การพัฒนากระบวนการวางแผนการขายและการดำเนินการเพื่อเพิ่มความแม่นยำการพยากรณ์และลดระดับสินค้าคงคลัง: กรณีศึกษาโรงงานแปรรูปสินค้าเกษตร

Development of a Sales and Operations Planning Process to Improve Forecast Accuracy and Reduce Inventory Level: A Case Study of an Agricultural Processing Plant

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บทคัดย่อ

การวางแผนการขายและการดำเนินการ หรือ Sales and Operations Planning (S&OP) เป็นกลไกสำคัญที่เชื่อมโยงการตลาด การขาย การผลิต การจัดซื้อ และคลังสินค้า เพื่อให้สามารถตัดสินใจบนฐานข้อมูลชุดเดียวกัน ซึ่งงานวิจัยที่อธิบายขั้นตอนการพัฒนากระบวนการและผลลัพธ์เชิงปริมาณอย่างเป็นระบบยังมีอยู่อย่างจำกัด งานวิจัยนี้จึงมีวัตถุประสงค์เพื่อ (1) ศึกษาปัญหาของการขายและการดำเนินการในโรงงานแปรรูปสินค้าเกษตรขนาดกลางแห่งหนึ่งในภาคตะวันออกเฉียงเหนือของประเทศไทย ซึ่งมีผลิตภัณฑ์หลัก 5 รายการและมีรอบการผลิตแบบรายสัปดาห์ (2) พัฒนากระบวนการ S&OP ที่สอดคล้องกับบริบทขององค์กร และ (3) ประเมินผลของการนำกระบวนการดังกล่าวไปใช้ การวิจัยใช้เวลาเก็บข้อมูลเชิงปริมาณย้อนหลัง 6 เดือนก่อนการปรับปรุง (มกราคม-มิถุนายน) เปรียบเทียบกับ 6 เดือนหลังการปรับปรุง (กรกฎาคม-ธันวาคม) ของปีเดียวกัน ร่วมกับข้อมูลเชิงคุณภาพจากการสัมภาษณ์ผู้เกี่ยวข้องจำนวน 12 คน จากฝ่ายขาย ฝ่ายวางแผน ฝ่ายผลิต และฝ่ายคลังสินค้า จากนั้นออกแบบกระบวนการ S&OP รายเดือน 5 ขั้นตอน ประกอบด้วย การรวบรวมข้อมูล การทบทวนอุปสงค์ การทบทวนอุปทาน การประชุมก่อน S&OP และการประชุมผู้บริหารเพื่ออนุมัติแผนกลางขององค์กร ผลการวิเคราะห์เชิงคุณภาพชี้ว่าการขาดฐานข้อมูลร่วมและเวทีประสานงานข้ามสายงานเป็นสาเหตุหลักของความคลาดเคลื่อนในการวางแผน ผลการวิจัยเชิงปริมาณพบว่า หลังการนำกระบวนการ S&OP ไปใช้ ค่า MAPE ลดลงจากร้อยละ 28.40 เหลือร้อยละ 16.90 ระดับสินค้าคงคลังเฉลี่ยลดลงจาก 240 ตัน เหลือ 195 ตัน อัตราการส่งมอบตรงเวลาเพิ่มขึ้นจากร้อยละ 82.30 เป็น 93.10 จำนวนคำสั่งผลิตเร่งด่วนลดลงจาก 11 เหลือ 5 ครั้งต่อเดือน และค่า Forecast Bias ลดลงจากร้อยละ 12.60 เหลือ 4.20 โดยผลการทดสอบทางสถิติแบบ Paired t-test แบบ One-tailed (n = 6 คู่ข้อมูลรายเดือน) และการทดสอบยืนยันแบบ Wilcoxon signed-rank test ยืนยันว่าการเปลี่ยนแปลงของตัวชี้วัดทั้ง 5 ตัวมีนัยสำคัญทางสถิติที่ระดับ 0.05 ผลการวิจัยในกรณีศึกษานี้ชี้ให้เห็นว่า S&OP ช่วยสร้างความสอดคล้องระหว่างอุปสงค์และอุปทาน เพิ่มความแม่นยำของการพยากรณ์ ลดการถือครองสินค้าคงคลังเกินจำเป็น และสนับสนุนการตัดสินใจเชิงบูรณาการในองค์กร อย่างไรก็ตาม เนื่องจากเป็นการศึกษากรณีเดียวในระยะเวลา 6 เดือน ผลการวิจัยนี้จึงควรได้รับการตีความในขอบเขตของบริบทเฉพาะนี้ และควรมีการศึกษาเพิ่มเติมในหลายกรณีก่อนสรุปอ้างอิงในวงกว้าง

คำสำคัญ: การวางแผนการขายและการดำเนินการ, การพยากรณ์อุปสงค์, สินค้าคงคลัง, การวางแผนการผลิต, โลจิสติกส์

Abstract

Sales and Operations Planning (S&OP) is a critical managerial mechanism that integrates marketing, sales, production, procurement, and inventory functions through a shared information base. Despite its proven value, empirical studies on S&OP implementation in agricultural processing industries remain limited, particularly in Thailand and other emerging economies where raw material uncertainty and demand seasonality are pronounced. This study aimed to (1) investigate the problems and limitations of sales and operations planning in a medium-sized agricultural processing plant in northeastern Thailand, which produces five main product lines on a weekly production cycle, (2) develop an S&OP process appropriate to the organizational context, and (3) evaluate the effects of its implementation. A mixed-methods, applied case study approach was employed. Quantitative data were collected for six months before (January-June) and six months after (July-December) implementation, while qualitative data were obtained from semi-structured interviews with 12 personnel from sales, planning, production, and warehouse departments. The qualitative findings indicated that the absence of a shared database and a cross-functional coordination forum was the primary driver of planning inconsistency. A five-step monthly S&OP process was then developed, consisting of data gathering, demand review, supply review, pre-S&OP meeting, and executive S&OP meeting. The quantitative results showed that, after implementation, MAPE decreased from 28.40% to 16.90%, average inventory decreased from 240 tons to 195 tons, on-time delivery increased from 82.30% to 93.10%, the number of urgent production orders declined from 11 to 5 times per month, and forecast bias decreased from 12.60% to 4.20%. One-tailed paired t-test results (n = 6 paired months), corroborated by the Wilcoxon signed-rank test, confirmed that all five indicators changed significantly at the 0.05 level. Within the scope of this single case study, the findings suggest that S&OP can enhance demand-supply alignment, improve forecasting accuracy, reduce excess inventory, and strengthen integrated decision-making, particularly in agricultural processing plants facing uncertainty in raw material supply and market demand; broader generalization awaits multi-case confirmation.

