INTERNATIONAL JOURNAL OF SOCIAL AND MANAGEMENT STUDIES (IJOSMAS)

Volume: 6 No. 5 https://www.ijosmas.org e-ISSN: 2775-0809

Operational Efficiency Improvement through Integrated Inventory Management and Control: Case Study of PT XYZ

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Abstract - *This study examines how integrated inventory control improves operational efficiency at PT XYZ, a wholesaler of imported frozen beef. We apply ABC classification, three time-series forecasting techniques (Moving Average, Exponential Smoothing, Least Squares), and the Economic Order Quantity (EOQ) model. At the SKU level, Exponential Smoothing consistently yields the lowest forecasting error across 2023–2024 and most closely tracks actual demand patterns. EOQ analysis indicates substantial cost efficiency relative to actual practices for the majority of SKUs; for instance, TRRL00068 achieves 43–45% annual savings over 2022–2024 and TRSFF00066 achieves 43–46% savings in the same period. These findings demonstrate that disciplined inventory control—anchored in accurate forecasting and EOQ-based ordering—reduces total inventory costs and supports more reliable service levels. The implications align with sustainable operations by lowering waste from overstock and mitigating stockout risks.*

Keywords: *inventory management, inventory control, ABC classification, forecasting method, economic order quantity.*

I. INTRODUCTION

Food security has become a strategic issue for Indonesia as a developing country with a population exceeding 280 million. Growing demand for protein sources, particularly beef, continues to outpace domestic production capacity, forcing the government and industry players to rely on imports. This condition generates complex challenges for companies engaged in the distribution of perishable goods, where effective inventory management becomes a critical determinant of operational continuity and customer satisfaction.

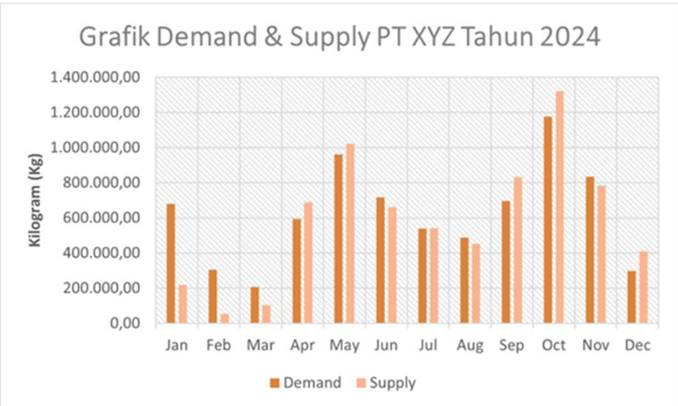

Figure 1.1. PT XYZs Demand-Supply Chart 2024

PT XYZ, a wholesaler specializing in imported frozen beef, illustrates these challenges. In recent years, the company has experienced significant fluctuations in demand and supply (Figure 1.1), which resulted in periods of overstock as well as frequent stockouts (Figure 1.2). Such imbalances not only disrupt service levels but also increase holding costs and the risk of lost sales opportunities. The situation reflects broader operational inefficiencies that, if left unresolved, could erode competitiveness and undermine long-term business sustainability.

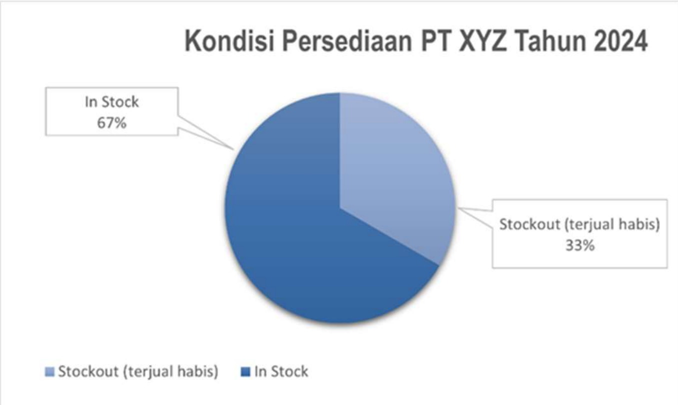

Figure 1.2. PT XYZ Inventory Conditions 2024

To address these challenges, structured inventory control methods offer practical solutions. Prior studies have demonstrated the effectiveness of tools such as ABC classification for prioritizing critical items, time-series forecasting for anticipating demand trends, and Economic Order Quantity (EOQ) for determining optimal order sizes. However, the application of these approaches in the context of perishable goods with fluctuating demand remains underexplored. This study seeks to bridge that gap by applying an integrated inventory control framework to the case of PT XYZ.

