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Optimization of Aggregate Planning Using Linear Regression: An Integrated Approach to Demand Forecasting, Production Capacity, and Inventory Management

Rajendar Dommeti

Principal SAP Supply Chain & AI-Driven Solution Architect, Tennessee, USA.

Abstract

Integrated planning plays a key role in production management, through which it is improved resource allocation, workforce utilization, inventory levels, and production capacity to meet forecasted demand while minimizing costs. This study examines the integrated planning framework for a manufacturing environment, focusing on the relationships between demand forecasting, production capacity, inventory management, and total cost optimization. Using a dataset of 300 observations, descriptive statistical analysis reveals significant variability in demand forecasts and production capacity, with mean values of 2973.9 and 3015.7 units respectively. Linear regression modeling demonstrates strong predictive performance, it has achieved an R^2 value of 0.9159 for the training dataset and 0.8028 for the test dataset.Correlation analysis identifies inventory level as the primary cost driver, showing a strong positive correlation of 0.81 with total cost, while demand forecast exhibits a moderate correlation of 0.41, and production capacity shows minimal direct impact at 0.24. The findings underscore the importance of balanced decision-making in aggregate planning, where effective coordination between forecasting accuracy, capacity alignment, and inventory optimization is essential for cost control and operational efficiency. This research contributes to the development of data-driven decision support systems for sustainable supply chain management.

Key Words: Aggregate Planning, Linear Regression, Demand Forecasting, Inventory Optimization, Production Capacity.

Introduction

Aggregate planning methods, in their dynamic operation, are similar to supply chains.This is not unexpected, since the fundamental mathematical models employed in aggregate planning function by making decisions grounded in present circumstances—including available labor force, manufacturing capacity, stock on hand, pending orders, and projected future customer requirements. From this perspective, it mirrors the decision-making approaches used in supply chain management [1]. Significant demand variability necessitates constant revisions to production schedules across successive planning cycles, which generates stress within manufacturing operations and serves as a primary cost driver through its negative impact on workforce management and stock levels [2].Aggregate planning is a strategic process for determining production volumes and establishing output targets over a medium-term timeframe (usually spanning three months to one year) by adjusting production rates, labor force size, stock levels, and other flexible parameters. This planning approach enables companies to make optimal use of available resources to attain efficient and productive operations aligned with anticipated future customer demand [3]. A production planning system is composed of several interrelated subsystems, including aggregate planning, hierarchical production planning, material requirements planning, capacity planning, manufacturing resource planning, inventory management, and supply chain planning. Of these components, aggregate production planning (APP) emerges as one of the most vital elements in the broader production planning structure [4]. The aggregate planning problem addresses critical decisions regarding production capacities, workforce deployment, stock levels, backorders when demand cannot be fulfilled promptly, and outsourcing requirements.

Consequently, the aggregate planning problem serves as an essential mechanism for translating strategic-level goals into practice while defining parameters for operational-level challenges. Additionally, the aggregate planning problem incorporates economic, environmental, and social considerations into its framework [5]. Additional forms of uncertainties, including ambiguous demand requirements, fluctuating production capabilities, and inexact processing durations, are frequently experienced in aggregate production planning. These categories of uncertainties cannot be adequately represented through frequency-based probabilistic models [6].Optimal production targets are determined using demand forecasts and total resource limitations. The outcomes generated at the aggregate planning level must then be broken down over time intervals and specified in greater detail regarding individual products and materials, while considering

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Corresponding Author: Rajendar Dommeti, Principal SAP Supply Chain & AI-Driven Solution Architect, Tennessee, USA.; Email: Rajdommeti23@gmail.com

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specific fundamental constraints that emerge from operational-level requirements [7]. The goal of production planning is to coordinate the entire production operation and fulfill demand at minimal cost by optimally leveraging manufacturing resources. The objective of this study is to forecast demand for PT. Anela company for the period spanning May 2015 to April 2016 and to conduct aggregate planning with the purpose of minimizing production expenses [8].It is important to note that the majority of distributed energy resource owners (commonly referred to as prosumers or producer-consumers) lack sufficient scale to engage directly in energy markets because of prevailing market entry barriers. Consequently, the aggregator's function becomes essential for coordinating all distributed energy resource systems and facilitating market participation [9]. Integrated planning, embedded within sustainable development models, addresses three-dimensional goals encompassing economic feasibility, environmental protection, and social responsibility [10].

Materials and Methods

Materials

Demand Forecasting: Demand forecasting refers to the estimated quantity of goods or services that customers are expected to demand over a specific future period. It is typically derived using historical data, statistical methods, or forecasting models, and serves as the basis for production, inventory, and capacity planning decisions.

