Integrating Demand Forecasting, Aggregate Planning, and Sensitivity Analysis for Cost-Efficient Production: A Case Study in Furniture Manufacturing

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Abstract: Production planning under demand uncertainty remains a critical challenge in make-to-stock manufacturing systems, particularly when forecasting results are not explicitly linked to cost-based planning decisions. This study develops an integrated framework that combines demand forecasting, aggregate planning, and sensitivity analysis to identify a cost-efficient production policy in a furniture manufacturing company. A quantitative case study was conducted using 12 months of historical demand data for S4S products from July 2024 to June 2025. Three forecasting methods, namely Single Exponential Smoothing, Linear Regression, and Holt's Trend Method, were evaluated using MAPE, MAD, and RMSE. The best-performing forecast was then used as input for aggregate planning under Level and Chase strategies. To assess the robustness of the planning decision, a one-way sensitivity analysis was conducted by varying key cost parameters by ±20%. The results show that Holt's Trend Method with $\alpha = 0.4$ and $\beta = 0.1$ provided the best overall forecasting performance, with a MAPE of 1.63%, MAD of 67.34 units, and RMSE of 106.08 units. Using this forecast as the demand input, the Chase Strategy generated the lowest total production cost of Rp.185,900,000, compared with Rp.189,523,750 under the Level Strategy. Sensitivity analysis confirmed that the Chase Strategy remained the preferred strategy under all tested cost-parameter scenarios. These findings demonstrate that integrating forecasting validation, aggregate planning, and sensitivity analysis can improve medium-term production planning decisions and provide practical guidance for manufacturing firms facing fluctuating demand.

Keywords: production planning, demand forecasting, aggregate planning, sensitivity analysis, Holt's Trend Method, chase strategy.

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Introduction

The increasingly competitive manufacturing environment requires firms to maintain operational efficiency by delivering products in the right quantity, at the right time, and at minimum cost. In this context, production planning plays a critical role in synchronizing demand, production capacity, workforce availability, inventory, and other operational resources (Amoako-Gyampah & Acquaah, 2008; Amoako-Gyampah & Boye, 2001). Ineffective production planning may create two major operational problems. On one hand, insufficient production capacity can lead to delivery delays, stockouts, and declining customer service levels. On the other hand, excessive production may result in inventory accumulation, idle resources, and higher operating costs (Rajani, Heggde, & Kumar, 2022). Therefore, manufacturing firms require a systematic and data-driven planning approach to reduce mismatches between demand and production output (Biegel, 2000; Ginting, 2007; Rhufyano, Robbani, Arifin, Mufti, & Lazuardy, 2022). Demand uncertainty further increases the complexity of production planning, particularly in make-to-stock manufacturing systems. In such systems, companies produce goods in anticipation of future demand, making forecast accuracy an important determinant of production effectiveness. Demand forecasting provides a basis for medium-term decisions related to production quantity, workforce allocation, inventory control, and capacity planning (Gaspersz, 2001; Heizer, Render, & Munson, 2016). Inaccurate forecasts may propagate into downstream operational decisions. Demand overestimation may cause excessive inventory and additional holding costs, while demand underestimation may result in shortages, backorders, or service disruptions. For this reason, forecasting model selection should be based on transparent and measurable accuracy evaluation using established error metrics such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Square Error (RMSE) (Hyndman & Athanasopoulos, 2021; Nasution & Prasetyawan, 2008). Although forecasting is essential, it is not sufficient to support production decision-making if the forecast is not translated into an operational plan. Forecast outputs must be connected to aggregate planning, which determines production levels, workforce requirements, inventory positions, and shortage levels over a medium-term planning horizon. Aggregate planning aims to satisfy forecasted demand while minimizing relevant planning costs, including labor cost, hiring cost, firing cost, inventory holding cost, and shortage cost (Chapman, Arnold, Gatewood, & Clive, 2017; Eunike et al., 2021). In aggregate planning, firms commonly compare alternative strategies such as the Level Strategy and the Chase Strategy. The Level Strategy maintains relatively stable production and uses inventory as a buffer against demand fluctuation, while the Chase Strategy adjusts production more closely to demand changes. Each strategy creates different cost implications depending on the firm's demand pattern and cost structure. Previous studies have extensively discussed forecasting and aggregate planning, but several limitations remain. First, forecasting and aggregate planning are often treated as separate analytical stages, even though forecasting accuracy directly affects production quantity, inventory levels, workforce decisions, and total planning cost (Gansterer, 2015; Widiarta, Viswanathan, & Piplani, 2009). Second, forecasting model selection is frequently based only on statistical accuracy, without explicitly examining how the selected forecast influences aggregate planning cost. Third, many aggregate planning studies focus primarily on baseline cost comparison and provide limited evaluation of whether the selected strategy remains robust when cost parameters change. This is important because real manufacturing systems face cost uncertainty, including changes in labor cost, inventory holding cost, hiring cost, and shortage cost (Türkay, Saraçoğlu, & Arslan, 2016). To address these gaps, this study develops an integrated production planning framework that combines forecasting model evaluation, aggregate planning comparison, and sensitivity analysis in a single empirical case study. The study focuses on a furniture manufacturing company producing Solid Surface Four Sides (S4S) products under a make-to-stock system. The company faces recurring challenges in determining appropriate production quantities under fluctuating demand conditions. Therefore, this study evaluates three forecasting methods, namely Single Exponential Smoothing, Linear Regression, and Holt's Trend Method, using MAPE, MAD, and RMSE. The selected forecast is then used as the demand input for comparing Level and Chase aggregate planning strategies. Finally, a one-way sensitivity analysis is conducted by varying key cost parameters by ±20% to test the robustness of the selected strategy. The objectives of this study are threefold. First, this study aims to identify the most appropriate forecasting method for S4S demand based on multiple accuracy measures. Second, it aims to determine the most cost-efficient aggregate planning strategy by comparing Level and Chase strategies using the selected forecast. Third, it aims to evaluate whether the preferred aggregate planning strategy remains robust under changes in key cost parameters. The contribution of this study lies in linking forecasting validation directly to aggregate planning cost consequences and extending the analysis with a robustness-oriented sensitivity assessment. From a practical perspective, the proposed framework provides a structured decision-support approach for manufacturing firms seeking to improve medium-term production planning under demand uncertainty.

