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Big Data and ML Applications for Supply Chain Control Tower & Digital Twin

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Abstract- In today's fast-changing world of business, supply chains are becoming more complicated because of unpredictable customer needs, many layers of suppliers, and more uncertainty in how things are run. Using Big Data analytics and Machine Learning in supply chain management changes how things work by improving visibility, giving better predictions, and helping make smarter decisions. This study looks at how Big Data and Machine Learning are used in Supply Chain Control Towers and Digital Twin systems. These tools cover the entire supply chain process and assist in real-time supply chain monitoring, scenario testing, and risk management. ERP systems, IoT devices, and logistics platforms are just a few examples of the types of sources that control towers use to gather data. They also use machine learning to predict demand, spot unusual activity, and improve how inventory and transportation work. Digital twins work with these tools by making virtual copies of parts of the supply chain, which lets you test how disruptions might affect things and check different ways to fix problems. A single approach that combines Big Data systems, machine learning predictions, and digital twin technology is introduced and shown through a real-world example in a global manufacturing and shipping network. The results show better operational transparency, more accurate predictions, stronger resilience, and quicker responsiveness. The study offers a real-world guide for companies that want to use AI-powered control towers and digital twins to make their supply chains more efficient, strong, and able to change as needed.

Index Terms- Supply Chain Control Tower, Digital Twin, Big Data Analytics, Machine Learning, Predictive Analytics, Supply Chain Resilience

I. INTRODUCTION

In the current dynamic environment characterized by an increase in uncertainty and an increasing level of complexity resulting from several factors in practice, the main concern for businesses remains the need to address environmental fluctuations with an increasing sense of urgency. There exists a continued need to address concerns regarding matters of cost in the achievement of an increase in quality within the area of service delivery. Traditional concepts in the management of the Supply Chain seem to address issues to an increasing level, to a lesser extent. In the current Supply Chain management practices, characterized by the adoption of technological means through the use of Big Data Analytics in the management of the Supply Chain through Machine Learning to address decision-making in the Supply Chain management arena.

A great challenge identified within the scope of the current Supply Chain management strategies is the need to ensure the achievement of the end-to-end supply chain vision within the different tiers of suppliers, production sites, distribution hubs, and transport infrastructure. In view of the current gaps in the supply chain within the relevant scope, there is a negative impact on swift strategies of decision-making as well as the challenges pertaining to the inefficiencies with regard to the scope of Supply Chain management strategies. In such a case, for instance, if there is a need to increase the supplier pattern within the scope of the Supply Chain management strategies or an increase in the challenges pertaining to the transport infrastructure characterized by the need for an increase in the capacity within the scope of Supply Chain management strategies, organizations are beginning to leverage the idea of Supply Chain Control Towers as the entities utilized with the aim of monitoring and increasing the efficiency of Supply Chain management strategies. Regarding such an idea, Supply Chain Control Towers are characterized by the utilization of effective data gathering strategies with the ablity to leverage the utilization of information technologies. (Supply Chain Control Towers: Defined and Explained, 2026) Apart from this, there exists the added advantage of the improved understanding provided through control towers.

