ANALYSIS OF PT SEMEN INDONESIA'S SUPPLY CHAIN USING PRODUCTION ORDER QUANTITY AND FORECASTING MODELS FOR ORDER OPTIMIZATION

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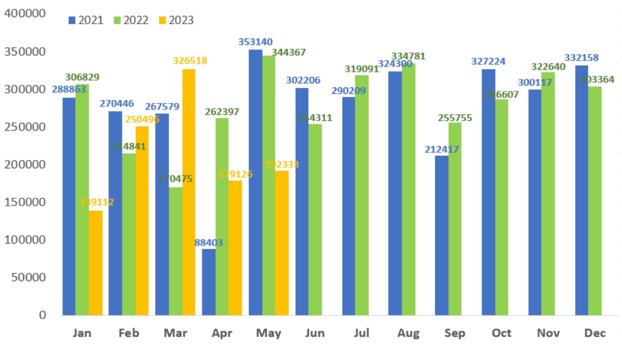
***ABSTRACT**: This study investigates the integration of quantitative inventory management techniques—Mean Absolute Deviation (MAD), Economic Order Quantity (EOQ), and Production Order Quantity (POQ)—within the production operations of PT Semen Merah Putih Indonesia, a major cement manufacturer. Analysis of clinker production data from 2021 to 2023 identified a substantial decline in output in 2023, attributed to an increase in kiln stoppage days (82 days), which adversely affected production continuity and efficiency. The MAD method quantified significant deviations between forecasted and actual demand, indicating inadequate forecasting accuracy. EOQ modelling yielded an optimal order quantity of 740,548.45 tons, effectively minimizing total inventory costs through a balance of ordering and holding costs. The POQ model recommended a 24-day production cycle, providing a more consistent and cost-effective scheduling approach aligned with production capacity and demand variability. The results highlight the operational benefits of integrating statistical forecasting with inventory control models in large-scale manufacturing environments. The combined application of EOQ and POQ supports both cost reduction and production stability, enhancing the responsiveness of the supply chain. Future research should focus on dynamic EOQ adaptations under fluctuating demand, integration with Just-In-Time (JIT) methodologies, and the inclusion of sustainability parameters—such as energy consumption and waste reduction—into inventory optimization frameworks.*

***KEYWORDS**: Supply Chain, Production Order Quantity (POQ), Economic Order Quantity (EOQ), Mean Absolute Deviation (MAD), Inventory Optimization*

1 INTRODUCTION

Economic growth and global development are interconnected but have distinct focuses. Economic growth refers to the increase in the total value of goods and services produced, typically measured by GDP. In contrast, global development encompasses a broader spectrum, including poverty reduction, environmental sustainability, and improvements in the quality of life. Economic growth is one component of international development, but without equitable distribution and environmental protection, it can lead to inequality and instability (Qiu et al., 2021). Global development, emphasized by the Sustainable Development Goals (SDGs), stresses the importance of holistic approaches, combining economic, social, and environmental aspects to improve well-being worldwide. Infrastructure development plays a key role in global development, supporting economic growth and improving the quality of life. However, there are challenges, such as unequal access to infrastructure between developed and developing nations, as well as the need for sustainable and environmentally conscious infrastructure. Financing and investment limitations in developing countries also hinder progress in infrastructure development. In Indonesia, companies like Semen Indonesia Group (SIG) play a significant role in the nation's construction industry and infrastructure development. With a focus on sustainability and innovation, SIG exemplifies how companies can balance economic growth with environmental responsibility (Andini & Mirwan, 2023).

Figure 1 shows the data summarizes monthly Clinker Production from 2021 to 2023, including year-to-date (YTD) totals, annual totals, and kiln stop days. It highlights production patterns and variations due to operational factors, particularly kiln stoppages. The differences in production across the years provide insights into factors affecting production efficiency, serving as a foundation for strategies to enhance stability and performance.



