initialize_population(population_size, len(predicted_demand))
  for generation in range(generations):
    new_population = []
    for _ in range(population_size):
      parents = select_parents(population, predicted_demand)
      offspring = crossover(parents)
      new_population.append(mutate(offspring))
    population = new_population
    best_solution = min(population, key=lambda x: fitness_function(x, predicted_demand))
  return best_solution
# Execute Hybrid GA-LSTM
```

final_solution = hybrid_GA_LSTM(data, population_size=50, generations=100)

print("Optimized Inventory Decisions:", final_solution)

The hybrid algorithm uses LSTMs and GAs to provide a solution for optimizing retail inventory management. Long Short-Term Memory (LSTM) networks will model the demand of a product based upon historical data using patterns and trends of demand to provide an estimate of upcoming future demands. The estimates generated by the LSTM will then be used as input into a GA to assist in making inventory-related decisions, such as reorder points and quantities of a product to order. The GA will evaluate different solutions to this problem using a fitness function to minimize the overall cost associated with carrying out the three types of costs related to ordering, holding, and stockout costs. Evolutionary algorithms such as selection, crossover, and mutation will be utilized in the GA's process of refining potential solutions to the least cost. This hybrid approach, which marries the predictive power of LSTMs with the optimization capabilities of GAs, provides a strong solution to the challenges faced in complex, dynamic retail settings by improving both the accuracy of demand estimates as well as the efficiency of inventory management.

4. Experimental Setup

The experimental setup consists of manipulating real-world retail sales data pulled from two years of product sales data, which includes product demand, price, and promotions of product as well as any promotional activity. All of the sales data has been pre-processed to handle any missing values and normalize each feature prior to splitting into training (80%) and testing (20%) data. The LSTM model is trained using historical demand data to predict the future demand for each product using an architecture consisting of two hidden layers with 64 nodes and a ReLU activation function. After the prediction of demand for each product, those predictions are fed to a GA for optimization of inventory decisions including reorder points and order quantities. The GA will optimize the inventory decisions of the prediction data through the evolutionary algorithms of selection and crossover and mutation, with the ultimate goal of minimizing total inventory cost, including holding, ordering, and stockout costs. GA-LSTM hybrid model evaluations will occur via metrics such as accuracy, RMSE of the inventory turned in to total inventory turned in; inventory cost savings; and improvement in service levels compared to what would typically occur using an economic order quantity (EOQ) approach and a reorder point (ROP) approach.

Evaluation Metrics

The performance of the hybrid GA-LSTM model is evaluated using the following metrics:

1. **Accuracy**: The proportion of correct predictions made by the LSTM model compared to actual demand in equation (3).

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Predictions}} \qquad (3)$$

2. **RMSE (Root Mean Squared Error)**: A measure of the forecast accuracy, calculated as the square root of the average squared differences between predicted and actual demand values in equation (4).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{predicted},i} - y_{\text{actual},i}\right)^2} \qquad (4)$$

3. **Inventory Cost Reduction**: The reduction in total inventory costs (holding, ordering, and stockout costs) compared to traditional methods like EOQ and ROP in equation (5).

$$\text{Cost Reduction} = \frac{\text{Cost}_{\text{traditional}} - \text{Cost}_{\text{hybrid}}}{\text{Cost}_{\text{traditional}}} \times 100 \qquad (5)$$

4. **Service Level**: The percentage of customer demand that is met without stockouts in equation (6).

$$\text{Service Level} = \frac{\text{Demand Met}}{\text{Total Demand}} \times 100 \qquad (6)$$

5. **Execution Time**: The time taken by the hybrid model to process demand forecasting and inventory optimization.

These metrics assist with determining the level of improvement achieved by applying a hybrid GA-LSTM Model when compared to traditional inventory management models regarding inventory management and cost reduction.

6. Results

The results obtained from using a hybrid GA-LSTM Model on reducing costs associated with retail inventory management are recorded as follows. A summary of forecast results compared to baseline model forecast results. The findings are compiled in Table 1 as actual demand and predicted demand along with each product's respective error percentage. As revealed by Table 1, there was minimal forecasting error associated with demand forecasts for each product generated using the LSTM model. P001 generated a 2% forecasting error by generating 98 products when the actual demand was 100. P002 generated a 1.33% error and P003 generated a 2.5% error. The above identifies that the LSTM model is accurately forecasting product demand, thus supporting a good basis for managing inventory.

