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A Multi-Echelon Genetic Algorithm and Just-in-Time Approach for Supply Chain Optimization

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Abstract

In today's highly competitive and demand-driven markets, the effectiveness of supply chain operations has a significant impact on organizational performance and customer satisfaction. Traditional methods often fall short in addressing the dynamic and complex challenges of modern supply chains, such as fluctuating demand, varying lead time uncertainties, and cost optimization. This study examines the integration of Genetic Algorithms (GAs) and Just-in-Time (JIT) principles

Aims and Objective: To apply Genetic Algorithms (GAs) and Just-in-Time (JIT) principles for the optimization of supply chain processes and facilitate informed decision-making in multi-echelon supply chains.

Methodology: The model focuses on inventory management, optimizing production schedules, optimizing distribution centers, and delivery timings while minimizing overall costs, reducing lead time, improving quality performance, and maintaining service level targets. The GA component of the model was used to navigate large solution spaces, adapt to dynamic conditions, and enhance the JIT performance through efficient inventory and scheduling strategies. The Just-in-Time (JIT) principle was used for waste reduction, inventory minimization, and responsiveness upgrade, while offering a lean framework for managing supply chains.

Result: The experimental study of the model established the effectiveness of the GA for identifying optimal solutions for raw material procurement, production scheduling, and distribution, as well as minimizing costs and reducing lead times. The study also how the JIT principle suitably reinforces lean manufacturing practices by ensuring materials and products are available precisely and as needed, thereby reducing inventory holding and wastage.

Conclusion: The study revealed that the integration of GA and JIT led to improved production efficiency, lower stock levels, and enhanced responsiveness to customer demand, which are critical for achieving a competitive market and enhancing supply chain performance. .

Keywords: Supply chain, Just-in-Time, Genetic Algorithm, Genes, Chromosomes

1. Introduction

Supply chain management plays a central role in businesses and industries. It is the apparatus that energizes the processes that aid establishments in coordinating the whole process, from obtaining raw materials to distributing finished goods. Manufacturing is a significant catalyst for driving a country's economy. It's an influential vigor that circles around the development, output, and competitiveness paths. A country's general fiscal development can momentously hinge on the robustness and performance of the industrial sector (KPMG, 2023). The very kernel of any commercial activity is to meet the desires of customers through the provision of goods and services, while creating value for clients and addressing their challenges. As technology grows, evolving competition, and consumer hopes constrain companies to reconsider their product and service approaches. Producers have come to the knowledge that it is no longer sufficient to basically drive goods and services through the factory and the market. Consumers require good quality at judicious prices and expect manufacturers to deliver products without delay. Before now, the association between buyers and producers was often competitive and sometimes incompatible, resulting in recurrent shifts. At present, several businesses are changing to a novel idea in supplier affairs in which importance is progressively on evolving a robust supply chain. A supply chain offers a universal system of establishments that work together to achieve customer satisfaction via enhanced flow of material and information among suppliers and customers at a very negligible cost and heightened speed (Jaipur National University, 2013).

Supply chain is the act of securing the parts, goods, and raw materials necessary to complete the production of specific goods and products. It is an enormously complex task that encompasses schmoozing with numerous suppliers and handling the transportation and conveyance processes. It can also be said to be a system of retailers, wholesalers, transporters, storage facilities, and providers that contribute to the production, delivery, and sale of a product to the consumer (JNU, 2013; Ebbers, 2022).

In recent years, metaheuristic systems have been engaged for addressing real-life complex problems associated with various fields, including economics, engineering, politics, management, and engineering. Escalation and variation are the cogent ingredients of a metaheuristic system. The proper equilibria between these ingredients are needed to solve the real-life problem most appropriately. Several of the metaheuristic systems were motivated by the genetic progression process, group deeds, and corporeal acts. These systems are widely grouped into single-solution and population-based metaheuristic systems. Single-solution-based metaheuristic systems utilize single candidate results and advance the result via local search. However, the result may get trapped in local optima. Well-known single-solution-based metaheuristics systems comprise simulated annealing, tabu search (TS), microcanonical annealing (MA), and guided local search (GLS). Population-based metaheuristics systems rely on several candidate results during the search process and comprise the genetic algorithm, which is a well-known algorithm that is motivated by the genetic progression process. The system is known for resolving problems when deterministic systems proved too costly, like in the traveling salesperson or the knapsack tasks. In business organizations, genetic algorithms are often deployed when the old ways prove inefficient. Genetic algorithms are mathematical optimization methods that are motivated by the philosophies of natural selection and genetics and are often engaged for providing solutions to complex problems through mirroring the process of evolution to expand a population of potential solutions iteratively (Holland, 1992; Katosh et.*al*., 2020).

Just-in-time (JIT) supply chain is a type of inventory management system in which raw materials, parts, and other resources are ordered and transported as required by the manufacturer (Iwasokun *et al.,* 2023). Preferably, the JIT supply chain moderates the production flow and eradicates superfluous costs that are connected to keeping huge inventory hoards. When adopted appropriately, it can lessen lead times, raise quality control, and improve the level of efficiency. Supply chains are anchored on distributing the right number of resources and components at the right time to satisfy customer requests, while minimizing storage costs and waste. Through the provision of a continuous torrent of resources, producers bypass the necessity for huge catalogues, lessening warehousing charges and releasing capital for more fruitful uses. The resulting speedy delivery times allow manufacturers to regulate production yield in real-time according to ever-changing market situations. Minor inventories, accurate forecasts, and unceasing communication between suppliers and customers are vivacious rudiments of JIT systems. By reducing the level of inventory, JIT significantly lessens warehousing maintenance costs and eradicates excess stocking and inventory by maintaining inventory levels as low as possible. This significantly cuts the risk of inventory desk unsold or unused and minimizes leftovers by effortlessly recognizing and addressing faulty inventory items when production capacities are little (Custard, 2023).

The progressive trend of the manufacturing sector has been scrawny and slow since its recovery from the COVID-19 pandemic, with a mean yearly growth of 3.4% in 2021 and 2.5% in 2022, resulting in the segment's input to Nigeria's GDP dropping far below the globally competitive levels, averaging 10% in its yearly input to GDP in nearly two decades. With the rising global and local encounters, the growth of the Nigerian manufacturing industries has been hindered, culminating in its poor performance when compared to other nations, which has made it obviously obligatory to reconsider growth tactics within the sector and address serious concerns (KPMG, 2023).

