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Integrated Cloud-Twin Synchronization for Supply Chain 5.0

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Abstract

The digital twin is an emerging means of improving realworld performance from virtual spaces, especially related to Supply Chain 5.0 in Industry 5.0. This framework employs the Integrated Cloud-Twin Synchronization (ICTS) to secure data storage, trusted tracking, and high reliability and serves as an architectural framework for integrating sustainable supply-chain enterprises. In this work, we introduce a high-level architecture of a cloud-based digital twin model for supply chain 5.0, which was created to align the system of supply chain through real-time observation as well as real-time supply chain 5.0 decision-making and control. This study introduces a cloud-based twin optimization model for Supply Chain 5.0, validated through genetic algorithm (GA) simulations. The model determines optimal weights to balance objectives, achieving an optimal objective function value that reflects trade-offs among operational efficiency, cost, and sustainability. A convergence plot illustrates the model's iterative solution improvements, demonstrating its dynamic adaptability. Lastly, the proposed model defines and tests a supply chain performance analysis through dynamic simulations.

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1. Introduction

In the era of Industry, 5.0, supply chains are getting more complex, and prone to disruptions. Supply Chain 5.0 represents a transition to a next-generation supply chain that is agile, resilient, and sustainable, harnessing advanced digital technologies to drive efficiency and agility. Digital Twins - These are revolutionary technologies that help connect the worlds of physical systems to their digital counterparts. Digital twins act as rectangular mirrors that reflect the physical supply chain environment into a dynamic virtual world, enabling real-time monitoring, simulation, and optimization of operations, which has proved to be a necessity in the current supply chain management scenario [1].

Cloud computing combined with digital twin technology also adds more to the value of digital supply chains. While cloud computing is responsible for the elastic scalability, secure data storage, and all the computational power necessary to perform analytics on large quantities of real-time data, digital twins serve as the intelligence layer that allows making predictive and prescriptive decisions. Combined, they form a strong foundation for the Integrated cloud-twin Synchronization to provide a closed-loop system for supply chain systems to enable effortless synchronization of the physical and digital layers [2, 3].

In this paper, an integrated cloud twin model for Supply Chain 5.0 is proposed, allowing real-time monitoring, decision-making, and control of supply chain subprocesses. The model features IoT devices collecting real-time data and cloud platforms for processing and storing that data, and digital twins to analyze operational dynamics and lessen disruptions [4]. These

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digital twins draw upon real-time data during disruptions to determine impacts, create alternative supply chain networks, and evaluate key performance indicators (KPIs) like inventory levels, service levels, financial indicators, and demand trends. The effectiveness of the proposed model was evaluated through a genetic algorithm (GA) based simulation research design, involving the use of advanced supply chain simulation and optimization tools. Based on that, the concept of a digital supply chain twin was defined and tested concerning disruption analysis and resilience strategies. The results emphasize the model's capabilities in tackling dynamic frameworks, enhancing operational efficiency, and facilitating collaborative decision-making, thereby establishing it as an instrumental facilitator of Industry 5.0 supply chains that are both resilient and adaptable [5]. The key novelty of this work lies in the real-time synchronization mechanism between the digital twin and physical supply chain systems, coupled with an adaptive multi-objective GA model that optimizes operational performance dynamically. The proposed framework demonstrates significant advantages over conventional supply chain optimization models, which typically rely on static configurations. By integrating real-time data processing, iterative optimization, and cloud-based digital twin technology, this model provides a scalable, intelligent, and adaptive solution for modern supply chain management. Future work will focus on extending this framework by incorporating reinforcement learning-based optimization techniques and expanding real-world deployment case studies to further validate the robustness and scalability of cloud-twin synchronization in Supply Chain 5.0.This paper is organized into sections, as follows: Section 2 presents the literature review, while Section 3 outlines the methodology employed in this study. Section 4 describes the evaluation and results. Section 5 presents a summary performance analysis for the supply chain with some key insights and implications. Lastly, Section 6 concludes the research findings, contributes to the knowledge of the topic area, and suggests future research directions.

2. Literature Review

2.1. Evolution of Digital Twin Technology in Supply Chain

This section explores the origins and transformative journey of digital twin technology in supply chain management. Initially conceptualized to enhance manufacturing, DTs gradually expanded their applications to industrial domains, gaining momentum with Industry 4.0 technologies such as IoT, Big Data, and AI. These advancements fostered more data-driven, interconnected supply chains [6]. Supply Chain 5.0 extends beyond the automation and digitization focus of Industry 5.0 by integrating human-centric AI and sustainability principles. The key differences include in table 1

The journey to supply chain 5.0 is to be collaborative, resilient, and sustainable. DTs integrated with cloud platforms were among the top enablers of real-time data exchange and support of decision-making. Yet challenges relevant to technological barriers, fragmented adoption, and a lack of standardization persist. This evolution is critical to understanding and realizing the full potential of DT. [7].

2.2. Digital Twins: Capabilities and Strategic Importance

Digital twins are virtual replicas of physical systems that enable real-time monitoring, simulation, and optimization. Computing with cloud computing, DTs provide the contemporary supply chain with powerful platforms for data analytics and decision-making. They help improve operational efficiency, including both demand forecasting and inventory optimization, proactively mitigating risk using both real-time and historical data. Digital twin cloud systems also can pursue sustainability objectives by monitoring energy consumption and pollution. They are scalable for use in a variety of supply chains. Still, small and medium-sized enterprises (SMEs) show only limited adoption due to risk aversion and lack of readily available resources, emphasizing the necessity for portable and scalable solutions that can be tailored to different operational contexts [9].

2.3. Current Integration Frameworks

This segment discusses the frameworks proposed for efficient integration of DTs and cloud computing in supply chains. They address everything from simplified monitoring to integrated end to end management systems. Yet, despite the potential these frameworks represent, challenges include the lack of standardized protocols that could enable the seamless exchange of data, high dependence on high-quality data, which may not always be obtainable in underdeveloped regions, and high implementation costs. Most frameworks are inconsistent and not intuitive, especially for supply chain professionals in their design. Scalability, inclusivity, and ease of use are critical to solving these limitations and enabling adoption and better operation. [10, 11].