The purpose of this research is to analyze how inventory control methods can be optimized to improve operational efficiency. Specifically, the study evaluates the role of ABC classification in inventory prioritization, the accuracy of different forecasting methods, and the potential of EOQ to reduce overall inventory costs. By addressing these dimensions, the research contributes not only to operational improvements within PT XYZ but also to broader discussions on sustainable supply chain practices that align with global development objectives such as SDG 2 (Zero Hunger), SDG 8 (Decent Work and Economic Growth), and SDG 12 (Responsible Consumption and Production).

II. METHOD

This study employs a descriptive quantitative design to analyze the inventory management of frozen beef products at PT XYZ. The focus is to evaluate how structured inventory control approaches can improve operational efficiency. The research population consists of all products in PT XYZ's inventory, defined as units with specific characteristics relevant to the study. A total of 1,521 products recorded in the company's warehouse system formed the basis of the analysis. From this population, samples were determined using two criteria: products categorized as Class A in ABC classification and those actively distributed during the past three years.

Table 2.1. Research Samples

No	Item Code	Category	Source	Lead Time (Day)
1	BBSFF00066	A	Australia	23
2	KNKALN00001	A	New Zealand	23
3	LIPSFF00066	A	Australia	23
4	NMSFF000001	A	Australia	23
5	SPSWUS00082	A	USA	23
6	SRiSWUS01138	A	USA	23
7	TRRL00068	A	New Zealand	23
8	TRSFF00066	A	Australia	23

Based on these criteria, eight stock keeping units (SKUs) were selected for further analysis. Data were collected from the company's ERP/SAP system, ensuring completeness and accuracy. This included historical sales and inventory data covering the last 36 months, representing the operational involvement of products in the company's distribution activities. Three analytical techniques were applied. First, ABC classification was used to prioritize products based on their contribution to overall inventory value. Second, forecasting methods were employed to estimate future demand patterns, allowing more precise planning. Finally, the Economic Order

Quantity (EOQ) model was applied to determine optimal order sizes, with the objective of minimizing total inventory costs and aligning procurement decisions with operational needs.

III. RESULT AND DISCUSSION

A. Result

1. ABC Classification Results

Table 3.1. ABC Analysis

Klasifikasi	2022			2023			2024		
	Value	SKU	%	Value	SKU	%	Value	SKU	%
A	294.426	36	75%	381.963	30	75%	227.693	25	75%
B	57.382	28	15%	73.033	27	15%	43.321	25	15%
C	38.214	159	10%	49.521	135	10%	29.097	87	10%
Total	390.021	223	100%	504.517	192	100%	300.110	137	100%

Based on the ABC analysis of PT XYZ's sales data for the period 2022–2024, it was found that Category A consistently accounted for approximately 75% of total sales value each year. Interestingly, the number of SKUs in this category declined from 36 SKUs in 2022 to 25 SKUs in 2024. Despite the reduction, the value contribution remained dominant, reaffirming Category A as the primary driver of the company's sales performance. Category B contributed around 15% of total sales value, with the number of SKUs decreasing from 28 in 2022 to 25 in 2024. This trend suggests that the company has tightened control over medium-contribution products to avoid excess inventory. Meanwhile, Category C, which only contributed about 10% of total sales value, experienced a significant SKU reduction from 159 in 2022 to 87 in 2024, reflecting a rationalization of low-contribution products to improve warehouse efficiency. Overall, the decline in SKU numbers across all categories indicates an effort to streamline the product portfolio and focus on items with the highest value contribution. These results provide important implications for procurement planning, distribution strategies, and inventory control. By concentrating resources on high-impact products, the company can allocate inventory management efforts more effectively.

Following this classification, the study focuses on Category A as the main research sample, given its strategic importance. Although Category A consists of fewer SKUs compared to other categories, its consistent contribution of around 75% of total sales value positions it as a critical determinant of operational performance. Enhancing inventory control within this category is therefore expected to yield the most significant improvements in PT XYZ's efficiency and business sustainability.