Keywords: Sales and Operations Planning, Demand Forecasting, Inventory Management, Production Planning, Logistics

1. Introduction

In highly volatile and competitive business environments, manufacturing organizations must continuously align demand and supply in order to respond effectively to customer requirements while controlling operational costs. One of the major challenges faced by manufacturing firms is the inconsistency among sales plans, production plans, procurement activities, and inventory management due to fragmented decision-making across departments. In many organizations, each department uses different forecasting assumptions, data sources, and performance targets, resulting in inefficient coordination and operational instability (Thomé et al., 2012). In logistics and supply chain management, integrated planning mechanisms are considered essential for improving coordination among procurement, production, inventory management, and distribution activities (Rabop, 2013).

Sales and Operations Planning (S&OP) has emerged as an important managerial process that integrates sales, marketing, production, procurement, and logistics functions through a shared planning platform and cross-functional decision-making mechanism. The S&OP process enables organizations to balance demand and supply systematically by integrating forecasting, capacity planning, inventory management, and operational decision-making into a unified organizational plan. Wallace and Stahl (2008),

in one of the foundational practitioner-oriented accounts of S&OP, argued that the process functions effectively only when it combines a disciplined monthly cadence with a designated process owner and sustained executive participation; Ptak and Smith (2011) similarly emphasized that S&OP's value depends on tight integration between demand forecasting, material requirements planning, and production scheduling, rather than on any single component in isolation. Wagner et al. (2014) further argued that the organizational alignment created by structured planning processes, including clearly defined roles and shared performance metrics, is itself a critical driver of operational performance improvement, independent of the specific forecasting technique used. Accurate demand forecasting is particularly important because forecasting errors directly influence inventory levels, production planning, and customer service performance (Chase, 2013), and supports strategic alignment across organizational functions (Tuomikangas & Kaipia, 2014).

In the context of agricultural processing industries, planning and coordination challenges become even more critical due to the uncertainty of raw material availability, seasonality of agricultural products, fluctuating customer demand, and product shelf-life limitations. Agricultural processing plants frequently experience problems related to inaccurate forecasting, excessive inventory holding, urgent production scheduling, and delayed deliveries. These issues negatively affect operational efficiency, inventory costs, and customer satisfaction. Therefore, organizations operating in agro-industrial environments require an integrated planning mechanism capable of improving coordination between demand and supply under uncertain conditions. These characteristics distinguish agricultural processing from general discrete manufacturing in three important ways. First, raw material supply in agro-industries is governed by harvest cycles and weather conditions rather than purchase lead times, making the supply side of the S&OP balance inherently less controllable. Second, many agricultural products carry strict shelf-life constraints, which limit the feasibility of building safety stock as a buffer against forecast error, a strategy that is more readily available in general manufacturing. Third, demand for processed agricultural products is frequently linked to seasonal consumption patterns and agricultural commodity cycles, introducing a layer of demand variability that compounds, rather than substitutes for, ordinary market uncertainty. These distinctive characteristics mean that S&OP mechanisms validated in general manufacturing settings cannot be assumed to transfer directly to agricultural processing without contextual adaptation, which is a central motivation for the present study as shown in Table 1.

Table 1. Summarizes how the present study addresses three gaps identified in the existing S&OP literature, situating its contribution relative to prior research

Previous Studies	Research Gap	This Study
Concentrated in large-scale, general manufacturing in developed economies (Thomé et al., 2012; Tuomikangas & Kaipia, 2014)	Limited empirical evidence from agro-industrial contexts in emerging economies	Agricultural processing plant in northeastern Thailand

Table 1. (Continued)

Previous Studies	Research Gap	This Study
Report a single or narrow KPI, mainly forecast accuracy (Goh & Eldridge, 2019)	Limited evidence on how S&OP components jointly affect a fuller set of operational outcomes	Five linked KPIs: MAPE, inventory level, OTD, expedited orders, forecast bias
Predominantly quantitative or predominantly qualitative, rarely combined (Kreuter et al., 2022)	Few studies explain the mechanisms behind quantitative improvement using organizational evidence	Mixed-methods design: KPI tracking integrated with 12 informant interviews

Previous studies have extensively examined the role of S&OP in improving organizational performance. Thomé et al. (2012) synthesized that S&OP serves as a strategic coordination mechanism linking demand and supply functions across the organization. Tuomikangas and Kaipia (2014) further emphasized that S&OP contributes significantly to organizational integration, forecasting improvement, and operational responsiveness. More recent studies have highlighted the importance of information processing capability, cross-functional collaboration, and adaptability in S&OP implementation. Goh and Eldridge (2019) argued that organizational performance improvement depends not only on formal planning structures but also on effective coordination mechanisms and information alignment. Similarly, Kreuter et al. (2022) identified S&OP as a context-dependent capability requiring adaptation to specific industrial environments and organizational conditions.

Recent literature also emphasizes the increasing role of digital technologies, predictive analytics, and data integration in supporting S&OP effectiveness. AI-supported forecasting and data-driven planning systems have been reported to improve responsiveness and operational efficiency in complex supply chains (Kreuter et al., 2022). A recent systematic review by Walter et al. (2025) similarly found that artificial intelligence applications in demand planning are still concentrated in large, data-rich manufacturing environments, with limited evidence from smaller agro-industrial operations where digital infrastructure and historical data systems are less mature. In addition, Wu and Møller (2024) proposed that S&OP effectiveness depends on maintaining alignment between internal planning processes and external environmental uncertainty. These studies collectively indicate that S&OP is evolving from a traditional planning routine into an integrated and adaptive organizational capability. It is important to note that the digital and AI-supported S&OP literature cited above represents the broader trajectory of the field rather than the specific intervention evaluated in this study: the case-study factory's planning capability and data infrastructure corresponded to a foundational, meeting-based S&OP process built on shared spreadsheets and structured forms, not an AI-supported or fully digitalized system. This study therefore evaluates the foundational organizational mechanism that typically precedes digital S&OP adoption, a stage that remains under-documented in the literature despite being the practical starting point for most small and medium-sized agricultural processors in emerging economies (Kreuter et al., 2022; Walter et al., 2025).

