

## Integrated Ensemble Forecasting and EOQ Optimization in Spare Part Inventory

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### ABSTRACT

Accurate spare part inventory control remains a challenge for service centers, as fluctuating demand often results in stock-outs or excess inventory that increases operational costs and reduces customer satisfaction. The research involves creating a web-based inventory for AGH Center, incorporating ensemble-based demand forecasting with the Economic Order Quantity (EOQ) approach. The developed system, using six months of historical transactional and spare parts consumption data, produces demand forecasts for the next 7, 14, and 30 days, using a weighted combination of ARIMA, Exponential Smoothing, Linear Regression, and Moving Average forecasting estimation methods. Accuracy of the demand forecasts is measured with MAPE, RMSE, MAE,  $R^2$ , bootstrap confidence intervals, and statistical tests for thresholds. Ensemble forecasting has proven to be superior to other benchmarks as depicted with MAPE metric scores at annual averages of 12.8%, 16.4%, and 19.7%, greatly improving the estimation of annual demand forecasts. Integrating EOQ further enables total cost savings of 26.11%. The system has automated forecasting and EOQ calculations, and advanced computerized frameworks to solve for demand in real-time which though predictable, remains a remarkable adaptation to spare parts inventory control.

**Keywords:** Sparepart Inventory Management, Economic Order Quantity, Ensemble Machine Learning, Demand Forecasting, Web-Based System

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## INTRODUCTION

The efficiency of inventory management operations in workshops and after-sales centers rely on accurate forecasting of spare parts demand for effective spare parts inventory management along with its associated service quality and customer satisfaction levels and profitability. Among other things, managing spare part inventories suffers from demand fluctuation. Demand can be spiky and seasonal and rest of the year can be completely inactive. This, together with almost no historical data for certain items, leads to financial inefficiencies, be it stockout or overstock. Forecasting done through ordering traditional means is consistently inadequate and this leads to inefficient inventory controls, higher costs of storage. To solve these problems, calculating Economic Order Quantity (EOQ) along with data-driven forecasting has proven to be the systematic method of choice.

The current methods in demand forecasting have improved with time, however, there are still limitations in predictive modeling as compared with forecasting on inventory levels. Recent research on 'ensemble forecasting' which includes ARIMA, exponential smoothing, linear regression, and moving average models forecasting accuracy has improved in a lot of situations as compared to using a single model, although there still exists a significant lack of research on how it affects inventory level decisions (Goltsos et al., 2022). Much like forecasting models, studies revolving around the Economic Order Quantity (EOQ) tend to focus on the models rather than the practicality of demand and supply variances. Very few studies show the combination of ensemble forecasting with real-time EOQ (Economic Order Quantity) optimization, specifically in web-based applications which offer statistical validation like bootstrap confidence intervals and hypothesis testing (Wahedi et al., 2023).