2. Time-Forecasting Results

Forecasting simulations were conducted for eight selected SKUs representing Category A, using historical monthly demand data for the period 2022–2024.

Table 3.2. 2023 Moving Average Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	324	388	402	358	362	412	420	497	399	398	287	352	4.599
KNKALN00001	4	6	6	7	5	5	4	6	7	8	7	9	75
LIPSFF00066	167	183	178	160	130	148	172	183	177	184	200	213	2.095
NMSFF000001	173	263	279	293	219	248	307	321	314	236	220	262	3.137
SPSWUS00082	292	338	409	530	546	578	556	545	562	560	594	564	6.074
SRiSWUS01138	9	12	13	15	13	11	10	12	14	13	12	9	145
TRRL00068	167	168	145	118	125	137	108	114	103	114	117	133	1.549
TRSFF00066	241	258	332	450	437	336	267	358	389	391	362	400	4.221

Table 3.3. 2023 Exponential Smoothing Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	367	386	340	391	448	356	538	369	348	360	362	316	4.582
KNKALN00001	7	5	7	6	5	4	7	7	7	8	9	8	79
LIPSFF00066	208	138	159	160	138	180	182	156	204	212	184	188	2.108
NMSFF000001	295	250	253	243	272	326	272	312	242	212	325	363	3.364
SPSWUS00082	368	418	529	511	570	580	507	594	570	561	574	449	6.230
SRiSWUS01138	12	13	14	12	10	12	12	14	12	13	9	10	144
TRRL00068	143	124	150	129	120	103	133	98	102	142	123	141	1.507
TRSFF00066	271	389	430	356	328	328	401	335	357	419	396	393	4.402

Table 3.4. 2023 Least Square Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	288	278	268	257	247	237	226	216	206	195	185	175	2.778
KNKALN00001	4	4	4	4	4	4	4	3	3	3	3	3	43
LIPSFF00066	148	149	151	152	153	155	156	157	159	160	162	163	1.866
NMSFF000001	181	182	183	185	186	188	189	191	192	194	195	196	2.262
SPSWUS00082	314	315	317	318	320	321	323	324	326	327	329	330	3.866
SRiSWUS01138	7	7	7	7	7	6	6	6	6	6	6	5	77
TRRL00068	191	187	182	178	173	169	164	160	155	151	146	142	2.001
TRSFF00066	252	245	238	232	225	218	212	205	198	192	185	178	2.579

Moving Average, Exponential Smoothing, and Least Squares were applied to eight Category A SKUs. Moving Average (MA). Produced moderate and stable projections, smoothing fluctuations but showing limited responsiveness to sudden changes in demand. Exponential Smoothing (ES). Generated the highest projections for most SKUs, reflecting its sensitivity to recent upward trends and short-term variability. Least Squares (LS). Delivered results similar to MA, capturing long-term linear patterns but less effective in representing short-term fluctuations.

Table 3.5. 2024 Moving Average Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	346	297	213	219	216	214	242	245	272	211	228	237	2.938
KNKALN00001	8	8	6	5	4	4	5	7	6	5	4	5	67
LIPSFF00066	191	171	165	159	149	123	113	120	158	148	139	110	1.746
NMSFF000001	361	364	302	216	212	162	178	200	209	190	184	228	2.806
SPSWUS00082	483	451	388	407	329	336	354	476	468	434	371	348	4.846
SRiSWUS01138	9	10	10	9	8	7	9	9	9	8	8	9	104
TRRL00068	149	129	117	103	90	97	81	96	104	104	92	76	1.237
TRSFF00066	421	363	307	293	262	283	284	330	268	233	234	297	3.574

Table 3.6. 2024 Exponential Smoothing Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	261	241	255	192	198	297	208	252	234	218	257	186	2.799
KNKALN00001	7	7	5	4	5	5	6	5	5	4	6	5	65
LIPSFF00066	186	161	155	155	110	120	143	152	123	146	117	99	1.668
NMSFF000001	279	304	254	200	154	207	215	162	202	211	221	247	2.657
SPSWUS00082	475	406	390	320	357	390	476	419	405	422	333	328	4.721
SRiSWUS01138	11	8	9	9	6	10	9	7	8	10	8	11	106
TRRL00068	129	111	111	86	102	77	98	118	80	91	93	84	1.182
TRSFF00066	348	312	325	238	293	313	303	233	253	279	280	328	3.506