However, the effectiveness is still conditional on the extent to which the large amounts of heterogeneous information can still be processed and evaluated appropriately. It is from this context that the prominence of Big Data also becomes highly unbearable to consider while integrating these tools, since the integration provides the capabilities to undertake analyses on both structured and unstructured information in real-time. (Wasi et al., 2025) From this context, the question that thus emerges is whether information is useful and available on its own while ensuring predictive and prescriptive tools become an inevitability if information is to translate to anything more than merely information towards ensuring some form of knowledge is developed to inform the various decision-making processes tied to the existing supply chains that characterise the operations and functionalities of different entities in business today have been addressed through the presence and utility of various tools and applications tied to Machine Learning since these have the capabilities to ensure addressing nonlinear functionalities linked to different existing and considered supply chains that define various functionalities in different entities. One other emerging solution would be the adoption of Digital Twin technology to "create a virtual representation of physical entities in the supply network," whereby an organization would be able to "simulate various kinds of situations in an operation to test alterations in the processes or determine the outcome of risks before the situation actually happens." (Digital Twin: Theory and Concepts, 2023) This would, in essence, allow an organization to link the control towers to the digital twins to transform a reactive supply chain into a proactive supply chain by making the supply chain more adaptable to environmental situations. (Jefferson & Musa, n.d.) Nonetheless, there exist different challenges regarding their efficient/_effective_ implementations too; for example, the integration of heterogeneous data sources and high-level analytics/organizational goals/operations seamlessly is the major challenge to their efficient implementations. (Wasi et al., 2025) Besides that, the main challenge relates to the high performance of the ML model resulting from different factors such as the quality of the data and the need for model retraining in dynamic circumstances/changing scenarios/conditions too. (Peixoto et al., 2025) In fact, highly promising tools such as twins provide challenges regarding their efficient implementations in different sectors of industries for the exact and precise simulations of real-world systems/entities that require huge investments in their construction/description/formatting/data developing/validating on their own behalf too. (Sharma et al., 2020) With this current study, these challenges will be met through an integrated framework considering aspects concerning the integration of Big Data analytics, ML techniques, and DT models with regard to a control tower concept. With this concern, it is worth noting that implementing this concept of an intelligent control tower and DT will fulfill this researcher's practical aspects with regard to meeting its challenges with regard to managing and satisfying supply chain complexities of a multinational firm dealing with manufacturing and distribution activities. Moreover, it is worth establishing this present study's usefulness with regard to addressing aspects concerning individuals who are interested in exploring these concepts with regard to addressing operational and strategic aspects concerning these technologies with regard to supply chain improvements in an evolving competitive environment. Thus, with these arguments and notions, this author opines that, in conclusion, this synergy that is created through Big Data, ML, and DT technologies has resulted in many changes pertaining to the way that organizations manage their respective SCs. This is because these new tools have emerged to have such capabilities to improve visibility, resiliency, and response time. (Supply Chain 4.0 and the Digital Twin Approach: A Framework for Improving Supply Chain Visibility, 2024, pp. 321-326) Finally, this research aims to explore how to implement these new trends through control towers.

II. BACKGROUND AND LITERATURE REVIEW

2.1 Evolution of Supply Chain Control Towers

The idea of the Supply Chain Control Tower has become a key advancement in today's logistics and operations management. It was difficult to see everything clearly and respond quickly when supply chains used separate information systems and manual reports. These problems are solved by control towers, which act as central hubs for bringing together data from a variety of operational sources, enabling real-time tracking, alerts, and decision-making. They help companies spot unusual activities, evaluate potential dangers, and take steps to fix problems before they get worse. According to Ivanov et al. In 2020, control towers are becoming more common for managing global supply chains that involve many suppliers, production locations, and distribution systems. This shows how they help improve coordination, transparency, and how efficiently operations run.

2.2 Big Data Analytics in Supply Chains

Big Data analytics has become a powerful tool for managing and controlling supply chain operations. Supply chains create a lot of data, both organized and not organized, from places like ERP systems, warehouse management systems, IoT sensors, transportation management platforms, and outside market information. Using this data and studying it helps companies find hidden patterns, connections, and unusual things that can guide their day-to-day decisions. According to Wamba et al. In 2017, big data analytics helps with predicting demand, managing inventory better, and assessing risks with suppliers by giving useful information almost instantly. Advanced analytics methods like data mining, predictive modeling, and visualization help companies move from reacting to supply chain issues to anticipating them. This strategy reduces disruptions and improves service quality.

2.3 Supply Chain Machine Learning Applications

In supply chain management, strong prediction and recommendation tools are provided by machine learning (ML). Supervised learning models, like regression and classification algorithms, are often used for predicting demand, assessing suppliers, and planning maintenance ahead of time. Unsupervised learning methods like clustering and anomaly detection find patterns, unusual data points, and possible issues in operational data. Reinforcement learning has also been used to improve inventory and transportation plans by mimicking how decisions are made in changing environments. Research by Choi et al. In 2018, it was shown that machine learning models can do better than traditional statistical methods when it comes to predicting outcomes and making operations more efficient. Putting machine learning into control towers helps them keep learning and changing, which makes supply chains stronger and better able to handle changing market situations.