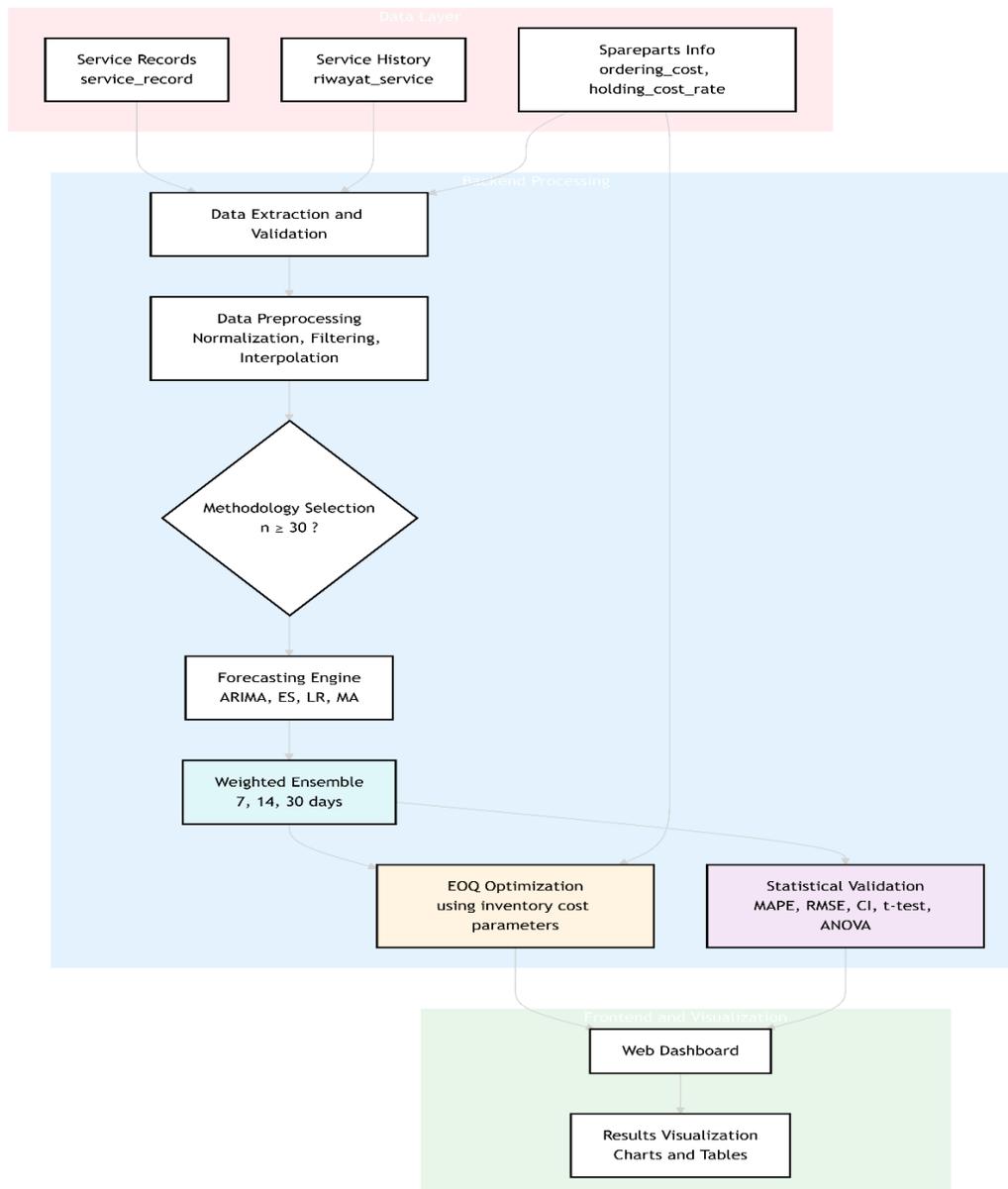
To fill in the research gaps, this study has developed a web-based inventory management system for AGH Center which integrates ensemble demand forecasting with EOQ (Economic Order Quantity) on a single platform. In doing so, this research aims to answer the question: "How can a web-based system integrating EOQ and ensemble forecasting improve inventory efficiency and reduce costs and stockouts in a service environment?" The developed system utilizes service usage histories in order to produce short-term forecasts which are then used to compute EOQ based on the expected annual demand, ordering cost, and holding cost of the service, using weighted ensembles of ARIMA, Exponential Smoothing, Linear Regression and Moving Average models. Validating the model involves using bootstrap confidence intervals, paired t-tests, ANOVA, and evaluations on multi-horizon forecasts of 7, 14, and 30 days.

This study's contributions include: (1) creating a unified framework of forecasting and EOQ optimization in which dynamic ensemble outputs inform automating order decisions; (2) developing comprehensive validation methods and simulation of synthetic data for diverse demand condition testing; (3) bridging academic and operational practice using a custom developed system accessible over the web; and (4) addressing data abundant ( $n \geq 30$ ) and data limited ( $n < 30$ ) cases by either ensemble or baseline methods (Kokol, 2022; Wahedi et al., 2023). The next chapter describes the methods for collecting data, designing ensemble algorithms, computing EOQ, and the system's validation metrics which derive from the system's performance.