Table 3.7. 2024 Least Square Forecast's Result

SKU	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total Forecast
BBSFF00066	339	333	326	320	313	307	301	294	288	281	275	269	3.646
KNKALN00001	8	9	9	9	9	9	10	10	10	10	10	11	114
LIPSFF00066	193	196	198	201	203	206	208	211	213	216	219	221	2.485
NMSFF000001	337	342	348	354	359	365	371	377	382	388	394	400	4.417
SPSWUS00082	513	510	506	503	500	497	494	491	488	485	482	479	5.951
SRiSWUS01138	9	8	8	7	7	7	6	6	5	5	4	4	76
TRRL00068	137	139	142	144	146	149	151	153	156	158	160	162	1.797
TRSFF00066	391	392	393	394	396	397	398	400	401	402	403	405	4.772

3. Economic Order Quantity (EOQ)

According to Heizer et al. (2017, p. 496), the Economic Order Quantity (EOQ) is a widely used and straightforward inventory control technique, making it a popular choice in inventory management. The application of EOQ, however, requires the fulfillment of several key assumptions to ensure its effectiveness. These include the accuracy of demand and cost estimations, as well as stability in production rates and market conditions, all of which support cost optimization and efficiency in inventory management.

The EOQ model is a classical approach to determining the optimal order quantity that minimizes total inventory costs. The fundamental equation is expressed as:

- Economic Order Quantity (Q*)

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

- Number of Orders (N)

$$\mathrm{N} = \frac{D}{Q^*}$$

- Cycle Time (T)

$$\mathrm{T} = \frac{Count\ of\ Working\ Days\ in\ a\ Year}{N}$$

- Safety Stocks (SS)

$$\mathrm{SS} = \mathrm{Z} \times \sigma \mathrm{LT}$$

- Reorder Point (ROP)

$$\mathrm{ROP} = \mathrm{d} \times \mathrm{L}$$

- Total Cost (TC)

$$\text{Total Costs} = \frac{D}{Q}S + \frac{Q}{2}H$$

EOQ Formula Notation:

- D : Annual demand (units/year)
- S : Ordering cost per order (currency/order)
- H : Holding cost per unit per year (currency/unit/year)
- Q : Economic Order Quantity (units/order)
- N : Number of orders per year

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- T : Cycle time, average interval between orders (days)
- d : Average daily demand (units/day)
- L : Lead time (days)
- Z : Z-score based on the desired service level
- σd : Standard deviation of daily demand (units/day)
- SS : Safety Stock (units)
- ROP : Reorder Point (units)
- TC : Total annual inventory cost (currency/year)

Table 3.8. 2022 EOQ Result

2022										
SKU	Demand (D)	Setup Cost (S)	Holding Cost (H)	EOQ (Q*)	N	Daily Demand (d)	Reorder Point	Safety Stock (SS)	Reorder Point (ROP) + SS	Total Costs (TC)
BBSFF00066	426.397	5.799	1,84	51.843	8	1.481	34.053	1.540	35.592	95.391
KNKALN00001	6.000	82	1,84	730	8	21	479	22	501	1.342
LIPSFF00066	157.325	2.140	1,84	19.128	8	546	12.564	568	13.132	35.196
NMSFF000001	181.943	2.474	1,84	22.121	8	632	14.530	657	15.187	40.703
SPSWUS00082	249.871	3.398	1,84	30.380	8	868	19.955	902	20.857	55.900
SRISWUS01138	10.276	140	1,84	1.249	8	36	821	37	858	2.299
TRRI00068	249.748	3.397	1,84	30.365	8	867	19.945	902	20.847	55.872
TRSFF00066	353.002	4.801	1,84	42.919	8	1.226	28.191	1.275	29.466	78.972