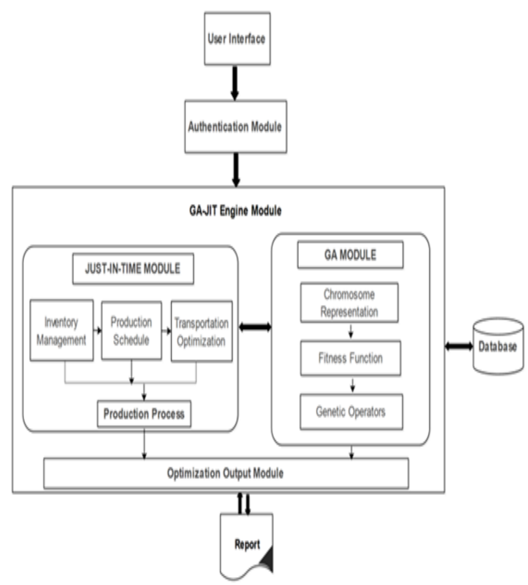
In the manufacturing sector, supply chain disruptions can have very extensive implications, such as increasing costs, deteriorating sales, failed deadlines, and strained customer relationships. Disturbances can equally hurt a manufacturer's image and lessen depositor morale. In the manufacturing sector, supply chain disturbances can be instigated by various factors, such as natural disasters, diseases around the world, lead time challenges, prolonged port processes, and cybersecurity errors. The prevailing old-style manufacturing preparation and control system for steering production processes exposed letdowns in record management, negligible lead time, viable advantage, slight waste generation, real-time data, income generation, and quality of goods and services. This paper discusses the combination of JIT and GA for addressing these failures based on optimization or minimization of distribution centers, production schedules and quantities, transportation routes, inventory level, wastages, and lead time.

2. Literature Review

Alfayoumi *et al.* (2023) presented an AI-driven optimization approach in mass customization supply and manufacturing. The focus was to optimize supply and manufacturing processes while minimizing time and cost. It was stated that the model successfully solved the multi-objective optimization problem and enhanced time optimization by 20.4%, cost optimization by 29% and combined time and cost optimization by 25% compared to traditional factory methods. Gao and Liu (2023) presented a blockchain and GA model for logistics and supply chain optimization. The aim was to optimize the supply chain logistics network, so as to reduce cost and improve the level of comprehensive logistic management. The simulation of the model established its ability to reduce the transportation cost. Leuveano et al. (2023) presented a GA optimization model for a dynamic lot sizing in perishable product manufacturing. The model focuses on minimizing the supply chain cost and adapting to unconstrained and constrained inventory capacities. An experimental approach was used to optimize the model for perishable products with and without inventory constraints and it was recognized that the total system cost was significantly reduced. Gursoy and Soner Kara (2021) established a multi-stage, multi-period mixed-integer and linear programming model for JIT distribution network. The experimental study of the model showed that manufacturers' predilection for high-quality raw materials, lower costs, and apt delivery as well as its inappositeness with large-scale real-life data. Indra et al. (2020) applied genetic algorithm, random local search and particle swarm algorithm for resolving the three-level supply chain distribution problems on the way to achieving the target inventory and transportation quantity through minimization of the total cost of the system. Results from the experimental study of the model demonstrated its positive influence in solving the problem of the distribution of goods and obtaining the lowest distribution and transportation costs. Ahmad and Kamruzzaman (2020) presented an Artificial Neural Network (ANN) and genetic algorithm model for analyzing the best and possible ways of selecting the right supplier in real time in order to advance the optimization level of the overall supply chain. The experimental study of the model confirmed its ability to improve the accomplishment rank of the production and selection of the right and best supplier in real time.

Ahmed *et al.* (2019) presented a model for minimizing the total transportation costs of the inbound logistics system and determining the optimal truck load transported from the plant to the depot. Parameter setting was based on the Taguchi method, and a Lingo 17.0-based investigation was used to establish effectiveness. Practical implementation of the model established that Lingo generates better solutions than the genetic algorithm, while the genetic algorithm performs better than Lingo in terms of quality of solutions and computational time. The model, however, failed with multi-period planning problems. Jadhav and Bajaj (2016) proposed a model for e-shopping supply chain management. JIT was used to minimize the costs of distribution, holding, replacement, and backorder; GA was used to handle the distribution decisions of a three-level supply chain, and fuzzy logic was used to select the most preferred solution or final solution. The results obtained from the implementation of the model confirmed its worthiness in the minimization of the production, holding, transport, and indirect costs. A model for operational planning of supply chains in a production and distribution center with JIT was presented by Biswas and Sarker (2020). The model uses a single facility that trails JIT delivery and produces manifold products to mollify customers' demand, while a rotational cycle was developed to optimize the facility operations. The experimental results showed its ability to minimize total system cost and establish optimum production quantity, batch sizes, and number of shipments. However, the model lacks contemplation for the costs associated with the supply chain. Xuan *et al.* (2023) used GA to handle the nonlinear programming challenge associated with line balancing in garment manufacturing. The experimental study of the algorithm based on data from a clothing company demonstrated the usefulness of the algorithm for solving the line balancing problem, leading to minimal production lead time, production efficiency, and competitive advantages for the company.

Some of the limitations of the reviewed works presently pose a research gap. The summaries of the limitations of the works reported in (Alfayoumi *et al.,* 2023; Gao and Liu 2023; Xu and Song 2022; Leuveano et al., 2023; Gursoy and Soner Kara, 2021; Indra et al., 2020; Ahmed *et al.*, 2019; Ahmad and Kamruzzaman, 2020; Jadhav and Bajaj, 2016; Biswas and Sarker, 2020; and Xuan *et al.*, 2023) include poor information resource sharing and collaboration, lack of consideration for large-scale real data, uncertainty of



costs, absence of implementation, and computational complexity. This research was therefore motivated by the need to address some of these limitations based on the adoption of a GA and JIT-inspired model to optimize inventory and service levels, total costs, and lead times. The goal is to achieve a balanced relationship between cost-efficiency and responsiveness, while reducing waste and improving the overall system's agility and ability.

3. Research Methodology

This section focuses on the methods used in the implementation of a software testing model that is ancThe conceptualization of the proposed genetic algorithm and Just-in-Time system for the supply chain optimization model is presented in Figure 1. The model adopts a modular, microservices-based architecture to ensure scalability, maintainability, and extensibility. It is built around six core modules, namely User Interface (UI), Authentication, GA-JIT, Optimization, Database Framework, and Reporting modules. Each module was designed to handle specific functionalities while seamlessly integrating with others through well-defined Application Programming Interfaces (APIs) and asynchronous task processing.

Figure 1: Conceptual diagram of the framework for the proposed hybrid system

3.1 User Interface

This is the visual part of the proposed system through which input is fed into the system and output is displayed to the user. It provides an intuitive interface for data input, configuration of optimization parameters, monitoring progress, and results visualization

3.2. Authentication Module

This module is used to protect sensitive supply chain data and operations by enforcing strict access controls based on user roles and permissions. The module is designed to integrate seamlessly with the User Interface and backend API while maintaining high security standards and auditability. It provides stateless and secured authentication using JavaScript Object Notation (JSON) web tokens and enforces role-based access control (RBAC) to restrict access to system functionalities based on user roles. The authentication module incorporates advanced security features such as multi-factor authentication (MFA), session management, data encryption, and audit logging. MFA adds security by verifying identity with multiple factor types (knowledge, possession, or inherence) and requires users to provide at least two different forms of verification to prove their identity. The adopted factor for this study is the password. Session Management maintains a user's authenticated state and tracks their activity using session tokens/ids or cookies or server-side session data; Data Encryption secures data by transforming readable text into unreadable ciphertext using the AES algorithm, and then uses keys to reverse the process as well as audit the logging records system events and user actions in a chronological log for accountability and security monitoring.