Within the Thai context specifically, related work on demand forecasting and inventory management in food and agricultural product businesses remains scarce relative to general manufacturing. Tabporn et al. (2018), in a study of sales forecasting and inventory management for a frozen seafood product line, demonstrated that systematic time-series forecasting combined with economic order quantity techniques could materially reduce inventory holding in a Thai food-processing setting, illustrating the

practical relevance of structured forecasting discipline in this sector. Similarly, Chuchotthaworn (2020) showed that combining demand forecasting with optimal order-quantity determination reduced packaging inventory costs in a Thai agricultural product processing company. However, both studies, like most local work in this area, addressed forecasting and inventory control as isolated functions rather than as components of an integrated, cross-functional S&OP process. This further supports the research gap motivating the present study: namely, the need for an integrated, mixed-methods account of how a complete S&OP cycle, rather than forecasting alone, affects operational performance in a Thai agricultural processing context.

Despite these developments, several important research gaps remain. First, empirical studies focusing on S&OP implementation in agricultural processing industries remain limited, particularly in emerging economies and agro-industrial contexts where uncertainty in raw materials and demand variability are highly significant. Existing studies are largely concentrated in large-scale manufacturing sectors and developed-country environments. Second, although previous studies have reported positive relationships between S&OP implementation and organizational performance, limited empirical evidence explains how specific S&OP process components contribute to operational performance indicators such as forecast accuracy, inventory reduction, on-time delivery, and production stability. Third, few studies integrate both quantitative performance measurement and qualitative organizational analysis within a unified case-study framework to explain the mechanisms underlying operational improvements.

To address these gaps, this study aims to develop and evaluate an Sales and Operations Planning (S&OP) process for an agricultural processing plant. Specifically, the objectives of this research are: (1) to investigate the problems and limitations of the existing planning system in an agricultural processing factory, (2) to develop an S&OP process appropriate for the organizational context, and (3) to evaluate the operational outcomes of the implemented process using key performance indicators including forecast accuracy, inventory levels, on-time delivery rate, expedited production orders, and forecast bias.

Based on these objectives, five research hypotheses (H1-H5) were formulated, predicting a statistically significant improvement after S&OP implementation in the forecast accuracy (MAPE), the average inventory level, the On-Time Delivery rate, the number of expedited production orders, and forecast bias, respectively. Specifically, H1 predicts lower MAPE, H2 lower average inventory, H3 higher on-time delivery, H4 fewer expedited production orders, and H5 lower forecast bias after implementation. The inclusion of H4 and H5 reflects an established line of literature linking poor forecast quality to costly downstream symptoms: Chase (2013) demonstrated that forecast error is a direct driver of expediting and emergency production, while Wallace and Stahl (2008) identified persistent forecast bias as a recurring symptom of unresolved demand-supply misalignment that a properly functioning S&OP cycle is designed to correct. H4 and H5 were therefore included as operational consequences of improved forecasting discipline, rather than as independent constructs requiring separate theoretical grounding.

This study contributes to the literature by providing empirical evidence of S&OP implementation in an agricultural processing and by integrating quantitative and qualitative analyses to explain how cross-functional planning mechanisms improve operational performance under conditions of uncertainty.

2. Materials and Methods

2.1 Research Framework

The research framework defines "S&OP process development" as the independent variable, which consists of four main components: (1) Single Data Source, (2) Systematic Demand Forecasting, (3) Supply Constraint Review, and (4) Cross-Functional Decision Meeting. The dependent variables consist of the five operational indicators corresponding to the five research hypotheses: (1) forecast accuracy, measured by MAPE, (2) average inventory level, (3) On-Time Delivery rate, (4) the number of expedited production orders per month, and (5) Forecast Bias. It is expected that the developed S&OP process will lead to tangible improvement in all five indicators, as illustrated in Figure 1.



Figure 1. Conceptual Framework

2.2 Research Design

This research is an applied case study design, focusing on the development and evaluation of the Sales and Operations Planning (S&OP) process in the context of an agricultural processing factory in northeastern Thailand. The choice of a case study approach is appropriate for understanding the dimensions of decision-making processes, cross-functional coordination, and operational outcomes in the real organizational context.

The research employs a mixed-methods approach, combining quantitative and qualitative data. Specifically, quantitative data are used to evaluate the implementation of the S&OP process through key performance indicators such as forecast accuracy, inventory levels, and on-time delivery rates. Qualitative data are used to analyze existing system issues, diagnose the causes of demand-supply discrepancies, and explain the mechanisms by which the developed process impacts the organization's operations.

2.3 Case study unit and organizational context

The case study was an agricultural processing factory with a production plan scheduled on a weekly and monthly basis. The factory had five main products and faces operational issues related to inaccurate sales forecasts, high inventory holding, and continuous delays in product delivery during certain periods. The criteria used for selecting case studies are:

To provide sufficient context for assessing the transferability of the findings, the case organization is a medium-sized agricultural processing plant employing approximately 110 production and administrative staff, with a normal monthly production capacity of approximately 260-280 tons across its five product lines. Prior to the study, demand for each product was forecast using simple moving averages or, in several months, the sales department's unaided judgment, with no formal cross-functional review of the resulting plan. As part of the S&OP process developed in this study, the demand review step introduced a structured forecasting approach combining a three-month weighted moving average of historical sales

with a qualitative adjustment discussed and agreed upon during the monthly Demand Review meeting, replacing the prior practice of unadjusted judgmental forecasting by the sales department alone. The pre-implementation period spanned January-June and the post-implementation period spanned July-December of the same calendar year. Because these two windows fall in different halves of the annual agricultural cycle, the comparison is not free of seasonal influence (see Section 5 for this limitation).

