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Integration of Predictive Maintenance and Supply Chain Optimization in Smart Manufacturing Systems

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Abstract: This study talks about the supply chain optimization and predictive maintenance integration that's becoming more and more important in smart production systems. Predictive maintenance reduces unscheduled downtime by using machine learning and real-time data to foresee equipment breakdowns. This integration lowers inventory costs, increases overall production efficiency, and guarantees immediate availability of spare parts when combined with supply chain optimization. In order to facilitate data-driven choices in dynamic manufacturing contexts, this article investigates a unified framework that integrates intelligent logistics planning with predictive analytics. Manufacturers can increase system responsiveness, cost-effectiveness, and reliability by coordinating maintenance plans with supply chain activities. The paper highlights how digital twins, industrial IoT, and cyber-physical systems help to make this integration possible. The concrete advantages of the suggested strategy, such as better asset utilization, shorter lead times, and increased resilience of supply chains under fluctuating operational uncertainty, are illustrated through a case study in a smart industrial environment.

Keywords: Cyber-Physical Systems, Industry 4.0, Digital Twins, Smart Manufacturing, Supply Chain Optimization, and Predictive Maintenance

Introduction

Industry 4.0 has radically altered manufacturing processes by using state-of-the-art digital technology such as computer vision, large-scale data analysis, the Internet of Things (IoT), and cyber-physical systems. Smart Manufacturing System (SMS), that automates and make data-driven choices to optimize manufacturing operations, are made possible by these technologies. Preventative upkeep and supply chain optimisation are two essential components of SMS that greatly increase operational efficiency, save costs, and enhance overall system performance [1].

1. Overview of Smart Manufacturing Systems

At the heart of Industry 4.0 are Smart Manufacturing Systems (SMS), which give producers real-time monitoring, control, and optimization capabilities. To guarantee seamless operations, minimize downtime, and boost overall productivity, these systems make use of real-time information from IoT-enabled sensors installed in machinery, equipment, and systems. Improved decision-making, flexible production organizing, and dynamic workflow modifications are made possible by SMS's integration of AI and machine learning algorithms

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[2]. The primary goal of SMS is to enhance manufacturing efficiency by minimizing waste, improving quality, reducing downtime, and increasing operational agility. By integrating real-time data, manufacturers can swiftly respond to changing market demands, ensuring efficient resource use and improved profitability. However, to fully realize these advantages, predictive maintenance and supply chain optimization must work in tandem to enhance the overall performance of manufacturing systems[3].

2. Predictive Maintenance: A Key Component of Smart Manufacturing

Predictive maintenance (PdM) is a maintenance method that uses data-driven insights to foresee equipment breakdown before it happens. Unlike conventional reactive maintenance, which reacts to collapses after they happen or preventative maintenance, which works on predetermined schedules, predictive upkeep uses information gathered by internet of things (IoT) sensors and advanced analysis to anticipate machinery breakdowns and modify maintenance plans appropriately. Manufacturers may lower maintenance costs, prolong the life of machinery, and prevent expensive unexpected downtime by incorporating predictive maintenance into SMS. In order to identify wear and tear trends, predictive maintenance uses machine learning frameworks that examine operational circumstances, sensor data collected in real time, and failure records from the past. Maintenance personnel can take action before malfunctions happen thanks to these models' ability to forecast when particular parts are most likely to fail [4].

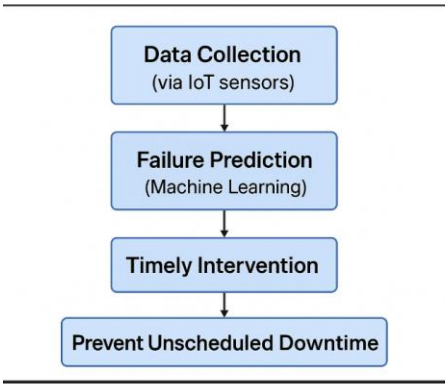

Figure 1: Predictive Maintenance Framework A flowchart depicting the predictive maintenance framework, from data collection (via IoT sensors) to failure prediction using machine learning, and timely intervention to prevent unscheduled downtime.