2.4 Digital Twin Technology

Digital twins are a virtual copy of real-world systems, processes, or things, allowing for a live simulation that helps in analyzing and improving how they work. In supply chain management, digital twins can copy production plants, storage areas, shipping routes, and whole supply chain systems. This technology lets companies test different situations, figure out how problems might affect things, and check ways to handle those issues without messing up actual work. According to Tao et al. In 2019, combining digital twins with control towers allowed for making decisions based on different scenarios, improving operations, and assessing risks. This approach gave useful information that helped with both long-term planning and daily activities. Digital twins help with predicting future events by using real-time data, allowing companies to foresee changes in customer demand, possible production delays, or issues with transportation.

2.5 Integration of Big Data, ML, and Digital Twins

The combination of Big Data, machine learning, and digital twin technology creates the base for smart supply chain control towers. Big Data pipelines collect and handle different types of data, ML algorithms create predictions and suggestions, and digital twins show how operations might work to check what could happen with different choices. This integration allows companies to take a forward-thinking and flexible approach to managing their supply chain, helping them handle unexpected changes better. Research done by Ivanov and Dolgui in 2020 shows that using these combined systems makes supply chains stronger, lowers costs, and boosts service quality. This is because they offer a clear picture of what's happening now in the supply chain and what could happen next.

2.6 Challenges and Research Gaps

Even though these technologies have shown tremendous promise, there are certain challenges that need to be overcome, like data integrity, where these technologies can pose a big problem if the quality of data is poor, leading to a decrease in the efficiency level of predictions by ML-based models. Additionally, if model complexity is high, then models are still a major problem, especially for organizations that need transparency-based models to take decisions. Lastly, digital twin implementation also demands significant model development, data acquisition, and validation efforts. As much research is being done on individual technologies like Big Data, ML models, digital twin-based models, no research study is available on the integration aspect, especially in control towers for overall optimization of the supply chain. This research, therefore, aims to address that.

III. METHODOLOGY

3.1 Research Framework Overview

This study uses a clear and organized approach to examine how Big Data analytics, Machine Learning, and Digital Twin technologies can be combined in Supply Chain Control Towers. The main goal is to create a system that can predict and adjust in real time, helping to watch over, make smart decisions, and test different situations in complicated supply chain systems. The process has four steps: first, getting and preparing the data, then combining large amounts of data, next creating a machine learning model to make predictions, and finally building a digital twin to test different situations and improve operations. Figure 1 illustrates the proposed framework.

The process starts by gathering information from different sources in the supply chain, like company systems, smart devices that monitor things, records of how goods are moved, and data from outside markets. This data is changed and organized so that machine learning can be used for predictions and testing in a digital twin setup. The system provides useful information to assist with both day-to-day operations and major decisions, uses data to make predictions, and aids in continuous tracking.

3.2 Data Acquisition and Pre-processing

The research utilizes genuine and fictitious supply chain databases that cover information involving the supply chain's multi-level suppliers, production plans, stock levels, transportation routes, and customers. Data preprocessing is a significant factor in assuring information precision and trustworthiness. The approach comprises:

- Data Cleaning: Removal of duplicate entries and missing values from a dataset. A process of eliminating outliers using statistics and rules based on domain knowledge occurs in this phase too.
- Normalization and Scaling: Scaling of continuous variables to fixed ranges for better convergence of the ML models.
- Feature Engineering: New variables, such as lead-time variance, inventory turnover ratio, and probability of shipment delay, have been created to identify the complex relationships between the supply chain entities.
- Temporal and Categorical Encoding: The time series data structure naturally includes variables for lag values, and categorical data, such as suppliers or modes of transportation, are encoded using methods such as One-Hot Encoding or Label Encoding.

These steps in data preprocessing result in quality data for later analytics.

