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Dynamic Economic Order Quantity (EOQ) Model Integrating Sustainability and Industry 4.0 for Inventory Cost Efficiency

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Abstract
Efficient inventory management has become a critical challenge for the manufacturing industry due to market demand fluctuations, digital transformation, and sustainability pressures. This research proposes a dynamic EOQ framework that integrates Monte Carlo simulation, sustainability principles, and Industry 4.0 technologies to support adaptive inventory decision-making.The research employs a quantitative exploratory approach utilizing operational data from a corrugated box manufacturing company in Surabaya, Indonesia. A Monte Carlo simulation with 1,000 iterations is used to model stochastic demand uncertainty and determine the optimal order quantity.The results show that the proposed dynamic EOQ model can reduce inventory costs by approximately 8–12% compared to the conventional EOQ approach. The optimal order quantity is identified as 70,890 kg per cycle, while the integration of sustainability principles successfully reduces material waste by around 5% per production cycle. This research contributes theoretically by integrating sustainability concepts and Industry 4.0, including the Internet of Things (IoT) and closed-loop supply chain concepts, into inventory management optimization. This integration has proven to improve resource use efficiency and reduce production waste. The findings confirm that implementing a sustainability- and digital technology-based EOQ model can be an effective strategy to enhance economic efficiency while supporting environmental responsibility in the manufacturing industry in the Industry 4.0 era. Practically, the research offers a more adaptive inventory control framework for the manufacturing industry.

Abstrak
Pengelolaan persediaan yang efisien telah menjadi tantangan kritis bagi industri manufaktur akibat fluktuasi permintaan pasar, transformasi digital, dan tekanan keberlanjutan. Penelitian ini mengusulkan sebuah kerangka kerja *Economic* EOQ dinamis yang mengintegrasikan simulasi Monte Carlo, prinsip keberlanjutan, dan teknologi Industri 4.0 untuk mendukung pengambilan keputusan inventaris yang adaptif. Penelitian ini menggunakan pendekatan eksploratif kuantitatif dengan memanfaatkan data operasional dari perusahaan manufaktur kotak karton gelombang (*corrugated box*) di Surabaya, Indonesia. Simulasi Monte Carlo dengan 1.000 iterasi digunakan untuk memodelkan ketidakpastian permintaan stokastik dan menentukan kuantitas pemesanan yang optimal. Hasil penelitian menunjukkan bahwa model EOQ dinamis yang diusulkan mampu mengurangi biaya inventaris sekitar 8–12% dibandingkan dengan pendekatan EOQ konvensional. Kuantitas pemesanan optimal

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diidentifikasi sebesar 70.890 kg per siklus, sementara integrasi prinsip keberlanjutan berhasil mengurangi limbah material sekitar 5% per siklus produksi. Penelitian ini memberikan kontribusi teoretis dengan mengintegrasikan konsep keberlanjutan dan Industri 4.0 dengan integrasi konsep IoT dan *closed-loop supply chain* ke dalam optimasi pengelolaan persediaan karena terbukti meningkatkan efisiensi penggunaan sumber daya serta mengurangi limbah produksi. Temuan ini menegaskan bahwa penerapan model EOQ yang berbasis keberlanjutan dan teknologi digital dapat menjadi strategi efektif untuk meningkatkan efisiensi ekonomi sekaligus mendukung tanggung jawab lingkungan pada industri manufaktur di era Industri 4.0., serta kontribusi praktis dengan menawarkan kerangka kerja pengendalian persediaan yang lebih adaptif bagi industri manufaktur.

Introduction

Inventory management has become one of the most critical operational activities in modern manufacturing industries due to increasing market uncertainty, global competition, and rapid technological transformation. Manufacturing companies are required to maintain inventory availability while simultaneously minimizing procurement, storage, and operational costs. Ineffective inventory management may lead to excessive stock accumulation, production delays, increased holding costs, and inefficient resource utilization. Therefore, inventory optimization has an essential role in improving operational efficiency and maintaining industrial competitiveness in dynamic business environments.