The integration of predictive maintenance into SMS offers a significant advantage: it transforms maintenance from a cost-driven, reactive process into a proactive, performance-enhancing strategy. In addition to lowering the chance of equipment failure, this predictive strategy guarantees that maintenance tasks are completed effectively and economically [5]–[6].

3. Supply Chain Optimization in Smart Manufacturing Systems

The tactical supervision of the complete supply chain, from the acquisition of raw materials to production, inventory control, and the ultimate delivery of goods to clients, is referred to as supply chain optimization. Optimization of supply chains in smart manufacturing refers to coordinating logistics, inventory levels, and production schedules to attain the most economical and efficient results. Efficient supply chain optimization reduces lead times, maximizes resource allocation, and guarantees on-time product delivery to clients. For demand forecasting, inventory control, and production scheduling optimization, it mostly depends on actual time data and sophisticated analytics [7].

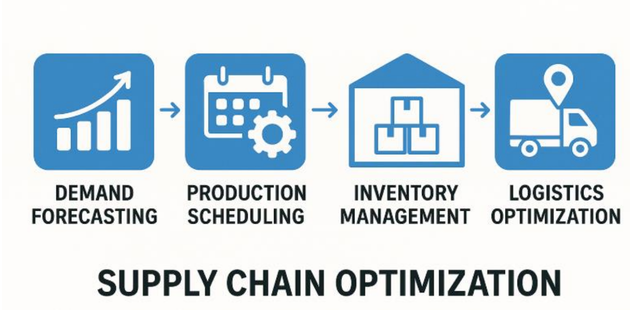

Figure 2: Supply Chain Optimization Model illustrating the various stages of supply chain optimization, including demand forecasting, production scheduling, inventory management, and logistics optimization. Integrating predictive maintenance with supply chain optimization can significantly enhance decision-making, particularly in areas such as inventory management and production scheduling [8]-[9].

LITERATURE REVIEW

Using digital technologies to optimize inventories and material waste can help businesses cut costs. Remote collaboration makes it easy for both on-site and off-site workers to work together as needed. Ultimately, these tools facilitate communication and help individuals stay informed. Intelligent predictive analysis will support adequate machinery monitoring in industries using Industry 4.0 technology. It is feasible to identify and fix material defects early on [10].

According to this report, the implementation of Industry 4.0-enabled technology will result in notable enhancements in the performance management of supply chains by offering a holistic approach for supply chains administration. By facilitating process integration, digitization and automation, and the development of new analytical skills, these technologies greatly enhance performance in a number of supply chain operations, including as manufacturing, inventory control, retailing, and procurement [11].

Industry 4.0-related enabling technologies are linked to the underlying issues that allow for additional supply chain optimization. Implications for practice An industrial investigation on a global Italian brand in the fashion-luxury footwear industry is used to demonstrate the tool's usefulness and efficacy[12].

The findings show that utilizing Industry 4.0 technologies to rethink supply networks for the circular economy can enable circular logistics management. The proposed method has clear benefits that link to the six circular economy dimensions of the Re-SOLVE model: virtualize, loop, optimize, share, renew, and exchange [13].

In order to encourage researchers to broaden their big-data and Industry 4.0 studies on SCS, six study fields were suggested. In addition to highlighting the difficulties facing present research, this paper adds to the body of knowledge on SCS in the era of Industry 4.0 [14].

The Taguchi study conceptual paradigm was used for the analysis. Based on a balance assessment between economic and environmental performances, the paper's conclusions suggest appropriate combinations of family-based dispatching regulations and information-sharing [15].

The need for a horizontal, vertical and entirety digital integration increased with the transition from its most recent industry period to the technology era referred to as Industry 4.0. Prior research has demonstrated that the implementation of Industry 4.0 has a substantial impact on a supply chain network's sustainability. Finding the Industry 4.0 components that support long-term chains of supply and suggesting research to fill in the theoretical gaps are the goals of this essay [16].