Research Method

Research Design

This study employed a quantitative case-study approach to develop an integrated production planning framework for a make-to-stock manufacturing environment. The framework combines demand forecasting, aggregate planning, and sensitivity analysis to support cost-based production decision-making. A case-study design was selected because it enables the application of quantitative planning methods to an actual operational setting and allows the evaluation of forecasting and aggregate planning decisions using real company data (Gansterer, 2015; Oey, Wijaya, & Hansopaheluwakan, 2020). The research process consisted of four main stages. First, historical demand data were analyzed to identify the demand pattern. Second, alternative forecasting methods were evaluated using multiple accuracy measures. Third, the selected forecast was used as the demand input for aggregate planning under Level and Chase strategies. Fourth, sensitivity analysis was conducted to assess whether the selected aggregate planning strategy remained robust under cost-parameter changes.

Data Collection

The study used data collected from a furniture manufacturing company producing Solid the S4S products. Two main datasets were used. The first dataset consisted of monthly historical demand data over 12 months, from July 2024 to June 2025. This dataset was used to evaluate demand patterns and compare forecasting methods. The second dataset consisted of operational cost and capacity parameters required for aggregate planning, including labor cost, hiring cost, firing cost, inventory holding cost, shortage cost, initial workforce level, and production capacity per worker. The 12-month data period was selected because aggregate production planning generally supports short-term decisions over several months up to one year. In this study, the July 2024-June 2025 dataset was therefore treated as a short-term planning horizon suitable for linking demand forecasting results to workforce, production quantity, and inventory planning decisions (Chapman et al., 2017; Heizer et al., 2016). Nevertheless, the limited observation period remains a methodological limitation because it may reduce the generalizability of the forecasting results and restrict the ability to detect seasonal demand patterns. Therefore, the findings should be interpreted as case-specific evidence for the observed planning horizon rather than as a universal demand pattern for all periods.

Demand Forecasting Model

To estimate future demand, three forecasting methods were evaluated: Single Exponential Smoothing, Linear Regression, and Holt's Trend Method. These methods were selected because they are commonly used in operational forecasting and production planning, particularly for short- to medium-term demand estimation. Exponential smoothing methods are widely used because they are simple, adaptive, and effective for many business and operational time series. Holt's Trend Method is especially appropriate when the data contain a trend component but do not show strong seasonality (Hyndman & Athanasopoulos, 2021; Makridakis, Spiliotis, & Assimakopoulos, 2018). Single Exponential Smoothing was used to generate forecasts by assigning greater weight to recent observations. The equation is expressed as Equation (1) :

$$F_t = \alpha A_{t-1} + (1-\alpha)F_{t-1} \tag{1}$$

Where F_t is the forecat for period t, A_{t-1} is the actual demand in the previous period F_{t-1} s the forecast for the previous period, and α is the smoothing constant. In this study, several candidate values of α were tested, and the value producing the best forecasting accuracy was selected. Linear Regression was applied to capture the underlying linear relationship between demand and time. The regression model is expressed as Equation (2)