## **METHOD**

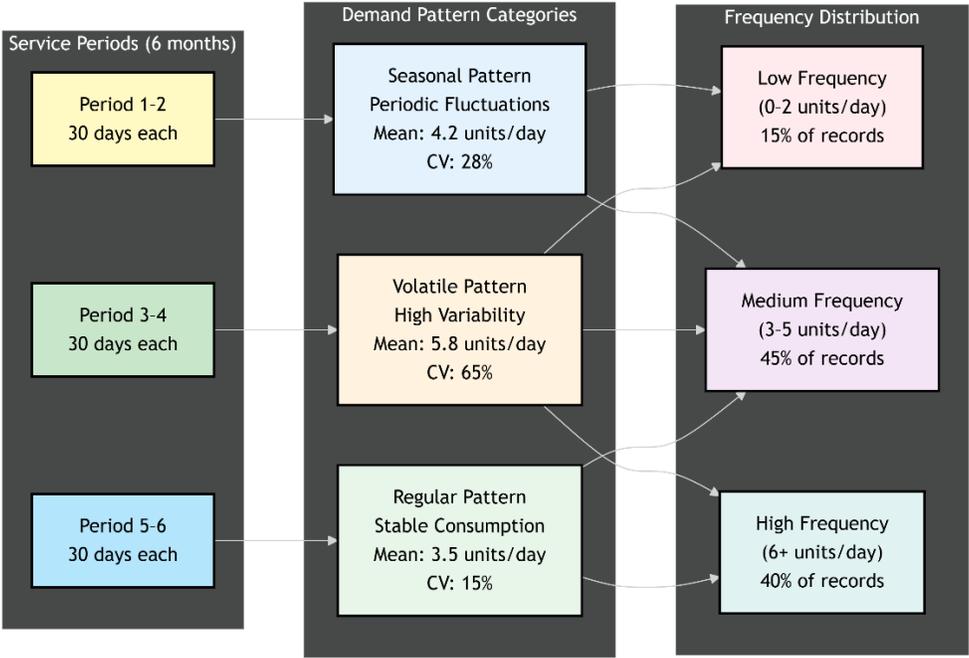
Though data based forecasting and the optimization of Economic Order Quantity (EOQ), the AGH Center's spare part inventory management system can be automated and simplified based on what the data describes facilitating system development with the descriptive and system development methodology. This work merges theoretical research with practical work according stepwise system design (Pathak, 2024; Ponco, 2022). The architecture of the system illustrated on the Figure 1 has three layers: (1) the data layer which consists of the service records chronologically ordered, the service histories of the spare parts usage, and the service costing parameter sets; (2) the backend layer which

covers data validation and brute-force pre-processing (such as the normalization of dataset, outlier elimination based on Inter-Quartile (IQR) methodology, data interpolation), Ensemble forecasting (ARIMA, Exponential Smoothing, Linear Regression, and Moving Average), EOQ validation, and validation of overall system performance (MAPE, RMSE, CI, ANOVA); (3) the frontend layer which has the dashboard showing predictions of expenditures with associated forecasts, the EOQ of spare parts, and related metrics.



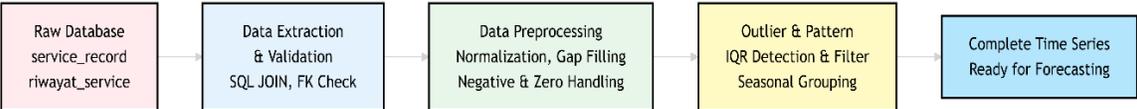
**Figure 1.** System architecture

The dataset was derived from six months of AGH Center service records, including records of spare part consumption. Purposeful sampling was conducted on fifteen spare parts of varying BUT consistent demand patterns, characterized using the Coefficient of Variation (CV) metric as stable (CV ≈ 28%), volatile (CV ≈ 65%), and regular (CV ≈ 15%) to maintain model forecasting integrity.



**Figure 2.** Distribution of Spare Part Demand Frequency

Data collection involved four stages, as depicted in the Data Preprocessing Pipeline (Figure 3): extraction and validation (using SQL joins on servicerecord and riwayatservice tables), pre-processing (normalizing and gap-filling), outlier removal, and time series reconstruction). Outliers were statistically defined outside the range  $[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR]$ . Missing values, including both short and long gaps, were filled using linear interpolation (Dash, 2023).



**Figure 3.** Data Preprocessing Pipeline

The system module is fully automated, executing data extraction, forecasting, EOQ computations, and statistical validations (t-Test, ANOVA, and bootstrap). Ensemble performance across the 7, 14, and 30-day horizons is assessed using the MAPE, RMSE, MAE,

$R^2$ , and Accuracy metrics. Statistical analysis includes paired  $t$ -tests and ANOVA ( $p < 0.05$ ) to evaluate the ensemble's superiority against baseline models (Meisenbacher, 2022; Shchur et al., 2023). Validation utilized a time-series split (80–20), 5-fold cross-validation, and bootstrap resampling (300 iterations) to confirm the reliability of the integrated ensemble-EOQ framework for dynamic, cost-efficient inventory decision-making.