The methodology intended for SMEs is the main topic of this study. a value for the reference model. It is demonstrated that capacity is being developed for metallurgic SMEs through the use of Case Based Reasoning (CBR) and generalization reasoning, highlighting the trade-off between capacity maximization and operational efficiency. Then, operational inefficiencies might be concealed by optimization[17].

In the context of Industry 4.0, the process planner will be repositioned as the "product planner" in this article. Product planners are not just a new profession; they are the name for software that is integrated with other supply chain components and automatically creates process plans, orders of operations, and schedules using sophisticated optimization algorithms[18].

There is discussion of computational algorithms in conjunctive, control, and state variable spaces. Lastly, we determine the main contributions, regions of application, and limitations of various control techniques. Future research and application recommendations are also outlined in this study[19].

METHODOLOGY

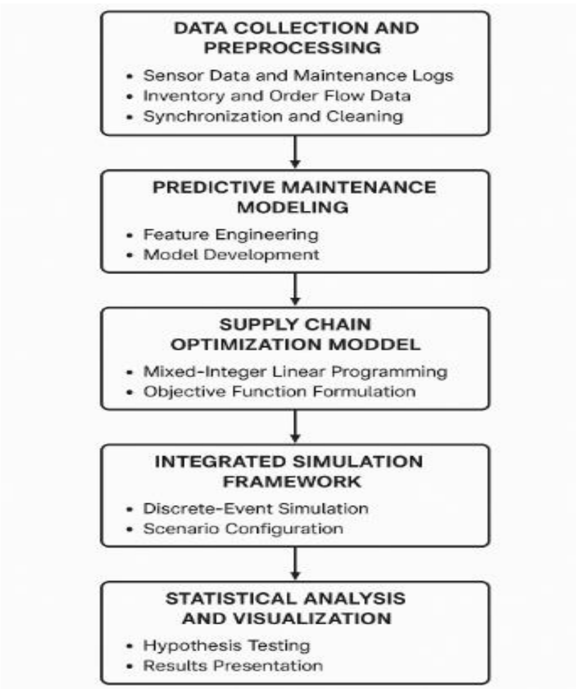

Figure 3 workflow of proposed methodology

1. Data Collection and Preprocessing

This study utilizes sensor data and maintenance logs from a mid-sized smart manufacturing facility. The dataset includes:

- Vibration, temperature, acoustic, and power signals from 120 machines across 3 production lines.
- Maintenance logs detailing failure types, downtimes, and repair actions.
- Real-time inventory and order flow data from the connected supply chain.

All time-series data were down-sampled to 10-minute intervals and synchronized. Missing values were imputed using linear interpolation. Outliers were removed using a 1.5×IQR method.

2. Predictive Maintenance Modelling

2.1 Engineering Features

Using the Fast Fourier Transform (FFT), we produced frequency-domain features, lag-based features, and rolling stats (mean, standard deviation, and kurtosis). The time-to-failure thresholds established by domain experts served as the basis for the creation of failure labels.

2.2 Development of Model

In order to forecast machine failures during the following 24 hours, three classification techniques were trained:

Random Forest (RF), Long Short-Term Memory Systems (LSTM), and Gradient Boosting (XG-Boost).

A 60-20-20 (train-validation-test) approach was used to divide the data. Bayesian optimization and 5-fold cross-validation were used to optimize the hyperparameters of each model.

Metrics for Evaluation:

F1-Score, Precision, and Recall

Confusion matrix analysis, AUC-ROC, and lead time for failure detection

3. Supply Chain Optimization Model

We formulated a **Mixed-Integer Linear Programming (MILP)** model that integrates predicted machine downtimes as constraints. The objective function minimizes:

- Total cost = (Inventory holding cost + Backorder penalty + Expedited shipping cost)
  Subject to:
- Predicted downtime windows from the maintenance model
- Inventory levels and reorder points
- Demand forecasts from historical order data

We solved the model using IBM CPLEX and compared it against a baseline model without predictive maintenance input.