	Jan	Feb	Mar	Apr	May	YTD	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total	Kiln Stop
2021	288863	270446	267579	88403	353140	1268432	302206	290209	324300	212417	327224	300117	332158	3357063	48 (Days)
2022	306829	214841	170475	262397	344367	1298908	254311	319091	334781	255755	286607	322640	303364	3375457	47 (Days)
2023	139112	250496	326518	179126	192333	1087585								1087585	22(Days)

Fig. 1 Data Production Clinker

From the data obtained, this research aims to evaluate and optimize the production planning and inventory management processes at PT Semen Merah Putih by applying Mean Absolute Deviation (*MAD*), Economic Order Quantity (*EOQ*), and Production Order Quantity (*POQ*) methods, with the goal of improving forecasting accuracy, minimizing inventory-related costs, and enhancing operational efficiency.

2 OVERVIEW ON PREVIOUS WORK

Mean Absolute Deviation (*MAD*), Production Order Quantity (*POQ*), and Economic Order Quantity (*EOQ*) are fundamental tools in production planning and inventory management (Josef Packowski, 2013). Each method addresses distinct aspects of inventory control and production efficiency, helping companies manage resources more effectively (Susilowati et al., 2025) (Kustiantoro, 2020). By examining each approach individually, we can understand how these methodologies work together to optimize production and reduce costs, enabling businesses to respond better to market demands and operational needs (Z. Dai et al., 2020). *MAD* is primarily used to measure the accuracy of demand forecasting by calculating the average deviation between forecasted and actual demand. This method enables companies to assess forecasting errors and make adjustments accordingly (Dmitry Ivanov, Alexander Tsipoulanidis, 2021). Accurate demand forecasting is critical for efficient inventory management, as it allows companies to align stock levels more closely with actual demand, reducing the chances of overproduction or stockouts. By continuously evaluating forecast accuracy with *MAD*, businesses can enhance their inventory management strategies, better predict demand fluctuations, and allocate resources more effectively (Hertini et al., 2018).

POQ offers a flexible approach to determining optimal production or order quantities, especially in industries where demand is variable. Unlike *EOQ*, which assumes a constant demand rate, *POQ* adjusts production quantities based on fluctuating consumption rates, making it ideal for sectors such as oil and gas where production needs vary frequently (Thyagaraj S. Kuthambalayan and Samiran Bera, 2020). *POQ*'s adaptability allows businesses to produce quantities that align more closely with real-time consumption, reducing excess inventory and lowering setup costs (Banias, 2019). By matching production with demand cycles, *POQ* helps minimize holding costs and ensures resources are utilized efficiently, avoiding the financial strain of overstock (Zhang et al., 2012). The Economic Order Quantity (*EOQ*) model is a classic inventory management tool that calculates the optimal order size to balance the combined costs of ordering and holding inventory (Du et al., 2021). *EOQ* is particularly suitable for environments with stable demand, where companies can maintain a consistent inventory level to meet steady consumption (Wang et al., 2024) (Haris et al., 2018). The *EOQ* model helps businesses strike a balance between frequent ordering and holding adequate stock to meet demand. By applying *EOQ*, companies can reduce unnecessary costs, optimize inventory levels, and streamline supply chain operations, enhancing overall operational efficiency in stable-demand environments (Juneho Um and Neungho Han, 2021).

Together, *MAD*, *POQ*, and *EOQ* provide a comprehensive approach to optimizing production planning and inventory management (B. Dai et al., 2021). *MAD* offers insights into forecast accuracy, *POQ* enables flexibility for variable demand, and *EOQ* provides cost-efficiency in stable settings (Tordecilla et al., 2021). Integrating these methodologies allows companies to improve accuracy, adaptability, and cost efficiency, aligning production more closely with demand while minimizing waste. This combined approach supports robust inventory control and enhances companies' ability to meet market demands effectively, fostering long-term operational success (Haris et al., 2018). *EOQ* model, as applied in the current research, assumes constant demand and simplified cost structures, revealing several potential research gaps.

First, real-world demand often fluctuates, yet this model presumes a stable demand rate. Future research could explore *EOQ* adjustments in response to variable demand patterns and their impact on total costs. Moreover, incorporating additional cost factors such as stockout and transportation costs could provide a more comprehensive understanding, as the current model only considers ordering and holding costs.

