Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 47 No. 02 (2026)

Supply Chain Optimization with Integrated Twin Learning Systems Empowering Sustainability

S Ramana Reddy[1], Ashwin Jashitha[2]

[1] Associate Professor, Vignan Institute of Technology and Science, Deshmukhi, Telangana, India

[2] Student of PG, Department of AI & DS, Vignan Institute of Technology and Science, Deshmukhi, Telangana, India

Abstract:- In The modern supply chain management systems are highly associated with IoT and AI environments. Traditional analytical systems to be revitalized with optimized strategies to support efficient decision making systems. The proposed framework model is an Integrated Twin Learning System with adaptive sustainability addressing. Twin Learning Systems configured with high adaptive decision making with feedback assisted self learners. Making traditional supply chains to proactive respondents to demand and supply risks with environmental monitor ability. Well focused over process optimization, service collaboration efficiency, cost effectiveness and sustainability objectives. Our model enhances supply chain resilience in various real time environments.

Keywords: Supply Chain Management, Digital twin Systems, IoT, Machine Learning. Sustainability.

1. Introduction

In Human Centric Digital Twins (HCDTs) is a transformative approach which integrates real-time data, human interfacing and advanced analytics for optimized supply chain management services [1]. The new Supply Chain 5.0 introduced intelligent, human centric, IoT supportive, Modern industry standards and cloud-twin systems enhancing supply chain management towards adaptive eco systems [2]. The practice of intelligent systems and sustainable approaches collaboration in supply chain management system is in demand [3]. The environmental friendly supply chain management frameworks are developed with ML and Cloud service integration enabling scalable, secure, intelligent and eco friendly nature [5]. Green marketing is another dimension strategic approach enhancing sustainability supported e-business marketing and supply chain management with ecological harmonic impact [6]. Cyber security protecting sensitive financial transactions during supply chain management focusing over trading platform security against threats, risks and data protection strategies [7]. Digital twin systems with Reinforced Learning is an another research direction to improve supply chain and logistic operations [8]. The application of Neural Networks insights new knowledge patterns in supply chain data [9]. RFID technology is implemented in some major industries during product delivery to forecast the demand and supply chain [4]. Some machine Learning algorithms linear regression, random forest, Long Term Shortest Memory and K-means are useful to optimize the inventory management and logistics over e-commerce SCM [11]. Three main tasks we need to focus during SCM model construction are Design, planning and execution of SCM pipelines [10][12].

2. IDTL Systems

A recent advancement in learning systems which continuously optimizes the physical system in real time with continuous training data using Machine Learning and Big data analytics. A Twin learning system in machine learning generally a fusion of two models works in synchronization with self constrained to improve each other. These models are multi standardized to analyze several concepts of domain in several perspectives.

Table 1: Twin Learning System Variants

Feature	Description
Siamese Networks	Two identical networks with shared weights. Co-training Two models trained on different views over same training data.
Digital Twins	More applicable in industries as cyber physical systems with twin learning.
Twin Support Vector Machine (TWSVM)	Standard TWVSM learn with two non parallel hyper planes, faster than SVM
Least Squares TWSVM	Replace the inequality constraints with equality constraints very faster training
Kernel TWVSM	Uses Radial kernel basis functions for non linear separation
Fuzzy TWVSM	Assigns membership among learning model concepts. Reduces effect of noise and outliers.
Weighted TWSVM	Enumerates error rates for different classes. Applied effectively for imbalanced datasets.
Multi-class TWSVM	A one-one and one-all hyper plane relationships more complex direct multi-class formulations made possible.

Table 1 illustrates various types of twin learner systems available to support real time applications. The selection of the learner system purely depends on the environment where the system is working under sustainability constraints.

3. Proposed System

In the proposed twin learning system we mainly focused to overcome real-time supply chain management challenges.

A. External Environment Phase

A collection of Market demand dynamics. The environmental effects influence the supply chain management. Twin learning system allows to improve decision support system by applying Block chain enables transaction security over decentralized servers. Machine Learning enables knowledge pattern extraction and decision support strategies to empower environment phase to overcome the challenges of SCM in modern environments with sustainability practices.