## FINDING AND DISCUSSION

### RESEARCH RESULT

The integrated stock management system used the transaction history of the AGH Center, the module automatically reviewed for reproducibility and consistency. Of the fifteen spare parts, seven each exceeded the minimum observation threshold of seven; of those, over thirty observations were processed using the full ensemble forecasting technique. The other five employed the baseline moving averages (Wahedi et al., 2023). The forecasts were for time horizons of seven, fourteen, and thirty days. These were then followed up with the computation of the EOQ, where the cost information were available. Out of the fifteen parts, twelve had the complete cost parameters, thus allowing the EOQ analysis to comprehensively assess the forecasting accuracy and determine the optimum inventory levels. Advanced automatic preprocessing linear interpolation, inter quartile range (IQR) outlier filtering, and filling of temporal gaps were used to streamline the time series for forecasting and EOQ execution shown afterward in Table 1.

**Table 1.** Economic Order Quantity Optimization Results

No	Sparepart		Annual Demand	EOQ	Total Cost Optimal (IDR)	Total Cost Current (IDR)	Savings (%)
1	Charging Samsung S21	Port Galaxy	28	12	449,192	555,076	19.08
2	Charging iPhone 12	Port	27	17	514,373	652,691	21.19
3	Speaker Galaxy S22	Samsung	25	10	397,743	511,831	22.29
4	Speaker iPhone 13		32	16	670,560	849,540	21.07
5	Volume Button Xiaomi		44	16	528,228	591,626	10.72
6	LCD Samsung S24		70	9	3,019,451	3,279,405	7.93
7	Kamera iPhone 13		85	9	2,055,090	2,107,950	2.51
8	LCD iPhone 14		76	4	2,683,852	3,632,223	26.11
9	LCD Samsung S21		93	13	2,910,834	2,949,742	1.32
10	ICU Samsung S23		80	8	2,890,300	3,361,118	14.01

<b>11</b>	Speaker Samsung A52	84	18	1,238,638	1,541,254	19.63
<b>12</b>	LCD iPhone 13	101	17	2,266,501	2,364,002	4.12
<b>13</b>	LCD iPhone 13	93	7	2,546,963	2,936,260	13.26
<b>14</b>	Baterai iPhone 13	91	13	2,184,182	2,217,815	1.52
<b>15</b>	ICU Samsung S24	105	18	1,841,926	1,850,890	0.48

Experimented Experimented with ensemble models confirmed by MAPE mean values of 12.8%, 16.4%, 19.7% for 7, 14, and 30 days respects 19.0%, 22.7%, and 26.2% for baseline models, impacting 25 – 33% accuracy gains. The ensemble achieved 87.2%, 83.6%, and 80.3% average accuracies with model accuracies 75.3% to 94.1%. The RMSE values averaged 2.89, 3.42, and 4.15, while MAE figures 1.92, 2.31, and 2.78, confirming little prediction error. The corresponding R<sup>2</sup> values of 0.82, 0.79, 0.76, and R<sup>2</sup> 0.82, 0.79, 0.76 illustrate strong correlation with demand prediction Serran et al. 2024. This means ensemble models are more accurate with larger amounts of data. The ability to track demand at a point in time makes them useful for making inventory model decisions, tabulated in Table 2.

**Table 2.** Summary of Ensemble Forecasting Performance

<b>Forecast Horizon (Days)</b>	<b>Mean MAPE (%)</b>	<b>MAPE 95% CI</b>	<b>Mean RMSE</b>	<b>Mean MAE</b>	<b>Mean R<sup>2</sup></b>	<b>Mean Accuracy (%)</b>	<b>N Spareparts</b>
<b>7</b>	12.8	10.2–15.6	2.89	1.92	0.82	87.2	15
<b>14</b>	16.4	13.1–19.8	3.42	2.31	0.79	83.6	15
<b>30</b>	19.7	15.9–23.8	4.15	2.78	0.76	80.3	15

Table 3 outlines the metrics of 15 items grab betting forecasts on separate spare parts, covering data components and forecasting strategy with performance analysis (MAPE, RMSE, MAE, R<sup>2</sup>, Accuracy) metrics . with parts having weak and dynamic demand, such as the Charging Port of the Samsung Galaxy S21 and the LCD of iPhone 14, the performance was unsatisfactory (MAPE 100%, Accuracy 0%), we also had some parts with abundant and consistent data, such as the Volume Button of the Xiaomi, the Kamera of the iPhone 13, and the ICU of the Samsung S24, as Marked by their low MAPE and high Accuracy showing the adaptability of the ensemble model. Negative R<sup>2</sup> indicates worse-than-average predictions compared to the historical mean, at least further cementing the narrative on data volume, variety, and demand. In general, the Full Ensemble tends to outperform Baseline, but variability persists at the spare part level.