Table 3.9. 2023 EOQ Result

2023										
SKU	Demand (D)	Setup Cost (S)	Holding Cost (H)	EOQ (Q*)	N	Daily Demand (d)	Reorder Point	Safety Stock (SS)	Reorder Point (ROP) + SS	Total Costs (TC)
BBSFF00066	456.508	6.446	1,85	56.402	8	1.585	36.457	1.649	38.106	104.344
KNKALN00001	8.340	118	1,85	1.030	8	29	666	30	696	1.906
LIPSFF00066	212.024	2.994	1,85	26.196	8	736	16.932	766	17.698	48.462
NMSFF000001	359.130	5.071	1,85	44.371	8	1.247	28.681	1.297	29.977	82.086
SPSWUS00082	638.603	9.017	1,85	78.900	8	2.217	51.000	2.306	53.306	145.965
SRISWUS01138	14.284	202	1,85	1.765	8	50	1.141	52	1.192	3.265
TRRI00068	146.579	2.070	1,85	18.110	8	509	11.706	529	12.235	33.503
TRSFF00066	458.429	6.473	1,85	56.639	8	1.592	36.611	1.655	38.266	104.783

Table 3.10. 2024 EOQ Result

2024										
SKU	Demand (D)	Setup Cost (S)	Holding Cost (H)	EOQ (Q*)	N	Daily Demand (d)	Reorder Point	Safety Stock (SS)	Reorder Point (ROP) + SS	Total Costs (TC)
BBSFF00066	266.046	3.906	1,85	33.516	8	924	21.247	961	22.207	62.004
KNKALN00001	6.255	92	1,85	788	8	22	500	23	522	1.458
LIPSFF00066	159.018	2.334	1,85	20.033	8	552	12.699	574	13.274	37.060
NMSFF000001	250.765	3.681	1,85	31.591	8	871	20.026	906	20.932	58.443
SPSWUS00082	498.588	7.319	1,85	62.811	8	1.731	39.818	1.800	41.618	116.200
SRISWUS01138	10.713	157	1,85	1.350	8	37	856	39	894	2.497
TRRI00068	112.801	1.656	1,85	14.210	8	392	9.008	407	9.416	26.289
TRSFF00066	343.822	5.047	1,85	43.314	8	1.194	27.458	1.242	28.700	80.130

B. Discussion

1. Time-Series Forecasting

Figures 3.1 and Figures 3.2 present a comparison of the three forecasting methods (Moving Average, Exponential Smoothing, and Least Squares) against actual demand data for the eight SKUs analyzed in this study. The visualizations highlight the extent to which each method is able to represent the observed demand patterns.