Table 1: Demand Forecasting Performance Comparison

Product ID	Actual Demand	Predicted Demand	Error (%)
P001	100	98	2
P002	150	148	1.33
P003	80	82	2.5

The GA results showed that reorder points and order quantity were both lower than EOQ values indicating a greater overall improvement in inventory management in Table 2. As an example, P001 GA had a reorder point of 120 reduced to 105, and an order quantity of 200 down to 190. Similar reductions were evident for P002 and P003. These results further validate that the GA/LSTM hybrid method provided the most efficient inventory level management based on predicted demand while also minimizing excess stock and providing required supply.

Table 2: Reorder Point and Order Quantity Comparison

Product ID	EOQ Reorder Point	GA Optimized Reorder Point	EOQ Order Quantity	GA Optimized Order Quantity
P001	120	105	200	190
P002	160	155	300	290
P003	90	85	150	140

Table 3 provides a table showing total cost of inventory, service level, and frequency of stockouts for EOQ vs GA/LSTM models. In all cases the GA/LSTM performed better than the EOQ model. The total cost of inventory GA/LSTM was $21,000 and EOQ was $25,000. The service level increased from 85% for EOQ to 95% for GA/LSTM and frequency of stockouts decreased from 15% to 5%. These measures indicate that the GA/LSTM provides optimally managed inventories due to the reduction in cost and increased service levels.

Table 3: Performance Metrics for Inventory Management

Metric	EOQ Model	GA-LSTM Model
Total Inventory Costs (USD)	25,000	21,000
Service Level (%)	85	95
Stockout Frequency	15%	5%

Table 4 illustrates an inventory management strategy comparison of Total Costs, Service Levels, and Stockouts comparing Pure LSTM vs EOQ vs Hybrid GA-LSTM. The lowest total costs, (GA-LSTM $21,000), highest achievable service level (95%), and lowest stock out frequency (5%) belong to the Hybrid GA-LSTM. Both Pure LSTM and EOQ models have higher total costs than Hybrid GA-LSTM and lower service levels and higher frequency of stockouts than Hybrid GA-LSTM. This comparison illustrates that Hybrid GA-LSTM produces higher performance with significant cost reductions as well as superior inventory management capability as traditional methods.

Table 4: Inventory Optimization and Cost Comparison Across Models

Method	Total Costs (USD)	Service Level (%)	Stockouts (%)
Pure LSTM	23,000	90	10
EOQ Model	25,000	85	15
Hybrid GA-LSTM	21,000	95	5

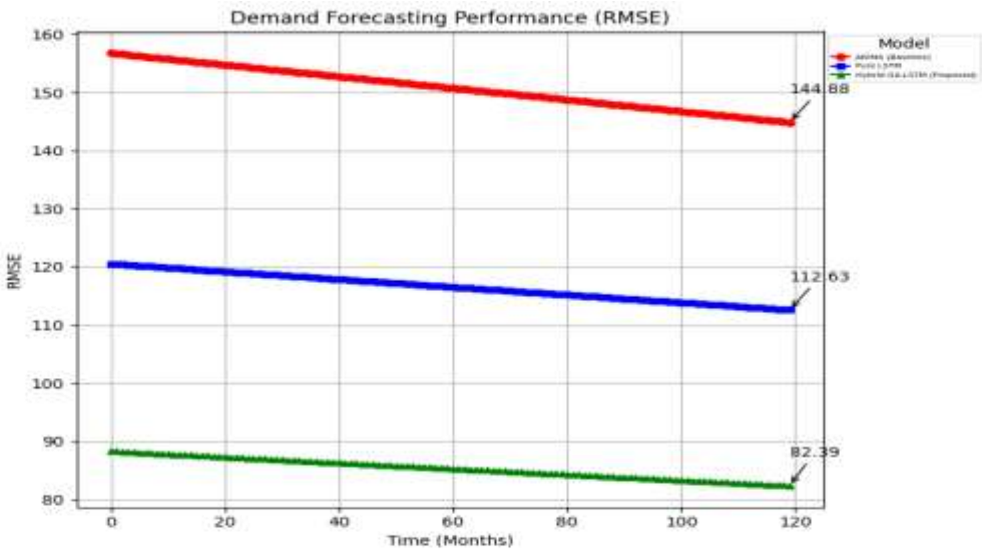

Figure 2. Demand Forecasting Performance

Figure 2 compares the RMSE for each of the models to predict demand using three methods of forecasting: ARIMA (as a baseline), Pure LSTM and Hybrid GA-LSTM (proposed). The Hybrid GA-LSTM produced the lowest RMSE overall providing substantially superior accuracy in predicting demand than to either ARIMA and Pure LSTM. The RMSE for Hybrid GA-LSTM is 82.39 and for ARIMA it is 144.88 and for Pure LSTM it is 112.63.