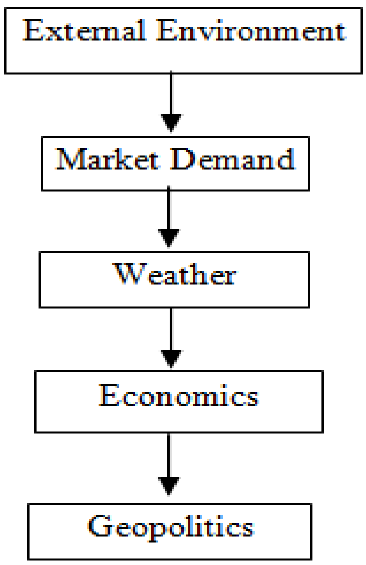

Figure 1: External Environment modules

B. Data Acquition Phase

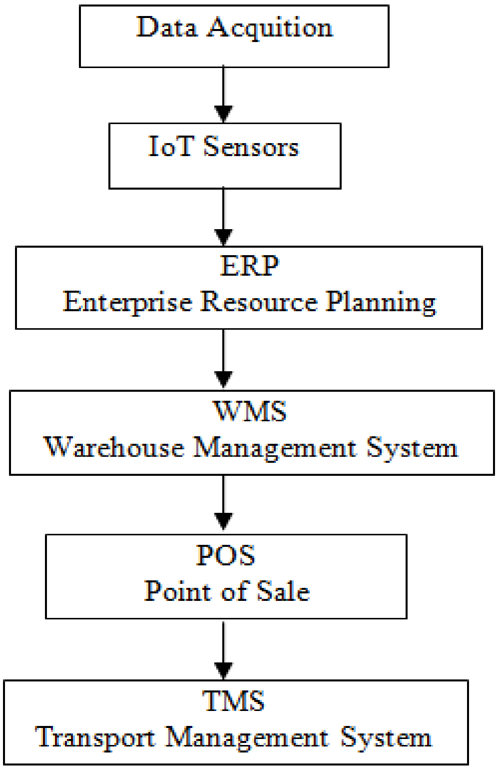

Figure 2: Data acquition phase modules

Data acquition phase applies twin learner systems to monitor and manage effectively data transmission among IoT devices to cloud systems. Various format encoders with data refinement schemes available in ML are applied in necessary acquition channels. The Enterprise Resource Planning based quality measures enforced during knowledge extraction and transformation. The warehouse architectures are completely scalable among dynamic environments in cost efficiency perspective. Various AI techniques are applicable for improved decision making system with great precision. The point of sales are vital for supply chain management as customers are directly involved through purchase portals. Major transaction governance is carried here with twin learner systems intelligent agents are more improved to understand customer behavior and trend analysis.

The machine learning extracts knowledge insights from transport logistics scenarios. The management of integrated IoT environments in TMS becomes more flexible and economic with twin learner systems adopted with deep learning and reinforcement learner activities. Twin learner systems gradually improve the analytic strengths with mutual coordinative assessments.

C. Data Management Phase

Twin learning based data management phase is a 360° efficient data storage and access phase. Supported with data cleaning techniques available in ML. The data integration among OLAP (*Online Analytical Processing*), OLTP (*Online Transaction Processing*) and Data Cubes optimizes the data access. The twin learner performs feature engineering over training data to identify new features useful for future classification. AI twin learner on the other hand establishes a granulated storage platform with dynamically configurable and scalable using AI agents. Intelligent Storage adaptively identifies optimal storage structures suitable to environment. FTSSD (Fault Tolerant Solid State Drive) is a collection of fault tolerant schemes and metrics to improve storage robustness. MLDSM (Machine Learning Driven Storage Manager) are more effective storage management systems supported with learner systems using neural networks to generate new knowledge patterns for optimizing storage management services dynamically in real-time environments.