$$\hat{Y}_t = \alpha + bt \tag{2}$$

Where $\hat{Y}_t$ is the forecasted demand for period t, α is the intercept, b is the slope coefficient, and t is the time index. Holt's Trend Method was included to account for the possibility of a trend component in the demand series. The proposed model is defined by Equation (3):

$$\begin{aligned} L_t &= \alpha A_t + (1-\alpha)(L_{t-1} + T_{t-1}) \\ L_t &= \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \\ \hat{Y}_{t+m} &= (L_t + mT_t) \end{aligned} \tag{3}$$

Where L_t represents the level component, T_t denotes the trend component, α and β are smoothing parameters, and $\hat{Y}_{t+m}$ is the forecast for m periods ahead. The model parameters were selected based on the lowest forecasting error obtained during evaluation (Hyndman & Athanasopoulos, 2021).

Forecast Accuracy Evaluation

The forecasting performance of each method was evaluated using three error measures: Mean Absolute Percentage Error, Mean Absolute Deviation, and Root Mean Square Error. The use of multiple accuracy measures provides a more comprehensive evaluation because each metric captures different characteristics of forecasting error. MAPE expresses forecasting error in percentage terms, MAD measures the average absolute deviation in demand units, and RMSE gives greater weight to larger forecasting errors (Hyndman & Athanasopoulos, 2021; Kim & Kim, 2016). MAPE was used to measure forecast error in percentage terms, as defined in Equation (4):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| x100 \tag{4}$$

MAD was used to measure the average absolute deviation between actual and forecasted demand, as defined in Equation (5):

$$MAD = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{5}$$

RMSE was used to measure forecast error by giving greater weight to larger errors, as defined in Equation (6):

$$RMSE \sqrt{\frac{1}{n}\sum_{t-1}^{n}(A_t - F_t)^2} \tag{6}$$

Where A_t denotes actual demand, F_t denotes forecasted demand, and n is the number of observations. The forecasting model with the best overall accuracy was selected as the demand input for aggregate planning. In this study, model selection emphasized consistency across the three error measures rather than relying on a single indicator alone (Gansterer, 2015).

Aggregate Planning Model

The selected forecasting method was used as the demand input for aggregate planning over a 12-month planning horizon. Aggregate planning was applied to determine the monthly production quantity, workforce level, inventory position, and shortage level required to satisfy forecasted demand at minimum total cost. Aggregate planning is commonly used in operations management to translate demand forecasts into medium-term production decisions by balancing capacity, workforce, inventory, and cost considerations (Chapman et al., 2017; Heizer et al., 2016). To formulate the aggregate production planning model, the following notation is used. D_t denotes the forecasted demand in period t, P_t represents the production quantity in period t, and W_t indicates the workforce level in period t. The variables H_t and $F_t$denote the number of workers hired and fired in period t, respectively. Furthermore, $I_t$represents the ending inventory in period t, while B_t denotes the shortage (backorder) in period t. The parameter $k$refers to the production capacity per worker per period. Cost parameters include $c_L$for labor cost per worker, c_H for hiring cost per worker, c_F for firing cost per worker, c_I for inventory holding cost per unit, and $c_S$for shortage cost per unit. Finally, T represents the total number of planning periods. The aggregate production planning model was developed based on a set of operational constraints in order to ensure production feasibility and workforce consistency during the planning horizon. These constraints are in terms of inventory balance, workforce balance, production capacity and non-negativity requirements (7)–(10). The objective function is to minimize the total aggregate production planning cost as shown in Equation (11).

a. Inventory balance constraint:

$$I_t - B_t = I_{t-1} - B_{t-1} + P_t - D_t \tag{7}$$

b. Workforce balance constraint:

$$W_t = W_{t-1} + H_t - F_t \tag{8}$$

c. Capacity constraint

$$P_t \leq kW_t \tag{9}$$

d. Non-negativity constraint

$$P_t, W_t, H_t, F_t, I_t, B_t \geq 0 \tag{10}$$

e. Objective function:

$$TC = \sum_{t=1}^{T} (C_L W_t + C_H H_t + C_F F_t + C_I L_t + C_S S_t) \tag{11}$$

where TC denotes the total aggregate production planning cost over the planning horizon. The objective function minimizes the overall production cost by considering labor, hiring, firing, inventory holding, and shortage costs incurred across all planning periods. Two aggregate planning strategies were evaluated. Under the Level Strategy, production was maintained at a relatively stable rate, and demand fluctuations were absorbed through inventory or shortage. Under the Chase Strategy, production was adjusted more closely to forecasted demand in each period. The total cost of each strategy was calculated and compared. The strategy with the lower total cost was selected as the preferred aggregate planning policy. The comparison between Level and Chase strategies is commonly used in aggregate planning because both strategies represent different trade-offs between production stability, inventory holding cost, and workforce adjustment cost (Chapman et al., 2017; Heizer et al., 2016).