3.3 GA and JIT Module

This module **combines** GA with JIT constraints to solve supply chain problems. The JIT component first establishes a baseline for production scheduling based on demand forecasts and inventory management principles and works side-by-side with the GA component. It also manages inventory, production schedules, and transportation while following the "just-in-time" principles, which focus on eliminating waste, particularly in the form of inventory, by producing goods only when they are needed based on actual customer demand through a pull production system. The JIT constraints enforce zero-inventory targets, pull-based production, and waste minimization. The GA module handles the genetic algorithm process, starting with chromosome representation (encoding potential solutions), then evaluating them with the fitness function, and finally applying genetic operators to find better solutions.

a. JIT Module

This module entails analyzing the capacity and resource requirements of a company in advance for the manufacturing process and controlling the raw materials in the inventory needed for producing finished goods. It reviews sales forecasts and customer demand and schedules production batches based on inventory levels and production times. Its operation is in the following areas:

i. **Inventory management**: This focuses on minimizing inventory levels, reducing waste, and ensuring that materials and products are available only when they are needed in the production process. It requires precise demand forecasting, reliable suppliers, and strong communication across the supply chain. Its mathematical concept is represented as follows:

$$\boldsymbol{I}(\boldsymbol{t}+\mathbf{1}) = \boldsymbol{I}(\boldsymbol{t}) - \boldsymbol{D}(\boldsymbol{t}) + \boldsymbol{P}(\boldsymbol{t}) - \boldsymbol{B}(\boldsymbol{t}) \quad (1)$$

$\boldsymbol{I}(\boldsymbol{t}+\mathbf{1})$ is the inventory level at time t, $\boldsymbol{I}(\boldsymbol{t})$is the inventory at time t, $\boldsymbol{D}(\boldsymbol{t})$is the demand at time t, $\boldsymbol{P}(\boldsymbol{t})$ is the production output, and $\boldsymbol{B}(\boldsymbol{t})$ is the back-orders.

ii. Production scheduling: Production scheduling in JIT is aimed at optimizing resources, avoiding overproduction, and ensuring that materials and components are available exactly when required. Production scheduling is a critical process that ensures manufacturing happens at the right time and with the right resources. This requires careful synchronization between different parts of the production system, suppliers, and demand fluctuations. It demands flexibility, real-time communication, and continuous monitoring of production flows. The objective function of the JIT system generally focuses on minimizing inventory costs, waste, and ensuring production matches the demand. The goal is to avoid overproduction based on the minimization function:

$$Minimize\ Z = \sum_{m,p,t} (h_{c*} I_p(t) + p_{c*} x_{mp}(t)) \quad (2)$$

Subject to the production, machine capacity, inventory, and lead time constraints presented in Equations (3), (4), (5), and (6), respectively.

$$I_p(t-1) + \sum_m x_{mp}\,(t) = D_p(t) + I_p(t) \quad (3)$$

$$\sum_m T_m * x_{mp}(t) \leq C_m\ , \forall\ \mathrm{m,t} \quad (4)$$

$$I_p(t) \geq 0\ ,\ \forall\ \mathrm{p,t} \quad (5)$$

$$\sum_m x_{mp\ (t-L_p)} = D_p(t), \forall\ \mathrm{p,t} \quad (6)$$

Z is minimizing the total cost of inventory holding, setup, and production time. h_c is the holding cost per unit of product p in inventory at time t. p_c is the production cost per unit of product p. $I_p(t-1)$ is inventory from the previous period. $\sum_m T_p\,(t)$ is the total production of product p during time t. $D_p(t)$ is the demand for product p at time t. $I_p(t)$ is the remaining inventory at the end of time t. $x_{mp}(t)$ is the number of units of product p produced on machine m during period t, and C_m represents the maximum capacity of machine m. T_m and L_p represent the time required for machine m to produce one unit of product p and the lead time for product p, respectively. Equation (4) established the constraint that the total production time on the machine m does not exceed its capacity C_m. Equation (5) also ensured that the inventory level of the product p does not go below zero at any time. Equation (6) ensured that the production of the product p in the period $t - L_p$ meets the demand $D_p(t)$ at time t, accounting for the lead time.

a. **Transportation optimization:** This involves the optimization of the process of movement of goods from suppliers to plants, distribution centers (DCs), and customers, reducing costs and delivery times. The optimization algorithm finds the best routes for delivery trucks to minimize distance, time, and costs and effectively handles real-time constraints such as traffic conditions, delays, and urgent requests. The algorithm combines the strengths of heuristic path finding and evolutionary optimization and addresses both route-level and fleet-level challenges as presented below:

// The optimization Algorithm
1. Prepare the open list
2. Prepare the closed list and assign the initial node to the open list
3. For a non-empty open list:
   a) Compute the node 'n', with the smallest s on the open list
   b) Remove n from the open list
   c) obtain n's 8 inheritors and initialize their parents to n
   d) for each inheritor:
      i) If the inheritor is the target, halt the search
      ii) else, derive values for n and i for the inheritor
         inheritor.s = s.s + distance between inheritor and n
         inheritor.i = distance from goal to
inheritor.s = inheritor.s + inheritor.i

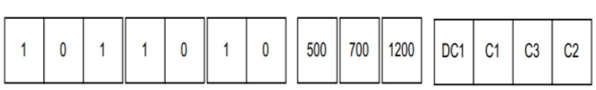
      iii) if a node with the same location as the inheritor is in the OPEN list, which has a lower

         s than the inheritor, omit the inheritor
      iv) if a node with the same position as the inheritor is in the CLOSED list, which

         possesses lower s than inheritor, skip this inheritor, hence add the node to the open

         list

      end (for loop)
      e) Add n to the closed list



      end (for loop)

b. GA Module

This is the core of the optimization system where the **GA** is implemented. It starts with a population of initial solutions (chromosomes), and then evolves the solutions using **selection**, **crossover**, **mutation**, and a **fitness function** that is designed to optimize key factors such as cost, lead time, and service levels. The GA will output optimized supply chain configurations based on evaluation, and its implementation includes the following:

i. **Chromosome Representation**: This involves how GA encodes possible supply chain solutions. The process includes supply chain configuration, which includes binary encoding, permutation-based representation, and value coding. In binary encoding, each gene in the chromosome is represented as a bit (0 or 1), where 1 represents 'included' for Supplier, Plant, and Distribution Centre, while 0 means 'excluded'. The permutation-based representation is as follows:

$$C = [S, P, DC] \tag{7}$$

C is the supply chain network, S is the Suppliers, P is the Plants, and DC is the Distribution Center. Based on this representation, Chromosome: [1,0,1] implies Supplier is included, Plant is excluded, and Distribution Centre is included.