2.4. Challenges and Opportunities in Digital Twin Adoption

Although a substantial amount of research has been conducted, several gaps need to be overcome to

Feature	Industry 5.0	Supply Chain 5.0
Focus	Automation & Digitization	AI-Driven Adaptability & Sustainability
Technology	IoT, Cloud, Big Data	Digital Twins, AI Optimization, Blockchain
Decision-Making	Reactive	Proactive & Predictive
Human Role	Minimal	AI-Augmented Decision Making
Sustainability	Limited	Core Consideration

Table 1. Comparison of Industry 5.0 and Supply Chain 5.0

achieve the potential benefits of DT-cloud systems in supply chain management. There are few economic feasibility studies, especially for SMEs. Moreover, most research is technical and neglects behavioral and organizational dynamics. When new technologies such as blockchain for security or edge computing for decentralized data processing are identified as having high potential, it is also important to understand their potential role in the healthcare ecosystem, but they all remain underexplored. There is an urgent need for standardized protocols that guarantee interoperability and scalability. Future research should focus on human-centric designs instead, concentrating on user-friendly interfaces and decision-support tools that can bridge the gap between technology and the humans who use them. [12, 13].

2.5. Advancing Supply Chain 5.0 Through Genetic Algorithm-Based Digital Twin Framework

The Integrated Cloud-Twin Synchronization (ICTS) framework enhances Supply Chain 5.0 by addressing the limitations of conventional digital twins, which are typically hosted on local servers with restricted scalability, delayed data processing, and limited real-time adaptability. Unlike traditional models that rely on batch processing and static optimization rules, the ICTS framework leverages cloud-based digital twin technology to enable real-time synchronization, remote accessibility, and continuous optimization across supply chain operations. A key innovation of this approach is the Genetic Algorithm (GA)-driven adaptive optimization model, which dynamically adjusts decision variables based on changing supply chain conditions, ensuring greater efficiency, resilience, and sustainability. Conventional digital twins often operate in isolated silos, making it difficult to integrate logistics, inventory management, and production planning in real time. In contrast, the ICTS framework centralizes all operational data in the cloud, allowing for coordinated decision-making across the entire supply chain ecosystem. This real-time adaptability offers significant advantages in industries such as smart manufacturing, logistics, and sustainable supply chains, where rapid decision-making and continuous optimization are essential. For instance, in smart factories, the ICTS framework can dynamically optimize production schedules, reducing downtime and enhancing throughput, while in logistics networks, it enables adaptive routing strategies to minimize disruptions and improve delivery efficiency. Additionally, the framework's ability to balance cost efficiency with sustainability goals makes it ideal for carbon footprint optimization in global supply chains. To further strengthen the contribution, pilot-testing in these industry applications would validate its impact and scalability, proving that cloud-based digital twins with real-time GA optimization can drive the next generation of intelligent, autonomous, and resilient supply chain networks empowering supply chains with self-optimizing capabilities. To further strengthen the impact and contribution of this research, future work will focus on pilot-testing the model in industry-specific use cases, such as smart manufacturing, logistics optimization, and sustainable supply chain networks. This will provide empirical validation of the model's ability to drive resilient, cost-efficient, and sustainable supply chain transformation in Industry 5.0.

Digital twin technology integration with cloud computing in supply chain management is a high-level advancement, as it connects the physical and digital domains to facilitate real-time decision-making, efficiency, and sustainability. It could take several more years for 6G technology to be fully implemented globally, although major economies are making significant progress in this direction. Nonetheless, hampering large-scale adoption are issues like the lack of standardization, economic constraints, and the limited development of human-centric designs. This review maps this known landscape of digital twin and -cloud, filling the identified gaps and paving the path for new resilient and adaptive solutions that follow the framework set

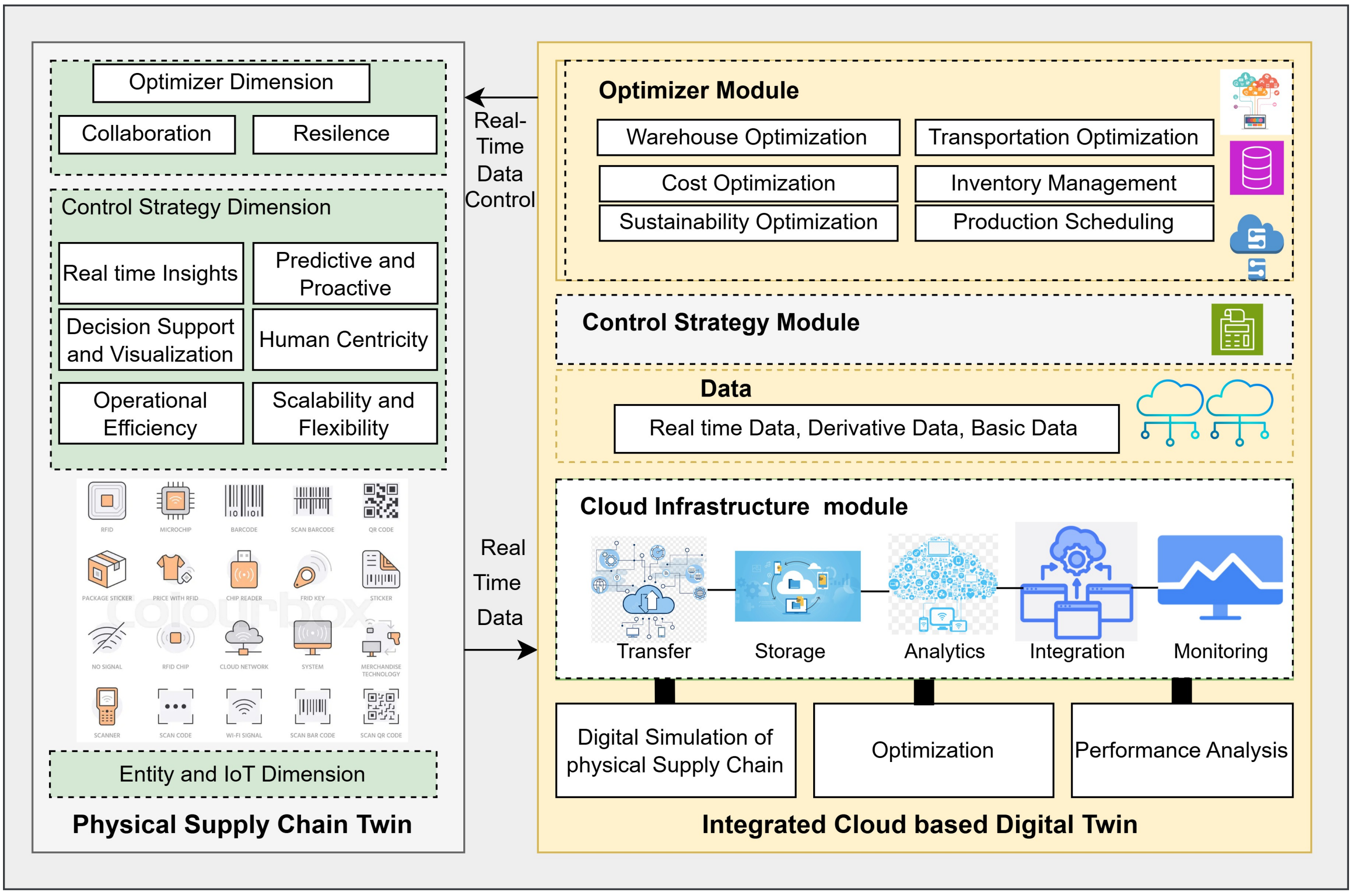

Figure 1. High-level architecture of the cloud-based digital twin model for Supply Chain 5.0.