Model Assumptions

Several assumptions were used to simplify the analysis and ensure comparability between strategies. First, the selected forecast was treated as the demand input for aggregate planning. Second, worker productivity was assumed to remain constant throughout the planning horizon. Third, shortages, if they occurred, were treated as backorders and penalized using shortage cost. Fourth, machine capacity and material availability were assumed sufficient to support the planned production volume. Fifth, the analysis focused on planning-related costs that differed between strategies, namely labor cost, hiring cost, firing cost, inventory holding cost, and shortage cost.

Sensitivity Analysis

A one-way sensitivity analysis was conducted to evaluate the robustness of the selected aggregate planning strategy. This analysis examined whether the preferred strategy remained unchanged when key cost parameters varied individually while other parameters were held constant. Sensitivity analysis is useful in production planning because cost parameters may change under real operating conditions, and such changes can influence the preferred planning strategy (Gansterer, 2015; Türkay et al., 2016). The cost parameters tested were labor cost, hiring cost, firing cost, inventory holding cost, and shortage cost. Each parameter was varied by ±20% from its baseline value. The total cost of both Level and Chase strategies was recalculated under each scenario. The preferred strategy in each scenario was then identified based on the lower total cost. The sensitivity analysis was conducted to determine whether the selected production strategy was only optimal under baseline assumptions or remained stable under reasonable cost uncertainty. This step is important because real manufacturing systems may experience changes in wage levels, recruitment costs, storage costs, and shortage penalties.

Research Framework

The research framework combines demand forecasting and aggregate production planning into a systematic decision-making process. The study begins with analysis of historical demand pattern and evaluation of several forecasting methods based on MAPE, MAD and RMSE. Then, the forecasting method with the best performance is selected to forecast the demand for the planning horizon. The forecast is the primary input to the aggregate production planning model. Then, the Level and Chase strategies are developed and compared based on their total production costs to find the most cost-effective production plan. Finally, a sensitivity analysis is performed by varying the key cost parameters by ±20%, in order to evaluate the robustness of the selected strategy under different operating conditions. This framework provides an integrated approach to link demand forecast, production planning, cost optimization and robustness assessment to facilitate effective decision making in production planning.

Results

Demand Pattern Analysis

Historical sales data of S4S products from July 2024 to June 2025 show moderate fluctuations with an overall upward trend. Monthly demand ranges between 3,900 and 4,300 units, indicating relatively stable variability without strong seasonal effects. The available company data were limited to one complete and validated 12-month period; therefore, the historical base could not be extended to 24-36 months. This limitation reduces the ability to confirm longer seasonal cycles, so the forecasting results should be interpreted as short-term, case-based planning estimates rather than long-term seasonal forecasts. This indicates that the series is relatively stable and does not show clear seasonal spikes, making it suitable for evaluating forecasting methods that can handle moderate variability and gradual change. The scatterplot supports this interpretation by showing dispersed observations around an increasing trend line, implying that short-term noise exists, but the long-run direction is positive. Implication: Because the data do not demonstrate strong seasonality, the forecasting comparison can focus on smoothing-based and regression-based approaches without requiring seasonal models (Harahap, Rahim, Malinjasari, Salleh, & Ma'arof, 2025; Kourentzes & Petropoulos, 2016).

Forecasting Performance Comparison

Three forecasting models were evaluated: Single Exponential Smoothing (SES), Linear Regression, and Holt's Trend Method. Model performance was assessed using three accuracy measures: MAPE, MAD, RMSE.