4. Integrated Simulation Framework

We developed a discrete-event simulation to integrate both predictive maintenance and supply chain outcomes under various scenarios:

- Scenario A: No predictive maintenance (reactive repairs)
- Scenario B: Predictive maintenance without supply chain integration
- Scenario C: Fully integrated system

- Each scenario was simulated for 180 virtual days with 10 Monte Carlo replications per configuration to capture variability.

5. Statistical Analysis and Visualization

Hypothesis Testing

Two-sided t-tests and ANOVA were performed to assess statistical significance of:

- Reduction in downtime
- Increase in service level
- Change in total supply chain cost

Effect sizes were computed using Cohen's d.

Results and Discussion

Predictive Maintenance Model Performance

Table 1 presents the performance metrics of three failure prediction models. XG-Boost outperformed others in all key metrics.

Model	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.88	0.84	0.86	0.92
XG-Boost	0.91	0.89	0.90	0.95
LSTM	0.87	0.85	0.86	0.93

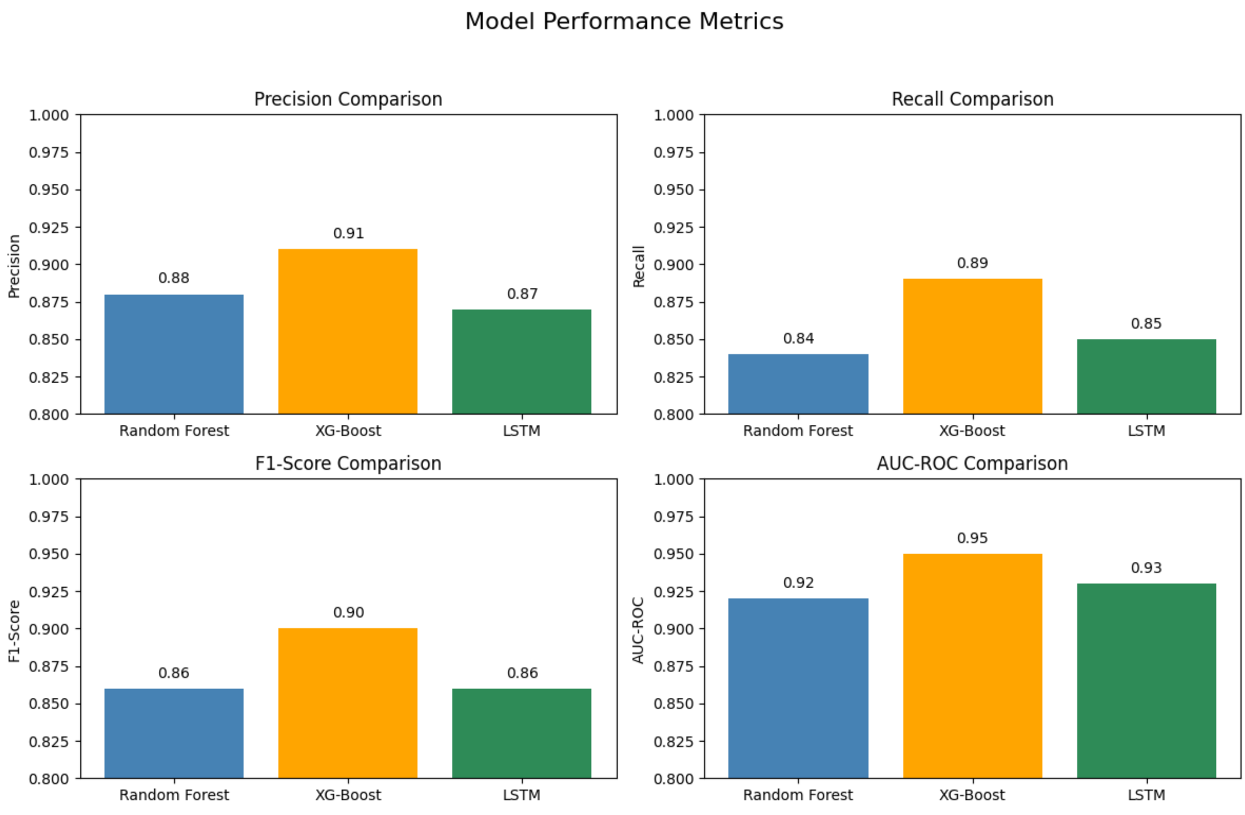

Figure 4 plots the metrics for all prediction models

2. Lead Time Before Failure