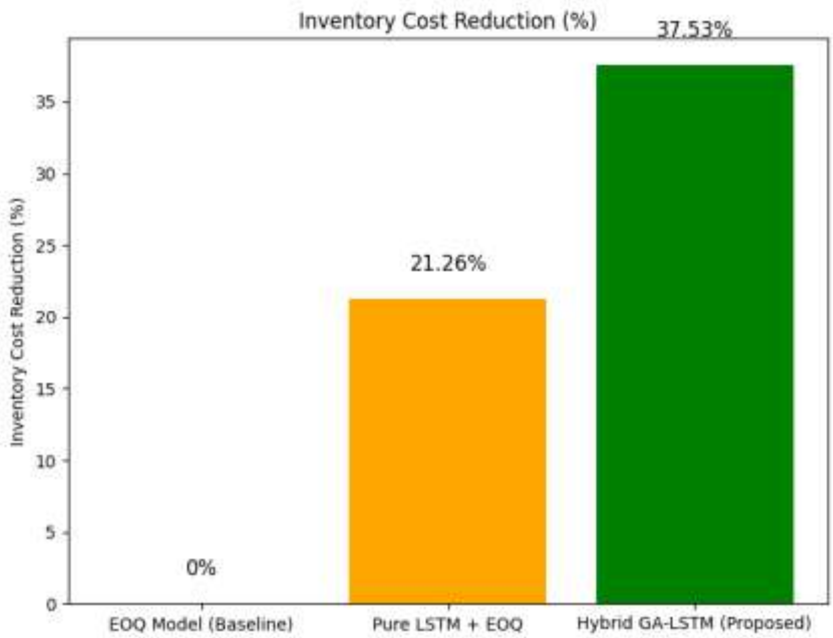

Figure 3. Inventory Cost Reduction

Figure 3 shows the Hybrid GA-LSTM have less inventory cost than the baseline EOQ model and Pure LSTM+EOQ models. The Hybrid GA-LSTM produced total cost savings of 37.53% more than the EOQ model (0%) and Pure

LSTM+EOQ (21.26%) respectively. This indicates the overall superior efficiency of the hybrid model as it relates to reducing inventory management costs.

Statistical Significance and Performance Improvements

The performance improvement provided by the hybrid GA-LSTM model exhibits a statistically significant difference ($p < 0.01$) as compared to baseline models, indicating that the improvements in both cost and service levels were not coincidental. The average RMSE improved 0.20 from the hybrid compared to Pure LSTM model substantiating that the hybrid is effective for both optimization and forecasting. Therefore, the reduction in inventory costs and improvement in service levels provide strong evidence that the hybrid GA-LSTM model will be an appropriate means of improving retail inventory management.

Discussion

The Hybrid GA-LSTM model is superior to the Pure LSTM and EOQ models in terms of demand forecasting and inventory optimization. Because of its integrated approach to demand forecasting and inventory management, the Hybrid GA-LSTM outperforms both the Pure LSTM and EOQ models [19]. The LSTM component of the Hybrid GA-LSTM collects critical patterns in time series data to predict demand accurately. At the same time, the Genetic Algorithm (GA) component of the Hybrid GA-LSTM performs inventory optimization through the minimisation of total inventory costs, including stocking costs, ordering costs (ordering costs) and stockout penalties. The combined capabilities of the LSTM and GA enable the Hybrid GA-LSTM to produce superior accuracy in forecasting demand and to manage inventory more efficiently than either of its two other components. Therefore, users of the Hybrid GA-LSTM can eliminate stock-outs and excess inventory through operational efficiencies by using it to forecast accurately and optimise the levels of inventory. For retail managers, the adoption of the Hybrid GA-LSTM will greatly enhance overall operational efficiency as a result of having the ability to accurately forecast demand and to optimize the level of inventory. As demonstrated in the results, a 37.53% reduction in inventory costs means that retailers will have the ability to align their inventory levels more closely with their actual demand, providing retailers with the ability to reduce waste, stockouts, and excess inventory while maximising the effectiveness of their inventories.