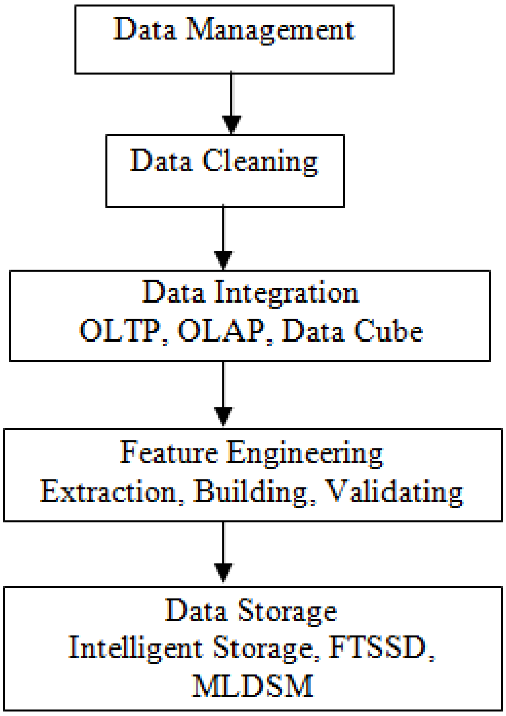

Figure 3: Data management modules

D. Physical Twin System

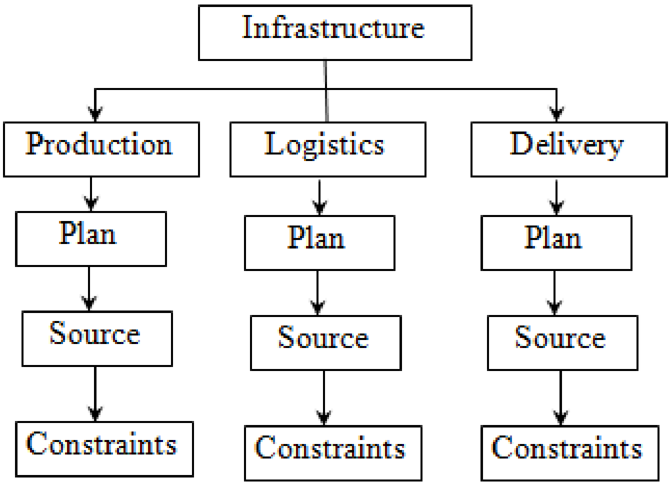

Figure 4: Physical Twin System

Physical infrastructure such as warehouses, manufacturing units and supply logistics are managed by this module. Planning strategies to efficient resource management and energy grid sustainability with real time constraint satisfaction is key goal to this module. It creates building blocks for effective deliver chains.

E. Proposed SCM Digital Twin Learn System

The integration of digital twin learner systems into SCM remarkably optimized the service architectures with more energy efficient and sustainability maintenance.

Physical Supply Chain Layer:

This layer is foundation for communication infrastructure associated with Cloud Services. *Supplier IaaS* provide infrastructure supportive to customized supply services. *Retailer IaaS* provide infrastructure to support retailer services from cloud. *Warehouse IoT* is a module interlaces IoT devices with data warehouses as bridge drivers. *IoT & Networking Service Stack* is a service stack integrated with collective network protocols and services to establish high efficient communication under privacy governance among IoT devices and networks (LANs, WANs). *Manufacturer IaaS* collection of essential manufacture driver services infrastructure provided by cloud. *Customer AaaS* is a cloud anything as a service dynamically scaled with services suitable to current environment. The distributors play a crucial role in SCM where *Distributor IaaS* provides a platform supporting all necessary distribution service modules with management tools. *Edge Computing* provides facility to track metrics on site of manufacturing units and transport zones with IoT devices coordinated with digital twin learners.