Production Capacity: Production capacity represents the highest level of output that a manufacturing or service operation can generate during a specified period under standard working conditions. It reflects the availability of resources such as labor, machinery, and technology, and determines how well a company can meet projected demand.

Inventory Level: Inventory level refers to the quantity of raw materials, work-in-process, or finished products kept in storage at any given moment. Sustaining optimal inventory levels helps achieve equilibrium between satisfying customer requirements and reducing holding, storage, and obsolescence costs.

Total Cost: Total cost refers to the overall expenses associated with operations, including production costs, inventory costs, transportation, and other operating expenses. It is a key performance indicator used to evaluate the efficiency and effectiveness of planning and resource allocation decisions.

Optimization Techniques:

Linear Regression: This is a valuable technique used to predict quantitative outcomes. It is a statistical method and has been thoroughly examined in countless textbooks throughout the years. While it may not appear as captivating as contemporary statistical learning approaches, it remains widely utilized and extremely pertinent. Moreover, it provides the groundwork for more sophisticated techniques, since many advanced statistical learning methods can be viewed as expansions or broader applications of linear regression. Consequently, a strong grasp of linear regression is crucial prior to delving into more intricate methodologies. In this chapter, the core principles of linear regression are investigated, alongside the least squares approach typically employed to construct a model. Regression fulfills two main functions. First, it is extensively employed for prediction and forecasting, frequently sharing substantial overlap with machine learning uses. In regression analysis, the dependent variable 'y' is estimated using various values of the independent variable 'x'. This study emphasizes linear regression and multiple regression, both of which hold significant importance for predictive modeling. Regression may take the form of simple linear regression or multiple regression, which represents one type of regression. Simple linear regression consists of a model containing a single independent variable to assess its influence on a dependent variable. This is expressed through the equation $\Upsilon = \beta_0 + \beta_1 + \dot{\varepsilon}$, which illustrates the connection between the variables. Furthermore, simple regression aids in distinguishing the effect of independent variables from the interactions occurring within the dependent variables.

Analysis and Discussion

This dataset provides a comprehensive view of four key integrated planning parameters: demand forecast, production capacity, inventory level, and total cost, illustrating their interrelationships across a large number of observations. The data reflects realistic operational scenarios commonly found in manufacturing and supply chain planning environments. Demand forecast values vary widely, indicating fluctuating market demands. This variability underscores the importance of accurate forecasting, as demand directly impacts production decisions and inventory holdings. Production capacity also shows significant variation, indicating flexibility and constraints in manufacturing capabilities. In many instances, production capacity exceeds demand, which can help avoid stock outs but can also lead to inefficiencies if not optimally utilized.

Inventory levels exhibit considerable variation, reflecting diverse inventory management strategies such as buffering against uncertainty or minimizing holding costs. Higher inventory levels often correlate with higher total costs due to storage, insurance, and capital tie-up. Conversely, lower inventory levels may reduce holding costs but increase the risk of unmet demand, potentially impacting service levels. The total cost parameter integrates the effects of demand, production, and inventory decisions. Total costs are observed to be higher when demand forecasts are high and inventory levels increase, indicating the combined impact of production costs and inventory holding costs. However, the data also suggests that efficient alignment between demand and production capacity can help control total costs, even under high-demand conditions. The dataset highlights the critical need for balanced decision-making in planning processes. Effective coordination between demand forecasting, capacity planning, and inventory management is essential to reduce overall costs while maintaining service reliability. These insights are valuable for developing data-driven optimization models and decision-support systems in operations and supply chain management.

Table 1: Presents descriptive statistics for the four integrated planning parameters demand forecast, production capacity

	Demand Forecast	Production Capacity	Inventory Level	Total Cost
Count	300	300	300	300
Mean	2973.9	3015.727	1010.713	5692.487
Std	1186.677	1268.503	579.4323	1431.726
Min	816	704	100	2432
25%	1945	1936.5	461.25	4533.75
50%	3046	2979.5	961	5640.5

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75%	3970.25	4060.25	1529.25	6807.25
Max	4999	5192	1991	9030

Table 1 presents descriptive statistics for the four integrated planning parameters demand forecast, production capacity, inventory level, and total cost based on 300 data points each. This provides a comprehensive overview of their distribution and variability. The demand forecast shows a mean value of 2973.9, indicating a moderate to high average demand level across the dataset. The wide range between the minimum (816) and maximum (4999) values highlights significant demand variability, further reflected by the relatively high standard deviation of 1186.677.