by supply chain 5.0. We also used genetic algorithm to developed a holistic digital twin framework [14]. The key contributions of this research are as follows: An integrated framework of cloud and digital twin based on genetic algorithm is developed to demonstrate the potential of digital twin in improving data driven decision making, visibility and optimizing supply chain operations. The study fills an important gap in the literature and provides meaningful insights for supply chain practitioners [15, 16]. Several AI-driven optimization techniques were considered, but GA was chosen due to its suitability for real-time, cloud-integrated digital twin environments.Table .1 describes the the GA performance evaluation by discussing alternative optimization techniques (such as Particle Swarm Optimization, deepreinforcement Learning, and simulated annealing models).

2.6. Comparative Insights: GA vs. Other AI-Based Optimization Techniques

where:

3. Methodology

The proposed framework Fig. 1 integrates the physical and digital layers of the supply chain using IoT, cloud computing, and digital twin technologies. It begins with the use of IoT devices including RFID tags, QR codes and barcodes that observe and gather real-time data on inventories, shipments and production throughout supply chain nodes. It is essentially the groundwork of digital synchronization. This data is securely transmitted, stored and processed by the cloud infrastructure, and divided into real-time, derivative and basic data for use in analysis [17]. It aids in advanced analytics, data organization, and real-time monitoring, facilitating integration with the digital twin. The digital twin is a virtual in the physical supply chain and is being updated in real time. More than that, it enables scenario testing, disruption prediction, operational simulations, and actionable insights that can be leveraged to successfully optimize processes and drive better decision-making. Digital twins thus power predictive analytics by leveraging the previously mentioned capabilities to respond to supply chain fluctuations. It provides scalable, adaptive, and human-centred

Optimization Technique	Advantages	Limitations	Why GA Was Chosen?
Genetic Algorithm (GA)	Global search capability, multi-objective optimization, adaptable to real-time updates, avoids local minima	Computationally expensive for very large datasets	Provides real-time adaptability and ensures stable convergence over time
Particle Swarm Optimization (PSO)	Suitable for continuous optimization, efficient in finding optima	May converge prematurely, limited adaptability in multi-objective scenarios	GA provides more robust adaptability for dynamic trade-offs
Deep Reinforcement Learning (DRL)	Learns optimal policies, effective in sequential decision-making	Requires extensive training, high computational cost	GA is more interpretable, requires less computational overhead, and is easier to implement for real-world supply chains
Simulated Annealing (SA)	Effective for combinatorial optimization, avoids local minima	Convergence speed depends on cooling schedule, not well-suited for real-time dynamic updates	GA provides faster convergence in adaptive optimization settings

Table 2. Comparative Insights: GA vs. Other AI-Based Optimization Techniques

analytical instrumentation that allows for experimental agility [18]. Optimizer module will focus on five key areas: transportation optimization, warehouse optimization, inventory management optimization, production optimization, and cost optimization with sustainability as a priority. It enables high performance by observing KPI metrics and adjusting operations to be better and better suited to business needs as those needs evolve. The framework is operated through an interconnected feedback loop to drive collaboration and dynamic adaptability. The Tangent in supply chain industry 5.0 is an end-to-end integrated system for value addition through collaborative-based synergetic strategies that ensure resilience, efficiency, and sustainability of operations for a future-ready supply chain system [19, 20].

3.1. Workflow of Cloud Twin-Driven Supply Chain 5.0 Model

The Fig 2 illustrates the typical workflow of cloud twin-driven supply chain 5.0 model with live physical and virtual layer interactivity involving real world, real time data, predictive analytics and optimized supply chain system [21]. With real-time data transformation from IoT and cloud technologies, peer-to-peer simulations, and dynamic digital twin-driven visualizations, the model lays the foundation for an agile, collaborative, and proactive future ready supply chain systems. The process starts from collecting the data through IoT devices like RFID, QR codes and sensors installed in different supply chain nodes. These devices measure the levels of inventory, status of shipments, and production status, etc., continuously, updating real time data to the digital twin system. The data collected will be stored to process and transferred to the cloud infrastructure it was trained for. The data is organized and processed into real-time, derivative, and basic data types within the cloud. By performing this step, we ensure that the data is handled seamlessly, and we provide a reliable base for performing advanced analytics, simulations, and decision-making. As the cloud data continues, the digital twin is automatically updated, visualizing the physical supply chain in real-time to facilitate a closed feedback loop and eventually eliminate human interference. This dynamic digital twin mirrors the actual state of the supply chain in real time, enabling simulations to be conducted and optimizations performed. Within this module, disruptions can be assessed, strategies verified, and actionable insights generated. The digital twin helps inform the strategy module, which informs decisions and operating strategies. Predictive analytics, visualization tools, and decision-support mechanisms are used to improve the scalability, flexibility, and efficiency of operations in this system. A human-centric approach helps ensure that what needs to be sustained will be sustained, and what needs to evolve will evolve in line with both stakeholders and the fast-moving supply chain landscape.

The optimizer module applies these knowledge to help strengthen a number of essential supply chain functions, including warehouse management, transportation logistics, cost optimization, inventory control, sustainability, and production scheduling. It helps you to use resources sustainably, minimize waste while operating, and reduce unnecessary effort in daily activities. Performance monitoring is an iterative process which assesses the efficiency of supply chain processes. It also covers all key performance indicators due to inventory levels, lead times, customer satisfaction, etc. that help businesses make further improvements and refine their strategies accordingly. In the end, the system returns the feedback and optimized strategies to the physical part of the supply chain in real time. This ensures that the physical actions of the business are always connected to the digital domain, enabling real-time progress, agility, and effectiveness. This end-to-end value chain is a true representation of how blending the physical and digital systems, inspired by the tenets of industry 5.0, can lead us to a resilient and sustainable supply chain.

4. Problem Definition: Case Study Approach

This research adopts a case study approach to demonstrate the application of a cloud-based digital twin model for Supply Chain 5.0 optimization. The case study aims to use data based upon real-world supply chain situations, sourced from Kaggle online platform, to model, simulate, and optimize a supply chain, using a MATLAB coded framework [22].