1) It is an organization that has sales, production, and inventory planning interconnected at the operational level.

2) There is historical data that can be used for analysis before and after the improvement.

3) Executives and operators are ready to provide information and participate in the improvement process.

4) The organization has clear issues suitable for the application of S&OP, such as urgent production, fragmented planning, and the lack of shared metrics.

2.4 Population, informants, and analytical units

This research uses both qualitative informants and quantitative units of analysis.

2.4.1 Qualitative informant

A total of 12 key informants were selected through purposive sampling, choosing individuals who have direct roles in planning, decision-making, and plan implementation. There are two of each: sales manager, production planners, warehouse staff, middle management and four Production supervisors.

The informants in this group were selected based on three criteria: they have at least one year of planning-related experience, they are responsible for using or preparing data for decision-making, and they can clearly reflect the problems and limitations of the existing system.

The number of informants was considered appropriate for qualitative case study research because data saturation was achieved during the interview process. Recurrent themes and operational issues began to converge after the tenth interview, and no substantial new information emerged from the final interviews. The selected participants also represented all major functions involved in the S&OP process, including sales, production planning, operations, warehousing, and middle management, thereby ensuring cross-functional perspectives and analytical completeness.

2.4.2 Quantitative Analysis Unit

The main unit of analysis for quantitative data is "monthly data on planning processes and performance outcomes," considering two time periods, namely

1) The period before implementing the S&OP process

2) The period after implementing the S&OP process for 6 months

2.5 Data Sources

The sources of information used in the research were divided into two categories: primary data and secondary data. Primary data came from 12 key informants, stakeholders, observation the planning process and cross-functional meetings and the indicators used in S&OP. Secondary data consisted of actual sales data for the past 12 months, historical and post-improvement demand forecast data, production plan data and actual production results, customer delivery information, record urgent production orders and emergency plan adjustments and internal documents, such as meeting schedules, monthly reports, and related action plans.

2.6 Research tools

The tools used in the research consist of three main sets as follows.

2.6.1 Semi-structured interview

Used to collect information about the current state of planning, issues in inter-departmental coordination, causes of discrepancies, and suggestions for improving the S&OP process.

2.6.2 S&OP meeting form

Used as a tool to support the collection and presentation of information in each monthly meeting round, including performance results of the previous month, estimation of next month's demand, production capacity, raw materials and labor constraints and Issues to decide and management options.

2.6.3 Performance Indicator Record Form

Used for recording monthly data of key performance indicators, including MAPE, Forecast Bias, average inventory level, on-time delivery rate, and number of expedited production orders, for comparison before and after implementation.

2.7 Quality inspection of research instruments

The quality of research instruments was evaluated through content validity assessment, pilot testing, and data triangulation.

First, the interview protocol and S&OP meeting forms were reviewed by three experts in logistics, operations management, and supply chain planning to assess content relevance, clarity, and consistency with the research objectives. The Index of Item-Objective Congruence (IOC) values ranged between 0.80 and 1.00, indicating acceptable content validity.

Second, pilot interviews were conducted with two representatives from the case organization to evaluate question clarity, sequence, and practical applicability. Minor revisions were subsequently made to improve wording and reduce ambiguity.

Third, methodological triangulation was employed to enhance reliability and credibility. Information obtained from interviews was cross validated with organizational documents, historical operational records, production reports, and meeting observations. This triangulation process helped reduce potential bias and improve the trustworthiness of the findings.

2.8 Data collection methods

Data collection proceeded in three phases: (1) current situation study — collecting 12 months of historical data and conducting interviews to diagnose planning system issues; (2) S&OP process design — synthesizing Phase 1 findings into a five-step monthly process and validating with stakeholders; and (3) pilot implementation and monitoring — running the S&OP process for six months with continuous KPI tracking and event recording.

2.9 Quantitative data analysis

Quantitative data analysis uses descriptive statistics and comparisons before and after the improvement as follows.

2.9.1 Descriptive statistics

Use the average, percentage, standard deviation, and rate of change to describe the characteristics of the indicators.

2.9.2 Calculation of key performance indicators

The main indicators consist of Mean Absolute Percentage Error (MAPE), Forecast Bias, Percentage decrease in inventory and On-Time Delivery (OTD), calculated using the standard formulas below:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \quad (1)$$

$$\text{Forecast Bias} = \frac{\sum_{t=1}^{n}(A_t - F_t)}{\sum_{t=1}^{n} A_t} \times 100\% \quad (2)$$

$$\text{OTD Rate} = \frac{\text{Number of On-Time Deliveries}}{\text{Total Number of Deliveries}} \times 100\% \quad (3)$$

where A_t and F_t denote the actual and forecast demand in month t, respectively, and n is the number of months in the evaluation period. A positive Forecast Bias indicates a tendency toward over-forecasting and a negative value indicates under-forecasting.

Before selecting the statistical test method, the normality of paired differences was examined using the Shapiro-Wilk test for each indicator (n = 6 pairs). The results are presented in Table 6. Since all variables yielded W-statistics greater than the critical value and p-values exceeding 0.05, the normality assumption was not rejected. Therefore, the paired t-test was selected as the primary hypothesis testing method, with the Wilcoxon signed-rank test applied as a non-parametric verification. It should be noted that, with only six paired observations, the Shapiro-Wilk test has limited statistical power to detect departures from normality; the non-rejection of normality at this sample size should therefore be interpreted as inconclusive rather than as strong confirmatory evidence, which is precisely why the Wilcoxon signed-rank test was retained as a non-parametric cross-check rather than treated as a redundant formality. In addition to significance testing, Cohen's d was calculated for each paired comparison to quantify the magnitude of improvement independently of sample size, since statistical significance alone does not indicate the practical size of an effect.

2.9.3 Comparison before and after implementing S&OP

Compare the monthly indicators before and after the improvement during the corresponding periods. If the data was normally distributed, use the paired t-test statistics. However, if the data did not meet the normal distribution assumption, use the Wilcoxon signed-rank test statistic to test the difference between the values before and after the improvement. Because the research hypotheses were directional and explicitly predicted performance improvement after S&OP implementation, one-tailed statistical tests were considered appropriate for hypothesis testing. Nevertheless, non-parametric verification using the Wilcoxon signed-rank test was additionally conducted to ensure the robustness of the findings under the small-sample condition.