The chromosomes could also be represented with a logical representation presented in Figure 2, where Supplier S1, Supplier S3, Plant P1, and Distribution Center DC1 are all selected. Figure 3 represents a typical chromosome structure for the [Binary], [Value] [Permutation].

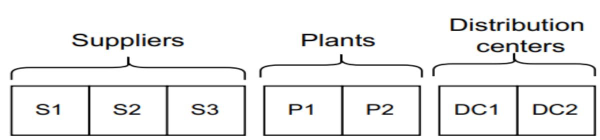


Figure 2: Encoding of chromosomes with supply chain configuration

Figure 3: Chromosome Structure for Production Planning

The chromosome components are derived as follows:

- Binary: Select the supplier (S1, S3), Plant (P1), Distribution Center (DC1)

- Value: Select the shipment quantities (S1→P1:500, S3→P1:700, P1→DC1:1200)
- Permutation: Select the delivery route from DC1 to Customers DC1→C1→C3→C2).

ii. **Fitness Function**: This function is designed to **optimize the production and the distribution system** by balancing costs, lead times, and penalties for undesirable outcomes. It is based on constraints such as supplier and plant capacity limits, transportation and inventory costs, lead-time restrictions, and JIT delivery adherence. The function evaluates how good each configuration is based on total cost minimization, lead time reduction, service level optimization, and resource utilization maximization. It evaluates the fitness of a solution based on the following mathematical models:

$$F(f) = \frac{1}{(Z+\mu+\rho)} \quad (8)$$

$$Z = \alpha + \beta + \delta + \gamma + \sigma \quad (9)$$

$$\mu = c \times T_l \quad (10)$$

$$\rho = C_v \times p_f \quad (11)$$

$$\alpha = F_c \times J_f \quad (12)$$

$$\beta = V_c \times J_e \quad (13)$$

$$\delta = H_c \times J_z \quad (14)$$

$$\gamma = T_c \times J_l \quad (15)$$

$$\sigma = Q_c \times J_q \quad (16)$$

$F(f)$ is the fitness function, Z is the total weight cost, μ is the lead time component, ρ is the penalty component, c is the lead time component constant, T_l is the total lead time, C_v constraints violations, p_f is the penalty factor, F_c is the fixed cost, J_f is the JIT facility factor and V_c is the variable Cost. J_e, H_c, J_z, T_c, $J_l,\ Q_c,\ and\ J_q$ represent the JIT efficiency factor, holding cost, JIT zero inventory factor, transportation cost, JIT lead time factor, quality cost, and JIT quality cost, respectively. The JIT Factors constants are:

$$J_f = a(P_{fv} - J_p) \quad (17)$$

$$J_e = b(R_{ep} - J_p) \quad (18)$$

$$J_z = c(P_{lp} - J_p) \quad (19)$$

$$J_l = d(P_{lt} - J_p) \quad (20)$$

$$J_q = e(P_{dr} - J_p) \quad (21)$$

$$J_s = f(P_{sv} - J_p) \quad (22)$$

$J_s,\ P_{fv},\ R_{ep}, p_{lp}, P_{lt}, P_{dr},\ P_{sl} and\ J_p$ represent the JIT service factor, penalty for facility violation, rewards for efficient production, penalty for excess inventory, penalty for long lead times, penalty for defect, penalty for service level violation, and JIT principle index, respectively. The constants a, b, c, d, e, and f are the respective factor coefficients. The fixed cost, F_c component is obtained as follows:

$$F_c = (S_c + M_d + M_s + I_p + P_t + U_c)\ x\ J_f \quad (23)$$

$S_c, M_{d,}, M_s, I_p, P_t, and\ U_c$ represent the facility setup cost, machinery depreciation, management salaries, insurance premiums, property taxes, and utility costs, respectively. The variable cost, V_c is derived from:

$$V_c = (R_c\ x\ P_q + D_l\ x\ P_q + U_{vc}\ x\ P_h + P_c\ x\ P_q + Q_c\ x\ B_n)\ x\ J_e \quad (24)$$

$R_c, P_q, D_l,\ U_{vc,}\ P_{h,} P_{c,}\ Q_c, and\ B_n$ give the raw material cost per unit, production quantity, direct labour cost per unit, utility variable cost, production hour, packaging cost per unit, quantity control cost per batch, and number of batches. The holding cost, H_c, is also derived from:

$$H_c = ((I_l\ x\ H_c\ x\ D_h) + W_s + I_p + O_r + (C_t\ x\ I_r))\ x\ J_z \quad (25)$$

$I_l, H_c, D_h, W_s,\ O_r, C_t,\ and\ I_r$ are the inventory level, daily holding cost per unit, days held, warehouse space cost, obsolescence risk cost, tied up capital cost, and interest rate, respectively. The transportation cost, T_c is based on the formula:

$$T_c = ((S_c\ x\ T_d) + F_c + D_w + V_m + L_o + R_o)\ x\ J_l \quad (26)$$

$S_c, T_d, F_c, D_w, V_{m\ ,} L_{o,} and\ R_o$ represent the shipping cost per kilometer, total distance, fuel cost, driver wages and benefits, vehicle maintenance cost, loading and unloading cost, and route optimization cost, respectively.

The quality cost, Q_c is estimated based on the following formula:

$$Q_c = ((D_r x\, R_c) + Q_i + C_c + W_c + S_q) x\, J_q \quad (27)$$

D_r, R_c, Q_i, C_c, W_c , $and\ S_q$ give the defect rate, rework cost per unit, quality inspection cost, customer compliance resolution cost, warranty and return processing cost, and supplier quality audit cost, respectively. Similarly, the penalty cost, E_c is based on the formula:

$$E_c = ((S_p\ x\ S_f) + (L_p\ x\ L_c) + (C_v\ x\ C_o) + (S_l\ x\ S_r) + (P_f\ x\ S_s)) x\, J_s \quad (28)$$

$S_p, S_{f,}\ L_p\ L_c, C_v, C_o, S_l, S_r, P_f, S_s$ represent the stock penalty, stock frequency, late delivery penalty, late delivery count, capacity violation penalty, capacity overrun hours, service level penalty, service level shortfall, supplier performance penalty, and supplier failures, respectively.