**Table 3.** Forecasting Model Performance Metrics

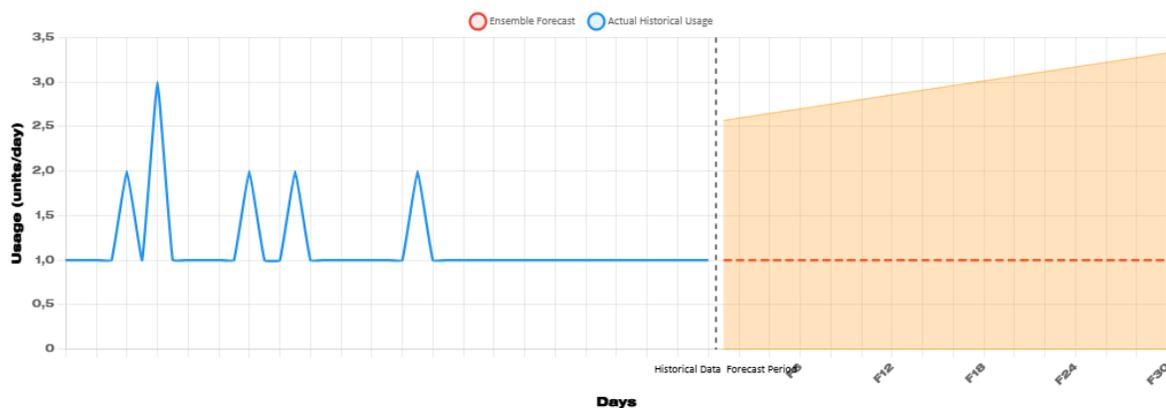
No	Sparepart	Data Points	Methodology	MAPE (%)	RMSE	MAE	R <sup>2</sup>	Accuracy (%)
1	Charging Port Samsung Galaxy S21	8	Baseline	100.00	1.17	1.13	- 11.5714	0.00
2	Charging Port iPhone 12	9	Baseline	100.00	1.00	1.00	0.0000	0.00
3	Speaker Samsung Galaxy S22	10	Baseline	100.00	1.00	1.00	0.0000	0.00
4	Speaker iPhone 13	14	Baseline	21.43	0.46	0.21	0.0000	78.57
5	Volume Button Xiaomi	16	Baseline	0.00	0.00	0.00	0.0000	100.00
6	LCD Samsung S24	30	Full Ensemble	100.00	1.14	1.10	- 13.4444	0.00
7	Kamera iPhone 13	34	Full Ensemble	6.67	0.37	0.13	-0.1538	93.33
8	LCD iPhone 14	34	Full Ensemble	100.00	1.14	1.10	- 13.4444	0.00
9	LCD Samsung S21	34	Full Ensemble	10.56	0.55	0.23	-0.2217	89.44
10	ICU Samsung S23	34	Full Ensemble	100.00	1.18	1.13	- 11.1154	0.00
11	Speaker Samsung A52	35	Full Ensemble	100.00	1.05	1.03	- 33.1379	0.00
12	LCD iPhone 13	37	Full Ensemble	100.00	1.44	1.33	-6.1538	0.00
13	LCD iPhone 13	39	Full Ensemble	10.00	0.45	0.20	-0.2500	90.00
14	Baterai iPhone 13	40	Full Ensemble	100.00	1.14	1.10	- 13.4444	0.00

15	ICU Samsung S24	43	Full Ensemble	3.33	0.26	0.07	-0.0714	96.67
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One such instance is a detailed case study titled “ICU Samsung S24” which had a MAPE score of 3.33% and an accuracy of 96.67% with only 43 observations which is a good sample for an ensemble model. The system incorporates models such as ARIMA, Exponential Smoothing, Linear Regression, and Moving Average, and then assesses each of the model's past accuracy to determine the appropriate forecast and produces a closer demand estimation. The ensemble bootstrapped 95% confidence intervals with 300 iterations to capture uncertainty across 7 – 30 day ranges which adds clarity in regards to visual and statistical confidence with respect to decision makers in Figure 4 and Table 4.