2.9.4 Statistical significance level

Set the statistical significance level at 0.05. Although the number of paired observations was relatively limited (n = 6 months before and after implementation), the paired analysis approach was considered appropriate because the study focused on repeated operational measurements within the same organizational system under comparable planning conditions. In addition, assumption testing was performed

prior to hypothesis testing, and both parametric and non-parametric methods were applied to improve statistical robustness and analytical reliability.

2.10 Qualitative data analysis

Interview and observation data were analyzed using content analysis: transcription, holistic review, thematic coding (forecasting issues, interdepartmental coordination, decision-making gaps), category grouping, and synthesis to explain the mechanisms underlying the quantitative results.

2.11 Research ethics and data confidentiality

This research prioritized the confidentiality of the case study organization's data. The researcher did not present the organization's name, individual names, or commercial information that could impact business competition. The presentation of research results used aggregated data solely for academic purposes and system development. All informants were informed of the research objectives and gave their consent before the interview.

3. Results

3.1 Current condition and issues before the improvement

The analysis of the current situation identified four main issues: (1) Sales forecasting relies primarily on the sales department's discretion without verifying historical data, (2) There are no systematic joint meetings between the sales and production departments, (3) There is a rush to produce when sudden orders are received, averaging 11 times per month, and (4) There are no shared performance indicators used by all parties to track results, leading to conflicts in decision-making between sales targets and cost control. Details are shown in Table 2.

Table 2. Summary of current problems and their impacts on operations

No.	Identified Problems	Key Causes	Impacts
1	Inaccurate sales forecasting	Reliance on personal experience without validation	Production does not align with demand
2	Lack of a cross-functional coordination platform	Sales, production, and warehouse work separately	Over production occurs and communication is misaligned
3	Inventory levels exceeding targets	Excessive planning buffers due to uncertainty	Inventory holding costs increase
4	Delayed deliveries during certain periods	Production capacity does not align with actual order demand	Customer satisfaction decreases

To substantiate the four issues summarized in Table 2 with first-hand organizational evidence, Table 3 presents the coded themes derived from content analysis of the 12 informant interviews, together with illustrative quotations for each theme.

Informants attributed to the absence of shared metrics in the fourth theme is consistent with the quantitative pattern reported in Section 3.3: because sales, production, and warehouse staff were each evaluated against different, unreconciled targets prior to the intervention, none of them had an incentive to flag a forecast or inventory problem before it escalated into an expedited order. This qualitative account helps explain, rather than merely describe, why the introduction of shared KPIs and a joint monthly review subsequently produced consistent month-on-month improvement across all five indicators.

Table 3. Coded qualitative themes from informant Interviews (n = 12)

Theme	Informants Citing	Illustrative Quotation
Forecasting by unaided judgment	9 of 12	*"We mostly go by feel and by what the customer tells us on the phone. We rarely pull up last year's numbers before sending the forecast to the factory." (Production Planner, Informant 4)*
Absence of cross-functional forum	11 of 12	*"Sales and the production floor barely talk except when something has already gone wrong. By then it's too late to plan properly." (Production Supervisor, Informant 7)*
Reactive expediting culture	8 of 12	*"Almost every week there's a rush order that throws off the whole production schedule. We just accept it as normal now." (Warehouse Staff, Informant 10)*
Conflicting goals, no shared metrics	10 of 12	*"Sales are measured in revenue, we are measured in cost. Nobody is measured on whether the two plans actually match." (Middle Management, Informant 12)*

3.2 The developed S&OP process

The developed S&OP process consists of 5 monthly steps: (1) Data Gathering - collecting actual sales, outstanding orders, inventory status, and production capacity; (2) Demand Review - reviewing market trends and preparing demand forecasts; (3) Supply Review - assessing constraints in production capacity, raw materials, and labor; (4) Pre-S&OP Meeting - comparing plan alternatives and identifying decision points; and (5) Executive S&OP Meeting-approving the mid-month plan. The process structure is shown in Table 4.

Table 4. Developed Structure of the Monthly S&OP Meeting

Process	Person in Charge	Inputs	Expected Outcomes
1. Data Gathering	Planner	Actual sales, orders, and inventory	Single source of data
2. Demand Review	Sales team	Market data, promotions, and seasonality	Monthly demand plan
3. Supply Review	Production/ Purchasing	Production Capacity, raw materials, and labor	Supply plan alternatives
4. Pre-S&OP	Department manager	Demand–supply gaps	Consensus plan proposal
5. Executive S&OP	Executives	Alternative plans and cost implications	Approved master plan

3.3 Results of the KPI assessment after using S&OP

The evaluation results of the key performance indicators after using S&OP for 6 months show that forecasting accuracy has continuously improved, inventory levels have decreased, and on-time delivery rates have increased. This is because all parties have shared information and can make better advance planning decisions. The overall results are shown in Table 5, and the monthly trends are shown in Fig 2.

Table 5. Comparison of Performance Indicators Before and After S&OP Implementation

Indicators	Before	After	Differences	Direction
MAPE (%)	28.40	16.90	-11.50 points	↓ (improved)
Average Inventory (tons)	240	195	-18.75%	↓ (improved)
On-Time Delivery Rate (%)	82.30	93.10	+10.80 points	↑ (improved)
Expedited Production Orders (times/month)	11	5	-54.55%	↓ (improved)
Forecast Bias (%)	12.60	4.20	-8.40 points	↓ (improved)