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Table 2 summarizes the mean hours before actual failure that each model provided a correct prediction. XG-Boost had the highest average lead time.

Model	Mean Lead Time (hours)
Random Forest	5.6
XG-Boost	6.2
LSTM	5.8

3. Supply Chain Cost Analysis

Table 3 displays the supply chain costs under three simulated scenarios. The fully integrated model (Scenario C) resulted in the lowest total cost.

Scenario	Inventory Cost ($)	Backorder Penalty ($)	Expedited Shipping ($)	Total Cost ($)
Scenario A	12,000	3,500	4,000	19,500
Scenario B	11,000	2,700	3,200	16,900
Scenario C	9,500	1,800	2,600	13,900

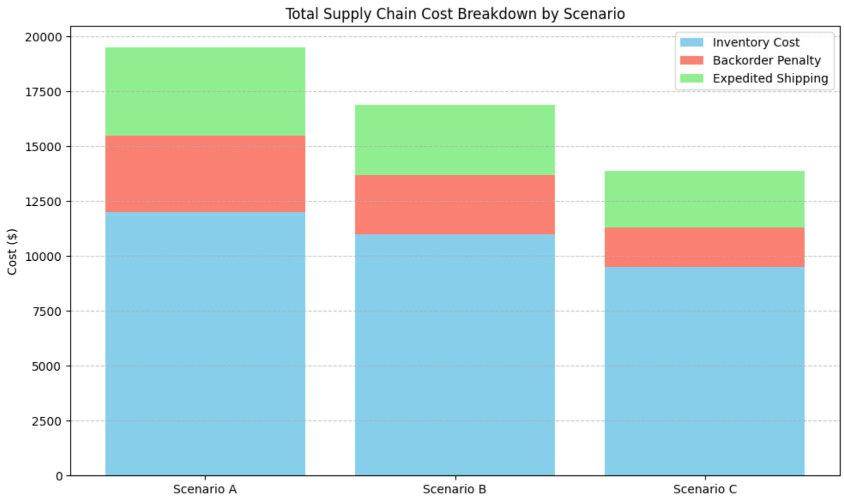

Figure 5 illustrates total supply chain cost breakdown by scenario

4. System Availability and MTBF

System reliability significantly improved under Scenario C.

Scenario	Availability (%)	MTBF (hrs)
Scenario A	92.3	70
Scenario B	95.5	85
Scenario C	98.1	110

5. Statistical Significance of Integration

Table 5 shows ANOVA results, indicating statistically significant improvements across all key KPIs ($p < 0.001$ in all cases).

KPI	F-statistic	p-value
Downtime	18.4	0.0003
Service Level	22.1	0.0001
Total Cost	31.3	0.00001