Another significant gap lies in the applicability of EOQ in lean supply chains, especially those adopting Just-In-Time (JIT) principles (Wazzan et al., 2021). Traditional *EOQ* models might not align with lean practices focused on inventory reduction. Research examining *EOQ* adaptations in lean or JIT systems could yield valuable insights into inventory management practices that align with modern supply chain efficiency goals. Additionally, exploring the influence of dynamic pricing and volume discounts, which frequently affect unit costs, would extend the *EOQ* model's relevance in competitive and fluctuating markets (Noche & Elhasia, 2013). Finally, environmental sustainability and technological advancements offer fertile grounds for extending the *EOQ* framework. Integrating sustainability considerations, like carbon emissions and waste reduction, could create an *EOQ* model aligned with environmental goals. Additionally, leveraging technologies such as blockchain and IoT to incorporate real-time data could significantly enhance *EOQ* optimization. Research that closes these gaps would contribute to an *EOQ* model that is more adaptable, sustainable, and suited to complex, data-rich environments (Gunasekaran & Ngai, 2009)

3 MEYHODOLOGY

This research addresses inefficiencies in PT Semen Indonesia's production planning by evaluating the integration of demand forecasting and the *POQ* system (Rebs et al., 2019). It identifies gaps between forecasted and actual demand, leading to issues like overproduction, underproduction, and increased costs. Using a mixed-methods approach, the study analyzes historical data and gathers insights from key stakeholders. The goal is to optimize production orders, reduce excess inventory, and improve operational efficiency to better meet market demand.

3.1 Operational framework

The operational framework of this study focuses on evaluating the integration of PT Semen Indonesia's demand forecasting models with the *POQ* system to enhance production planning and minimize inefficiencies. It begins with collecting and analyzing historical data on production, inventory, and sales, alongside reviewing the accuracy of current forecasting models. The next step involves identifying gaps between forecasted and actual market demand, which result in overproduction or underproduction, and assessing the impact of these gaps on costs and inventory management. Qualitative insights are gathered through interviews or surveys with key personnel in procurement, production, and distribution to uncover internal challenges affecting planning accuracy. Based on this analysis, optimization strategies are proposed to improve the alignment of forecasting models with the *POQ* system, ensuring better demand responsiveness (Gunasekaran & Ngai, 2009). The final stage includes evaluating the effectiveness of the proposed improvements by monitoring key performance indicators (KPIs) related to cost efficiency, inventory levels, and customer satisfaction. This comprehensive framework aims to drive long-term operational improvements in PT Semen Indonesia's supply chain.

3.2 Primary data

The collection of primary data in this study is conducted directly from PT Semen Indonesia using real data related to production planning, inventory management, and demand forecasting. This data includes factual information on production order quantities, inventory levels, and the accuracy of demand forecasts over a specific period. Primary data is gathered from various relevant departments such as production management, distribution, and supply chain to provide a comprehensive view of operational processes.

The data collection involves direct observation of the production processes, interviews with key staff involved in production planning and execution, and operational reports from the company. The data will be analyzed to identify inefficiencies in production planning, particularly the misalignment between market demand and production orders determined by the Production Order Quantity (*POQ*) and Economic Order Quantity (*EOQ*) systems. It will also include information on inventory surplus or shortages resulting from inaccurate demand forecasting. By utilizing this primary data, the study aims to provide real-world insights into operational conditions, allowing for a thorough evaluation of the effectiveness of the production planning methods employed by PT Semen Indonesia.

3.3 Data analysis

The data analysis in this study aims to evaluate the effectiveness of PT Semen Indonesia's production planning using the Production Order Quantity (*POQ*) and Economic Order Quantity

(*EOQ*) methods. These analyses will be conducted through both quantitative and qualitative approaches, utilizing real data on production volumes, inventory levels, and demand forecasts. Descriptive statistics will summarize key performance indicators such as average production volume and inventory turnover for quantitative analysis. The variance between forecasted and actual demand will be calculated using the formula for Mean Absolute Deviation (*MAD*),

$$MAD = \frac{\sum |D_i - F_i|}{n} \quad (1)$$

where, D_i represents the actual demand, F_i the forecasted demand, and n the number of periods. This measure helps to identify discrepancies and inefficiencies in production planning. For inventory management, the Economic Order Quantity (*EOQ*) formula will be used to determine the optimal order quantity,