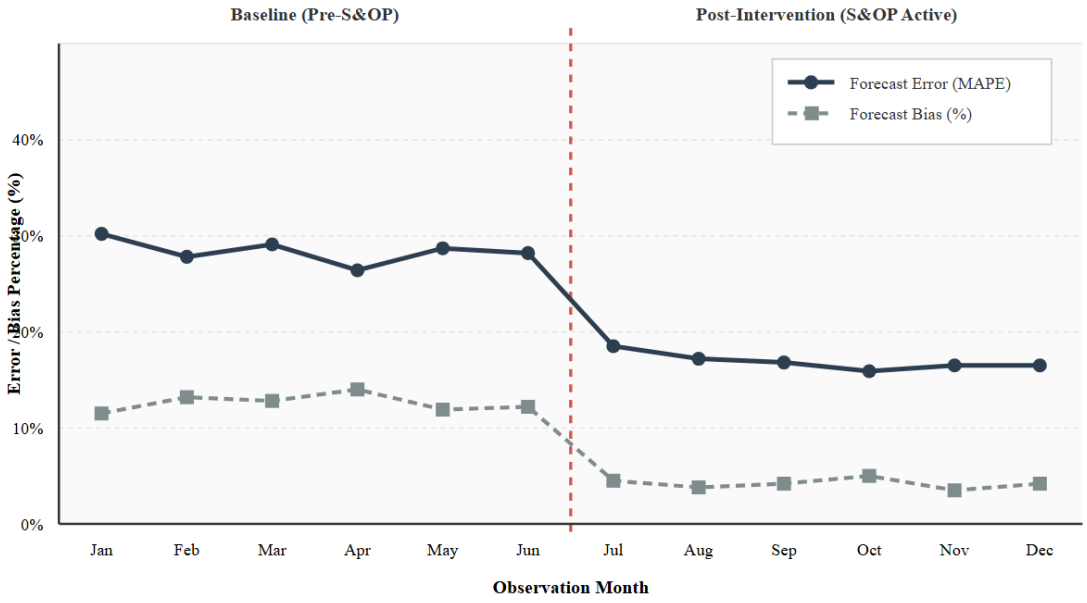

Figure 2. Monthly trend comparison of Mean Absolute Percentage Error (MAPE) before and after S&OP

From Table 5 and Figure 2, it can be seen that the trend in the results has improved in every indicator, especially the MAPE value, which has decreased by more than 10 points each month. The MAPE values after S&OP implementation were consistently lower across all six months compared with the pre-implementation period.

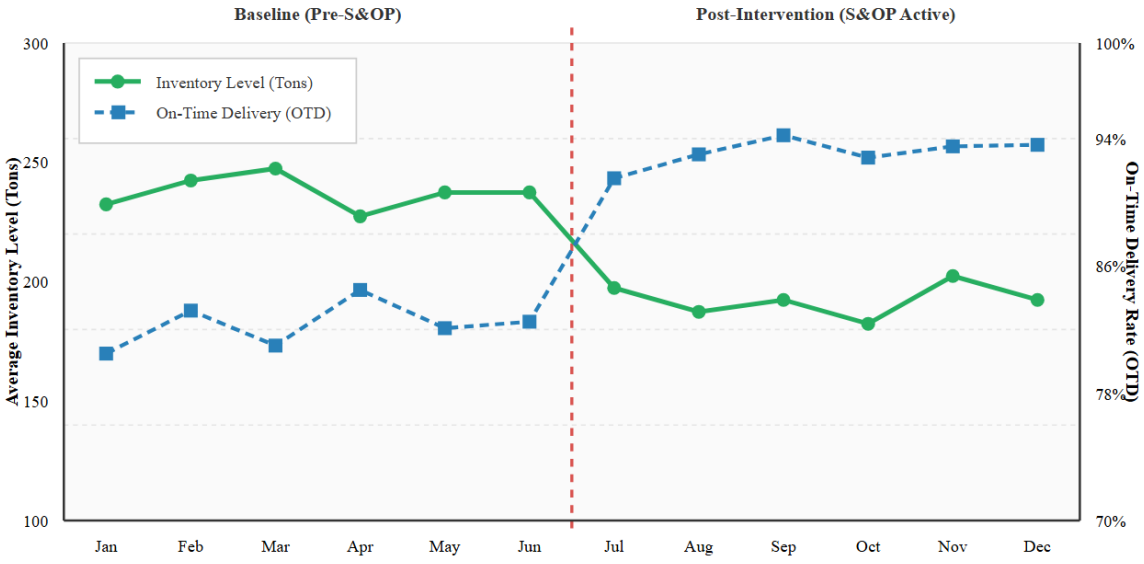

Figure 3. Monthly operational trajectories of Inventory Level, On-Time Delivery (OTD), Expedited Orders, and Forecast Bias.

From Figures 2 and 3, the paired monthly performance data over the six months before and after the implementation of the S&OP process shows that during the months when inventory decreased, the organization was still able to maintain a consistently high on-time delivery (OTD) rate. Additionally, the reduction in the number of monthly expedited production orders aligns with the steadily decreasing forecast bias. The monthly paired data showed consistent directional changes across all operational indicators following S&OP implementation, with no individual month showing a reversal in any of the five indicators. This uniform pattern should be read as a feature of this particular six-month trial rather than a guarantee of similar results elsewhere; possible seasonal confounding is discussed in Section 5.

Examining the monthly trend in Figure 2 more closely, the rate of MAPE improvement was not uniform: the largest month-on-month gain occurred between the first and third months after implementation (a drop of approximately 13.4 percentage points), coinciding with the period in which the Demand Review step was still being adjusted following the first two Pre-S&OP meetings, whereas the gain stabilized in the later months once the weighted moving-average forecast described in Section 2.3 had been consistently applied. This trajectory suggests that the early reduction in forecast error was driven primarily by the introduction of a structured forecasting method and the Demand Review step, while the more modest, stable gains in the later months reflect the Supply Review and Pre-S&OP Meeting steps absorbing the residual mismatch between demand estimates and production capacity. The parallel decline in expedited production orders (Figures 2 and 3) over the same months is therefore best interpreted not as an independent improvement but as a downstream consequence of the upstream gain in forecast accuracy: as the demand estimate used to trigger production runs became more reliable, the number of occasions on which production had to deviate from the plan to accommodate an unanticipated order fell correspondingly. This sequencing is consistent with the mechanism proposed in the conceptual framework (Figure 1), in which Systematic Demand Forecasting and Supply Constraint Review jointly, rather than independently, determine the downstream operational indicators.