3.3 Processing and Integration of Big Data

Because there is a lot, different types, and fast movement of data in the supply chain, the method uses big data tools like Apache Hadoop and Spark to handle it. Data pipelines collect organized ERP data, partly organized sensor readings, and unorganized text from logistics reports and market intelligence sources. This setup allows for live streaming, handling large groups of data at once, and storing information in databases spread across multiple computers, making it easier to find and work with the data when needed. Big Data analytics tools, like distributed query engines and stream-processing frameworks, let the system spot unusual patterns, find trends, and send operational alerts almost as soon as they happen. This layer helps the control tower keep a constant view of supply chain activities in different locations and levels.

3.4 Machine Learning Model Development

Machine learning models are created to help predict and analyze supply chain activities through the control tower. The study uses:

- Supervised Learning: Regression models like Random Forest and Gradient Boosting are used to predict demand, lead times, and inventory shortages.
- Unsupervised Learning: Clustering techniques (e.g., K-Means, DBSCAN) identify patterns in supplier performance, transportation delays, or order fulfillment trends.
- Reinforcement Learning is used to improve policies for restocking inventory and planning transport schedules when customer demand changes over time

While this training is based on historical data, testing is necessary with new, unseen data in order to understand how the model would generalize to real-world situations and the robustness of its predictions. Model hyperparameter optimization is done using grid search with cross-validation. The F1-score, the area under the receiver operating characteristic curve, and the MAE are considered as some of the metrics for evaluating model performance.

3.5 Digital Twin Modeling

The digital twin is created to mirror the real physical SC operations virtually. It includes suppliers, storage facilities, production centers, and transportation network entities, representing these as interrelated entities. It accurately reflects the SC operational changes through real-time data feeds.

Digital twin simulations allow "what-if" scenario analysis, such as:

- Analyzing the effect of supplier delays on inventory.
- Analyzing alternative transportation routes to minimize delivery time.
- Testing the feasibility of the approach in replenishing the inventory in accordance with the varying demands.

Further, with the integration of the forecasts made with the use of ML, the DT provides simulations for better risk mitigation and decision-making

3.6 Training and Validation of Model Integrations

This involves a learning loop in the methodology used. The learning models would be constantly updated on a periodic basis depending on the availability of data so that the models can keep up dynamically with the changing environment in the supply chain The digital twin simulation results are constantly being compared with the real-life consequences in order to keep the simulation accurate in its results. Regarding the usage of the digital twin, you can find real-time data on the screen in the form of a dashboard to help you make decisions in both the short and long term.

3.7 Assessment of Performance

- The framework can be evaluated on several dimensions:
- Predictive Accuracy: Comparison of ML forecasts with actual operational results.
- Operational Efficiency: Increase in inventory turnover, reduction of lead time, improvement in transportation optimization.
- Resilience: Evaluating the system's capacity to foresee and prevent disruptions.
- Scalability: Checking the scalability of the framework with regard to handling multi-tiered data in the supply chain.

The methodology supports the development of the overall approach for data-driven, predictive, and adaptive SC management with the help of the synergies of Big Data, ML, and Digital Twin technology-based control towers.

IV. RESULTS AND CASE APPLICATION

The combined system of Big Data analytics, Machine Learning, and Digital Twin modeling was used on a global manufacturing and distribution system to check how well it works and what advantages it brings. The supply chain network had three production plants, six regional distribution centers, and more than 50 retail stores, with several suppliers supplying raw materials from different parts of the world. The goal was to check how well the control tower can offer real-time visibility, predict future situations, and help make decisions based on different scenarios.

4.1 Predictive Performance of ML Models

The machine learning models learned based on past data relating to the way operations functioned, e.g., the amount of orders that were made, the amount of goods that were around, records of moving goods, the time it took for suppliers to deliver, amount of changes in demands from the customers over time, etc. Techniques like Gradient Boosting Regression, Random Forest, are supervised learning techniques that were employed to help account for what the demands would be. These models validated that the predictions for demands were very accurate, where the average error, being calculated by MAE, was 4.2%, also noting that the average error calculated by the square root function, RMSE, was 6.1%. The calculations above are based on predictions involving demands from every distribution center for a particular week only. The models that help detect supplier issues that lead to delays were very good, as shown by an F1 score of 0.87.