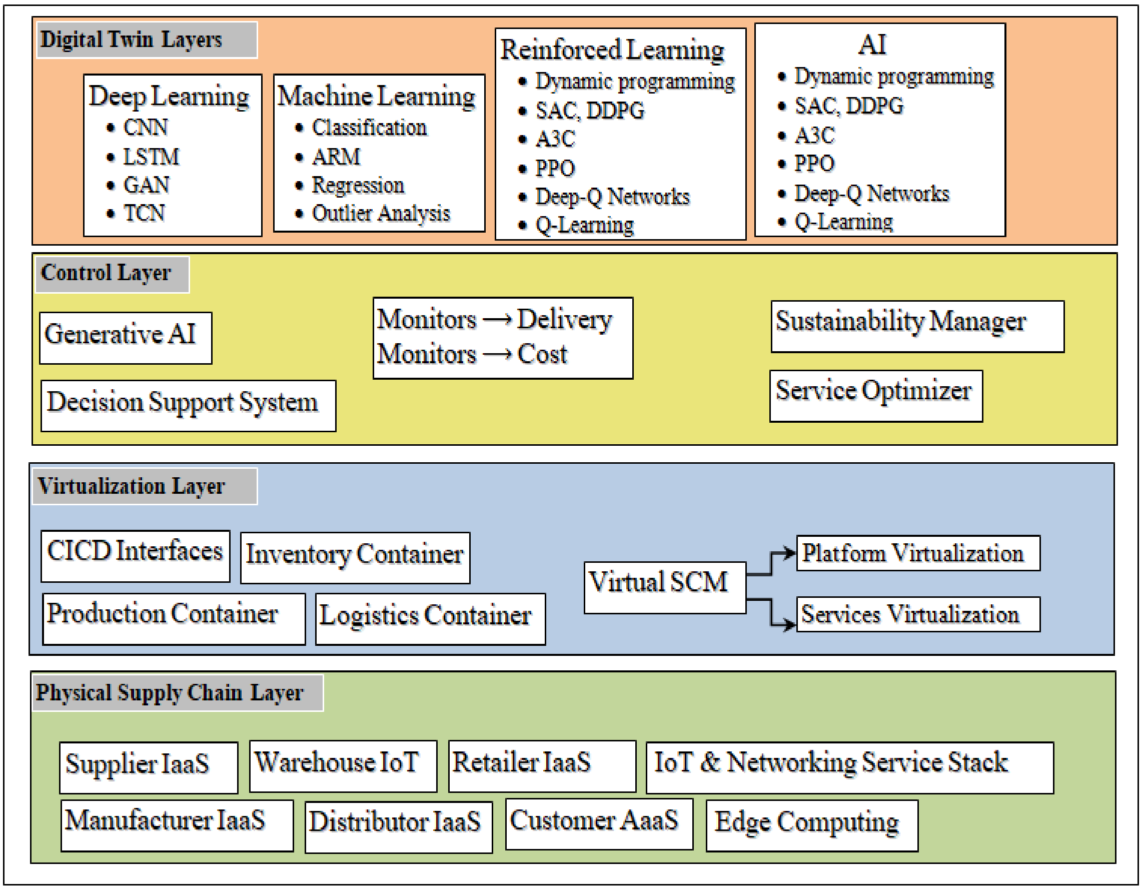

Figure 5: SCM Digital Twin Learner System

Virtualization Layer:

The modern CICD pipeline encourages agile SCM computation. This layer constructs the virtualization containers focusing over dynamic platform virtualization and service virtualizations. This enables greater connectivity and computations with light weight containerization model. Integrate various manufacturing units under as collaborative teams. The version control keeps tracks of updates and service optimization. Major modules in CICD umbrella are production container, inventory container, logistic container and virtual SCM.

Control Layer:

The layer comprises with constraint enforcement and policy enforcement over SCM. The regulation and quality assurance is key focus. *Monitors* are special trackers of delivery and cost services for anomalies. *Sustainability manager* enforces policies to support eco friendly transactions towards sustainability goals. *Service Optimizer* enables various tuning facilities to optimize SCM pipeline entities.

F. Digital twin SCM Vs Traditional SCMs

The below table gives a comparative analysis over Digital Twin, ML based and traditional SCM systems.

Table 1: 6G Network Features

Feature	Digital Twin	ML SCM	SCM
Data processing	Real-time AI driven	Real-time	Batch Manual
Decision Making	Predictive Perspective	Reactive	Manual
Predictive Analytics	Optimal	Better	Low
Simulation	High flexible	Medium, Static	No simulations
Resilience	Adaptive to disruptions	Adaptive to specific scenario	Rigid
Cost efficiency	High	Average	Low