The total lead time, L_t is derived from:

$$L_c = P_t + T_t + A_t + I_t \quad (29)$$

$$P_t = S_t + R_t + Q_t + H_t \quad (30)$$

$$T_t = O_t + G_t + U_t + C_t + M_t \quad (31)$$

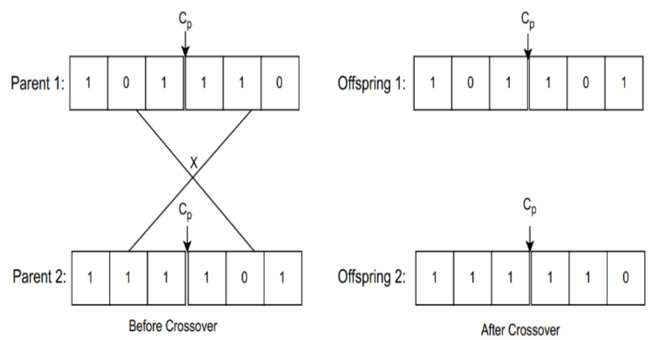
$$A_t = O_p + C_a + D_l + S_e + C_d \quad (32)$$

$$I_t = R_{mw} + W_{iq} + F_{gs} \quad (33)$$

$P_t, T_t, A_t\ and\ I_t$ are the production, transportation, administrative, and inventory times, respectively. $S_t, R_t, Q_t, and\ H_t$ are the setup, processing, quality, and changeover times, respectively. $O_t, G_t, U_t, C_t, and\ M_t$ represent the loading, transit, unloading, customs, and last mile times, respectively. $O_p, C_a, D_l, S_e, and\ C_d$ indicate order processing, credit approval, documentation, scheduling, and coordination, respectively. $R_{mw},\ W_{iq}, and\ F_{gs}$ represent the raw material wait, the WIP queue, and the finished goods storage.

C. **Genetic Operators**:

The GA operator uses selection, crossover, and mutation operations to evolve solutions to an optimization problem. In the model, the selection chooses the fittest individuals to reproduce, while each individual in the population could represent a possible configuration of the supply chain. The selection operator is done using the Tournament method, which is used to randomly choose individuals from a population to participate in the next generation. The best one among the randomly selected individuals is chosen based on the fitness function, which is carried out for each of the chromosomes sorted on the basis of the result of the fitness function. Each chromosome is subjected to the



crossover and mutation operations. For the crossover operation, a single-point crossover is adopted, where a single function crossover is performed. This involves swapping the genes located to the right of the crossover point in the two chromosomes to obtain two new chromosomes. As shown in Figure 4, during the crossover operation, the offspring (101101 and 111110) are added to the population to replace some of the older individuals in the next generation.

Figure 4: Chromosome representation before and after crossover

The mutation operation introduces random changes, in which the newly obtained chromosomes from the crossover operation are pushed for mutation. During mutation, a new chromosome is generated by randomly generating two points and then performing swaps between the genes. This helps to maintain genetic diversity and prevents the population from getting stuck in local optima. Random gene modification was adopted in this model to allow the exploration of new configurations that might not be reached through selection and crossover alone. After obtaining the new chromosome, another random chromosome is generated. The process is repeated for a particular number of iterations, with each iteration giving a best chromosome, which is considered a candidate for the optimal solution for the supply chain operations. As the number of iterations is increased, the obtained solution moves closer to a more accurate solution.

3.4 Optimization Module

This module processes and visualizes optimization results, providing actionable insights and decision support. The result of the optimized supply chain configuration satisfies cost minimization objectives, service level metrics, and JIT principles**.** The fitness function *was constrained by* JIT principles, such as maintaining minimal inventory and aligning production with demand to balance cost, lead time, and penalties for violating JIT principles. In essence, the JIT module offers the operational constraints and baseline scheduling, while the GA module optimizes the overall supply chain configuration within the constraints. The meet point is the fitness function evaluation stage, where solutions are scored based on cost efficiency and JIT adherence. The fitness function verifies adherence to JIT principles as part of its evaluation process, ensuring that solutions are optimized according to the established practices. The module established optimized values for total cost, lead time reduction, quality performance, and resource utilization.

3.5 Database Framework

The database framework manages transactional and analytical data storage for the system and employs PostgreSQL and MongoDB databases. PostgreSQL serves as the primary database while MongoDB serves as the secondary database. It also handles transactional data, which includes real-time supply chain operations, user account management and authentication, system configuration settings, and audit logs for tracking changes. The MongoDB section stores optimization results from the Genetic Algorithm (GA) processing, keeps historical data for analytics and trend analysis, and manages system logs for debugging and monitoring. It also holds analytics data required for performance evaluation and reporting. The combination of PostgreSQL and MongoDB helps to optimize supply chains with JIT and Genetic Algorithms (GAs), and form a polyglot persistence architecture where each database handles tasks aligned with its strengths.

3.6 Reporting Module

This module covers operational and analytical reports to support decision-making and performance tracking, such as operational and analytical reports. The operational reports include daily status, performance dashboards, and exception alerts, while the analytical reports entail optimization trends, cost analysis, and scenario comparisons.

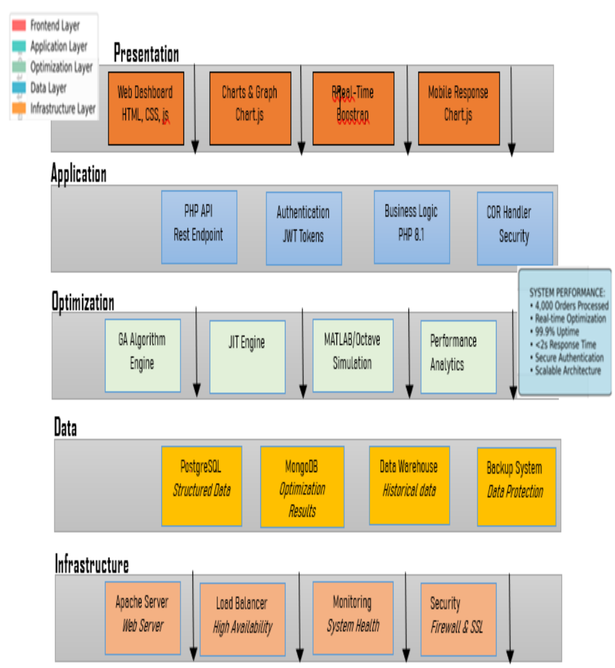


Figure 5: The Architecture of the proposed GA-JIT model

The outputs are transformed into actionable insights for supply chain stakeholders through visualization, such as cost breakdown analysis, lead-time trend analysis, inventory level monitoring, transportation route optimization, and service level reporting. Figure 5 is the structural view of the GA-JIT model. The system flowchart presented in Figure 6 shows its framework and summarizes the process involved in integrating optimization using a genetic algorithm with JIT to create a responsive and cost-effective supply chain.