Table 1 Forecasting Accuracy Comparison

Forecasting Method	Parameter	MAPE (%)	MAD	RMSE	Overall Rank
Holt's Trend Method	α = 0.4, β = 0.1	1.63	67.34	106.08	1
SES	α = 0.3	1.68	69.83	111.55	2
SES	α = 0.2	1.69	70.45	113.89	3
Linear Regression	-	1.75	71.21	91.01	4
SES	α = 0.1	1.72	71.82	117.17	5

The overall rank in Table 1 was determined using a composite ranking across MAPE, MAD, and RMSE, with lower average rank indicating better overall performance. When the composite score was close, MAPE and MAD were prioritized because aggregate planning in this study emphasizes average absolute demand deviation and percentage error. Although Linear Regression produced the lowest RMSE, Holt's Trend Method was selected because it generated the lowest MAPE and MAD and achieved the best composite forecasting performance for the observed demand pattern. Holt's Trend Method was also evaluated to account for the upward trend observed in the historical demand pattern. The best parameter combination was $\alpha = 0.4$ and $\beta = 0.1$, producing a MAPE of 1.63%, MAD of 67.34 units, and RMSE of 106.08 units. Compared with SES and Linear Regression, Holt's Trend Method generated the lowest MAPE and MAD values, indicating better overall forecasting accuracy for the S4S demand data. Therefore, Holt's Trend Method was selected as the forecasting model for the subsequent aggregate planning analysis.

Table 2 Selected Forecast Results

Period	Month	Forecast Demand
13	July 2025	4211
14	August 2025	4231
15	September 2025	4251
16	October 2025	4271
17	November 2025	4292
18	December 2025	4312
19	January 2026	4332
20	February 2026	4352
21	March 2026	4372
22	April 2026	4392
23	May 2026	4413
24	June 2026	4433
Total		**51,862**

The selected Holt's Trend Method forecast indicates a gradual increase in demand from 4,211 units in July 2025 to 4,433 units in June 2026. The total forecasted demand over the 12-month planning horizon is 51,862 units. This forecast was then used as the demand input for aggregate planning.

Aggregate Planning Cost Comparison

Using the selected forecast, aggregate planning was evaluated under two alternatives: Level Strategy and Chase Strategy (Ariela & Nursea, 2022; Oey et al., 2020). Total cost outcomes are presented in Table 3.

Table 3 Total Cost Comparison of Aggregate Planning Strategies

Strategy	Labor Cost	Hiring Cost	Firing Cost	Holding Cost	Shortage Cost	Total Cost
Level Strategy	184,800,000	1,100,000	0	3,623,750	0	**189,523,750**
Chase Strategy	184,800,000	1,100,000	0	0	0	**185,900,000**

Using the Holt's Trend Method forecast as the demand input, aggregate planning was evaluated under Level and Chase strategies. The Level Strategy generated a total cost of

Rp.189,523,750, while the Chase Strategy generated a total cost of Rp.185,900,000. The Chase Strategy therefore resulted in a lower total cost, with a cost difference of Rp.3,623,750 compared with the Level Strategy. Cost interpretation: The cost advantage is consistent with the operational logic that level production tends to accumulate inventory during lower-demand periods, increasing holding cost exposure. In contrast, chase planning reduces inventory build-up by aligning output more closely with demand changes.

Key Findings

The empirical results demonstrate three important findings: (1) S4S demand shows moderate variability with a mild upward trend and no strong seasonality. (2) Holt's Trend Method with $\alpha = 0.4$ and $\beta = 0.1$ achieves the best overall forecasting accuracy, with MAPE of 1.63%, MAD of 67.34 units, and RMSE of 106.08 units. (3) The Chase Strategy minimizes total aggregate planning cost, generating Rp185,900,000 compared with Rp.189,523,750 under the Level Strategy. These findings establish the quantitative basis for discussing why the selected forecasting method and the chase-oriented aggregate policy are appropriate for the studied production system.

Sensitivity Analysis Results

A one-way sensitivity analysis was conducted by varying key cost parameters by ±20% to evaluate whether the selected aggregate planning strategy remained robust under cost uncertainty. The analysis focused on labor cost, hiring cost, firing cost, inventory holding cost, and shortage cost.

Table 4 Sensitivity Analysis of Aggregate Planning Costs under ±20% Cost Parameter Changes

Cost Parameter Varied	Change	Level Strategy Cost (Rp)	Chase Strategy Cost (Rp)	Difference (Rp)	Preferred Strategy
Baseline	0%	189,523,750	185,900,000	3,623,750	Chase
Labor cost	-20%	152,563,750	148,940,000	3,623,750	Chase
Labor cost	+20%	226,483,750	222,860,000	3,623,750	Chase
Hiring cost	-20%	189,303,750	185,680,000	3,623,750	Chase
Hiring cost	+20%	189,743,750	186,120,000	3,623,750	Chase
Firing cost	-20%	189,523,750	185,900,000	3,623,750	Chase
Firing cost	+20%	189,523,750	185,900,000	3,623,750	Chase
Inventory holding cost	-20%	188,799,000	185,900,000	2,899,000	Chase
Inventory holding cost	+20%	190,248,500	185,900,000	4,348,500	Chase
Shortage cost	-20%	189,523,750	185,900,000	3,623,750	Chase
Shortage cost	+20%	189,523,750	185,900,000	3,623,750	Chase