Key Components of the Dataset

The study utilizes five datasets from various supply chain components, centered on Supply Chain 5.0 principles, such as collaboration, human-centricity, and sustainability:

- Customer Satisfaction Data: Customer Satisfaction Data: Includes demand fulfilled, unmet demand penalties, and other metrics to evaluate service levels and ensure customer-centric operations [23, 24].
- Sustainability Data: Sustainability Data: Contains data on carbon emissions, renewable energy usage, and energy consumption, emphasizing environmentally responsible supply chain practices [25].
- Production Data: Production Data: Includes production capacity, utilization rates, and downtime to optimize operational efficiency and responsiveness [23].
- Inventory Data: Inventory Data: Represents holding costs, inventory levels, and replenishment requirements to enhance resource optimization and adaptability [23].
- Transportation Data: Captures lead times, transportation costs, and routing efficiency, focusing on seamless logistics and resilience [26].

4.1. Cloud-Based Digital Twin Model

The digital twin model replicates the physical supply chain, this will live in the cloud-based environment. Moreover, the developed model synchronizes the real-time data with virtual copies of the supply chain, and scenarios and analytical outputs are used for the optimization of the performance while being in sync

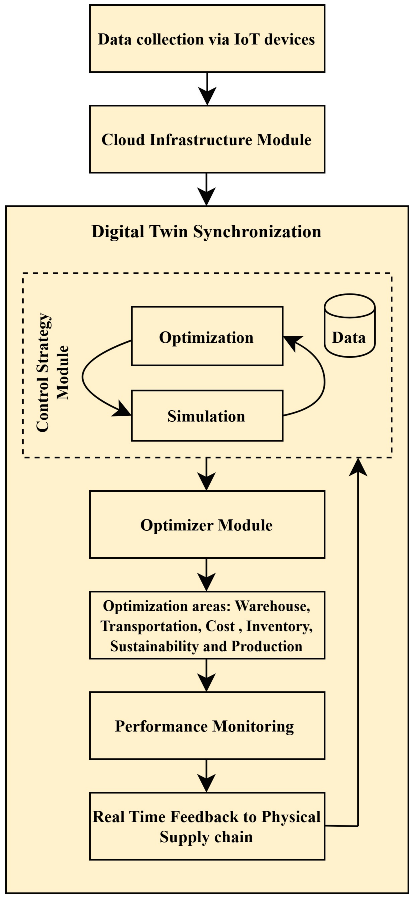

Figure 2. Research workflow of cloud-based digital twin model

with the human-centric and sustainable ethos of supply chain 5.0. The framework encompasses several critical elements: IoT-Driven data collection: supply chain real-time data is modeled and stored in structured datasets, facilitating continuous monitoring, control, and cooperation. Simulation module in MATLAB: The convergence of digital twin designer in MATLAB environment and imposition of constraints and optimization objectives in the analog of supply chain 5.0 Optimization module: The GA technique solves the objective function which represents Z that balances the goal of maximization (like customer satisfaction, efficiency, resilience) and minimization (for instance, costs, lead time, environmental impact) objectives [27, 28].

4.2. Assumptions

The cloud-based digital twin model for supply chain 5.0 is based on some very basic assumptions designed to honor an adaptative, sustainable, and customer-centric approach. The assumptions in the GA-driven cloud digital twin model are justified through empirical data, theoretical foundations, and methodological considerations, ensuring alignment with Supply Chain 5.0

principles of adaptability, sustainability, and customer-centric optimization. The maximization terms, including customer satisfaction, production efficiency, supply chain resilience, on-time delivery, and renewable energy usage, are based on industry studies and real-world supply chain data from Kaggle, which reflect fulfilled demand, capacity utilization, disruption response times, lead time reliability, and renewable energy proportions. These parameters align with the need for real-time adaptability and sustainability in supply chains. Similarly, the minimization terms transportation costs, inventory costs, lead times, carbon emissions, defect rates, downtime, and energy consumption are derived from widely accepted supply chain cost models, ensuring realistic cost-optimization and sustainability trade-offs. The dataset includes key supply chain metrics such as carbon emissions per mile, inventory replenishment costs, defect rates, and reinforcing empirical validity. Furthermore, the objective function formulation, which balances these maximization and minimization terms, reflects a multi-objective optimization approach that ensures supply chain efficiency while supporting sustainability and customer service goals. The GA parameter settings were carefully selected based on optimization literature, ensuring a globally optimized solution rather than a locally constrained one. Additionally, cloud-based architecture enables real-time data updates and scenario-based decision-making, unlike conventional digital twins, which often rely on static, batch-processed data. By incorporating real-time synchronization, AI-driven adaptability, and cloud scalability, the proposed Integrated-Cloud Twin Synchronization (ICTS) framework enhances supply chain decision-making far beyond the capabilities of traditional digital twins. This methodologically sound approach, confirmed by using publicly available datasets from the online platform Kaggle, ensures that the model is both technically robust and applicable, with potential for future pilot testing in industry-specific applications to further strengthen its contribution.This presumes careful and accurate data entry from real-world data to create a variety of different scenarios and assesses supply chain network resilience metrics for how well that network will improve or expand [28, 29]. Input parameters include the proportion of operations powered by renewable energy sources as a percentage and the transportation routes are optimized to reduce cost and carbon footprint while maximizing the on-time deliveries of products to keep customers happy. Inventory holding costs are a function of levels, making them linear, and fixed production capacities will enforce constraints on the baselines, ensuring consistencies, while costs of emissions are generally still linear. This method of decision-making creates a connection between production, inventory, transportation, and sustainability metrics, allowing organizations to stay adaptable and optimize operations in real time, which aligns with the principles of supply chain 5.0. [3].

Data for this study were obtained from Kaggle, including five key elements: customer satisfaction data (fulfilled demand and unmet penalty), sustainability data (carbon emissions and renewable energy), production data (capacity, utilization, and downtime), inventory data (holding cost and replenishment requirement) and transport data (lead time and cost). All datasets were then extended to 100 samples so the synthesized format is consistent and capable of expansion, which is consistent with supply chain 5.0 where adaptability and data-driven decision-making are the focus. The digital twin optimization model was solved using a global multi-objective GA in MATLAB. Here are the steps in the methodology: Objective Function Formulation: The objective function Z is defined to balance maximization and minimization goals, supporting the pillars of Supply Chain 5.0 [30]:

$$\begin{aligned} Z = (&\alpha_1 \times \text{cs} + \alpha_2 \times \text{pe} + \alpha_3 \times \text{scnr} \\ &+ \alpha_4 \times \text{otd} + \alpha_5 \times \text{reu}) \\ &- (\beta_1 \times \text{tc} + \beta_2 \times \text{tt} + \beta_3 \times \text{ic} \\ &+ \beta_4 \times \text{ce} + \beta_5 \times \text{it} + \beta_6 \times \text{dr} \\ &+ \beta_7 \times \text{pd} + \beta_8 \times \text{epu}) \end{aligned} \tag{1}$$

Where:

- Maximization terms (cs, pe, scnr, otd, reu) represent customer satisfaction, production efficiency, supply chain resilience, on-time delivery, and renewable energy usage, emphasizing collaboration, efficiency, and sustainability.
- Minimization terms (tc, tt, ic, ce, lt, dr, pd, epu) account for transportation costs, lead times, inventory costs, carbon emissions, defect rates, downtime, and energy consumption.