One of the most widely implemented inventory optimization approaches is the Economic EOQ model. The EOQ model is designed to determine the optimal ordering quantity that minimizes total inventory costs consisting of ordering costs and holding costs. Classical EOQ theory assumes stable demand conditions and deterministic operational environments. However, modern manufacturing industries increasingly operate under uncertain demand patterns and fluctuating market conditions, causing the conventional EOQ model to become less adaptive in addressing real operational complexity. According to Jumali and Siswoyo (2023), inventory instability significantly affects production continuity and operational efficiency, particularly in manufacturing systems with volatile raw material demand (Jumali & Siswoyo, 2023; Pratama et al., 2024).

The emergence of Industry 4.0 has created new opportunities for the development of adaptive and intelligent inventory management systems. Technologies such as the IoT, big data analytics, artificial intelligence, and real-time monitoring systems enable manufacturing companies to collect and process operational data more accurately and efficiently. These technologies support predictive inventory control, demand forecasting, and automated procurement decision-making. Khan et al. (2025) explained that Industry 4.0 technologies improve operational sustainability and supply chain responsiveness through data-driven decision support systems. Consequently, inventory systems are no longer limited to static calculations but are evolving into dynamic and adaptive decision-making frameworks (Purwanto, 2020).

Besides operational efficiency, sustainability has become an increasingly important issue in inventory and supply chain management. Sustainable inventory management emphasizes efficient resource utilization, waste reduction, energy optimization, and environmental responsibility. Manufacturing industries are currently under pressure to implement environmentally responsible operational systems capable of reducing production waste and minimizing resource inefficiency. Li et al. (2022) stated that sustainable supply chain systems improve organizational resilience while reducing environmental impacts through more efficient resource allocation and operational integration.

Another important concept related to sustainable inventory management is the closed-loop supply chain (CLSC). This concept enables companies to reuse production waste, recycle residual materials, and reduce unnecessary disposal activities. Closed-loop systems contribute not only to cost reduction but also to circular economy implementation within manufacturing industries (Alinovi et al, 2012). Nevertheless, many previous researchers still examine sustainability, Industry 4.0 technologies, stochastic inventory systems, and EOQ optimization separately rather than integrating them into a comprehensive inventory decision-making framework.

Several researchers have explored stochastic EOQ models and inventory optimization using simulation approaches. However, limited research has integrated Monte Carlo simulation, sustainability indicators, IoT technology, and Industry 4.0 concepts simultaneously into a dynamic EOQ framework. Most previous studies focus only on cost efficiency without considering environmental sustainability and digital transformation as integrated operational components. This limitation creates a research gap regarding how inventory optimization systems can simultaneously improve economic efficiency, environmental performance, and operational adaptability under uncertain demand conditions. Monte Carlo simulation provides an effective approach for modeling stochastic demand variability and operational uncertainty in inventory systems. The simulation method enables companies to evaluate multiple demand scenarios and identify optimal ordering policies under fluctuating operational conditions. Through repeated probabilistic iterations, Monte Carlo simulation improves the predictive capability of inventory decision-making systems and reduces the risk of inaccurate inventory policies. Furthermore, the integration of IoT technology and closed-loop supply chain systems strengthens inventory visibility and improves resource utilization efficiency in manufacturing operations (Riniwati et al., 2020; Umami et al., 2025).

Therefore, this reseach aims to develop a dynamic EOQ framework integrating Monte Carlo simulation, sustainability principles, Industry 4.0 technologies, IoT, and closed-loop supply chain systems to improve inventory cost efficiency in manufacturing industries. The proposed model is expected to contribute theoretically by extending conventional EOQ theory into a more adaptive and sustainability-oriented inventory management framework. Practically, the study provides manufacturing industries with a more responsive inventory control system capable of improving economic efficiency while simultaneously supporting environmental sustainability in the Industry 4.0 era.

Methods

This research employed a quantitative exploratory approach to develop a dynamic EOQ model integrating Monte Carlo simulation, sustainability principles, and Industry 4.0 technologies. The quantitative approach was selected because it enables objective and measurable analysis based on numerical operational data, while the exploratory orientation supports the identification of relationships among variables affecting inventory efficiency and adaptive decision-making in manufacturing systems. According to Sugiyono (2022), quantitative research is used to examine relationships among variables through measurable empirical data and systematic analysis.