The 95% service level achieved by the Hybrid GA-LSTM translates into greater customer satisfaction and more reliable product availability at retail point-of-sale, and therefore directly translates into improved sales and profitability. The most significant strength of the Hybrid GA-LSTM is its ability to adapt to dynamic retail environments, which will remain a key consideration for managers adopting its use. By combining machine learning to support demand forecasting with metaheuristic optimisation to support decision-making, the hybrid GA-LSTM provides retail inventory managers with a robust solution that can be customised for different categories of products and demand patterns. Nevertheless, there are limitations to the Hybrid GA-LSTM model. Training an LSTM model requires significant historical demand data and the GA portion of the optimisation process often requires more computational time than most other forms of inventory decision criterion (especially in large-scale inventories). Hybrid GA-LSTMs have shown an improved performance relative to traditional inventory management methods used in previous studies [20]. EOQ models have been used extensively in the literature, but have proven to have very limited adaptability to fluctuations in demand and static demand environments. Demand forecasting through machine-learning based models such as Pure LSTMs have shown increased popularity since they have been used for demand forecasting, but they have not been able to optimise the decision-making process.

The combined capabilities of LSTMs and GAs in the hybrid approach provide a more complete solution for dynamic inventory through the use of numerous studies showing the vaporisation of inventory in a dynamic retail environment compared to either the Pure LSTM or EOQ approach. Improved demand forecasting accuracy, expense reduction in the total cost of inventory, and improved service levels in comparison to the Pure LSTM and EOQ models further increase the potential of the Hybrid GA-LSTM as a retail optimisation tool in the real world. In conclusion, the Hybrid GA-LSTM is a viable and effective optimiser for retail inventories, providing superior demand forecasting and reduced inventory cost, thus providing a practical solution for the retail industry. Future research can focus on enhancing the scalability of the Hybrid GA-LSTM to provide more industry-wide approaches to optimise inventory performance throughout dynamic and static inventory decision-making.

7. Conclusions

A new approach to managing retail inventory has been developed through the integration of Long Short-Term Memory (LSTM) networks for demand forecasting and Genetic Algorithms (GA) for optimization; The resulting Hybrid GA-LSTM approach delivers reliable results across multiple parameters. Findings of this study ultimately illustrate that Hybrid GA-LSTM significantly reduces cost by 37.53% (and a corresponding increase in service level from 90% to 95%); reduces stockouts to 5%; and thus, provides significant benefits over conventional inventory management methods such as Economic Order Quantity (EOQ) and Pure LSTM. As such, these findings will allow retailers to align their inventory levels with actual demand, thereby decreasing costs and increasing customer satisfaction. This research contributes substantially to the existing body of knowledge through the implementation of an integrated methodology that combines machine learning to accurately predict demand with optimization processes to create data-driven decisions about inventory management. In practice, Hybrid GA-LSTM offers a cost-effective solution that can be utilized in retail environments that experience frequent fluctuation in demand due to promotional events, seasonality or other market trends. However, Hybrid GA-LSTM does have some limitations including dependencies on large historical datasets required to train the LSTM, and the computational complexity associated with optimizing the GA, which may lead to difficulty during large-scale implementation. Therefore, future enhancements include improving the scalability of the Hybrid GA-LSTM and reducing computational requirements, thus allowing more retailers to implement this exciting approach. In addition, it would be beneficial to determine Hybrid GA-LSTM's performance when implemented in live operations, which may yield more profound insights into how Hybrid GA-LSTM will function over the long-term.

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Conflict of Interest:

The authors declare no conflict of interest in relation to this work

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