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (2)$$

where, D is the annual demand, S is the setup cost per order, and H is the holding cost per unit per year. This will allow for the cost-effectiveness of inventory orders to be assessed. The *POQ* method will also be analyzed using its formula for production lot size.

$$POQ = \frac{\text{EOQ}}{\text{Prod. rate - Demand rate}} \quad (3)$$

This ensures production schedules align with fluctuating demand. Cost analysis will further determine the impact of overproduction (storage costs) and underproduction (lost sales opportunities). For qualitative analysis, insights from interviews will be coded and thematically analyzed, identifying operational challenges. A comparative analysis between the *EOQ* and *POQ* methodologies will highlight which approach better aligns production with real-time demand. The goal is to propose optimization strategies based on these findings, helping PT Semen Indonesia reduce costs and enhance supply chain efficiency.

Table 1 summarizes the monthly production records of Clinker Line #2 from 2021 to 2023, including monthly outputs, year-to-date (YTD) totals, annual totals, and kiln stop days. It provides essential insights into production performance, annual trends, and the impact of operational shutdowns. Analyzing this data helps optimize capacity planning, improve maintenance strategies to reduce downtime, and develop efficient, future-oriented production plans. It also serves as a guide for creating production schedules responsive to demand and operational needs, ensuring target achievement with maximum efficiency.

Table 1. Production Data Clinker

Year/ Month	Jan	Feb	Mar	Apr
2021	238809	255432	280555	281537
2022	347067	234818	352859	323351
2023	263341	236378	177444	309157
Year/ Month	**May**	**June**	**July**	**Aug**
2021	288557	220286	284111	253983
2022	325859	167090	321704	318265
2023	339472	290807	-	-
Year/ Month	**Sept**	**Oct**	**Nov**	**Dec**
2021	301511	204786	311131	268713
2022	321626	294408	312694	345995
2023	-	-	-	-

4 RESULTS AND DISCUSSION

The analysis of production planning and inventory management at PT Semen Indonesia, using Mean Absolute Deviation (*MAD*), Economic Order Quantity (*EOQ*), and Production Order Quantity (*POQ*) models, provides valuable insights into the company's operational efficiency and forecasting accuracy over the years 2020, 2021, and 2022.The primary result aim to discuss is the calculated Economic Order Quantity (*EOQ*) derived from the demand, ordering, and holding costs, as well as the visual representation of its impact on total costs. This *EOQ* value represents the optimal order quantity to minimize the combined ordering and holding costs. Discussing these results is essential because understanding the *EOQ* provides valuable insights into cost management and inventory optimization, helping businesses find the balance between ordering frequently (which increases ordering costs) and holding large quantities (which raises holding costs). By examining this result, we can see how *EOQ* functions as a tool to achieve cost-effective inventory management, which is crucial for businesses aiming to improve operational efficiency and reduce unnecessary expenses.

4.1 Mean Absolute Deviation (MAD)

The data includes only two years. For average monthly demand calculation (Forecast for *MAD*), the average demand for each month using data from 2021 and 2022 was used. These monthly averages will serve as our forecasted demand (Forecast Fi) for the *MAD* calculation. Average demand for January calculated as below.

$$Ave.\,demand = \frac{23{,}8809 + 34{,}7007 + 26{,}3341}{3}$$
$$= 28{,}3072.33 \text{ tons}$$

Table 2 below presents demand data for 2021 and 2022, along with the average monthly demand forecast, denoted as Fi. This forecast represents the anticipated monthly demand based on historical data and is measured in tons, offering a detailed month-by-month view essential for analyzing demand trends and assessing forecasting accuracy.