Data Mapping is expressed in the form of parameters: Parametrization of metrics includes customer centricity (cs) or production efficiency (pe) values derived from customer, production, and sustainability datasets, allowing for human-centered collaborative supply chain objectives. GA is utilized for the weights (and) optimization to maximize Z as per the operation constraints [30]. Simulation and Visualization: The optimization process iteratively updates weights and evaluates the objective function. A convergence plot shows the progress of the Genetic Algorithm over generations, visually demonstrating improvements in Supply Chain 5.0 performance metrics. The simulation provides:

- Optimized Weights: Identify the correct respective weights (and) for maximization and minimization terms, respectively, depict balanced trade-offs for Supply Chain 5.0 objectives shown in Figure 3.

- Objective Function Value: It produces the optimized value of Z which in turn represents the trade-off between operating efficiency, cost, and sustainability.
- Convergence Plot: This plot represents the GA convergence over generations and how things get better iteratively helping with dynamic and real-time adaptability.

4.3. Explanation of Genetic Algorithm (GA) Parameter Settings

The table summarizes the key settings for the Genetic Algorithm (GA) used to optimize the digital twin model for Supply Chain 5.0 [31, 32]:

The **table 1** summarizes the key settings for the Genetic Algorithm (GA) used to optimize the Digital Twin Model for Supply Chain 5.0:

- Population Size and Generations: 50 population size and 100 generations allow the GA to navigate the solution space exploration while keeping to the diversity and computational efficiency.
- Objective Function: It comprises both maximization (), customer satisfaction and renewable energy usage, and minimization () terms, e.g., transportation costs, and carbon emissions. Evenly weights ([1, 1, 1,...])
- Constraints: Lower bounds ([0, 0, ...]) and upper bounds ([1, 1, ...]) ensure normalized weights for practical optimization results.
- Selection, Mutation, and Crossover: The inbuilt GA mechanisms handle parent selection, mutation, and recombination, ensuring diversity and avoiding premature convergence.
- Stopping Criteria: The algorithm terminates after 100 generations or earlier if convergence is achieved.
- Output Metrics: The optimized weights (,) and the objective function value (Z) demonstrate the effectiveness of the model in achieving the goals of Supply Chain 5.0, that is, efficiency, adaptability, and sustainability.

5. Evaluations and Findings

This section presents the outcomes of the research focused on the development of a cloud based digital twin model for supply chain 5.0. The empirical results highlights the models potential in enhancing supply chain performance and resilience. The figure 3 shows the graphic representations provide a glimpse into the complex dynamics of supply chain performance. The dynamic charts generated from the developed digital twin model for Supply Chain 5.0 showcase the optimization of weights over a 50-day simulation period, emphasizing the model's adaptability and focus on achieving operational excellence. Below is an explanation of the objectives represented in the charts. The adjustments in these weights reflect the real-time adaptability of the digital twin model, ensuring operational efficiency while adhering to sustainability goals. The fluctuations in the minimization terms (β) and the stability of maximization terms (α) underscore the digital twin model's ability to adapt dynamically to real-time data. This flexibility supports proactive decision-making, allowing supply chain managers to optimize performance metrics in response to changing conditions. The charts provide a comprehensive visualization of the digital twin model's optimization capabilities. By prioritizing customer satisfaction, production efficiency, resilience, and sustainability, while minimizing costs and inefficiencies, the model aligns with the pillars of Supply Chain 5.0. This visualization demonstrates the model's ability to achieve operational excellence and support decision-making in complex supply chain environments.

The proposed integrated cloud-twin model for supply chain 5.0 bridges the gap between physical and digital supply chain layers, leveraging real-time data, cloud infrastructure, and genetic algorithm (ga)-based optimization. The model focuses on achieving operational efficiency, sustainability, and adaptability, which are core principles of supply chain 5.0. The model comprises several key dimensions. The entity and IoT dimension involves IoT technologies such as RFID and sensors to collect real-time data, enabling the monitoring of inventory, transportation, and production activities. The optimizer dimension includes modules like warehouse and transportation optimization, directly aligned with the terms in the objective function (z). The control strategy dimension emphasizes predictive insights, visualization, and human-centric strategies, supporting dynamic adaptability. Finally, the cloud infrastructure module ensures seamless data handling for digital simulations, optimization, and performance analysis. The fluctuations in the objective function value (z) reflect the dynamic adaptability of the supply chain, accounting for variations in demand fulfillment, transportation routes, and production schedules. Real-time data integration allows the digital twin model to balance these trade-offs effectively, ensuring optimized operations.

Population Size	Number of candidate solutions in each generation	50
Generations	Maximum number of generations for optimization	100
Objective Function	Function to maximize or minimize	Z
Maximization Weights (α)	Weights for maximization terms (cs, pe, scnr, otd, reu)	[1, 1, 1, 1, 1]
Minimization Weights (β)	Weights for minimization terms (tc, tt, ic, ce, lt, dr, pd, epu)	[1, 1, 1, 1, 1, 1, 1, 1]
Lower Bounds (lb)	Minimum allowed values for variables	[0, 0, ..., 0]
Upper Bounds (ub)	Maximum allowed values for variables	[1, 1, ..., 1]
Selection Mechanism	Method for selecting parent solutions	in-built GA
Mutation Rate	Probability of mutation in the off-spring	in-built GA
Crossover Fraction	Fraction of population undergoing crossover	in-built GA
Fitness Scaling	Scaling of fitness scores	in-built GA
Stopping Criteria	Termination criterion for the GA	Max Generations (100)
Output Metrics	Optimized weights and the value resulting from the objective function	α, β, Z