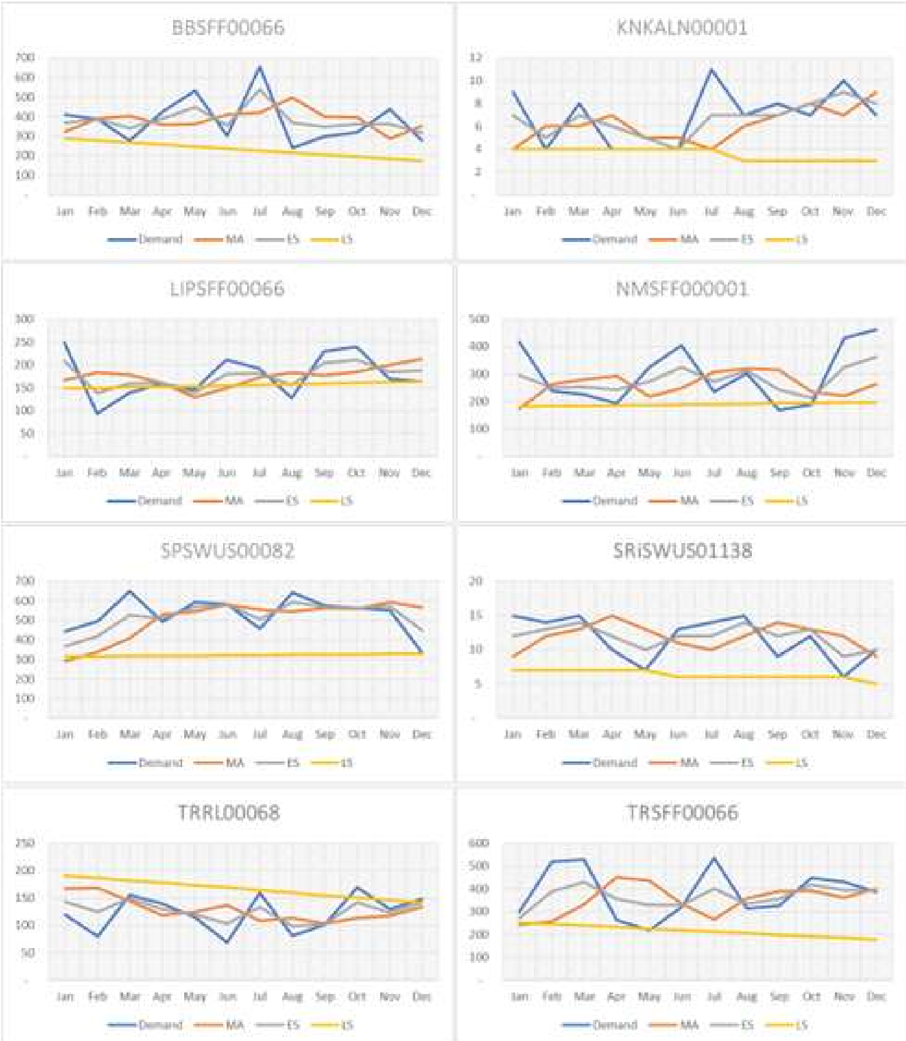

Figure 3.1. 2023 Forecast-Actual Comparation

In 2023 (Figure 4.3), the Exponential Smoothing (ES) method consistently produced results that were closest to actual demand. By contrast, Moving Average (MA) followed the general demand pattern but showed lagging effects for several SKUs, such as NMSFF00001 and TRRL00068. This is consistent with the nature of MA, which smooths data and therefore responds more slowly to sudden changes. The Least Squares (LS) method displayed the weakest performance, with forecast lines that were overly linear and unable to capture fluctuations in demand. This confirms that LS is more suitable for stable linear trends rather than highly volatile data such as those found in PT XYZ's inventory.