Table 2. Demand data for 2021 and 2022

Month	2021 Demand (Tons)	2021 Demand (Tons)	Forecast Fi (Tons)
Jan	238,809.00	347,067.00	283,072.33
Feb	255,432.00	234,818.00	242,209.33
Mar	280,555.00	352,859.00	270,286.00
Apr	281,537.00	323,351.00	304,681.67
May	288,557.00	325,859.00	317,962.67
Jun	220,286.00	167,090.00	226,061.00
July	284,111.00	321,704.00	302,907.50
Aug	253,983.00	318,265.00	286,124.00
Sep	301,511.00	321,629.00	311,070.00
Oct	204,786.00	294,408.00	249,597.00
Nov	311,131.00	312,694.00	311,912.50
Dec	268,713.00	345,995.00	307,354.00
Total	3,189,411.00	3,665,739.00	
Total Mean 2 Year		6.866,150.00	3,427,575.00

Figure 2 illustrates monthly demand patterns (in tons) for 2021, 2022, and the average forecast (Forecast F_i). The data reveals higher volatility in 2022, with demand peaks in March and December exceeding both 2021 figures and the forecasted average, while June 2022 shows a notable drop below previous years and projections. These patterns provide valuable insights for future stock and production planning, enabling strategic adjustments in anticipation of monthly demand trends.

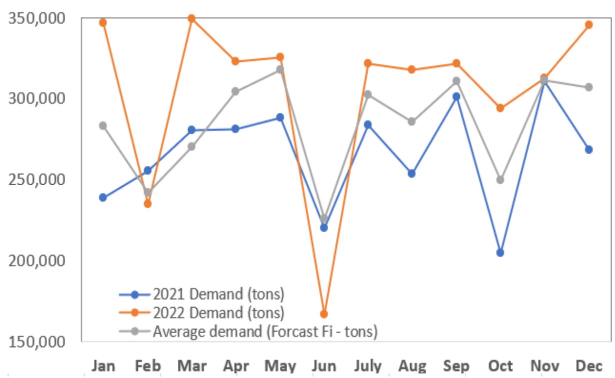


Fig. 2 Data Production

4.2 Economic Order Quantity (*EOQ*)

The Economic Order Quantity (*EOQ*) is calculated to be 740,548.45 tons, which means that ordering this quantity per order minimizes the total inventory costs by balancing ordering and holding costs effectively. With an annual demand, *D* = 3,427,575 tons, a setup cost, *S* = Rp1,000,000,000 every three months (with amount of Rp4,000,000,000), and a holding cost, *H* = Rp50,000 per ton per year, the *EOQ* model helps determine the optimal order size to reduce overall inventory expenses. The following is a sample calculation based on these values by using Eqn. 2. With the *EOQ* = 740,548.45 tons, it means that ordering 740,548.45 tons per order minimizes the total inventory costs, balancing the costs of ordering and holding inventory effectively.

$$EOQ = \sqrt{\frac{2DS}{H}}$$
$$= \sqrt{\frac{2 \times 3{,}427{,}575 \times 4{,}000{,}000{,}000}{50{,}000}}$$
$$= \sqrt{548{,}412{,}000{,}000}$$
$$= 740{,}548.45 \text{ tons}$$

Figure 3 represent the Economic Order Quantity (*EOQ*) model, showing the relationship between the order quantity (*Q*) and the total cost. The blue curve illustrates the total cost function, which decreases initially and reaches a minimum at the *EOQ* point, then starts to rise as the order quantity increases further. The blue dashed line marks the *EOQ* at approximately 740,548.45 tons, where the total cost is minimized. This optimal order quantity balances ordering and holding costs, providing the most cost-effective order size for inventory management.