3.4 Results of the statistical hypothesis test

To confirm that the changes in the indicators after implementing the Sales and Operations Planning (S&OP) process were not coincidental, the researchers conducted a paired comparison of the pre- and post-improvement data on key indicators according to the research hypothesis, including MAPE, average inventory level, On-Time Delivery (OTD) rate, average number of expedited production orders per month, and Forecast Bias, with a statistical significance level set at 0.05.

Prior to hypothesis testing, the normality of paired differences was assessed using the Shapiro-Wilk test. As reported in Table 6, all five variables yielded W-statistics above the critical value ($W_{critical} \approx 0.788$ for n = 6, $\alpha = 0.05$), with p-values ranging from 0.113 to 0.854, indicating that the normality assumption was not violated for any variable. The paired t-test was therefore applied as the primary statistical method. Detailed descriptive statistics of paired differences ($\overline{D}$, SD, and SE) and test results are reported in Table 7.

As a supplementary verification, the Wilcoxon signed-rank test was applied to all five variables. The results are presented in Table 7. All five variables produced a rank-sum statistic of T = 0 (W+ = 21, W– = 0) with a two-tailed p-value of 0.031. The uniform outcome is attributable to the consistent directionality of all six-monthly paired differences across every variable. That is no month showed a reversal in any indicator after S&OP implementation. Under this condition, with n = 6, the Wilcoxon statistic reaches its minimum possible value of T = 0, corresponding to the minimum attainable p-value of 0.031 (= $2/2^6$). These results are directionally consistent with the paired t-test findings. It is important to clarify that this agreement means only that no month reversed direction for any indicator; it does not, by itself, establish the statistical robustness of the underlying effect, since the Wilcoxon test is mechanically constrained to its minimum attainable p-value whenever a small sample shows no reversals. The two tests should be read as agreeing on the direction and statistical significance of the change.

Table 6. Results of the normality test of paired performance indicators using the Shapiro-Wilk method

Hyp.	Variable	Differences (D)	W-statistic	p-value	Result
H1	MAPE (%)	11.7, 10.6, 12.3, 10.5, 12.2, 11.7	0.8546	0.1713	Normal ($p > 0.05$)
H2	Inventory (tons)	35, 55, 55, 45, 35, 45	0.8532	0.1670	Normal ($p > 0.05$)
H3	OTD Rate (%)	11.0, 9.8, 13.2, 8.3, 11.4, 11.1	0.9646	0.8540	Normal ($p > 0.05$)
H4	Expedited Orders	4, 8, 8, 4, 7, 5	0.8326	0.1130	Normal ($p > 0.05$)
H5	Forecast Bias (%)	7.0, 9.4, 8.6, 9.0, 8.4, 8.0	0.9634	0.8454	Normal ($p > 0.05$)

Note: Shapiro-Wilk critical value for n = 6 at $\alpha = 0.05$ is approximately W = 0.788. All variables exceed this threshold

In addition to statistical significance, effect sizes (Cohen's d, calculated as the mean paired difference divided by the standard deviation of the differences) were computed to indicate the practical magnitude of each improvement, since p-values alone do not convey the size of an effect, particularly at a small sample size. The results, presented in Table 7, indicate very large effect sizes (d > 3.0) for all five indicators, consistent with the descriptive pattern that every monthly pair moved in the improving direction with no reversals.

4. Discussion

The research findings indicate that the implementation of the Sales and Operations Planning (S&OP) process in the case study factory coincided with enhanced coordination between the sales, planning, production, and warehouse departments. Previously, decisions relied on fragmented data and departmental discretion, but the interview evidence summarized in Table 3 suggests that this fragmentation persisted specifically because no informant, regardless of department, was evaluated against a metric that rewarded cross-functional accuracy; as one middle manager observed, "nobody is measured on whether the two plans actually match." After implementation, informants reported using shared data within a structured review cycle and meetings. These results are consistent with the concept proposed by Wallace and Stahl (2008), who argued that S&OP is effective when an organization has a clear joint decision-making process, a systematic agenda, and continuous executive support, and with Ptak and Smith (2011), who emphasized that effective coordination between forecasting, material planning, and production scheduling is essential for reducing operational instability. Because this study employed a single-case design without a control group, these findings should be read as evidence consistent with the mechanisms proposed in the literature rather than as definitive proof that S&OP, in isolation, caused the observed improvements.

In terms of forecasting accuracy, the research findings revealed that the MAPE value decreased from 28.40% to 16.90%, and statistical tests confirmed that this difference is statistically significant. This pattern is consistent with the introduction of the demand review process, the use of historical sales data, and inter-departmental information exchange, which together are the most plausible drivers of the improvement, although other contributing factors, such as a general learning effect among planning staff over the six-month trial, cannot be fully ruled out given the single-case design.

For the indicators of average inventory levels, on-time delivery rates, the number of expedited production orders, and Forecast Bias, this research found that all variables changed in a positive direction. When tested with paired monthly data, these differences were all statistically significant. This pattern is consistent with the qualitative account in Table 3, in which informants linked the prior reactive expediting culture directly to the absence of validated forecasts; once a shared, validated demand estimate was in place, the stated rationale for ad hoc rush orders was correspondingly reduced. This is consistent with the findings of Chuchotthaworn (2020) and Tabporn et al. (2018), who similarly found that structured forecasting and inventory control reduced holding costs and improved order fulfillment in Thai food-processing settings, although neither of those studies examined a full cross-functional S&OP cycle as the present study does.

Table 7. Consolidated statistical hypothesis tests with 95% confidence intervals and effect sizes (n = 6 paired months)

Hypothesis & Variable	Mean Values		Mean Diff. (*D*)	95% CI of Difference [Lower, Upper]	Std. Error (*SE*)	*t*-value (*df* = 5)	*p*-value (One-tailed)	Wilcoxon *T* (*p* - value)[a]	Cohen's *d* (Effect Size)[b]
	Before	After							
H1: Forecast Error (MAPE, %)	28.40	16.90	11.50	[10.68, 12.32]	0.317	36.25	< 0.001*	0 (0.031*)	14.80 (Very Large)
H2: Average Inventory (Tons)	240.00	195.00	45.00	[35.61, 54.39]	3.652	12.32	< 0.001*	0 (0.031*)	5.03 (Very Large)
H3: On-Time Delivery (OTD, %)	82.30	93.10	-10.80	[-12.53, -9.07]	0.671	-16.10	< 0.001*	0 (0.031*)	6.57 (Very Large)
H4: Expedited Orders (Times/Month)	11.00	5.00	6.00	[4.01, 7.99]	0.775	7.75	< 0.001*	0 (0.031*)	3.16 (Very Large)
H5: Forecast Bias (%)	12.60	4.20	8.40	[7.52, 9.28]	0.343	24.52	< 0.001*	0 (0.031*)	10.01 (Very Large)

Note: * Indicates statistical significance at the 0.05 level.