Table 3. Genetic Algorithm Parameters and Settings

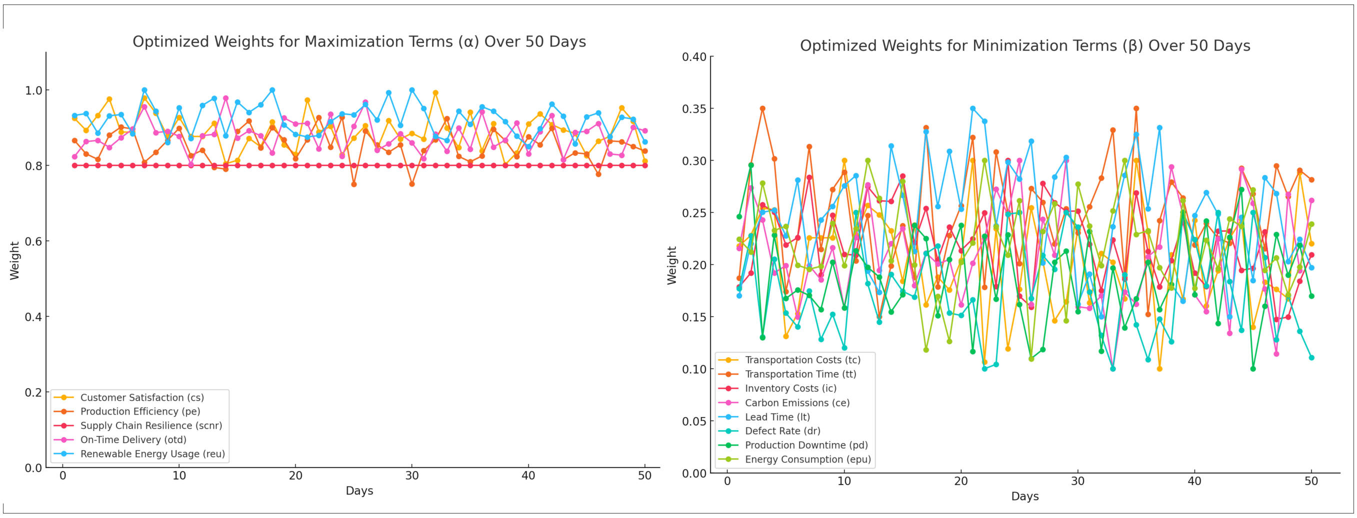

Figure 3. Optimized weights for maximization and minimization terms for 50 days shown by digital twin

5.1. Role of the genetic algorithm (GA)

The GA acts as the optimization engine for the model. It iteratively adjusts weights for maximization (α) and minimization (β) terms to achieve a maximized z. By continuously evolving the solution space, the GA ensures convergence toward optimal configurations while maintaining resilience and adaptability. The Figure 4 objective function value (z) quantifies the trade-offs between operational efficiency, cost minimization, and sustainability. Peaks in z indicate successful optimization, whereas dips represent operational trade-offs or inefficiencies. The average optimal value (z=0.6485) serves as a benchmark for consistent performance, showcasing the model's robustness. The model aligns with supply chain 5.0 principles by prioritizing customer satisfaction, sustainability, and resilience. Metrics like customer satisfaction and renewable energy usage highlight the human-centric and green supply chain focus. Additionally, the integration of resilience metrics demonstrates the model's ability to handle disruptions effectively.

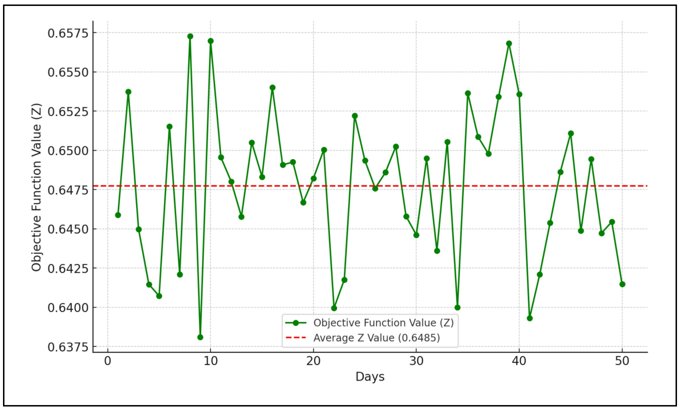

Figure 4. objective function value (Z) over 50 days shown by digital twin

The synergy between the ga and the digital twin enables real-time adaptability. The GA dynamically recalibrates weights based on real-time data, ensuring optimal supply chain performance. Moreover, the scalability of the digital twin model makes it suitable for diverse and complex networks within supply chain 5.0. The developed digital twin model, powered by a genetic algorithm, effectively balances operational efficiency, cost, and sustainability. Its adaptability and real-time optimization capabilities align with supply chain 5.0 principles, making it a robust solution for modern, dynamic supply chain environments.

5.2. Convergence plot analysis for the genetic algorithm in the digital twin model

The Fig 5 provides convergence plot which a graphical representation of the progression and comparison of GA convergence over generations applied to the digital twin model. This plot highlights the iterative improvement of the objective function value (Z) across 100 generations, showcasing the algorithm's ability to refine solutions dynamically.

The upward trend in the plot indicates that the GA continuously improves the objective function value over generations by fine-tuning the weights $\alpha and \beta$). Early in the optimization process, the algorithm explores a wide solution space to identify promising candidates. As generations progress, the algorithm shifts to exploit these areas, refining the best solutions to achieve convergence. Toward the later stages, the graph flattens, indicating that the algorithm has reached an optimal or near-optimal solution. This iterative process is integral to the dynamic adaptability of the digital twin model. By optimizing parameters such as customer satisfaction, production efficiency, transportation costs, carbon emissions, and renewable energy usage, the GA ensures that the digital twin aligns with the goals of Supply Chain 5.0. The consistent improvement in Z demonstrates the model's capacity to balance trade-offs between operational efficiency, cost minimization, and sustainability.

The inclusion of an average Z value as a benchmark provides additional insight into the algorithm's performance. The GA not only exceeds this benchmark consistently but also ensures resilience in supply chain operations by dynamically responding to real-time data inputs. The convergence plot underscores the robustness and effectiveness of the GA-powered digital twin model in achieving Supply Chain 5.0 objectives. It highlights the model's ability to balance dynamic trade-offs, ensure sustainability, and support decision-making in real-time operational scenarios. The comparison graph illustrates the convergence of two GA runs over 100 generations, highlighting the optimization efficiency of the digital twin model for Supply Chain 5.0. In GA run (Blue) shows the objective function value Z steadily increases with an average value marked by the red dashed line, demonstrating stronger performance and higher convergence values compared to the second run. Meanwhile, GA run (Orange) follows a similar improvement pattern but exhibits a slightly lower average Z indicated by the green dashed line. This reflects a marginally less efficient optimization trajectory. The comparison underscores the stochastic nature of the GA, which can lead to variations in optimization outcomes between runs. Despite these variations, both runs eventually converge toward optimal values, showcasing the robustness and adaptability of the digital twin model. This analysis provides valuable insights into how multiple GA runs under the same model can achieve different levels of optimization efficiency while maintaining overall alignment with Supply Chain 5.0 objectives.