4. Result Analysis

A. Accuracy Analysis

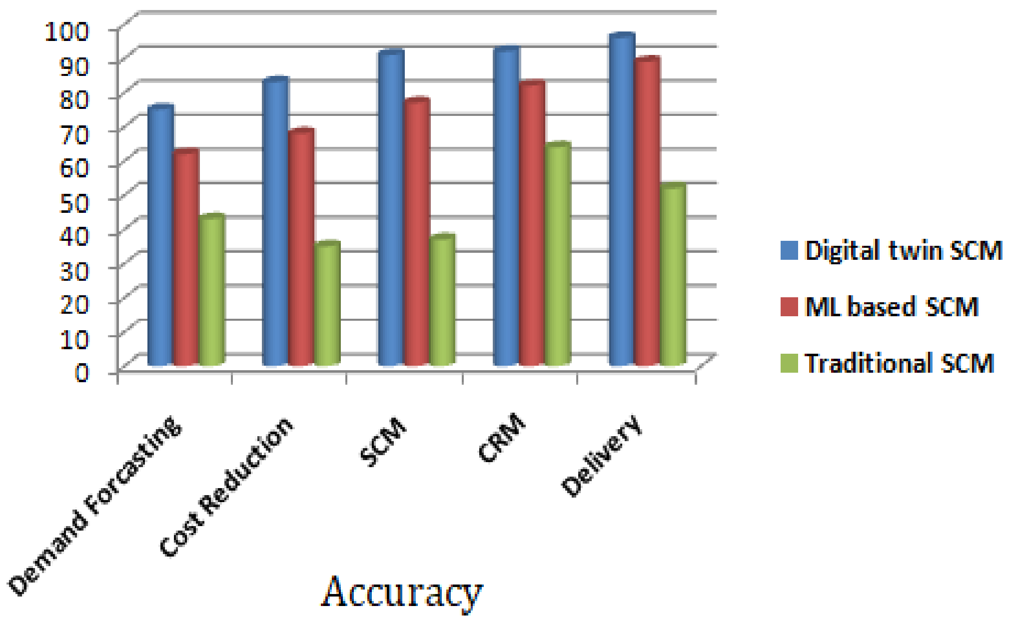

Figure 6: Accuracy rate among SCM systems

From the above graph it is clear that based on supply chain quality metrics such as demand forecasting, cost reduction, SCM, CRM and delivery chain management Digital twin learner system shown major improvement over ML based SCM and traditional SCMs. The accuracy levels reached almost 98% in DTL based SCM.

B. Data Efficiency Analysis

The data acquition rate and processing rate among various SCM models are compared with DTL based SCM. Figure 7 shows the data efficiency of DTL SCM among other SCMs. Twin learner based SCMs are also capable to handle large volumes of data with low latency in transmissions.

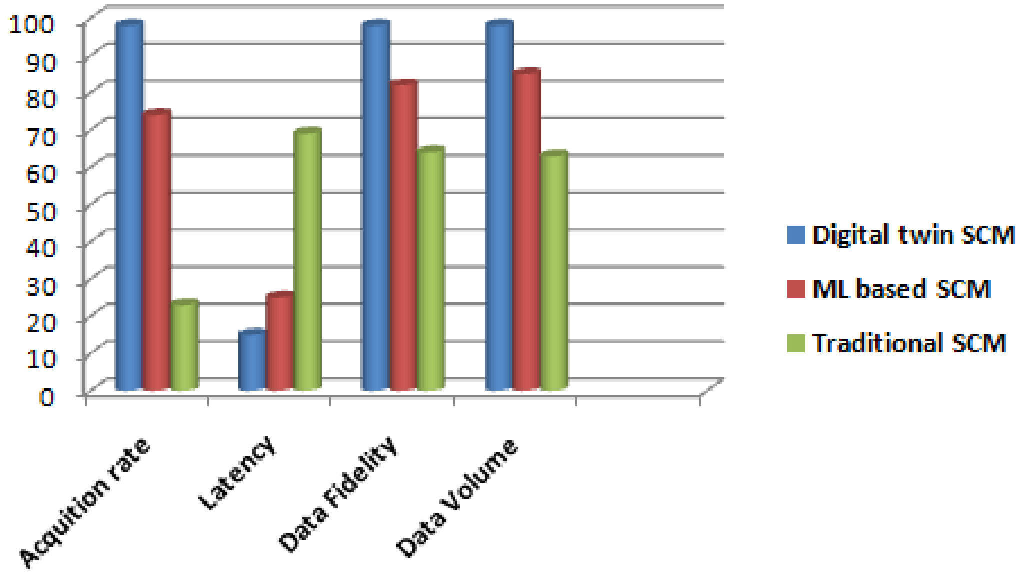

Figure 7: Data efficiency Analysis over SCMs

C. ROC Analysis

The ROC (receiver Operating Characteristics) curve is useful to study the performance of various systems under given conditions. Widely used to identify the classifier accuracy differences. Here we applied over various SCM systems under specific operating characteristics. Figure 8 shows that DTL based SCM showing good performance under given operational conditions among other SCM variations.