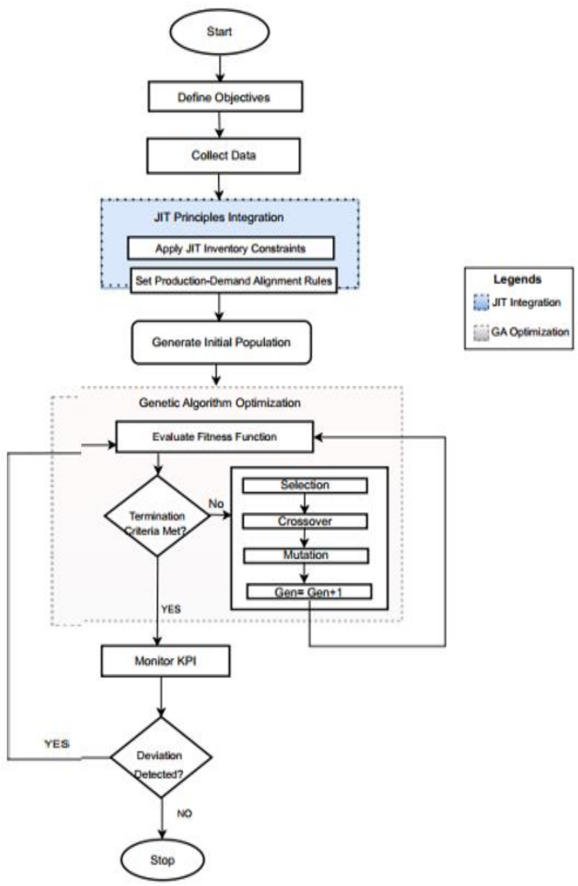


Figure 6: Flowchart of the proposed model for supply chain management

4 Experimental Study

The experimental study was conducted in an HP Laptop with a Windows 10 operating system, 4 GB RAM, 500 GB HDD, and high-speed Internet connectivity. The system utilizes a modern, scalable technology stack. The study leveraged HTML5, CSS3, and JavaScript with Chart.js as the frontend. The backend implements PHP 8.1 with RESTful API architecture, ensuring scalability and maintainability. Data management combines PostgreSQL for structured transactional data and MongoDB for optimization results storage. The optimization engine utilizes MATLAB/GNU Octave for GA-JIT algorithm implementation. Deployment supports Apache web server configurations with a built-in PHP server for development environments. The study focused on a dataset comprising 4,000 comprehensive order records representing authentic Nigerian market transactions and translates to over 912,000 individual data points across 38 distinct variables, covering 12 months of operational data across four major Nigerian regions. All the transactions were denominated in Nigerian Naira with realistic market pricing structures that focused on the Nigerian detergent manufacturing supply for Eko Supreme Resources Limited (Goodmama brand) and Natural Prime Resources Limited (SoKlin brand). The market encompasses 56 distinct product variants ranging from 22g to 935g SKUs across multiple formulations. The Operations span four major regional markets, including Lagos, Kano, Abuja, and Ibadan, with a total market value of ₦2.2B, based on comprehensive revenue analysis.

The analysis flow was initiated at the point of customer demand and production trigger for the period under consideration. Supply chain operations are focused on the movement of goods and services from suppliers to end customers. At various stages, different types of costs were incurred, as shown in Table 1. The genetic algorithm utilizes a population size of 100 individuals per generation, running for 500 iterations to ensure convergence. Tournament selection with elitism preserves the best solutions while maintaining genetic diversity. The system employs a 0.8 crossover rate (80% probability) and 0.1 mutation rate (10% probability) for an optimal exploration versus exploitation balance. Table 2 shows the statistical distribution specifications. The study revealed that optimization interventions yielded measurable improvements across financial, operational, and inventory management metrics. Total operating costs were reduced by 32% with lower variability, and order fulfillment performance improved from 85% to 95%. Average lead time indicates higher and more consistent quality, with fewer errors or defects. These changes indicate both cost efficiency and service level enhancements, with strong statistical backing from the distribution models applied. Figures 7, 8, and 9 show the order volume by region, the monthly revenue trend, and revenue distribution by region, respectively.

Table 1: Subset of the experimental data

order_id	customer_region	quantity	unit_price	gross_sales	order_date	delivery_date	lead_time_days	transportation_cost	inventory_holding_cost	quality_score	service_level
ORD002000	P/Harcourt	237	226.76	53740.99	1/27/2025	2/7/2025	11	7857.67	4160.03	3.8713062	0.754294739
ORD002001	Ibadan	768	2467.66	1895161.2	2/8/2025	2/20/2025	9	138215.4	120864.65	4.2392815	0.753170008
ORD002002	Abuja	165	2123.18	350324.58	10/17/2024	10/28/2024	8	33629.99	12590.91	3.6411481	0.852654005
ORD002003	Ibadan	222	222.63	49422.91	2/16/2025	3/1/2025	13	6934.49	3476.71	4.1497307	0.783074472
ORD002004	Benin City	260	527.52	137155.67	12/30/2024	1/21/2025	17	15586.7	7175.31	3.360373	0.849914734
ORD002005	Ibadan	599	90.26	54065.97	9/13/2024	10/3/2024	16	3259.63	3062.23	4.3448094	0.833352203
ORD002006	Lagos	584	273.36	159641.41	2/4/2025	2/27/2025	18	14548.73	7803.28	3.0312342	0.799007658
ORD002007	Abuja	227	188.9	42879.42	12/9/2024	12/31/2024	20	4994.33	1527.36	3.6568304	0.835959575
ORD002008	Abuja	894	2561.45	2289940.6	9/8/2025	9/25/2025	13	186561.13	113311.21	3.0517364	0.819248545
ORD002009	Ibadan	550	262.34	144288.6	12/20/2024	1/8/2025	15	8965.69	8874.18	3.1759476	0.857971742
ORD002010	Abuja	159	215.55	34272.1	10/24/2024	11/9/2024	15	3458.86	2633.45	4.3575219	0.869871741
ORD002011	Abuja	247	2213.94	546844.38	12/28/2024	1/12/2025	11	72494.51	22204.79	3.0197988	0.807339451
ORD002012	Enugu	484	2481.92	1201248.7	2/17/2025	3/7/2025	14	66536	43904.03	3.8923551	0.754232783
ORD002013	Kaduna	467	2119.13	989634.59	1/6/2025	1/20/2025	12	70860.17	68076.45	3.6729662	0.841069451
ORD002014	Kaduna	21	225.87	4743.3	12/19/2024	1/5/2025	17	513.17	123.35	3.2848406	0.884410437
ORD002015	Kano	399	232.62	92813.72	4/4/2025	4/26/2025	19	6801.35	3262.13	4.1869167	0.866855298
ORD002016	Lagos	114	184.53	21036.56	8/10/2025	8/28/2025	17	1279.08	734.19	3.2029104	0.87531242
ORD002017	Enugu	668	232.22	155124.89	2/23/2025	3/9/2025	14	19927.67	5768.38	3.2526231	0.806908073
ORD002018	Abuja	830	80.91	67153.03	12/1/2024	12/11/2024	7	5077.21	2046.09	3.1383872	0.812368482
ORD002019	Kaduna	459	211.49	97076	10/20/2024	11/2/2024	11	11450.68	5267.51	3.6686703	0.848427951
ORD002020	P/Harcourt	338	2345.36	792733.27	12/1/2024	12/24/2024	18	118139.63	49277.66	3.2330796	0.839910535
ORD002021	Abuja	769	73.06	56180.17	9/27/2024	10/12/2024	14	7229.08	2819.22	3.1053273	0.829888139
ORD002022	Enugu	706	1150.72	812405.46	12/29/2024	1/18/2025	16	69281.91	35911.3	3.5886141	0.782251422

Figure 10 presents a **correlation matrix** heatmap for a set of **operational metrics, s**uch as order volume, revenue, discounts, and shipping timelines to inform business strategy and operational efficiency. This identifies the strength and direction of linear relationships between pairs of variables. Order Quantity and Gross Sales have a moderately strong positive correlation (0.66), indicating that as the quantity ordered increases, gross sales tend to increase. Discount Percent shows no meaningful correlation with any other variables, suggesting discounts do not significantly impact order quantity, gross sales, or shipment days. Shipment Days Scheduled is also uncorrelated with other metrics, implying shipping time is independent of order size, sales, or discounts. Overall, order quantity is the primary driver of sales, while discounts and shipment schedules appear to operate independently in the experimental dataset.