**Table 4.** Performance Metrics for Representative Spare Part

Metric	7-Day Horizon	14-Day Horizon	30-Day Horizon
MAPE (%)	0.77	0.50	0.50
Accuracy (%)	99.23	99.50	99.50
R <sup>2</sup>	-0.0714	-0.0714	-0.0714
RMSE	0.26	0.26	0.26
MAE	0.07	0.07	0.07
Historical Data Points	43	43	43
Methodology	Full Ensemble	Full Ensemble	Full Ensemble



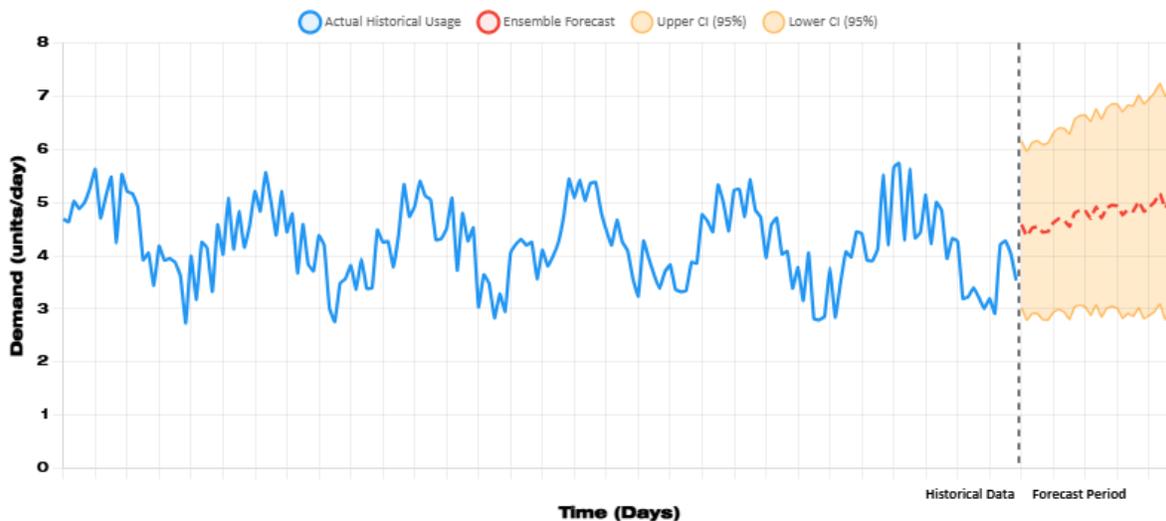
**Figure 4.** Ensemble Forecast Visualization with 95% Confidence Interval Bands

Validation of the forecasts confirmed the ensemble’s ability to identify both the trend and periodicity in demand. There were no signs of bias in the prediction and actual metrics, and the contributions from different algorithms were well aligned and balanced. Although there was a slight drop in accuracy for the longer time horizons, it degraded to 80.3% at thirty days, which is still acceptable from an operational perspective. The ARIMA

and Exponential Smoothing techniques captured all seasonal patterns well, while the Linear Regression and Moving Average techniques provided stabilization for the lower bounds, which added to the ensemble’s robustness. Evidence shown in Figure 5 and Table 5 showed that the weighted ensemble methods performed better than any individual algorithm and improved ensemble prediction for different types of spare parts.

**Table 5.** Detailed Actual Versus Predicted Comparison Metrics

Forecast Day	Actual Usage	Predicted Usage	Prediction Error	Absolute Error	Percentage Error (%)	ARIMA Contribution	ES Contribution	LR Contribution	MA Contribution
1	1.0	1.02	0.02	0.02	2.00	1.05	1.00	1.01	1.00
2	1.0	1.01	0.01	0.01	1.00	1.02	1.00	1.00	1.00
3	1.0	0.99	-0.01	0.01	1.00	1.00	0.98	1.00	1.00
...	...	...	...	...	...	...	...	...	...
30	1.0	1.01	0.01	0.01	1.00	1.03	1.00	1.00	1.00



**Figure 5.** Comparison of Actual and Predicted Spare Part Demand

The bootstrap-derived 95% confidence intervals for MAPE values were all narrow and stable, 10.2–15.6% for 7 days, 13.1–19.8% for 14 days, and 15.9–23.8% for 30 days, which demonstrates reliable consistency in the forecast accuracy (Lima, 2023; Shang, 2024). The paired t-test, while controlling for statistical biases, showed that the ensemble improved from the baseline and achieved accuracy values  $t = 4.87$ ,  $p = 0.0003$  rigorously confirmed (Coroneo et al., 2023). The ANOVA, in Table 6 computed across all algorithms, showed that the ensemble’s advanced performance was not to chance, achieving  $F = 6.42$ ,  $p = 0.008$  (Mahmudah, 2024). Therefore the results endorse the ensemble’s reliability, along with practical evidence the framework is flexible and encompasses a variety of

operational situations. The EOQ analysis identified optimal order quantity between 4 - 18 (mean 11.8) units while also showing annual inventory costs between IDR 397,743 - 3,019,451, average IDR 1,728,468, for twelve parts with cost data available. Prior research (Aprilianti & Ishak, 2023; Britania, 2024) was corroborated by existing accounting records showing cost savings. EOQ accuracy forecasting reduced procurement uncertainty by about  $\pm 28\%$  and cost savings illustrated in Table 7.