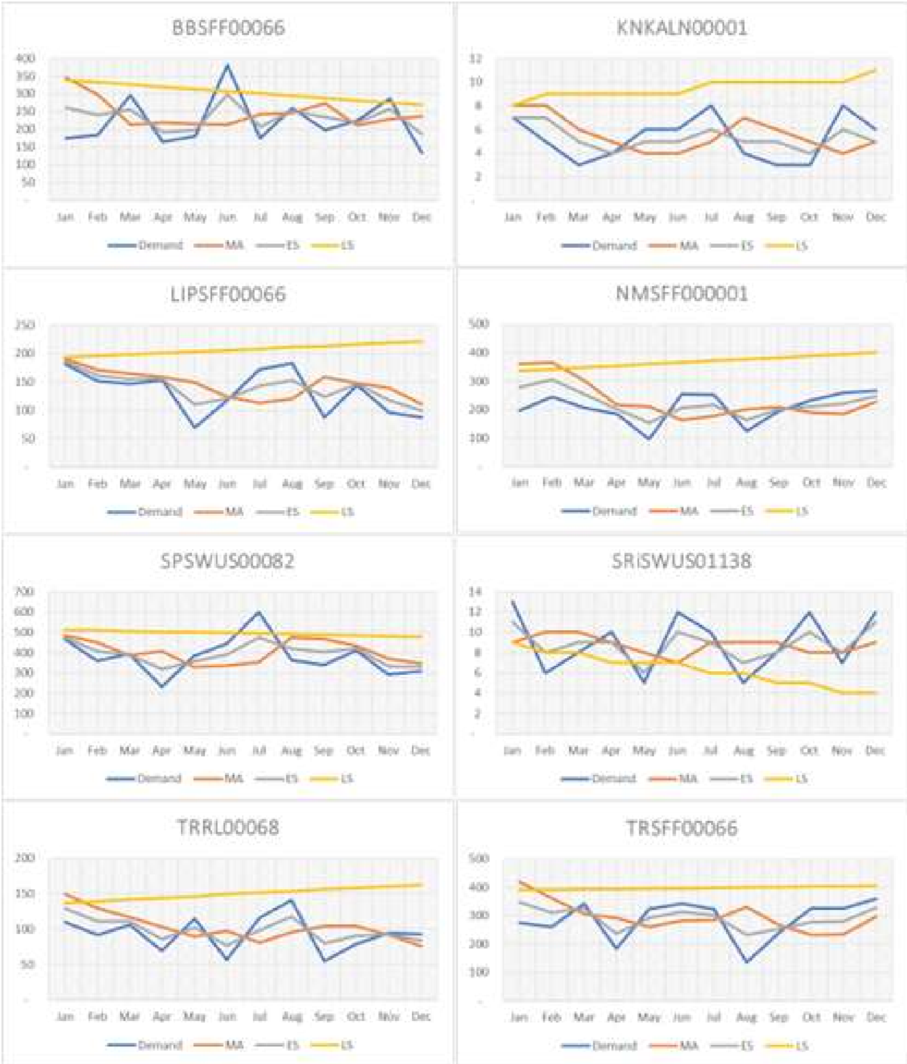

Figure 3.2. 2024 Forecast-Actual Comparation

A similar pattern is evident in 2024.ES produced the lowest average error, at 2.8% in 2023 and 4.2% in 2024, outperforming MA (5.6% and 7.2%) and LS, which recorded the highest error levels (37.8% and 49.8%). These results clearly demonstrate that Exponential Smoothing is the most accurate method for forecasting demand at PT XYZ and can serve as the basis for future planning. Beyond methodological accuracy, these findings have broader implications for sustainability. Accurate forecasting supports SDG 2 (Zero Hunger) by ensuring more reliable food availability while also contributing to SDG 12 (Responsible Consumption and Production) by reducing the risks of both overstocking and stockouts. In this way, the choice of forecasting method not only improves operational efficiency but also aligns with sustainable inventory management practices, enabling PT XYZ to balance economic performance with social responsibility.

2. Economic Order Quantity (EOQ)

The comparison of inventory costs in 2022, 2023, and 2024 reveals a consistent pattern in which actual costs were higher than those calculated using the Economic Order Quantity (EOQ) model. This confirms that EOQ consistently offers potential efficiency improvements for PT XYZ's inventory system.