A one-way sensitivity analysis was conducted by varying key cost parameters by ±20% to evaluate the robustness of the selected aggregate planning strategy. The parameters tested included labor cost, hiring cost, firing cost, inventory holding cost, and shortage cost. The results show that the Chase Strategy remained the preferred strategy under all sensitivity scenarios. Under baseline conditions, the Level Strategy generated a total cost of Rp189,523,750, while the Chase Strategy generated Rp185,900,000. When inventory holding cost was reduced by 20%, the Level Strategy cost decreased to Rp188,799,000, but it remained higher than the Chase Strategy. When inventory holding cost increased by 20%, the Level Strategy cost increased to Rp190,248,500, further widening the cost gap. Changes in labor cost and hiring cost did not alter the preferred strategy because both strategies used the same workforce level and hiring requirement. Firing cost and shortage cost also did not affect the total cost because no firing or shortage occurred in either strategy. Therefore, the sensitivity analysis confirms that the Chase Strategy is robust and remains the most cost-efficient aggregate planning policy for the studied production system.

Discussion

Interpretation of Demand Characteristics and Implications for Forecasting

The demand pattern of S4S products shows moderate month-to-month fluctuation with a mild upward trend and no clear seasonal spike during the observed July 2024-June 2025 period. This pattern supports the use of non-seasonal forecasting methods that can capture both short-term variation and gradual directional movement. However, because the available dataset covers only 12 monthly observations, the absence of seasonality should be interpreted cautiously and should not be generalized beyond the studied planning horizon without additional multi-year data. The forecasting comparison indicates that Holt's Trend Method provides the best overall performance because it matches the observed trend structure of the demand series. Although Linear Regression generated the lowest RMSE, Holt's Trend Method produced the lowest MAPE and MAD, making it more consistent across the evaluation criteria used in this study. This result supports the selection of Holt's Trend Method as the demand input for aggregate planning, while also showing why model selection should be based on multiple error measures rather than a single accuracy indicator (Hyndman & Athanasopoulos, 2021; Kim & Kim, 2016). From a production planning perspective, the forecasting result is important because demand estimates directly affect production quantity, inventory position, and cost outcomes. A method that captures the upward demand movement more reliably can reduce the risk of capacity mismatch and excessive inventory. Therefore, the forecasting stage in this study functions not only as a statistical exercise but also as a validated input for downstream aggregate planning decisions (Gansterer, 2015; Widiarta et al., 2009).

Aggregate Planning Cost Implications

The aggregate planning comparison shows that the Chase Strategy is more cost-efficient than the Level Strategy for the studied production system. The Level Strategy generated a total cost of Rp189,523,750, while the Chase Strategy generated Rp185,900,000, resulting in a cost saving of Rp3,623,750. The cost difference is mainly explained by inventory holding cost under the Level Strategy, whereas the Chase Strategy avoided inventory accumulation by aligning production more closely with forecasted demand. This result reflects the cost trade-off between production stability and inventory exposure. Level production can simplify production control by maintaining a relatively stable output, but it may create inventory when demand is lower than production. In contrast, chase planning is advantageous when the firm can adjust output to demand without creating excessive hiring, firing, or shortage costs. In this case, both strategies had the same labor and hiring costs, and neither strategy generated firing or shortage costs; therefore, inventory holding cost became the decisive factor. The implication is that the recommended production strategy should be evaluated in relation to the company's cost structure and operational flexibility. For the observed S4S production system, the Chase Strategy is appropriate because it reduces inventory-related cost without increasing workforce adjustment burden. Nevertheless, the recommendation should be revisited if future operating conditions change, particularly if workforce flexibility declines, material availability becomes constrained, or demand variability increases.

Robustness of the Selected Planning Strategy

The sensitivity analysis strengthens the aggregate planning result by showing that the Chase Strategy remains the lowest-cost alternative under all ±20% cost-parameter scenarios. Changes in labor cost and hiring cost did not alter the preferred strategy because both planning alternatives used the same workforce and hiring requirements. Similarly, firing cost and shortage cost had no impact because no firing or shortage occurred in either strategy. Inventory holding cost was the only parameter that changed the cost gap between the two strategies. When holding cost decreased by 20%, the Level Strategy became less costly but still remained more expensive than the Chase Strategy. When holding cost increased by 20%, the cost advantage of the Chase Strategy became larger. This confirms that the robustness of the Chase Strategy is primarily driven by its ability to prevent inventory accumulation. The integrated analysis demonstrates that forecasting validation, aggregate planning comparison, and sensitivity testing provide complementary decision support. Forecasting identifies the most reliable demand input, aggregate planning translates the forecast into cost consequences, and sensitivity analysis evaluates whether the selected strategy remains stable under reasonable cost uncertainty. This concise linkage clarifies the practical value of the proposed framework for make-to-stock manufacturing decisions.