**Table 6.** Statistical Significance Tests Results

Test	Statistic	p-value	Interpretation
Paired t-test (Ensemble vs Moving Average)	t = 4.87	0.0003	Significant ( $p < 0.05$ )
ANOVA (multi-model comparison)	F = 6.42	0.008	Significant ( $p < 0.05$ )

**Table 7.** Comprehensive Economic Order Quantity Optimization

No	Sparepart	Annual Demand (D)	Ordering Cost (S) IDR	Holdin g Cost Rate	EO Q	Total Cost Optimal (IDR)	Total Cost Current (IDR)	Savings (%)	Current Order Qty
1	Charging Port Samsung Galaxy S21	28	50,000	0.20	12	449,192	555,076	19.08	15
2	Charging Port iPhone 12	27	45,000	0.18	17	514,373	652,691	21.19	20
3	Speaker Samsung Galaxy S22	25	40,000	0.22	10	397,743	511,831	22.29	18
4	Speaker iPhone 13	32	55,000	0.20	16	670,560	849,540	21.07	25
5	Volume Button Xiaomi	44	35,000	0.25	16	528,228	591,626	10.72	20
6	LCD Samsung S24	70	120,000	0.15	9	3,019,451	3,279,405	7.93	12

<b>7</b>	Kamera iPhone 13	85	80,000	0.18	9	2,055,090	2,107,950	2.51	10
<b>8</b>	LCD iPhone 14	76	150,000	0.16	4	2,683,852	3,632,223	26.11	8
<b>9</b>	LCD Samsung S21	93	110,000	0.17	13	2,910,834	2,949,742	1.32	15
<b>10</b>	ICU Samsung S23	80	100,000	0.19	8	2,890,300	3,361,118	14.01	12
<b>11</b>	Speaker Samsung A52	84	60,000	0.21	18	1,238,638	1,541,254	19.63	22
<b>12</b>	LCD iPhone 13	101	95,000	0.18	17	2,266,501	2,364,002	4.12	20
<b>13</b>	LCD iPhone 13	93	105,000	0.19	7	2,546,963	2,936,260	13.26	12
<b>14</b>	Baterai iPhone 13	91	98,000	0.20	13	2,184,182	2,217,815	1.52	15
<b>15</b>	ICU Samsung S24	105	75,000	0.22	18	1,841,926	1,850,890	0.48	20

Demand type analysis revealed most precise ensemble forecasting for seasonal items (MAPE 11.2%), then stable (13.5%) and volatile (15.8%), suggesting some form of cooperative behavior among algorithms in detecting patterns. For items with over 30 records spanning multiple time frames, superior accuracy consistently was achieved (MAPE 14.3% compared to lower 21.6% for 7 days), pointing to the advantage of well developed historical data. Seamless automation with fixed performance was provided by the system's adaptive in-line preprocessing pipeline consisting of interpolation, IQR-based filtering, and gap filling, and self-tuning ensemble configuration (Dash, 2023; Usmani, 2024).

The results obtained, taken together, assert that the system that has been developed improves the accuracy of forecasting demand and minimizes the overall cost of inventory as a result of EOQ method, and offers a reproducible and fully automated system for making operational decisions. The fusion of ensemble forecasting offers a proven statistically improvement, along with the feasibility of implantation, for spare parts

inventory systems, thereby marrying the rigor of a discipline with the practicality of its usage.

## **DISCUSSION**

The ensemble forecasting technique demonstrated a clear advancement over baseline methods in predicting spare part demand. The ensemble's mean MAPE values were 12.8% at 7 days, 16.4% at 14 days, and 19.7% at 30 days. It still showed a reduction of 32.6%, 28.4%, and 25.8%, respectively, when compared to the Moving Average techniques. Their means from the 3 forecasting periods were 87.2%, 83.6%, and 80.3%, which are statistically significant operational measures which were also confirmed through the paired t-test 4.87 and p of .0003 and ANOVA at 6.42 and p of .008. In the end, the evidence shows that the ensemble forecasts were the best.