The research object was PT Golden Box Indonesia, a corrugated box manufacturing company located in Surabaya, Indonesia. The company was selected because it experiences fluctuating raw material demand, inventory instability, and operational challenges related to warehouse capacity utilization and procurement efficiency. The research focused on the logistics and procurement division responsible for inventory planning, purchasing activities, and warehouse management.

The research framework was developed based on several previous studies concerning inventory optimization, sustainability, and stochastic simulation. Heizer and Render (2009) explained that the EOQ model is effective in determining optimal ordering quantities by balancing ordering and holding costs. However, the conventional EOQ model remains deterministic and less adaptive to fluctuating demand conditions. To overcome this limitation, Ross (2021) emphasized that Monte Carlo simulation can effectively model uncertainty and stochastic systems through probabilistic iterations. In addition, Khan et al. (2025) highlighted that Industry 4.0 technologies improve operational sustainability and supply chain responsiveness through real-time data integration and predictive decision-making. Meanwhile, Li et al. (2022) explained that sustainability-oriented supply chain systems can improve resource efficiency and reduce environmental impact through integrated operational management.

This research did not utilize physical laboratory instruments because the research focused on mathematical modeling and stochastic simulation analysis. However, data analysis was supported by numerical processing software, namely Microsoft Excel 2019, for manual calculations, EOQ computation, data tabulation, and simulation graph visualization. In addition, a Monte Carlo simulation add-in integrated within Microsoft Excel was utilized to generate random demand scenarios and perform stochastic demand analysis through probabilistic iterations. The hardware specification used in this research consisted of a laptop equipped with an Intel Core i5 2.40 GHz processor, 8 GB of RAM, and a Windows 10 operating system. These specifications were considered sufficient to perform computational analysis and stochastic inventory modeling efficiently. The research was conducted systematically through several analytical stages. The first stage involved problem identification related to demand fluctuation and inventory inefficiency. The second stage involved operational data collection consisting of annual demand, ordering cost, holding cost, inventory utilization, and production waste data. The third stage involved conventional EOQ calculation as a baseline comparison. Subsequently, a dynamic EOQ model was developed using Monte Carlo simulation to model stochastic demand uncertainty and adaptive inventory behavior.

The research utilized secondary operational data collected from company reports during the 2020–2024 period. The collected data included raw material purchasing records, annual inventory demand reports, warehouse operational costs, procurement expenses, and production waste records. Additional supporting information was obtained through direct observation and structured interviews with logistics and procurement personnel to validate operational conditions and inventory management practices.

The population of the research consisted of inventory-related operational activities within the logistics division. Purposive sampling was applied because only the logistics department possessed operational data relevant to inventory management and procurement activities (Sugiyono, 2022). This sampling technique ensured that the collected data accurately represented the actual inventory management conditions within the company.

The variables analyzed in this research were classified into three categories, namely input variables, process variables, and output variables. The input variables consisted of annual demand (D), ordering cost per order (S), holding cost per unit per year (H), and sustainability indicators. The process variables included conventional EOQ calculations, Monte Carlo simulation procedures, and sustainability integration analysis. The output variables consisted of optimal order quantity (Q), total inventory cost (TC), waste reduction percentage, and warehouse utilization efficiency.

The conventional EOQ model was calculated using the following equation:

$$EOQ = \sqrt{\frac{2DS}{H}}$$

D = annual demand (kg/year)

S = ordering cost per order (Rp/order)

H = holding cost per unit per year (Rp/kg/year)

To address demand uncertainty, Monte Carlo simulation was applied using 1,000 iterations. The simulation modeled stochastic demand variability using a normal probability distribution based on historical demand data. The probability assumption followed a normal distribution because historical demand patterns demonstrated relatively symmetrical fluctuation characteristics. The historical annual demand data produced a mean demand value of 1,200,000 kg/year with a standard deviation of 25,000 kg/year.