Managerial Implications and Transferability

The findings of this study provide several practical implications for managers in make-to-stock manufacturing environments. First, managers should treat demand forecasting as a validated decision input rather than a routine administrative calculation. The results show that different forecasting methods produce different accuracy levels, and these differences can influence subsequent aggregate planning decisions. In this case, Holt's Trend Method was selected because it produced the lowest MAPE and MAD values among the evaluated models. This indicates that forecast validation using multiple accuracy measures is necessary before the forecast is used for production planning. This is consistent with operations management literature, which emphasizes that forecasting is a critical input for capacity planning, inventory control, workforce planning, and production scheduling (Heizer et al., 2016; Hyndman & Athanasopoulos, 2021). Second, the company should adopt a Chase-oriented aggregate planning policy for the next planning horizon, provided that production capacity and workforce flexibility remain sufficient. The Chase Strategy generated the lowest total cost because it aligned production more closely with forecasted demand and eliminated inventory holding cost. This implies that the company can improve cost efficiency by reducing unnecessary inventory accumulation rather than maintaining a constant production rate. For the studied S4S production system, the Chase Strategy is especially suitable because it did not require additional firing or shortage costs and used the same workforce level as the Level Strategy. Therefore, the cost advantage was achieved without creating additional labor adjustment burden. Third, managers should monitor inventory holding cost as a key cost driver in aggregate planning decisions. The sensitivity analysis showed that inventory holding cost had the strongest influence on the cost difference between Level and Chase strategies. When inventory holding cost increased by 20%, the total cost gap between the two strategies widened, further strengthening the preference for the Chase Strategy. This implies that companies operating in make-to-stock systems should pay close attention to storage cost, handling cost, space utilization, and capital tied up in inventory. Inventory should not only be viewed as a service-level buffer, but also as a cost component that can reduce operational efficiency when not properly controlled (Chapman et al., 2017).Fourth, the proposed integrated framework can be used as a practical decision-support tool for small- and medium-sized manufacturing firms facing fluctuating demand. The framework begins with demand pattern identification, continues with forecasting model validation, applies the selected forecast to aggregate planning, and finally evaluates the robustness of the selected strategy through sensitivity analysis. This step-by-step process helps managers connect statistical forecasting results with cost-based production decisions. Previous studies have emphasized that forecasting and aggregate planning should not be treated separately, because forecasting errors can affect production quantities, inventory levels, workforce decisions, and total planning costs (Gansterer, 2015; Widiarta et al., 2009).

In terms of transferability, the framework is most applicable to manufacturing firms with moderate demand variability, weak or no seasonality, and meaningful inventory holding costs. Firms with similar make-to-stock characteristics can replicate the approach by testing several forecasting methods, selecting the model with the best accuracy, and comparing alternative aggregate planning strategies based on total cost. However, the preferred strategy may differ in other contexts. For example, firms with high workforce adjustment costs, strict labor regulations, unstable material availability, or limited production flexibility may find a Level or hybrid strategy more appropriate. Therefore, while the framework is transferable, the selected production strategy should always be determined based on the firm’s specific demand pattern, capacity condition, and cost structure. Overall, the managerial implication of this study is that production planning decisions should be made through an integrated and data-driven process. Managers should not select a forecasting method or aggregate planning strategy Independently. Instead, forecast accuracy, production capacity, inventory implications, and cost sens itivity should be evaluated together. By applying this integrated approach, manufacturing firms can improve the reliability of production planning and reduce the risk of cost inefficiency caused by mismatches between demand forecasts and production decisions.

Research Contribution (Scientific Value)