6. Performance Analysis

The Fig 6 represents the performance analysis of developed digital twin model for Supply Chain 5.0,

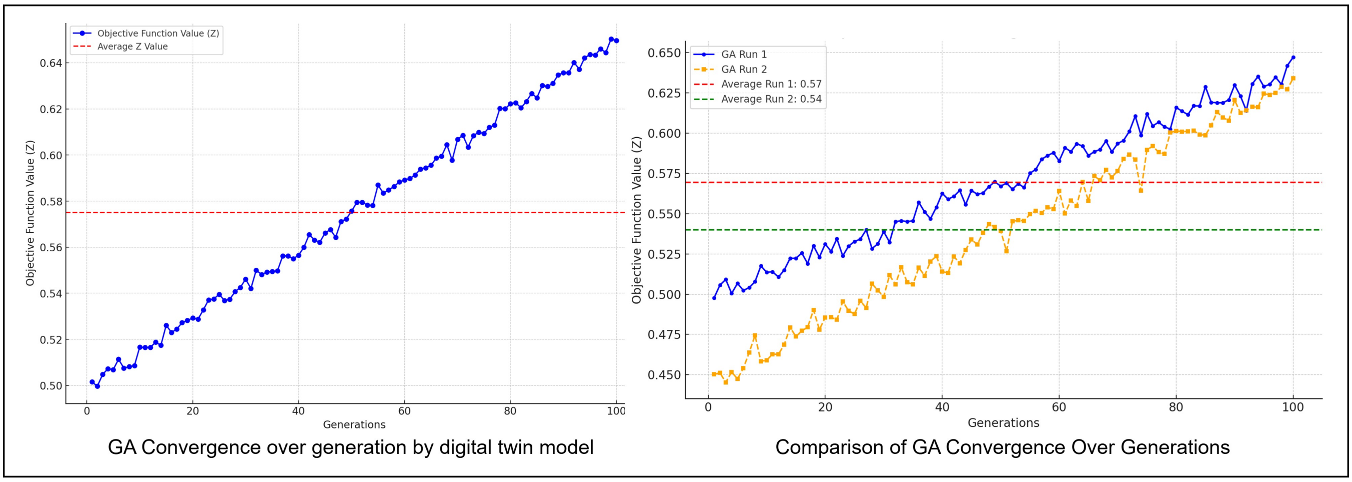

Figure 5. Comparative Analysis of GA Convergence for Digital Twin Model in Supply Chain 5.0

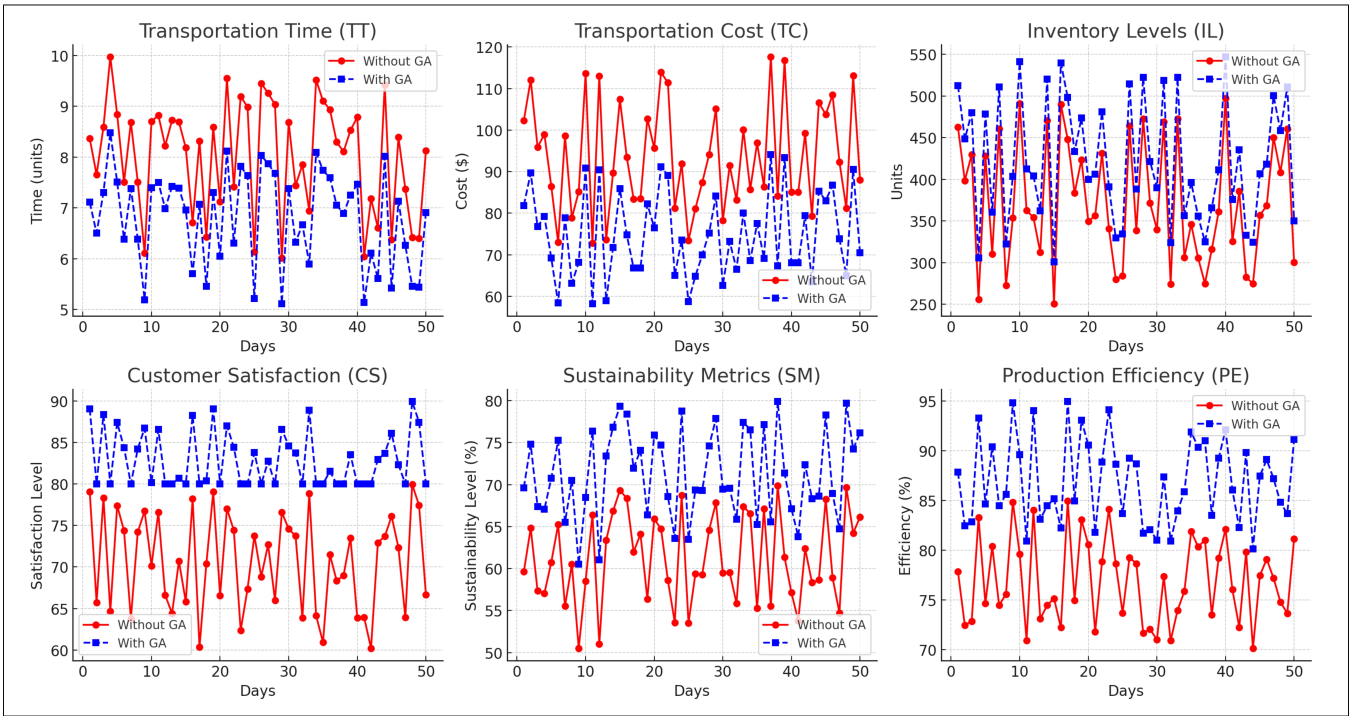

Figure 6. Supply chain performance analysis.