Random demand values were generated in each iteration using the following stochastic demand formulation:

$$Di = \mu + Z\sigma$$

Di = Simulated demand value

μ = Mean annual demand
σ = Standard deviation
Z = Random variable generated from standard normal distribution

Each simulated demand value was subsequently used to recalculate EOQ and total inventory cost during every iteration. The recalculation mechanism enabled the inventory model to adapt dynamically to fluctuating demand conditions. Similar stochastic simulation procedures were also implemented by Riniwati et al. (2020), who demonstrated that probabilistic simulation improves operational decision-making under uncertain logistics conditions. The simulation process consisted of the following stages:

1. Determining historical demand mean and standard deviation.
2. Generating random demand values using normal probability distribution.
3. Recalculating EOQ values for each demand scenario.
4. Estimating total inventory costs for each iteration.
5. Comparing conventional EOQ and dynamic EOQ performance results.
6. Evaluating simulation stability and confidence intervals.

The simulation outputs were analyzed using a 95% confidence interval to evaluate model consistency and operational reliability. Validation was conducted by comparing simulated inventory cost behavior with historical operational inventory data from the company. Sensitivity analysis was additionally performed to evaluate the stability of the proposed model under changing ordering costs and holding costs. Sustainability integration within the model was operationalized using measurable sustainability indicators. The sustainability variables are presented in Table 1.

Table 1
Sustainability Indicators Used in the Research

Sustainability Aspect	Indicator
Waste Reduction	Percentage of material reuse (%)
Resource Efficiency	Warehouse utilization efficiency (%)
Environmental Impact	Reduction of excess inventory (%)
Circular Logistics	Reuse of production residual materials (%)
Energy Efficiency	Reduction of unnecessary storage utilization

The sustainability indicators were integrated into the inventory evaluation process to ensure that the proposed EOQ framework considered not only economic efficiency but also environmental performance and resource optimization. The research also incorporated closed-loop supply chain principles through the reuse of residual production materials to minimize production waste and improve material utilization efficiency. This approach is consistent with Wang et al. (2021), who emphasized that sustainable operational systems improve environmental responsibility and resource efficiency within industrial activities.

In addition, sustainability integration within the proposed inventory model was conducted by considering energy efficiency, raw material utilization, and production waste reduction. According to Li et al. (2022), modern EOQ models should incorporate environmental considerations to achieve both economic and ecological efficiency simultaneously. Therefore, this research integrated sustainability indicators into the inventory evaluation process to measure operational efficiency and environmental performance concurrently.

This research also implemented the CLSC concept, which enables residual materials and production waste to be reused within the logistics cycle, thereby reducing unnecessary material disposal and improving resource utilization efficiency. Khan et al. (2025) explained that the integration of Industry 4.0 technologies and sustainable supply chain systems strengthens operational resilience and supports environmentally responsible manufacturing practices.

Data were collected through three primary techniques, namely direct observation of procurement and raw material storage activities, structured interviews with logistics and purchasing personnel, and documentation analysis consisting of purchasing reports, operational cost records, and inventory demand reports. Data validity was strengthened through source triangulation to ensure information consistency, reliability, and accuracy, as suggested (Sugiyono, 2022).

Data analysis was conducted through two major stages. First, a deterministic EOQ model was calculated to determine the baseline ordering quantity and total inventory cost under stable demand assumptions. Second, Monte Carlo simulation was performed to evaluate the impact of stochastic demand variability on EOQ values and inventory costs, thereby generating a dynamic inventory model capable of adapting to uncertain business environments.

The simulation results were subsequently utilized to compare the efficiency performance between the conventional EOQ model and the proposed dynamic EOQ framework. Finally, sensitivity analysis was conducted to evaluate model stability under changes in ordering costs and holding costs. This approach is consistent with Ross (2010), who explained that stochastic simulation-based risk analysis is effective in evaluating uncertainty and operational decision-making under probabilistic conditions. Data analysis was conducted in two major stages. The first stage involved conventional EOQ analysis to determine baseline inventory efficiency under deterministic conditions. The second stage involved Monte Carlo simulation analysis to evaluate dynamic inventory behavior under stochastic demand conditions. Comparative analysis was then conducted to evaluate differences in inventory cost efficiency, ordering behavior, waste reduction, and operational adaptability between conventional EOQ and dynamic EOQ models.