This study contributes to the production planning literature by developing and applying an integrated decision framework that connects demand forecasting validation, aggregate planning evaluation, and sensitivity analysis within a single empirical case study. Rather than treating forecasting and aggregate planning as separate analytical activities, this study demonstrates how forecasting accuracy can be directly linked to downstream production planning decisions. The selected forecast was not only evaluated statistically using MAPE, MAD, and RMSE, but was also translated into Level and Chase aggregate planning strategies to identify the cost consequences of forecasting-based production decisions. The first contribution of this study is the integration of forecasting model selection with cost-based aggregate planning. Previous studies have often emphasized either forecasting accuracy or aggregate planning optimization separately. In contrast, this study shows that the selected forecasting method should serve as a validated input for production planning. By using Holt’s Trend Method as the selected forecasting model and applying its forecast to aggregate planning, the study highlights the importance of aligning statistical accuracy with operational cost implications. This strengthens the argument that forecasting performance should be evaluated not only in terms of error reduction, but also in terms of its usefulness for production and inventory decision-making. The second contribution is the use of multiple forecasting accuracy measures to support model selection. The study evaluates forecasting models using MAPE, MAD, and RMSE, which provides a more balanced assessment than relying on a single indicator. This is important because different error measures capture different aspects of forecasting performance. The finding that Holt's Trend Method produced the lowest MAPE and MAD, while Linear Regression produced the lowest RMSE, demonstrates the value of multi-metric evaluation in avoiding overly narrow conclusions. This approach supports more transparent and defensible forecasting model selection in manufacturing planning contexts.

The third contribution lies in extending aggregate planning evaluation through sensitivity analysis. By varying key cost parameters by ±20%, the study assesses whether the selected Chase Strategy remains robust under cost uncertainty. The results show that the Chase Strategy remains the lowest-cost alternative across all tested scenarios, indicating that the selected planning policy is not only optimal under baseline assumptions but also stable under reasonable cost variations. This robustness-oriented perspective strengthens aggregate planning analysis by providing managers with greater confidence in the recommended strategy. From a practical contribution perspective, this study provides a replicable decision-support framework for make-to-stock manufacturing firms facing moderate demand variability and inventory-related cost concerns. The framework can help managers identify demand patterns, validate forecasting methods, compare aggregate planning alternatives, and test the robustness of production planning decisions. For small- and medium-sized manufacturers, this approach is useful because it can be implemented using relatively accessible quantitative tools while still producing actionable production planning recommendations. The study contributes by bridging the gap between forecasting accuracy and production cost efficiency. It shows that the value of forecasting in manufacturing is not limited to predicting future demand, but also lies in supporting cost-efficient and robust aggregate planning decisions. Therefore, the proposed framework advances both the methodological and practical understanding of how forecasting and production planning can be integrated to improve medium-term manufacturing decision-making.

Limitations and Future Research Directions

This study has several limitations that should be considered when interpreting the results. First, the analysis is based on 12 months of historical demand data from one product group in a single furniture manufacturing company. Although this period is suitable for a case-based aggregate planning horizon, it may limit forecasting generalizability and may not capture seasonal patterns that require observations across several annual cycles. Second, the aggregate planning comparison focuses on Level and Chase strategies using selected planning-related cost components, while other operational constraints, such as overtime, subcontracting, machine capacity, material availability, and service-level targets, were not explicitly modeled. Future research should extend the dataset to 24-36 months where available, test additional forecasting and hybrid aggregate planning strategies, and incorporate broader capacity and supply constraints to improve external validity.

Conclusions

This study confirms that an integrated framework combining demand forecasting, aggregate planning, and sensitivity analysis can improve medium-term production planning decisions in a make-to-stock furniture manufacturing system. Based on 12 months of historical S4S demand data, Holt's Trend Method with $\alpha = 0.4$ and $\beta = 0.1$ produced the best overall forecasting performance, with a MAPE of 1.63%, MAD of 67.34 units, and RMSE of 106.08 units. The selected forecast was then used as the input for aggregate planning. The results show that the Chase Strategy generated the lowest total cost of Rp185,900,000, compared with Rp189,523,750 under the Level Strategy. The elimination of inventory holding cost mainly drove the cost advantage of Rp3,623,750. Sensitivity analysis using ±20% changes in key cost parameters confirmed that the Chase Strategy remained the preferred strategy under all tested scenarios. Therefore, the Chase Strategy is recommended as a robust and cost-efficient aggregate planning policy for the S4S production system studied.

The company is recommended to use Holt's Trend Method with $\alpha = 0.4$ and $\beta = 0.1$ as the baseline forecasting model for the next planning horizon, while continuously updating the model as new demand data becomes available. Forecast accuracy should be monitored using multiple error measures to ensure that forecasting results remain reliable for production planning. For aggregate planning, the company should implement a Chase-oriented strategy because it produced the lowest total cost and remained robust under all sensitivity scenarios. However, the company should continue monitoring inventory holding cost, workforce capacity, machine availability, and material supply to ensure that production can follow demand without operational disruption. Given the 12-month dataset, future implementation should add new monthly observations, re-evaluate whether seasonal models become necessary when longer historical data are available, and extend the analysis to hybrid aggregate planning strategies and broader constraints such as overtime, subcontracting, machine capacity, material availability, and service-level requirements.

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