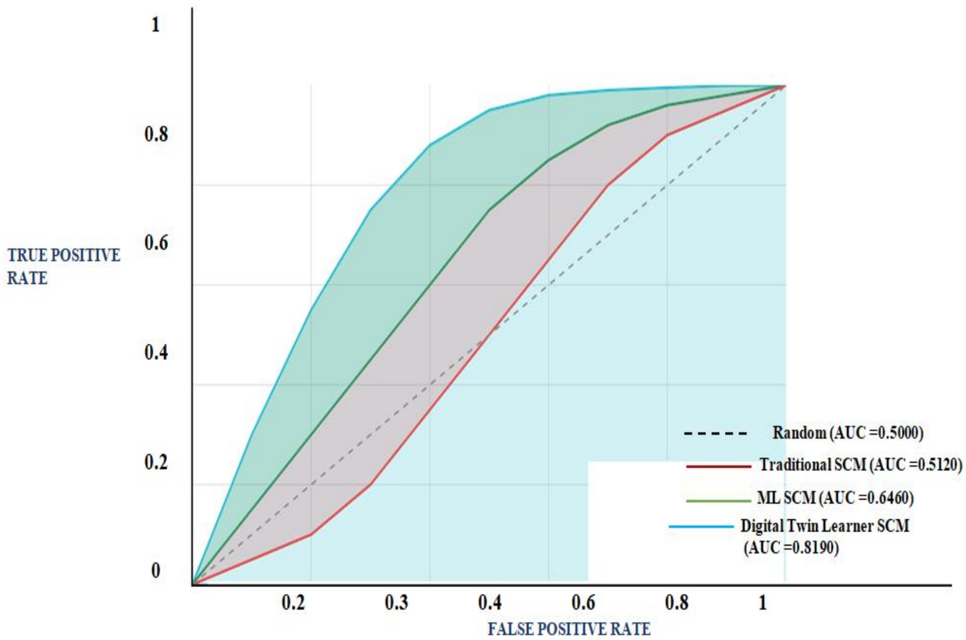

Figure 8: ROC Performance over SCMs

D. Risk Factor Analysis

Risk Mitigation and management is an important activity in SCM. Figure 9 provides a clear understanding about the efficiency of Digital twin Learning SCM over other variants of SCM with low risk rate in vital modules of SCM like Sourcing, manufacturing, distribution networks and delivery chains. With assistance of AI integrated learners capable to identify risks at early stage and even implement strategies with risk avoidance nature.