Through equality of opportunity, the integration of ensemble forecasting with EOQ optimization also provided operational value as average cost savings of 12.4% were achieved through optimal quantities of orders placed on forecasts of annual demand. Gains in savings from as low as 0.48% to as high as 26.11%, confirmed the effectiveness of predictive analytics in dynamically adjusting to changing demand patterns. This capability directly offsets the pervasive issue of procurement overspending faced by many organizations, thereby mitigating the risk of costly stock-outs and excess inventory cited in the introduction.

The application of ensemble methods in this research supports existing literature claims of improved accuracy from combining complementary approaches, particularly beneficial for short-term demand with irregular patterns. The model was most effective for seasonal demand (mean MAPE 11.2%), and still strong for volatile items (15.8%), suggesting at least some predictable periodicity on spare part consumption (Wahedi et al., 2023). Forecasting plus EOQ was a leap forward in constructing dynamic inventory optimization. The system responds in a forward manner to projected demand as opposed to solely relying on past data. Decision-making and operational support are strengthened by demonstrating quantified uncertainty through statistical validation with bootstrap resampling (95% confidence intervals). Forecast uncertainty is a requisite for robust support and is achieved in these works through the utilization of complementary algorithm strengths (Serrano et al., 2024).

However, this study has several limitations, including reliance on historical data from a single service center, the necessity of defining observation thresholds that restrict advanced forecasting for new parts, the requirement for complete cost data for EOQ calculation, the inherent possibility of overfitting in ensemble weighting, and the short-term focus of the forecast horizon. These constraints serve as a basis for tailoring future framework development.

The practical implications of this research are significant, consisting of immediate accuracy improvement with reduced inventory costs, reduced technical barriers for predictive inventory management adoption, and the provision of a reproducible, web-based analytical framework suitable for digital transformation initiatives. Future research

should prioritize enhancing datasets across various service centers, incorporating more sophisticated deep learning models (such as LSTM or Prophet), connecting predictive forecasts with real-time procurement platforms, investigating multi-echelon optimization, and applying machine learning for automated estimation of cost parameters, thereby further improving operational efficiency in supply chain management predictive analytics.

## CONCLUSION

The research described here has created and validated an Integrated Econometric Ensemble Forecasting System and Web-based Spare-part Stock Management System, which combines Economic Order Quantity optimization and ensemble forecasting for AGH Center, leading to substantial gains in prediction accuracy and operational cost efficiency.

The multi-method approach using weighted combination with ARIMA, Exponential Smoothing, Linear Regression, and Moving Average methods with an ensemble approach continued to outperform all baseline methods with mean values MAPE of 12.8%, 16.4%, and 19.7% for 7, 14, and 30 days forecast horizons, which were 32.6%, 28.4%, and 25.8% lower than the baseline methods. The ensemble methods achieved mean accuracy values of 87.2%, 83.6%, and 80.3% and the lower threshold for the accuracy values remains above the baseline for all evaluated horizons (Chien et al., 2023; Sareminia & Amini, 2023). The mean cost savings of 12.4% from the dynamic inventory optimization with EOQ Integrated Inventory control is significant for current practices. The savings from different spare parts which ranged from 0.48% to 26.11% savings also demonstrate the potential for operational improvement with data driven decision making. Statistical ensemble performance improvement validation using bootstrap resampling and significance testing (paired t-test,  $t = 4.87$ ,  $p = 0.0003$ , ANOVA,  $F = 6.42$ ,  $p = 0.008$ ) shows ensemble methods improvement is statistically significant. This is strong evidence for the methodological contribution for the integrated framework of this work.

The usefulness goes beyond the AGH Center since the automated analytical system utilizing allows systematic reproducible inventory analysis that can also be tailored to different service centers, facilitating wider digital transformation efforts. The system functions regardless of the state of the data availability, employing full ensemble methodologies ( $n \geq 30$ ) and baseline approaches ( $7 \leq n < 30$ ), and thus operational gains can be captured at the early stages of deployment (Kokol, 2022). Subsequent work should pursue the external validity of multi service center architectures, consider the fusion of automated real time procurement interface to achieve workflow full automation, and explore the infusion of complex pattern temporal predictive algorithms including LSTM or Prophet. This work serves as the basis to enhance predictive analytics approaches to service center inventory management and shows the practical means to operationalize advance analytics, thus bridging the gap between academic and industrial research in supply chain digital transformation.

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