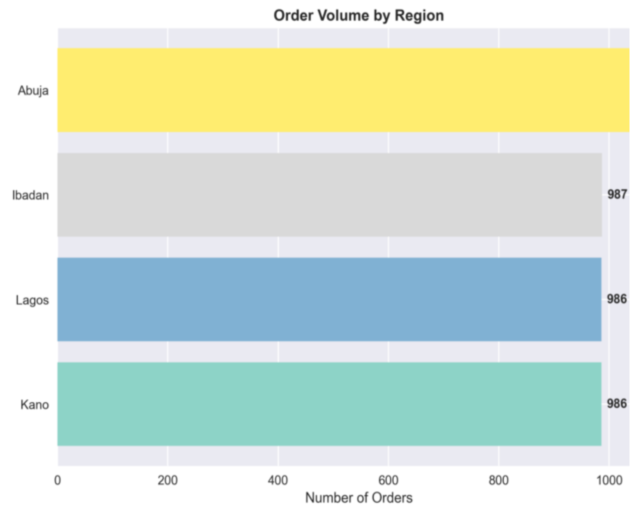


Figure 7: Order volume by region

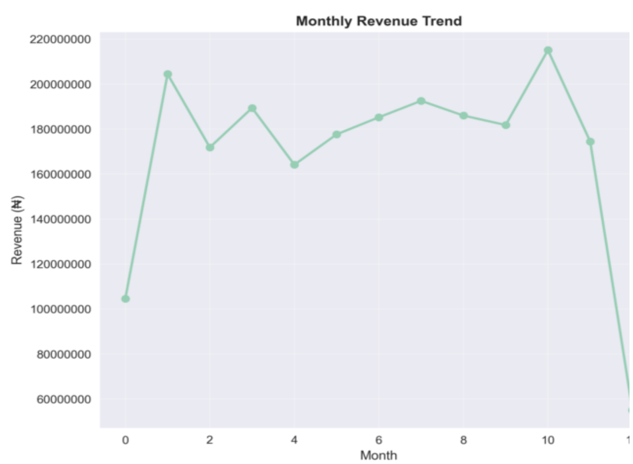


Figure 8: Monthly Revenue Trend

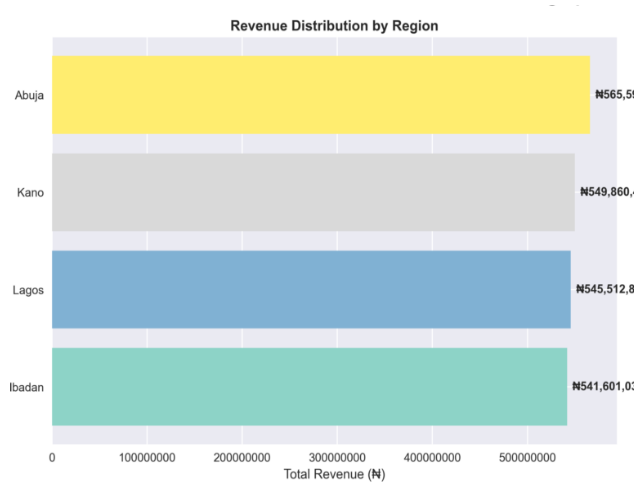


Figure 9: Revenue Distribution by Region

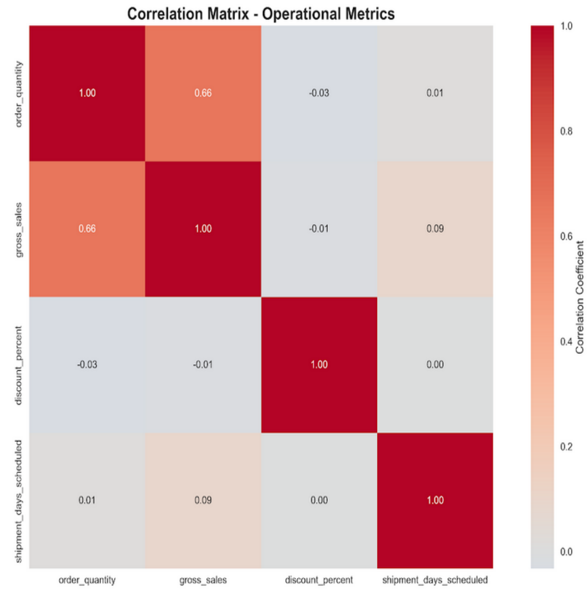


Figure 10: Correlation Matrix heatmap for operational metrics

Overall, pro GA-JIT results show a strong movement towards best-in-class benchmarks, with performance exceeding the industry average across all dimensions. This is a clear indicator of successful supply chain optimization. It reflects both operational excellence and strategic competitiveness. The standard key performance indicators for an inventory system include order fulfillment rate (O_r), lead time reduction rate (L_r), cost reduction rate (C_r), inventory turnover rate (I_r), and quality (defect) rate (Q_r). Others are cost performance (C_p), service excellence (S_e), time efficiency (T_e), quality performance (Q_p) and inventory optimization (I_o). O_r, L_r, C_r, I_r, Q_r, C_p S_e, T_e, Q_p, and I_o are derived as follows:

$$O_r = \alpha \times \frac{95}{100} \tag{34}$$

$$L_r = \frac{a-b}{a} \times 100 \tag{35}$$

$$C_r = \frac{\beta-\gamma}{\beta} \times 100 \tag{36}$$

$$I_r = \frac{\tau}{\mu} \times 100 \tag{37}$$

$$Q_r = \frac{\varphi-\omega}{\varphi} \times 100 \tag{38}$$

$$C_p = \frac{C_r}{40} * 100 \quad (39)$$

$$S_e = \frac{O_r}{0.95} * 100 \quad (40)$$

$$T_e = \frac{L_r}{50} * 100 \quad (41)$$

$$Q_p = \frac{100 - Q_r}{99} * 100 \quad (42)$$

$$I_O = \frac{I_r}{12} * 100 \quad (43)$$

α is the optimized fulfilment, a is the baseline lead time, b is the optimized lead time, β is the baseline cost, $\gamma$is the optimized cost, τ is the optimized inventory turnover ratio, μ is the inventory turnover ratio, φ and ω are the defect rate and optimized defect rate, respectively. Table 3 presents the standard computation rates and the obtained values for the key performance indicators.