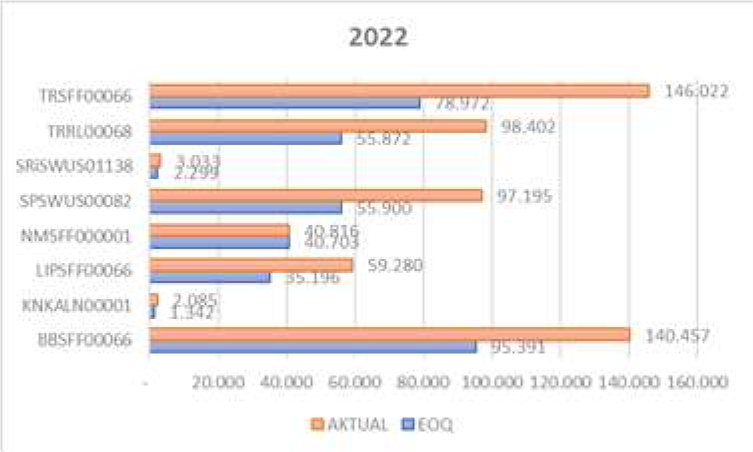

Figure 3.3. 2022 EOQ-Actual Comparation

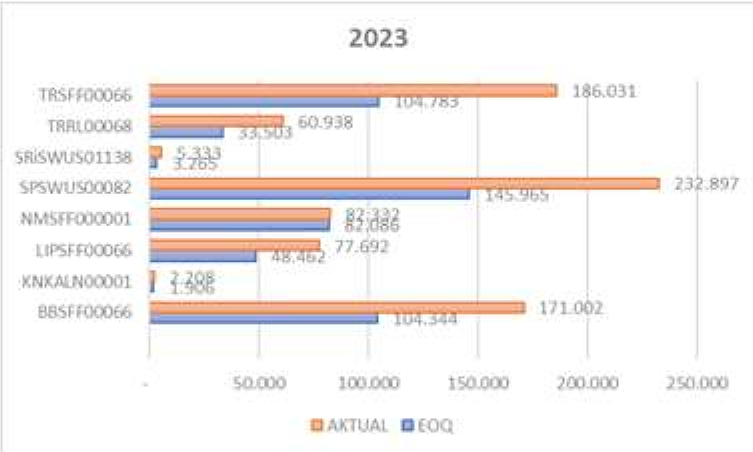

Figure 3.4. 2023 EOQ-Actual Comparation

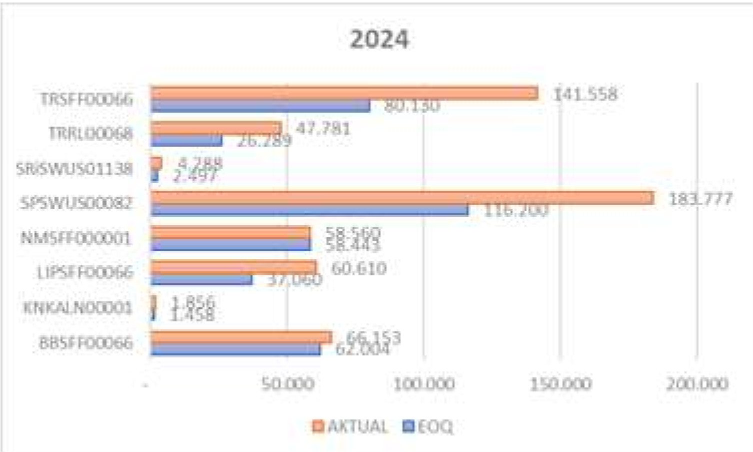

Figure 3.5. 2024 EOQ-Actual Comparation

In 2022, the most notable differences were observed in TRSFF00066 and BBSFF00066, which showed substantial cost savings under EOQ, while NMSFF00001 displayed only a minor difference, indicating limited efficiency gains. The year 2023 reinforced this pattern, with SPSWUS00082 and BBSFF00066 again demonstrating large cost gaps, suggesting significant room for optimization. In contrast, NMSFF00001 continued to show a narrow gap between actual and EOQ-based costs, implying that current practices for this SKU are already close to optimal. By 2024, most products maintained high efficiency potential under EOQ, particularly TRSFF00066, TRRL00068, and SPSWUS00082, whereas NMSFF00001 again showed marginal efficiency improvements.

Overall, the analysis highlights that EOQ consistently reduces inventory costs, though the level of efficiency varies across products. SKUs with large gaps between actual and EOQ costs offer the greatest potential for improvement, while those with minimal differences suggest that existing company practices are relatively efficient.

Beyond financial benefits, these findings carry broader implications for sustainable operations. From the perspective of SDG 8 (Decent Work and Economic Growth), significant cost savings enhance productivity and competitiveness while freeing resources for workforce development and operational improvements. In relation to SDG 12 (Responsible Consumption and Production), EOQ helps minimize overstocking and waste while reducing the risk of stockouts through better order timing and sizing. Finally, in alignment with SDG 2 (Zero Hunger), improved inventory control supports stable food availability ensuring more reliable distribution to consumers.

Thus, EOQ serves not only as a financial optimization tool but also as a mechanism to support sustainable development objectives in economic growth, responsible consumption, and food security.

IV. CONCLUSION

This study provides three key insights into inventory management at PT XYZ. First, the ABC analysis confirmed that inventory can be effectively divided into three categories: A, B, and C. Category A, though consisting of relatively few SKUs, consistently contributed the highest share of sales value, highlighting the need for stricter control. Category B represented medium-value items requiring careful monitoring, while Category C contained the largest number of SKUs but with minimal contribution. These findings demonstrate that ABC classification is effective in setting inventory management priorities, enabling resources to be focused on items with the greatest operational impact.

Second, the forecasting analysis compared three methods—Moving Average, Exponential Smoothing, and Least Squares. Among these, Exponential Smoothing achieved the highest accuracy, with the lowest error rates of 2.8% in 2023 and 4.2% in 2024. Its superior performance compared to the other methods makes it a more reliable basis for predicting inventory needs, thereby supporting more accurate purchasing decisions and reducing the risk of mismatches between stock and demand.

Third, the application of the Economic Order Quantity (EOQ) model demonstrated substantial cost efficiency, achieving average savings of 33% in 2022, 32% in 2023, and 29% in 2024. Despite slight fluctuations, these results consistently confirm that EOQ significantly reduces inventory costs compared to non-EOQ practices. Beyond cost savings, EOQ also provides a more structured framework for determining optimal order quantities, reorder points, and safety stock levels. This ensures continuity of supply, minimizes stockout risks, and strengthens overall operational efficiency.

In conclusion, integrating ABC classification, accurate forecasting methods, and the EOQ model enables PT XYZ to optimize inventory control, enhance cost efficiency, and improve service reliability. These strategies not only support operational excellence but also align with broader sustainability goals by reducing waste, stabilizing food supply, and fostering more responsible consumption practices..

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