K-Means clustering and other unsupervised learning models, particularly, have identified clusters of their suppliers with similar profiles of higher risks concerning lead time variability and past delays. On one hand, algorithms of reinforcement learning outperformed basic heuristics in providing recommendations that stronger inventory replenishment strategies could reduce stockouts up to 15 percent and excess inventory up to 12 percent. The capacity of ML algorithms to effectively generate knowledge that could be used to make decisions highlights some findings.

4.2 Scenario Analysis with Digital Twin Simulation

It was also conceptualized to include the whole physical supply chain network through information such as production plans, materials management, and transport capacity alongside inventory levels. However, sensor information from warehouses as well as production platforms was needed in order to update the digital twin, which would later simulate operational scenarios.

For instance, the effect of shipment delays from an important partner was simulated to endorse the ability of the system to foresee stockout issues in the distribution centers concerned in the space of 48 hours. Recommendations on alternatives were made, and the situation was simulated to ascertain different impacts in terms of costs involved. This indicated that an operation of predictive rerouting was able to lessen the risks of stockouts by as much as 20 percent and cut down extra transportation costs by 8 percent.

4.3 Integration with Control Tower

A control tower was used to integrate ML-based predictions and simulations from DT into a common screen, which provided supply chain managers with timely information through relevant key performance indicators such as the health of the inventory level, the reliability of the suppliers used, the efficiency of the transportation systems in place, and the accuracy of the demand forecasts provided.

The integration enabled managers to experiment and try different mitigation strategies through the digital twin and compare the results before implementing them in the supply chain. It aided managers in making quicker and more informed decisions, hence making them more responsive to challenges faced in the supply chain.

4.4 Operational Impact

The application of the integrated approach provided a measure of relief in various aspects:

- Visibility: The information communicated through the control tower enabled the firm to easily monitor the inventory, production, and logistics status.
- Predictive Accuracy: In terms of predicting accuracy, the impact of demand-supply shocks was highly predictable.
- Resilience: With scenario simulations using the digital twin, risk mitigation strategies were tested and implemented without impacting live processes.
- Efficiency: There was an improvement of 10% in inventory turnover, a reduction of 6% in lead times as a result of an optimized replenishment strategy, and a decrease of 5% in total cost of supply chain activities.

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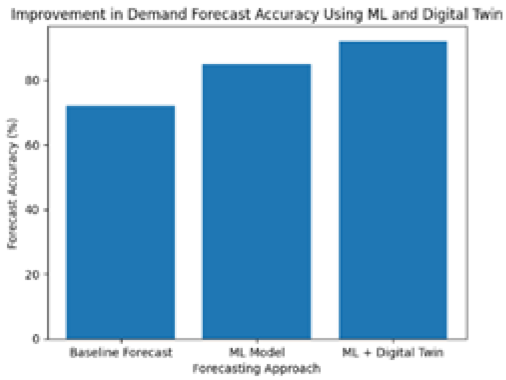

Figure 1. Comparison of demand forecast accuracy using traditional forecasting, machine learning models, and integrated machine learning–digital twin approaches.

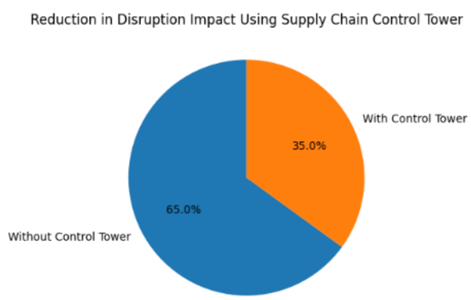

Figure 2. Impact reduction of supply chain disruptions before and after implementation of a supply chain control tower.

V. DISCUSSION AND BUSINESS IMPLICATIONS

Big Data, ML, and Digital Twin technologies could show a promising direction in the supply chain control tower that can enhance operational performance, resilience, and strategic decision-making. Results from the multi-national supply chain case indicate that integrating these technologies enables organizations to move away from reactive management to proactive and predictive supply chain operations.