integrated with a GA optimization framework. This advanced model leverages real-time data, simulation, and decision-making capabilities to optimize key supply chain parameters and ensure resilience during disruptions. By continuously analyzing and refining performance, the digital twin demonstrates significant improvements across various metrics. The model effectively minimizes Transportation Time by dynamically optimizing routes and schedules, reducing delays and ensuring stable delivery times. Similarly, it reduces Transportation Costs by implementing efficient logistics strategies, such as shipment consolidation and optimal mode selection. For Inventory Levels, the model prevents stockouts and overstocking by dynamically aligning stock with demand, maintaining balance and minimizing holding costs. The digital twin also enhances Production Efficiency by optimizing resource utilization and production schedules, ensuring consistent and high operational performance. Moreover, it improves Sustainability Metrics by reducing carbon emissions and energy consumption through greener and more efficient operations. Finally, the model significantly boosts Customer Satisfaction by delivering orders on time, meeting demand effectively, and maintaining reliable service levels. The integration of the genetic algorithm enables the digital twin to evaluate a wide range of scenarios and select the most beneficial solution at each step, ensuring globally optimal outcomes over time. The feedback loop between the digital twin and the physical supply chain facilitates real-time adjustments, further enhancing performance. In summary, the developed digital twin model, powered by GA, dynamically optimizes supply chain performance by addressing key parameters such as transportation, inventory, production, sustainability, and customer satisfaction. The diagram highlights its effectiveness in achieving a robust, efficient, and adaptive Supply Chain 5.0 environment.The proposed model addresses gaps in existing supply chain optimization frameworks. Traditional optimization frameworks often rely on static models that do not update dynamically. The GA-based digital twin model overcomes this by continuously adjusting in real-time based on evolving data, making it more resilient to disruptions and uncertainties. Conventional models tend to focus on isolated objectives such as cost minimization or efficiency. This model integrates multiple aims cost, efficiency, resilience, and sustainability into a single optimization framework, allowing for a more integrated approach. Many existing frameworks lack intuitive decision-support tools. By integrating GA with a cloud-oriented digital twin, this model provides managers with real-time visualized insights, allowing them to make informed, initiative-taking decisions rather than reactive ones. Expanded the discussion on how the proposed model addresses gaps in existing supply chain optimization frameworks by emphasizing real-time adaptability, multi-criteria optimization, enhanced decision support, integration with complex supply chains, and improved resilience.

The implementation potential of the proposed Integrated Cloud-Twin Synchronization (ICTS) framework is significant, as it aligns with the evolving needs of Supply Chain 5.0 by enabling real-time optimization, adaptability, and sustainability. However, for companies to successfully adopt this model in real-world supply chain environments, they must overcome key technical barriers, including interoperability, security, and data privacy concerns. To ensure seamless integration, businesses should adopt standardized communication protocols such as OPC UA, MQTT, and RESTful APIs, allowing for efficient data exchange across heterogeneous systems, IoT devices, and cloud-based platforms. Addressing security and data privacy challenges is critical, as supply chain operations involve sensitive trade data and real-time transactional information. Organizations can enhance security by implementing multi-layered encryption, blockchain-based authentication, and zero-trust architectures, ensuring data integrity, confidentiality, and compliance with global security regulations. Additionally, the scalability of digital twin adoption depends on the efficient management of real-time data streams, which can be optimized using edge computing and hybrid cloud architectures, reducing latency and computational overhead while maintaining high-speed analytics capabilities. For successful adoption, companies must also invest in workforce training programs to enhance AI-driven decision-making skills, ensuring that supply chain professionals can interpret real-time insights and optimize operations dynamically. By following a structured implementation roadmap, businesses can leverage the ICTS framework to improve operational efficiency, enhance resilience, and drive sustainable supply chain innovation, making their supply networks more agile, intelligent, and future-ready.

The Integrated Cloud-Twin Synchronization (ICTS) framework presented in this manuscript is well-aligned with the evolution of Supply Chain 5.0 and Industry 5.0, emphasizing digital twin technology as a key enabler for enhancing supply chain performance in real-time, adaptive, and sustainable ecosystems. While Industry 4.0 primarily focused on automation, IoT, and cyber-physical systems, Supply Chain 5.0 extends beyond these principles by integrating human-centric decision-making, sustainability, and real-time AI-driven optimization. The proposed framework directly addresses these unique challenges, differentiating it from traditional Industry 4.0 approaches and demonstrating new capabilities for supply chain adaptability, resilience, and efficiency. One of the key distinctions of Supply Chain 5.0 is its focus on real-time digital twin synchronization within a cloud computing environment, allowing for continuous monitoring, intelligent automation, and proactive decision-making. Unlike conventional Industry 4.0 models, which rely on predefined rule-based optimizations, our framework introduces a dynamic Genetic Algorithm (GA) driven optimization approach that iteratively refines supply chain parameters, ensuring continuous adaptation to operational changes. This advancement is crucial for enhancing decision agility, reducing inefficiencies, and perfecting multi-objective trade-offs in modern supply chains.

Furthermore, the ICTS framework integrates sustainability-driven metrics, a core principle of Industry 5.0, by optimizing carbon footprint reductions, renewable energy utilization, and energy-efficient logistics. This ensures that Supply Chain 5.0 not only enhances operational efficiency but also aligns with global sustainability goals. As highlighted in recent research, digital twin technology is revolutionizing industry-specific applications, such as the pharmaceutical cold chain, where high precision, real-time monitoring, and sustainability compliance are critical factors. Our study extends these principles to broader supply chain networks, demonstrating how cloud-integrated digital twins can create intelligent, resilient, and future-ready supply chain ecosystems. The research methodology ensures a comprehensive evaluation of the ICTS framework, utilizing real-world-inspired datasets from Kaggle, a MATLAB-coded optimization environment, and an extended dataset of 500 samples to confirm the model's scalability and adaptability. The conclusion further emphasizes the model's ability to dynamically perfect key supply chain performance indicators, reinforcing the transformation Supply Chain 5.0 brings beyond Industry 4.0 principles. Future research will focus on industry-level implementations to confirm the practical scalability and impact of this framework.

7. Conclusion

This section includes the results of the research project that concentrated on the concept of creating a cloud-oriented digital twin model for the supply chain 5.0. These empirical results underscore the model's ability to improve performance and resilience in supply chains. As indicated by the variation in the terms of the loss derived from minimization () and the stabilization for those derived from maximization (), the digital twin model is adaptive and responsive to real-time data. Figure 3 demonstrates graphic representation provides greater insight to understand the complexity of supply chain performance. The developed digital twin model for Supply Chain 5.0 generates real-time dynamic charts that demonstrate the optimization of weights over a 50-day experience where model adaptability dominates with a scale-down peak that emphasizes the model's focus on operational excellence. Here is a brief explanation of the goals these charts show. These weights are adjusted in response to new information, embodying the real-time adaptive nature of the digital twin model which allows us to balance operational efficiency within the framework of sustainability objectives. This adaptability enables supply chain managers to make proactive decisions to optimize performance metrics in real-time as conditions change. The charts give insights into what the digital twin model can optimize. In improving customer satisfaction, production performance, resilience, sustainability, and reducing costs and inefficiencies, the model covers the key pillars of Supply Chain 5.0. The model can be integrated into complex applications, and this visualization illustrates the model's potential for achieving operational excellence alongside your existing complex supply chain ecosystem.

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