The median value of 3046, close to the mean, suggests that the distribution of demand is somewhat symmetrical, while the interquartile range (1945 to 3970.25) shows considerable fluctuations in typical demand levels. Production capacity has a mean of 3015.727, which closely matches the average demand forecast, indicating that capacity planning is generally aligned with expected demand. However, the high standard deviation of 1268.503 and the wide range (704 to 5192) also suggest significant flexibility and limitations in production capacity. The median capacity of 2979.5 further confirms a balanced central tendency. Inventory level shows a mean of 1010.713 and a standard deviation of 579.4323, indicating moderate variability in inventory levels. The minimum value of 100 and the maximum of 1991 suggest diverse inventory strategies, ranging from minimal inventory practices to high safety stock levels. The quartile values show that half of the data points lie between 461.25 and 1529.25 units. The total cost has a mean of 5692.487 and a very high standard deviation (1431.726), reflecting the combined impact of demand, production, and inventory decisions. The wide cost range from 2432 to 9030 emphasizes how operational planning efficiency significantly impacts overall costs. Overall, these statistics underscore the importance of integrated planning to manage variability and control costs effectively.

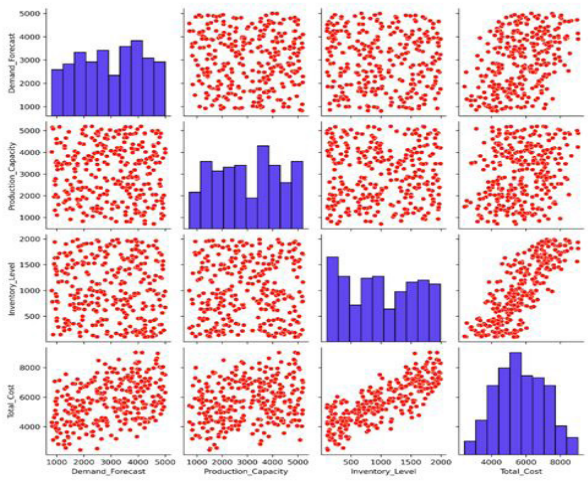

Figure 1: Pairwise Scatterplot Matrix of Aggregated PlanningParameters

Figure 1 presents a pairwise scatter plot matrix of integrated planning parameters demand forecast, production capacity, inventory level, and total cost providing a visual understanding of their relationships and distributions. The diagonal plots show a very wide spread for each variable, confirming the variability in planning conditions. The scatter plots indicate a positive relationship between inventory level and total cost, suggesting that higher inventory levels tend to increase overall costs. Demand forecast and production capacity show a broadly scattered pattern, indicating flexible capacity planning relative to demand fluctuations. The figure illustrates how cost is strongly influenced by inventory decisions, while demand and capacity are correlated with moderate variability, emphasizing the need for integrated operational planning.

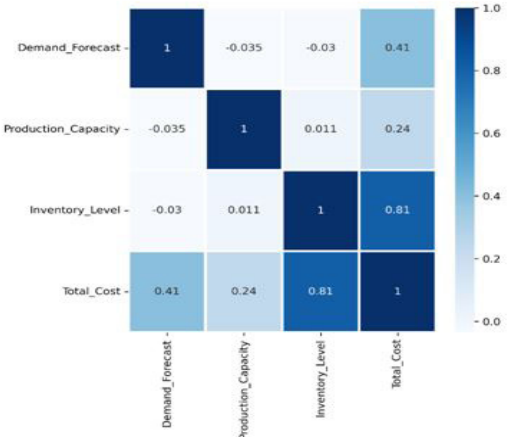

Figure 2: Correlation Heat Map Between the Process Parameters and the Responses

Figure 2 illustrates the heat map showing the relationship between process parameters, the response variable, and total cost. The results show a strong positive correlation between inventory level and total cost (0.81), indicating that inventory holding is the most influential factor driving the overall cost. Demand forecasting shows a moderate positive correlation with total cost (0.41), suggesting that higher demand generally leads to increased operational costs. Production capacity shows a weak positive correlation with total cost (0.24), indicating a limited direct impact on cost. The near-zero correlations between demand forecasting, production capacity, and inventory level indicate minimal interdependence, highlighting inventory level as the primary cost driver in the system.

Figure 3: Linear Regression (Training data)

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Figure 3 illustrates the performance of the linear regression model on the training dataset by comparing the predicted and actual total cost values. The data points are clustered closely around the diagonal reference line, indicating a strong agreement between the predicted and actual outcomes. This alignment suggests that the model effectively captures the underlying linear relationship between the input planning parameters and the total cost. Small deviations from the diagonal reflect prediction errors, which appear to be randomly distributed, indicating that there is no systematic bias in the model. The figure demonstrates that the linear regression model provides a good fit to the training data and is suitable for estimating the total cost based on the given parameters.