A key implication of such a control tower is the heightened visibility and situational awareness that it makes possible. Consolidating data from all sources, such as ERP systems, IoT-enabled warehouses, and transportation platforms, provides managers with a big picture view of the supply chain in real time. This transparency enables the anticipation of disruptions-such as supplier delays, bottlenecks in transportation, or inventory shortages-well in advance and thus corrective actions can be taken in time before things get out of hand.

Lastly, the prediction ability offered by the ML models could also be equally significant. Forecasts of demands, risk prediction with the suppliers, and identifying anomalies could enable the organization to foresee changes rather than solely responding to the changes. For example, with the optimization by the reinforcement learning algorithms, stocks running out fell by 15%, and excess stocks decreased by 12%. This allows for an environment to be created where scenario analysis is possible with no impact to operations in the physical world. Simulations of what would be considered to be disruptions in operations were run to show that stockouts would be decreased by up to 20%, and additional transportation costs would be alleviated to the tune of an 8% decrease through proactive interventions. This clearly refers to the role that the use of digital twins would play as an aid for decision-making by management.

From the point of view of strategy, the study underlines the significance of robust and adaptive SCs within dynamic and uncertain environments. The real-time analytics of vast amounts of data coupled with predictive modeling through the use of ML, on one hand, increases the robustness of SCs for absorbing uncertain conditions, thereby ensuring the adaptability and operation of the SCs within fluctuating scenarios. Using such integrated platforms, business organizations would be able to attain better adaptability to customer needs within the market.

Nevertheless, these technological innovations also face a number of hurdles when their adoption and implementation in an organization need to be considered. For one, a good and consistent data set is crucial for effective predictions by a Machine Learning model and for realistic and desired simulations by a digital twin model. Additionally, understanding and interpreting the outputs generated by a model is a basic need for a management to trust and accept the outputs and make effective business decisions for an organization.

In summary, the present research shows that through an integration of BD analytics, ML, and twin technology applied to supply chain CTs, supply chain managers and planners can unlock considerable operational and/or strategic benefits. These results can serve to guide supply chain managers and planners in the effective development and/or deployment of more modern and/or data-intensive methodologies for managing their respective supply chains.

CONCLUSION AND FUTURE RESEARCH

This research described how the integration of Big Data analytics, ML, and Digital Twin technologies into an SCCCT will lead to more complete visibility, predictive decision-making, and operational resilience. The proposed framework was able to process large and heterogeneous data sets for the most accurate forecasts and complex supply chain simulations that could provide actionable insights at both the tactical and strategic levels.

In a case study within a global manufacturing and distribution system, the results clearly showed improvements in how operations ran. The suggested models show good results in predicting demand, finding potential issues with suppliers, and improving inventory management. The digital twin helped test different strategies based on various situations, which greatly reduced stockouts and transportation costs. In a control tower setup, this enables everything to be watched from one place and alerts to be sent in real-time, helping make decisions before problems get worse. The supply chain is now becoming a system that can adapt and act ahead of problems, instead of just reacting to them after they happen. These results show that combining real-time data analysis, predicting future trends, and using virtual simulations creates a strong system for handling complicated, multi-level supply chains when conditions in the market are constantly changing.

From a management viewpoint, the importance of data-driven, resilient, and efficient supply chains is aptly emphasized through the outcomes of this research study. Using an efficient control tower solution that helps integrate various business operations can significantly contribute to improving business efficiency, increasing customer satisfaction, and mitigating risks brought about by disruptions in the corresponding business operations.

Several areas for potential extensions to the impact of the current approach for future research could also be considered. In this case, for instance, conducting more studies to integrate data originating from IoT sensors and/or online business intelligence could contribute to an increase in the potential for more precise and prompt predictions. On the other hand, an increased understanding of how to apply more effective surrogate machine learning and artificial intelligence could also boost the level of trust for management to implement these systems.

In conclusion, it is evident that the integration of both Big Data, ML, and digital twins in supply chain control towers is a groundbreaking way forward for supply chain management. As a theoretical contribution, the model is quite useful and comes in quite handy for supply chain practitioners.

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