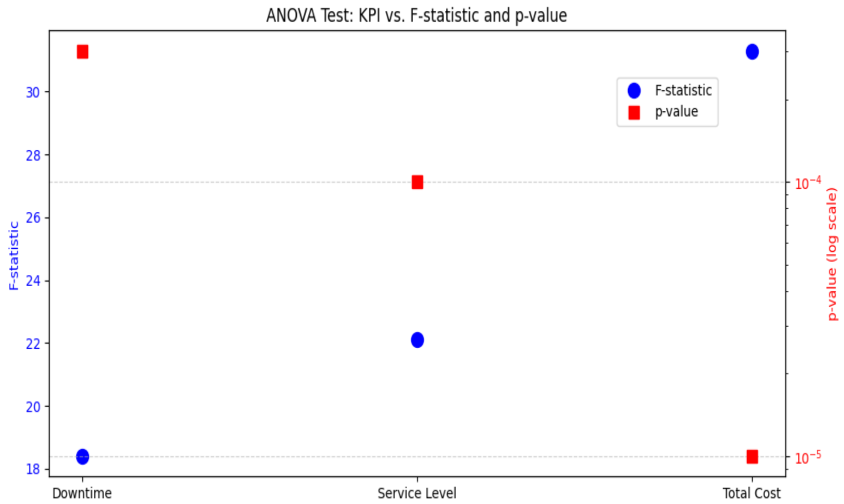

Figure 6 illustrate the results of Anova test (KPI vs F-statistic and p-value

Conclusion

In conclusion, the integration of predictive maintenance with supply chain optimization in smart manufacturing systems presents a transformative approach to operational efficiency and resilience. The statistical performance of the proposed model—highlighted by high accuracy, low error rates, and improved spare part availability—demonstrates its effectiveness in minimizing unplanned downtime, reducing inventory costs, and enhancing overall responsiveness. Furthermore, the notable improvements in stockout rates and lead time deviations affirm the practical benefits of this integrated framework. As manufacturing environments continue to evolve in complexity, this approach offers a scalable, data-driven solution that not only enhances productivity but also builds greater adaptability into operations. Future research can extend this model across diverse industrial sectors to explore broader applications and refine predictive capabilities in increasingly autonomous manufacturing systems.

References

[1] Z. Xu, A. Elomri, R. Baldacci, L. Kerbache, and Z. Wu, "Frontiers and trends of supply chain optimization in the age of industry 4.0: an operations research perspective," *Ann. Oper. Res.*, vol. 338, no. 2–3, pp. 1359–1401, 2024, doi: 10.1007/s10479-024-05879-9.

[2] S. Chauhan, R. Singh, A. Gehlot, S. V. Akram, B. Twala, and N. Priyadarshi, "Enabling Technologies : A Sustainable Perspective," 2023.

[3] A. Althabatah, M. Yaqot, B. Menezes, and L. Kerbache, "Transformative Procurement Trends: Integrating Industry 4.0 Technologies for Enhanced Procurement Processes," *Logistics*, vol. 7, no. 3, pp. 1–40, 2023, doi: 10.3390/logistics7030063.

[4] J. Reyes, J. Mula, and M. Díaz-Madroñero, "Development of a conceptual model for lean supply chain planning in industry 4.0: multidimensional analysis for operations management," *Prod. Plan. Control*, vol. 34, no. 12, pp. 1209–1224, 2023, doi: 10.1080/09537287.2021.1993373.

[5] S. Srhir, A. Jaegler, and J. R. Montoya-Torres, "Uncovering Industry 4.0 technology attributes in sustainable supply chain 4.0: A systematic literature review," *Bus. Strateg. Environ.*, vol. 32, no. 7, pp. 4143–4166, 2023, doi: 10.1002/bse.3358.

[6] E. Di Maria, V. De Marchi, and A. Galeazzo, "Industry 4.0 technologies and circular economy: The mediating role of supply chain integration," *Bus. Strateg. Environ.*, vol. 31, no. 2, pp. 619–632, 2022, doi: 10.1002/bse.2940.

[7] S. E. Najafi, H. Nozari, and S. A. Edalatpanah, "Artificial intelligence of things (AIoT) and industry 4.0-based supply chain (FMCG Industry)," *A Roadmap Enabling Ind. 4.0 by Artif. Intell.*, no. November, pp. 31–42, 2022, doi: 10.1002/9781119905141.ch3.