Result and Discussion

The research produced a dynamic EOQ framework integrating Monte Carlo simulation, sustainability principles, IoT, and Industry 4.0 concepts to improve inventory efficiency under uncertain demand conditions. The proposed model was evaluated using operational data obtained from PT Golden Box Indonesia, a corrugated box manufacturing company in Surabaya, Indonesia, during the 2020–2024 period.

Result

Conventional EOQ Analysis

The initial analysis was conducted using the deterministic EOQ model to determine the baseline inventory performance under stable demand assumptions. The calculation produced an optimal order quantity of 70,890 kg per order cycle with a total inventory cost of Rp 10,633,750 annually in Table 2.

Table 2

Conventinal EOQ Calculation Results

Parameter	Value (IDR)	Units
Annual Demand (*D*)	1.200.000	kg /year
Ordering Cost (*S*)	150.000	Rp/order
Holding Cost (*H*)	2.000	Rp /kg /year
Optimal EOQ (*Q*)	70.890	kg /order
Total Inventory Cost (*TC*)	10.633.750	Rp /year

Source: Data Processed (2024)

The conventional EOQ model successfully balanced ordering costs and holding costs under deterministic assumptions. However, the model remained limited because it assumed stable demand conditions and could not dynamically respond to stochastic fluctuations occurring in actual manufacturing operations. This limitation potentially increases the risk of excess inventory or stock shortages when market demand changes significantly.

Monte Carlo Simulation Results

To overcome the limitations of deterministic inventory systems, Monte Carlo simulation was applied using 1,000 stochastic demand iterations. The simulation generated probabilistic demand scenarios based on a normal distribution with a mean demand of 1,200,000 kg/year and a standard deviation of 25,000 kg/year.

The simulation results are presented in Table 3.

Table 3

Monte Carlo Simulation Dynamic EOQ Results

Iteration	Demand (kg)	EOQ (kg)	Total Cost (Rp)	Efficiency (%)
1	1.180.000	69.300	10.520.000	1,1
250	1.210.000	71.200	9.950.000	6,4
500	1.230.000	70.950	9.720.000	8,6
750	1.195.000	70.500	9.460.000	11,0
1.000	1.205.000	70.890	9.380.000	12,0
Average	–	**70.890 ± 2.500**	**9.806.000**	**9,0**

Source: Data Processed (2024)

The simulation results indicate that the proposed dynamic EOQ model reduced inventory costs by approximately 8–12% compared with the conventional EOQ approach. The average total inventory cost decreased from Rp 10,633,750 to Rp 9,806,000 annually.

The efficiency improvement occurred because the dynamic EOQ framework adapted ordering decisions according to stochastic demand variability. Unlike the deterministic EOQ model, which assumes fixed demand values, Monte Carlo simulation continuously recalculated ordering quantities based on probabilistic demand scenarios. Consequently, the inventory system became more responsive to operational uncertainty and reduced excessive stock accumulation.

The simulation results also demonstrate that stochastic variability significantly influenced ordering decisions. The EOQ fluctuation range of 70,890 ± 2,500 kg indicates that inventory requirements varied depending on demand uncertainty. This variability reflects actual industrial conditions where procurement decisions must continuously adjust to changing market demand patterns.

The simulation outputs were further evaluated using a 95% confidence interval to assess the reliability of the stochastic model. The relatively small deviation range indicates that the proposed dynamic EOQ model maintained operational stability despite demand fluctuations. The low variability level suggests that the inventory system was capable of controlling operational risk effectively while maintaining procurement efficiency.

From a risk analysis perspective, the stochastic simulation reduced the probability of inventory shortages and excessive inventory accumulation. The adaptive recalculation mechanism allowed procurement activities to remain flexible under uncertain business conditions. This finding supports Ross (2010), who explained that stochastic simulation improves decision-making quality by modeling uncertainty probabilistically.