Table 3: Standard and the obtained values for the key performance indicators

Performance indicator	Global Best practice Target for FMCG sector (%) (Gartner 2024; PwC, 2023; ASCM 2024)	Recorded Value (%)
Fulfillment rate	≥ 95	97.00
Lead time reduction rate	≥ 50	69.03
Cost reduction rate	≥ 40	41.90
Inventory turnover rate	≥ 12	51.67
Quality (defect) rate	≤ 1	0.60
Cost Performance	25	79.75
Service excellence	20	100.00
Time efficiency	20	138.06
Quality Performance	15	100.40
Inventory optimization	20	51.67

From Table 3, the overall score is obtained from:

$$\begin{aligned} Overall\_score &= (cost\_score * 0.25) \\ &\quad + (fulfillment\_score * 0.20) \\ &\quad + (time\_score * 0.20) \\ &\quad + (quality\_score * 0.15) \\ &\quad + (inventory\_score * 0.20) \\ &= (79.75 * 0.25) + (100 * 0.20) + (138.06 * 0.20) \\ &\quad + (100.4 * 0.15) + (51.67 \\ &\quad * 0.20) \end{aligned}$$

$$= (19.94) + (20) + (27.61) + (15.06) + (10.33)$$

$$\begin{aligned} overall\_score &= 92.94\% \\ &= 93.0\% \end{aligned}$$

The key performance indicators (KPI) dashboard components are categorized into cost reduction KPI, service excellence KPI, and time efficiency, respectively. KPI has a 32.0% reduction in cost, and 97% increase in fulfillment rate, 69.03% reduction in time, with an overall grade of A (93% average achievement). Table 4 presents the comparative analysis of results from the research with results from the implementation of the algorithms presented in some other related research using the experimental dataset.

4.1 DISCUSSION

The application of Genetic Algorithms and the Just-in-Time principle has proven effective in solving complex supply chain problems by providing near-optimal solutions for scheduling, inventory management, and logistics. There is a significant performance improvement after GA-JIT implementation across all six KPIs. Most notably, cost efficiency improved by 32% and inventory optimization jumped by 38%. Pro GA-JIT performance is either at par with or approaching global best-in-class standards. It clearly outperforms the Nigerian industry average in all categories, suggesting strategic success and operational gains. The implementation of GA-JIT (Just-in-Time guided by advanced analytics) appears to be highly effective. Sustaining and refining this model can help close the remaining gaps with global leaders, especially in quality and sustainability. The results reveal a robust, lean, and customer-centric supply chain that achieves superior operational efficiency and service quality while maintaining moderate cost competitiveness. The fulfillment rate (97%) meets global best practice standards, demonstrating effective demand management, logistics reliability, and process synchronization. The lead time reduction rate (69.03%) surpasses the expected threshold of 50%, signifying improved responsiveness and elimination of non-value-adding time, an attribute associated with JIT-based systems. However, the inventory turnover rate (51.67%) is exceptionally high, reflecting rapid inventory flow and effective synchronization between production and demand, which are hallmarks of JIT. From a managerial standpoint, these results imply that the system has achieved strategic agility, balancing efficiency, responsiveness, and quality. The enhanced cost performance (79.75%) and service excellence (100%) demonstrate that the GA–JIT integration has transformed traditional supply chain operations into an adaptive, data-driven framework capable of sustaining competitive advantage. Several key factors underlie the model's superior performance such as: data-driven optimization enabled by GA, allowing dynamic adaptation to changing demand and capacity constraints, elimination of waste through JIT-driven lean practices, reducing excess inventory, overproduction, and waiting times, supplier integration and real-time information sharing, leading to improved reliability and reduced stock-outs, commitment to total quality management, reflected in the low defect rate (0.6%). Collectively, these factors have established a system characterized by operational resilience and continuous improvement, consistent with contemporary agile supply chain frameworks (ASCM, 2024). The GA component played a central role in optimization, adaptability, and solution robustness: multi-objective optimization, global search efficiency, dynamic adaptability, and quantitative impact. The high time efficiency (138.06%) and inventory turnover (51.67%) indicate GA's success in refining lot sizing, production sequencing, and delivery scheduling. These findings

Table 4: Comparative analysis

Performance Metric	**Research and recorded Value**		**Recorded for current research**
Lead Time Reduction	Gao & Liu, 2023	50-65%	
	Xuan et al., 2022	16.00%	69.03%
Cost Reduction	Alfayoumi et al., 2023	29.80%	31.90%
Time efficiency	Alfayoumi et al., 2023	20.40%	138.06%
Inventory Turnover	Iwasokun et al., 2023	45.70%	51.67%
Quality Defect Rate	Womack & Jones, 2023	< 1.00%	00.60%
Service Excellence	Gartner, 2024	90-95%	100.00%

align with prior studies that identified GA as a reliable metaheuristic for solving NP-hard supply chain optimization problems (Chan et al., 2022).

JIT contributed to waste minimization, flow efficiency, and quality consistency. Lead time reduction (69.03%) is a direct reflection of JIT's impact in reducing waiting and process delays. Inventory turnover (51.67) demonstrates JIT's ability to maintain low stock levels while ensuring material availability. Quality improvement (defect rate 0.6%) shows the success of JIT's focus on prevention rather than detection of defects. Fulfillment performance (97%) confirms the synchronization of production with customer demand. Overall, JIT reinforced lean management principles and created an operational environment conducive to flexibility and continuous improvement. The integration of GA and JIT produced synergistic effects that exceeded the outcomes achievable by either method individually. This hybridization explains the superior service excellence (100%), time efficiency (138.06%), and quality performance (100.4%), validating the model's practical and theoretical potential. The findings demonstrate that the GA–JIT integrated approach yields: superior efficiency in time and service dimensions; excellent quality performance below defect thresholds; high inventory responsiveness with minimal holding costs; slightly moderate cost savings due to the prioritization of reliability and customer satisfaction. The model's outcomes confirm that the combination of evolutionary optimization and lean philosophy will enable business organizations to achieve smart, adaptive, and sustainable supply chain performance, consistent with emerging Industry 4.0 paradigms. The slight deviation in the cost reduction is consistent with the opinion of Christopher & Towill (2002), who stated that high-performing supply chains often incur higher operational costs in exchange for superior reliability and service quality. Therefore, the GA–JIT hybrid represents a strategically balanced system, combining lean efficiency with adaptive intelligence.

5. CONCLUSION

The development of Genetic Algorithms (GA) and Just-In-Time (JIT) principles to optimize supply chain operations within a soap manufacturing company has demonstrated the potential benefits. By applying GA, we were able to identify optimal solutions for raw material procurement, production scheduling, and distribution, effectively minimizing costs and reducing lead times. The adoption of JIT further reinforced lean manufacturing practices by ensuring materials and products are available precisely when needed, reducing inventory holding and wastage. The integrated GA-JIT approach led to improved production efficiency, lower stock levels, and enhanced responsiveness to customer demand, which are critical in a competitive market. The outcomes confirm that a data-driven, intelligent optimization strategy can significantly enhance supply chain performance while supporting sustainability goals through waste reduction and efficient resource usage. Future research will explore the development of hybrid optimization models to improve solution quality, convergence speed, and adaptability in complex, multi-variable environments

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