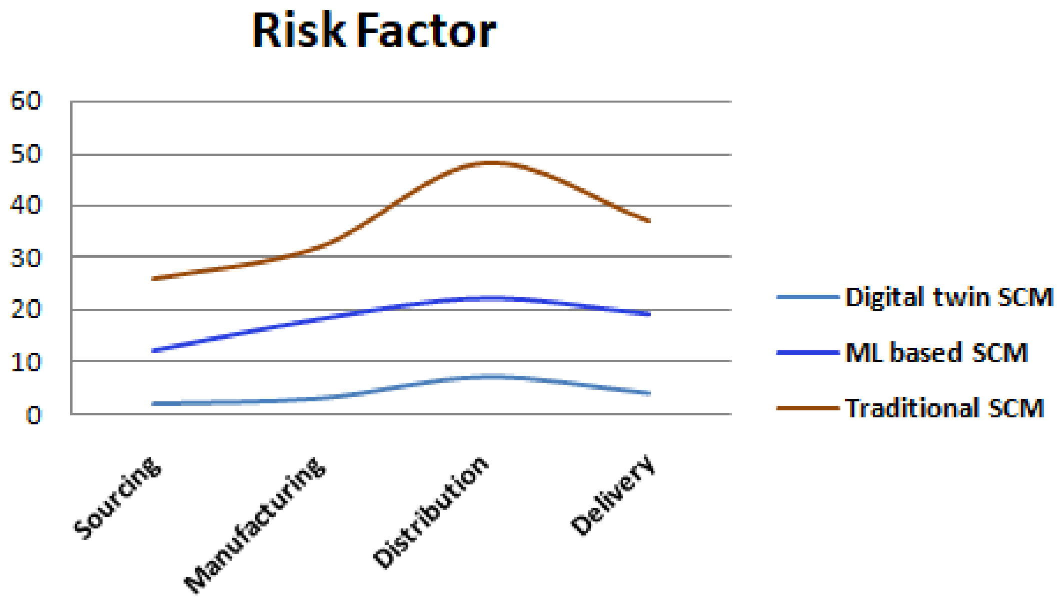

Figure 9: Network Latency Analytics

In overall analysis Digital twin learner supported SCM exhibited high performance in data acquition and processing. It can handle large volumes of data effectively. DTL based SCM supports large quantity of IoT devices across the environment with very low risk rate. Comparatively it is proved that almost 98.4% accuracy given by twin learner based SCM over ML based SCM and traditional SCM.

5. Conclusion

Proposed twin learning based SCM enhances the quality and accuracy of all modules in SCM. The ability to fuse two different learner systems gives more dimensional study on environment. Digital twin learner systems are most collaborative and improve their model accuracy with mutual data exchanges. These models are very flexible and can be suited to any environment for maintaining good accuracy in services. In majority of SCM modules twin learner systems improved quality of data. This model also allows for the handling of sparse data. AI integration supports enhanced decision making with high precision. Always these twin learner models are scalable and extendible with modern techniques in knowledge engineering. DTL SCM are suitable for modern real-time business environments very well.

References

[1] Thomas O. Okimi, "Human centric digital twins for sustainable supply chain in construction", Journal of Smart Construction and Sustainable Cities, Springer-Nature, DOI: 10.1007/s44268-025-00078-2,Vol.3, Issue-31, 2025.

[2] Daqiang Guo, "The role of digital twins in learn supply chain management: review and research directions", International Journal of Production Research, ISSN: 0020-7543, Vol.63, Issue-5, Taylor and Francis, 2025.

[3] Divya SasiLatha, T Mokkhamakkul, "Integrated Cloud-Twin Synchronization for Supply Chain 5.0", EAIETINIS Journal, ISSN: 2410-0218, Vol.12, Issue-2, 2025.

[4] Bh.V.RamaKrishna, S. Kavipriya, K. Suresh Kumar, "The Impact Of Cloud Computing On Machine Learning Applications For Environmental Startups ", International Journal of Environmental Sciences, ISSN: 2229-7359, Vol.11, Issue No, 18, pp. 1378-1385, 2025.

[5] B. Ranjan Mishra, P Kaur Keer, Bh.V.RamaKrishna, "The Role of Green marketing in Minimizing Environmental Impact of Small E-Business", International Journal of Environmental Sciences, ISSSN: 2229 - 7359, Vol.11, Issue-18, 2025.

[6] Lawal G. Anand, "Using Machine Learning in SAP IBP for Supply Chain Optimization", SAP IBP, DOI: 10.2139/ssrn.5240827, 2025.

[7] B.V.RamaKrishna, Md. Khayum, B. Akash Reddy, "Blockchain Based Agriculture Marketing Framework", IJAEMA, ISSN: 0886 - 9367, Vol.17, Issue-6, 2025.

[8] Harish Venkatsubramanian, Mansurali Anifa, "Optimizing Supply Chain Operations with Machine Learning: A Path to Efficient Business Decision Making", ICMMI-Conference, DOI: 10.1145/3647444. 3647845, ISBN: 979-8-4007- 0941-8, 2024.

[9] B Anjanidevi, T Sujith, V Nagesh, "Smart Supply Chain Management Using Machine Learning Algorithms", Journal of Electrical Systems, DOI:10.52783/jes.4231, Vol.20, Issue-3, 2024.

[10] MVSV Kiranmai, J P Ramirez, "The Impact of Machine Learning (ML) Optimization of supply chain management domain", IEEE Explore, ISBN: 979-8-3503-9927-1, ICACITE-Conference, 2023.

[11] Ahmed Zainul Abideen, V.Pandyan Sundaran, Jaafar Pyeman, "Digital Twin integrated Reinforced Learning in Supply Chain and Logistics", Logistics Journal, NDPI, DOI: 10.3390/logistics5040084, ISSN: 2305-6290, Vol.5, Issue-4, 2021.

[12] Dr B.V.RamaKrishna, V. Jayamanasa, Ch Srinivas, "Cyber Security Approach for Secured Online Trading", JICR, ISSN: 0022 - 1945, Vol. 14, Issue -11, 2022.