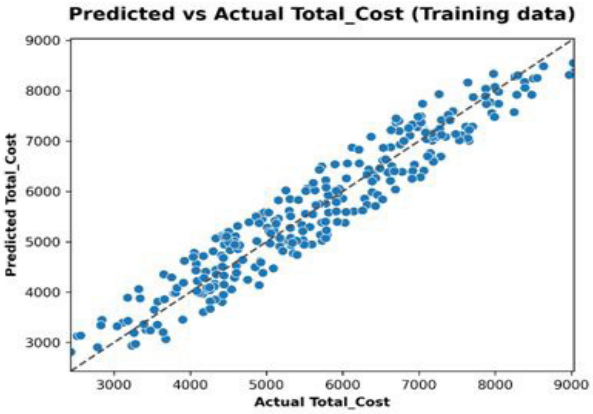

Figure 4: Linear Regression (Testing data)

Figure 4 presents the predicted versus actual total Cost values for the testing dataset using the linear regression model. The majority of data points lie close to the diagonal reference line, indicating good predictive accuracy on unseen data. Although the spread of points is slightly wider compared to the training results, the overall linear trend is well preserved, suggesting that the model generalizes effectively without significant overfitting. Minor deviations from the ideal line represent natural prediction errors due to data variability. The figure confirms the reliability and robustness of the linear regression model for estimating Total Cost under new operating conditions.

Table 2. Performance Metrics of Linear Regression (Training, Testing Data)

Data	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	0.9159	0.9159	180489.1436	424.8401	364.5113	770.8976	0.0069	343.0504
Test	0.8028	0.8135	214981.6003	463.6611	402.3166	723.1401	0.0073	466.9504

Table 2 summarizes the performance metrics of the linear regression model for both the training and testing datasets, providing insight into its accuracy and generalization capabilities. For the training data, the model achieves a high R^2 value of 0.9159, indicating that over 91% of the variance in total cost is explained by the input parameters. The low MSE and RMSE values (180,489.14 and 424.84) reflect strong predictive accuracy, while the relatively low MAE and median absolute error confirm consistent error behavior. For the testing data, the R^2 value decreases to 0.8028, which is expected when evaluating unseen data, yet still indicates good explanatory power. The slightly higher error metrics (RMSE = 463.66, MAE = 402.32) show moderate predictive deviation, although the low MSLE values in both cases indicate consistent logarithmic performance. The results demonstrate that the model performs reliably with good accuracy and acceptable generalization.

Conclusion

This research effectively illustrates the implementation of linear regression modeling for integrated aggregate planning in manufacturing environments, providing valuable insights into the optimization of production costs through effective resource management. The comprehensive analysis of 300 data points reveals critical relationships between demand forecasting, production capacity, inventory levels, and total cost, establishing a robust framework for operational decision-making. The linear regression model achieved exceptional predictive accuracy with an R^2 value of 0.9159 on training data and maintained strong generalization capability with an R^2 of 0.8028 on testing data, confirming its reliability for cost estimation under varying operational conditions.The correlation analysis yielded significant findings, identifying inventory level as the dominant cost driver with a correlation coefficient of 0.81 to total cost.

This strong relationship emphasizes the critical the importance of inventory management strategies in controlling operational expenses. The moderate correlation between demand forecasting and total cost (0.41) highlights the cascading effect of forecast accuracy on production planning decisions, while the weak correlation of production capacity (0.24) suggests that capacity planning, when properly aligned with demand, can be managed

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efficiently without disproportionately increasing costs. These insights provide actionable guidance for managers seeking to optimize their aggregate planning processes by prioritizing inventory control while maintaining responsive capacity and accurate demand forecasting systems.The applied significance of this study is substantial for manufacturing organizations operating in dynamic market environments. The validated linear regression model offers a straightforward yet powerful tool for predicting total costs based on planning parameters, enabling proactive cost management and strategic decision-making.

The study demonstrates that organizations can achieve significant cost reductions by focusing on inventory optimization strategies, improving forecast accuracy through advanced statistical methods, and ensuring production capacity flexibility to accommodate demand fluctuations without excessive resource commitments. Furthermore, the findings support the integration of data-driven approaches aggregate planning systems, facilitating more responsive and efficient supply chain operations. Future research should explore the incorporation of machine learning algorithms, multi-objective optimization techniques addressing environmental and social sustainability dimensions, and the development of dynamic planning models that can adapt to real-time market changes and uncertainties in Industry 4.0 contexts.

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