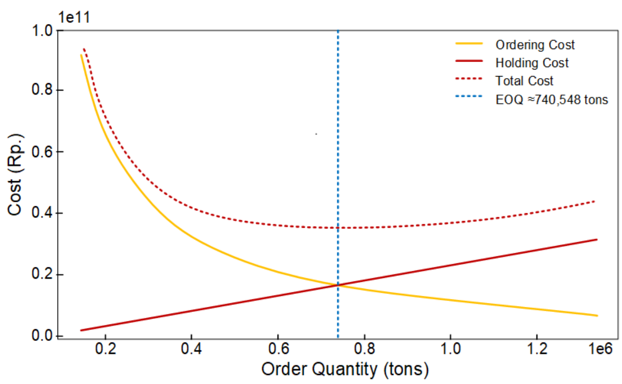


Fig. 3 Economic Order Quantity (EOQ) Model

4.3 Production Order Quantity (*POQ*)

The Period Order Quantity (*POQ*) method is utilized to determine the optimal replenishment interval that minimizes total inventory costs, particularly in systems where ordering and holding costs must be carefully balanced. In the present case, the *EOQ* is determined to be 740,548.45 tons, reflecting the order quantity that minimizes the combined ordering and holding costs. The annual demand, D = 3,427,575 tons, while the setup cost, S = Rp1,000,000,000 per order, incurred every three months. The annual holding cost, H = Rp50,000 per ton. To compute *POQ*, first need to determine the demand per period. Since the setup cost is incurred quarterly, each period is defined as three months (a quarter). Thus,

$$\text{Quarterly demand} = \frac{3{,}427{,}575}{4} = 856{,}893.75 \text{ tons}$$

Substituting into the *POQ* formula:

$$\text{POQ} = \frac{740{,}548.45}{856{,}893.75} \approx 0.8645 \text{ quarters}$$

To express *POQ* in months: 0.8645 x 2.59 months, the computed *POQ* of 0.8645 quarters (approximately 2.6 months) implies that the optimal ordering interval is slightly less than a full quarter. In practical terms, the firm should issue a replenishment order approximately every 2.6 months. This interval minimizes total inventory-related expenditures by aligning order frequency with both demand levels and cost structures. This *POQ*-based ordering strategy offers a more dynamic and responsive alternative to fixed-period replenishment, especially in high-volume inventory systems with significant setup costs. This study utilizes the *POQ* model to optimize the production cycle at PT Semen Merah Putih Indonesia, a leading cement manufacturing company in Indonesia. With a maximum production capacity of 40,000 tons per day, an annual production rate, P, for the company is,

$$\begin{aligned} P &= 40{,}000 \times 365 \\ &= 14{,}600{,}000 \text{ tons/year} \end{aligned}$$

Meanwhile, the anual demand for cement reorder dead at D = 3,427, 575 tons/year. Given an *EOQ* = 740,548.45 tons, the POQ is calculated using the Eqn. 3 for standard production inventory.

$$\begin{aligned} POQ &= \frac{EOQ}{P - D} \\ &= \frac{740{,}548.45}{14{,}600{,}000 - 3{,}427{,}575} \\ &\approx 0.06627 \text{ years} \\ &= 740{,}548.45 \text{ tons} \end{aligned}$$

To facilitate operational scheduling, this value is converted into days; The result indicates that the optimal production run per cycle should last approximately 24 days, aligning with the *EOQ* to minimize total inventory costs while preventing overproduction. The implementation of *POQ* in this context provides several strategic advantages, including stabilization of production schedules, reduction in holding costs particularly critical for cement storage and improved machinery maintenance planning. Moreover, due to the significant gap between production and demand rates, the use of *POQ* is highly effective in supporting lean inventory systems within large-scale continuous production environments.

5 CONCLUSION

This study demonstrates that integrating quantitative inventory management techniques, *MAD*, *EOQ*, and *POQ* can significantly enhance production planning and inventory control in the cement industry. At PT Semen Merah Putih Indonesia, analysis of clinker production from 2021 to 2023 revealed that a sharp decline in 2023 output, due largely to 82 days of kiln downtime, disrupted operational efficiency. The *MAD* method exposed significant deviations between forecasted and actual demand, underscoring weaknesses in demand planning. The *EOQ* model identified an optimal order quantity of 740,548.45 tons, effectively balancing setup and holding costs to reduce total inventory expenses. The *POQ* model suggested a 24-day production cycle, aligning production scheduling with capacity and demand fluctuations.

These findings highlight the value of combining accurate forecasting with data-driven inventory strategies. The integration of *EOQ* for cost efficiency and *POQ* for production rhythm offers a comprehensive approach to managing demand variability, reducing waste, and improving operational performance. Future research should focus on adapting *EOQ* models to dynamic demand environments, incorporating Just-In-Time (JIT) principles, and embedding sustainability metrics such as energy use and waste reduction - into inventory planning frameworks. Overall, this case study provides strong empirical support for the adoption of mathematical models in promoting efficient and sustainable operations within the cement manufacturing sector.

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