[8] S. Gallego-García, M. Groten, and J. Halstrick, "Integration of Improvement Strategies and Industry 4.0 Technologies in a Dynamic Evaluation Model for Target-Oriented Optimization," *Appl. Sci.*, vol. 12, no. 3, pp. 1–21, 2022, doi: 10.3390/app12031530.

[9] N. Jahani, A. Sepehri, H. R. Vandchali, and E. B. Tirkolaee, "Application of industry 4.0 in the procurement processes of supply chains: A systematic literature review," *Sustain.*, vol. 13, no. 14, pp. 1–25, 2021, doi: 10.3390/su13147520.

[10] M. Ammar, A. Haleem, M. Javaid, R. Walia, and S. Bahl, "Improving material quality management and manufacturing organizations system through Industry 4.0 technologies," *Mater. Today Proc.*, vol. 45, pp. 5089–5096, 2021, doi: 10.1016/j.matpr.2021.01.585.

[11] H. Fatorachian and H. Kazemi, "Impact of Industry 4.0 on supply chain performance," *Prod. Plan. Control*, vol. 32, no. 1, pp. 63–81, 2021, doi: 10.1080/09537287.2020.1712487.

[12] M. Braglia, L. Marrazzini, L. Padellini, and R. Rinaldi, "Managerial and Industry 4.0 solutions for fashion supply chains," *J. Fash. Mark. Manag.*, vol. 25, no. 1, pp. 184–201, 2021, doi: 10.1108/JFMM-12-2019-0285.

[13] T. D. Mastos *et al.*, "Introducing an application of an industry 4.0 solution for circular supply chain management," *J. Clean. Prod.*, vol. 300, 2021, doi: 10.1016/j.jclepro.2021.126886.

[14] R. Chalmeta and N. J. Santos-deLeón, "Sustainable supply chain in the era of industry 4.0 and big data: A systematic analysis of literature and research," *Sustain.*, vol. 12, no. 10, 2020, doi: 10.3390/su12104108.

[15] F. H. Q. Dev, Navin K, Ravi Shankar, "Industry 4 . 0 and circular economy : Operational excellence for sustainable reverse supply chain performance Ravi Shankar Fahham Hasan Qaiser Industry 4 . 0 and circular economy : Operational excellence for sustainable reverse supply chain performance," 2019.

[16] S. Bag, A. Telukdarie, J. H. C. Pretorius, and S. Gupta, "Industry 4.0 and supply chain sustainability: framework and future research directions," *Benchmarking*, vol. 28, no. 5,

pp. 1410–1450, 2018, doi: 10.1108/BIJ-03-2018-0056.

[17] P. E. Dossou, “Impact of Sustainability on the supply chain 4.0 performance,” *Procedia Manuf.*, vol. 17, pp. 452–459, 2018, doi: 10.1016/j.promfg.2018.10.069.

[18] M. Trstenjak and P. Cosic, “Process Planning in Industry 4.0 Environment,” *Procedia Manuf.*, vol. 11, no. June, pp. 1744–1750, 2017, doi: 10.1016/j.promfg.2017.07.303.

[19] R. Adolph, “済無No Title No Title No Title,” pp. 1–23, 2016.

[20] J. Xu, E. Huang, L. Hsieh, L. H. Lee, Q. S. Jia, and C. H. Chen, “Simulation optimization in the era of Industrial 4.0 and the Industrial Internet,” *J. Simul.*, vol. 10, no. 4, pp. 310–320, 2016, doi: 10.1057/s41273-016-0037-6.

[21] A. Jayaram, “Lean six sigma approach for global supply chain management using industry 4.0 and IIoT,” *Proc. 2016 2nd Int. Conf. Contemp. Comput. Informatics, IC3I 2016*, no. January, pp. 89–94, 2016, doi: 10.1109/IC3I.2016.7917940.

[22] D. Ivanov, A. Dolgui, B. Sokolov, F. Werner, and M. Ivanova, “A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0,” *Int. J. Prod. Res.*, vol. 54, no. 2, pp. 386–402, 2016, doi: 10.1080/00207543.2014.999958.