Inventory Cost Efficiency Analysis

The comparative analysis between conventional EOQ and dynamic EOQ models is presented in Table 4 and Figure 1.

Table 4

Comparison Between Conventional and Dynamic EOQ Models

Indicator	Conventional EOQ	Dynamic EOQ
Order quantity	70,890 kg	70,890 ± 2,500 kg
Inventory cost	Rp 10,633,750	Rp 9,806,000
Demand assumption	Deterministic	Stochastic
Operational adaptability	Low	High
Waste reduction	Limited	Integrated
Sustainability integration	No	Yes

Source: Data Processed (2024)

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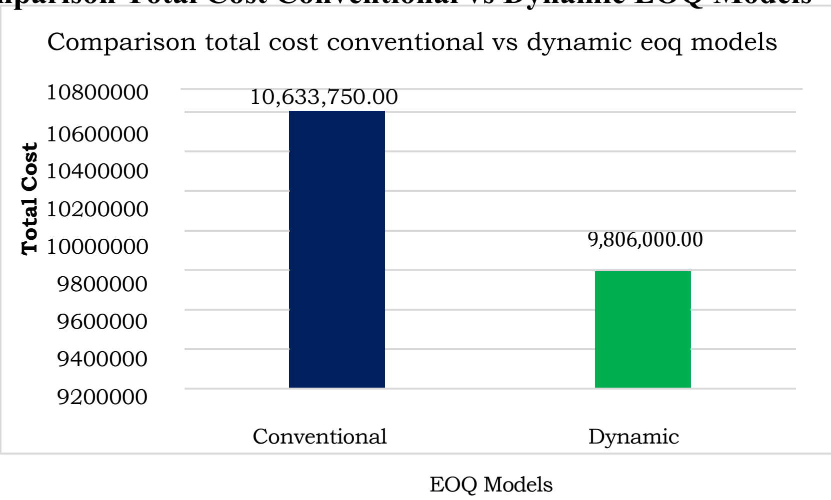
Figure 1

Comparison Total Cost Conventional vs Dynamic EOQ Models



Source: Data Processed using Excel

The results demonstrate that the dynamic EOQ model achieved better operational adaptability and inventory efficiency than the conventional model. The integration of Monte Carlo simulation enabled the inventory system to anticipate uncertain demand conditions more effectively, thereby minimizing unnecessary storage costs and procurement inefficiencies.

The implementation of Industry 4.0 concepts and IoT-based monitoring systems also improved inventory visibility and procurement responsiveness. Real-time operational monitoring allowed inventory data to be processed more accurately and supported faster inventory decision-making processes. Khan et al. (2025) explained that Industry 4.0 technologies strengthen supply chain responsiveness and operational sustainability through integrated digital systems.

Sustainability Performance Analysis

The proposed model also integrated sustainability indicators into inventory evaluation. Sustainability performance was measured through waste reduction percentage, warehouse utilization efficiency, and reuse of residual production materials through CLSC practices.

Sustainability Indicator	Before Integration	After Integration	Improvement
Material waste	12%	7%	5% reduction
Warehouse utilization	78%	88%	10% increase
Residual material reuse	15%	32%	17% increase
Excess inventory level	18%	9%	9% reduction

Source: Data Processed (2024)

The results indicate that sustainability integration improved both operational efficiency and environmental performance. Material waste decreased from 12% to 7% after the implementation of closed-loop supply chain practices. The reduction was achieved through the reuse of residual production materials within the logistics cycle, thereby minimizing unnecessary disposal activities and improving raw material utilization efficiency.

Warehouse utilization efficiency also increased from 78% to 88% because the adaptive EOQ framework reduced excessive inventory accumulation. The reduction of excess inventory indirectly decreased energy consumption related to warehouse operations and storage maintenance activities.

Furthermore, the percentage of residual material reuse increased significantly from 15% to 32%, indicating that sustainability-oriented inventory management contributed positively to circular resource utilization. These findings support Li et al. (2022), who emphasized that sustainable inventory systems improve both environmental and economic performance simultaneously.