[a] Wilcoxon T-statistic represents the minimum sum of ranks (T). Under $n = 6$, the minimum achievable two-tailed p-value is 0.031.

[b] Cohen's d is calculated as the mean difference divided by the standard deviation of paired differences. Standard benchmarks: 0.2 (small), 0.5 (medium), 0.8 (large).

"Mean Diff. (D) = mean of paired differences (Before–After for H1, H2, H4, H5; After–Before for H3); SE = standard error; df = 5."

These findings are broadly consistent with the synthesis of Tuomikangas and Kaipia (2014) and Thomé et al. (2012), who identified S&OP as a key mechanism linking demand and supply to improve cost and customer-service outcomes. A more specific comparison is also possible: Thomé et al. (2012) reported that organizations with mature S&OP implementations achieved inventory carrying-cost reductions in the range of 10 to 30 percent, within which the 18.75 percent inventory reduction observed in this case study falls, suggesting that the magnitude of improvement, though derived from a single case, is broadly within the range previously documented in the literature rather than an outlier. With respect to forecast accuracy specifically, comparable published MAPE improvements following S&OP-type interventions in manufacturing settings are less consistently reported in percentage-point terms, which limits the precision of cross-study comparison; the 11.5-percentage-point MAPE reduction found here should accordingly be read as a case-specific result rather than benchmarked against a well-established norm. In this case study, the decrease in average inventory and the number of urgent production orders are consistent with the organization being able to plan more proactively, while the increase in OTD suggests that the reduction in inventory did not come at the expense of customer service. The improvement in cross-functional coordination observed in this study is also consistent with Wagner et al. (2014), who argued that organizational alignment and integrated planning processes are associated with operational performance improvement.

In the context of agricultural processing factories, this study is particularly significant because this type of industry faces specific constraints such as seasonal fluctuations in raw materials, product shelf life, and order uncertainties. Having a platform for regular data review and joint decision-making appears to help bridge the gap between planning and actual implementation and may enhance the organization's ability to respond more flexibly to changes. At the same time, these same agro-specific constraints also represent the principal challenges to sustaining S&OP success beyond the six-month window observed here: the agro-specific constraints noted in the Introduction (harvest-dependent supply and shelf-life limits) restrict how far even a well-functioning S&OP cycle can eliminate supply-side forecast error. The research thus suggests that S&OP can serve as a useful management mechanism for agricultural processing businesses in the Thai context, while acknowledging that its success is conditional on factors, particularly raw-material seasonality, that are largely outside the direct control of the planning process itself. Consistent with Tuomikangas and Kaipia (2014), such initiatives may stall when executive sponsorship or cross-functional metrics are not sustained; this risk is discussed in Section 5.

5. Conclusions and Recommendations

This study set out to investigate the problems and limitations of S&OP in an agricultural processing plant, develop an S&OP process suited to its organizational context, and evaluate the resulting effects on five operational indicators. Within the scope of this single case, all five indicators improved to a statistically significant degree over a six-month trial, and the accompanying qualitative evidence indicated that the absence of a shared database and a cross-functional review forum had been the primary driver of the pre-existing planning inconsistency. In practical terms, organizations looking to implement S&OP should focus on four key areas: creating a shared database, setting a fixed meeting schedule, clearly appointing process owners, and establishing joint metrics that reflect the goals of the entire organization. Sustaining these gains beyond the trial period, however, is likely to depend on continued executive sponsorship and the durability of the joint metrics introduced during this study, since the broader S&OP literature indicates that initiatives of this kind frequently stall once initial momentum fades. Meanwhile, in academic terms,

future research should expand the study to multiple case studies, extend the follow-up period, and collect data at the product or weekly level to enhance the detail and robustness of the research conclusions.

This research has several limitations. First, the study employed a single-case design, which may limit the generalizability of the findings to other industrial contexts; the very large effect sizes and uniform monthly pattern reported in Section 3.4 are characteristic of this specific case and should not be read as typical of S&OP implementations generally. Second, the evaluation period covered only six months before and six months after the implementation of the S&OP process, and the two windows fell in different halves of the annual agricultural cycle (January-June before, July-December after); this means that part of the observed improvement may be confounded with seasonal differences between the two periods rather than being attributable to the S&OP process alone, and the study cannot disentangle the intervention effect from this seasonal contrast. Although the paired monthly analysis enabled direct operational comparison under similar planning conditions, the relatively small number of observations limits statistical power, and the Shapiro-Wilk normality tests reported in Table 6, given the same small sample, should be regarded as inconclusive rather than confirmatory. Third, external factors such as raw material variability and market fluctuations may also have influenced operational performance during the study period, and because no control group was available, the improvements reported here cannot be attributed to the S&OP process with the same confidence that a controlled or multi-case design would permit. Fourth, the demand forecasting method introduced as part of the S&OP process, a weighted moving average combined with qualitative adjustment, was not benchmarked against alternative forecasting techniques, so the relative contribution of the forecasting method itself, as opposed to the cross-functional review process around it, cannot be isolated. Finally, while the qualitative component of this study identified four key organizational themes from 12 informant interviews, the depth of that analysis was constrained by the case-study scope; a larger or longitudinal qualitative inquiry could further illuminate how these themes evolve as an S&OP process matures. Future research should therefore extend the implementation horizon to cover a full annual cycle, increase the number of analytical periods, benchmark alternative forecasting techniques, and conduct multi-case comparative studies to strengthen external validity and empirical generalizability.

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