Discussion

The findings demonstrate that integrating Monte Carlo simulation, sustainability principles, and Industry 4.0 technologies creates a more adaptive inventory management system capable of responding to uncertain operational conditions. The dynamic EOQ model improved procurement flexibility, reduced inventory costs, minimized waste generation, and strengthened resource efficiency. Unlike previous EOQ studies focusing solely on economic optimization, this research incorporated sustainability and digital transformation as operational variables within inventory decision-making. The integration of IoT technology and closed-loop supply chain systems strengthened inventory visibility and improved the utilization of residual materials in manufacturing activities. These findings reinforce the classical EOQ theory proposed by Heizer et al. (2009), which emphasizes the balance between ordering costs and holding costs, while simultaneously extending its application within modern industrial contexts. The reduction in total inventory costs by approximately 9% demonstrates the effectiveness of the dynamic model in improving economic efficiency and optimizing warehouse capacity utilization.

The integration of sustainability aspects also provides significant added value. Consistent with Li et al. (2022), sustainability integration within dynamic EOQ systems encourages companies not only to minimize operational costs but also to reduce ecological impacts through energy efficiency and waste management practices. Similarly, the closed-loop supply chain concept proposed by Wang (2021) strengthens the logistics cycle by enabling resources and residual materials to be reused productively within operational activities. Therefore, the sustainability-oriented dynamic EOQ model developed in this research not only improves inventory cost efficiency but also addresses industrial demands for adaptation to digital transformation and environmental responsibility principles in the Industry 4.0 era.

The research also contributes theoretically by extending classical EOQ concepts into a dynamic and sustainability-oriented inventory framework. Practically, the proposed model provides manufacturing companies with a more responsive inventory management approach suitable for Industry 4.0 environments characterized by uncertainty, digital transformation, and sustainability pressure.

However, this research still has several limitations. The simulation model utilized operational data from a single manufacturing company, limiting the generalizability of the findings across industrial sectors. In addition, environmental indicators were limited to waste reduction and warehouse utilization efficiency. Future research is recommended to incorporate broader sustainability indicators such as carbon emissions, energy consumption, and lifecycle environmental assessment to strengthen sustainability analysis comprehensively.

Conclusion

This research concludes that the dynamic EOQ model developed using Monte Carlo Simulation successfully improved inventory control efficiency at PT. Golden Box Indonesia under uncertain demand conditions. The proposed stochastic inventory model proved to be more adaptive than the conventional EOQ approach by dynamically adjusting ordering decisions according to fluctuating demand patterns, resulting in inventory cost efficiency improvements of approximately 8–12%. In addition, the integration of sustainability principles and CLSC practices contributed to reducing raw material waste and improving resource utilization efficiency within manufacturing operations.

These findings demonstrate that simulation-based stochastic models are more representative and reliable under conditions of demand uncertainty. In addition to cost efficiency improvements, this research also emphasizes the importance of integrating sustainability principles into inventory management systems. The implementation of the CLSC concept successfully reduced raw material waste by up to 5% per production cycle, aligning with industrial efforts to optimize resource utilization and minimize environmental impact. Therefore, the sustainability-oriented dynamic EOQ model developed in this research can serve as an effective strategy for enhancing economic efficiency while simultaneously supporting industrial sustainability objectives in the Industry 4.0 era. The integration of Monte Carlo simulation, IoT-based operational concepts, and sustainability indicators also extends the application of classical EOQ theory into a more adaptive and digitally integrated inventory management framework suitable for modern industrial challenges.

However, this research was limited by the use of operational data from a single manufacturing company and relatively limited sustainability indicators, which may restrict the generalizability of the findings across different industrial sectors. Therefore, future research is recommended to develop AI-based predictive EOQ systems, integrate real-time IoT inventory monitoring, apply hybrid machine learning forecasting methods, and incorporate multi-objective sustainability optimization variables such as carbon emissions, energy consumption, and environmental lifecycle assessment.

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