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SIMULATION-BASED PRODUCTION PLANNING FOR AN ELECTRONIC MANUFACTURING SERVICE PROVIDER USING COLLABORATIVE PLANNING

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ABSTRACT

The growing trend of specialization is significantly increasing the importance of Electronic Manufacturing Services (EMS) providers. Typically, EMS companies operate within global supply networks characterized by high complexity and dynamic interactions between multiple stakeholders. As a consequence, EMS providers frequently experience volatile and opaque procurement and production planning processes. This paper investigates the potential of collaborative planning between EMS providers and their customers to address these challenges. Using discrete-event simulation, we compare traditional isolated planning approaches with collaborative planning strategies. Based on empirical data from an EMS company, our findings highlight the benefits of collaborative planning, particularly in improving inventory management and service levels for EMS providers. We conclude by presenting recommendations for practical implementation of collaborative planning in the EMS industry.

1 INTRODUCTION

EMS providers offer customized manufacturing services for electronic components (Winzker 2023). Driven by increasing specialization and the emergence of global supply chains in the 21st century, EMS providers are becoming increasingly relevant. This trend is reflected in the steady growth of the revenue figures of the EMS industry (Valverde and Saadé 2015). However, the global spread of supply chain actors creates a highly complex and dynamic environment, which presents significant challenges for EMS providers, particularly in terms of planning.

On the procurement side, lead times for essential materials are often long and uncertain, especially when components are sourced internationally. Many of these components are highly specialized, and suitable substitutes are rarely available. On the customer side, order volumes tend to be highly volatile and short-term, an outcome of market demands for faster delivery and greater flexibility (Singh et al. 2018). Furthermore, EMS providers suspect that many customers do not place orders based on actual needs. Some customers build up excessive safety stocks out of fear of supply shortages, while others experience production downtimes due to inaccurate forecasts or delayed deliveries. These problems are symptomatic of the bullwhip effect (Chatfield et al. 2004).

The combination of long procurement lead times and short-term customer orders makes efficient production planning particularly difficult. Priorities frequently shift, and fluctuating order volumes limit production efficiency. As a result, EMS providers often rely on high safety stocks and still struggle to meet delivery deadlines. Since both EMS providers and their customers are affected by these challenges, it is worth exploring whether closer collaboration could yield mutual benefits. One promising approach is the active coordination of the supply chain. While EMS providers typically work within broader supply networks involving many suppliers and customers, the term *supply chain* will be used throughout this paper for simplicity. The central question is whether improved collaboration, particularly through

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enhanced information exchange - can support more efficient production planning for EMS providers and more transparent inventory management for customers. To investigate this, we use discrete-event simulation (DES) to compare traditional planning approaches with collaborative planning strategies. The study focuses on the specific challenges of the EMS industry in the Make-To-Order (MTO) environment. We use real-world data from an EMS provider to simulate and evaluate different environmental scenarios.

The remainder of this paper is structured as follows: Section 2 presents the current state of research. Section 3 describes the problem context in detail. Section 4 outlines the proposed solution and simulation models. Section 5 discusses the experimental design and results. Finally, Section 6 concludes with key findings and an outlook on future research directions.

2 STATE OF THE ART

Traditionally, production planning has relied on methods that do not take into account actual customer demand. However, with the high dynamics of production planning, these methods are no longer adequate, necessitating the search for alternatives (Auerbach et al. 2011). This paper considers collaborative planning as one such alternative. Unlike traditional planning, collaborative planning does not take place in isolation. The collaborative approach actively exploits the structure of the supply network by sharing information across firms. The exchange of information is based on the fact that companies closer to the end customer have more accurate information about the end customer's demand (Poppe 2017). This information can then be passed upstream through collaboration to companies with less accurate data, thereby mitigating the bullwhip effect. In the past, several collaborative planning methods have evolved, each with its own strengths.

Of particular relevance are Vendor Managed Inventory (VMI) and Collaborative Planning, Forecasting and Replenishment (CPFR). In VMI, the customer shares data on incoming orders and current stock levels. The supplier uses this information to plan replenishment without the customer placing an order. CPFR follows a defined process where the customer and supplier jointly plan the forecast and then adjust their production and deliveries accordingly (Skjoett-Larsen et al. 2003). Both parties synchronize their processes. However, the specific form of collaboration is not the focus of this paper. The requirements for all collaboration partners will be specified later.

Existing optimization models for supply chain collaboration have been studied in the literature, but the simulation approach is comparatively underrepresented (Ivanov 2017). Småros et al. (2003) compared the production utilization of a manufacturer with and without VMI. The study examined the impact of information sharing when all, only some, or none of the customers share their information. Full VMI provided the best results. Kamalapur and Lyth (2014) compare CPFR with traditional planning for a supplier and a manufacturer. The implementation of CPFR significantly reduces inventory carrying costs and backorder costs, especially when inventory carrying costs per unit are high. Gansterer (2015) compares service levels and inventory levels of a MTO company in different scenarios. Four different approaches are distinguished, three production planning tactics influenced by demand forecasts and one tactic without the influence of forecasts. The scenarios vary in the frequency of demand and the magnitude of demand variation. The no-forecast tactic always results in the lowest inventory levels, but at the expense of service levels. In cases of high demand and fluctuations, the tactics with the influence of demand forecasts achieve a significantly better service level.

2.1 Research Gap

Although there are no quantitative studies on the prevalence of collaborative planning in Make-To-Stock (MTS) vs. MTO environments, it can be inferred from the typical challenges that MTS systems particularly benefit from improved forecasting through collaboration and thus make greater use of such approaches. The application for companies in the MTO environment is somewhat underrepresented compared to MTS systems.

This paper also addresses the specific characteristics and issues for companies in the EMS industry. The particularly dynamic environment and international relations make this field unique. Furthermore, this paper integrates production planning with real parameters and data from an EMS provider's manufacturing process into the supply network. Interactions with and consequences for production planning are therefore considered. The fields of production planning and supply chain management are interrelated.

3 PROBLEM DESCRIPTION

The EMS provider in question faces industry-standard challenges on the procurement side. Many components critical to the final product, such as integrated circuits and connectors, are highly specialized. These components are often available only from a single manufacturer, and switching to alternative components is difficult to implement (Winzker 2023). Furthermore, in the electronics industry, components become obsolete very quickly due to technological advances, and their production is often discontinued at short notice (Winzker 2023). This results in irregular and long procurement lead times, which in turn makes it difficult to achieve a balanced, regular, and well-planned procurement process. High inventory levels are deliberately accepted because replenishment is often based on component availability rather than on purchase orders.

On the other hand, customer tolerance times for incoming orders are, on average, much shorter than order processing times for procurement. Although the company in question processes recurring orders, production cannot be synchronized with procurement. As a result, in practice, production planning and subordinate machine scheduling are often and frequently adjusted as the prioritization of orders changes. As Kück (2024) illustrates in Figure 1, for manufacturers with recurring orders, the customer order decoupling point is very early in the process chain. While manufacturing and subsequent steps are order-based, procurement is based on a demand forecast. According to Schönsleben (2020), procurement must be based on a demand forecast whenever the customer tolerance time exceeds the cumulative lead time.

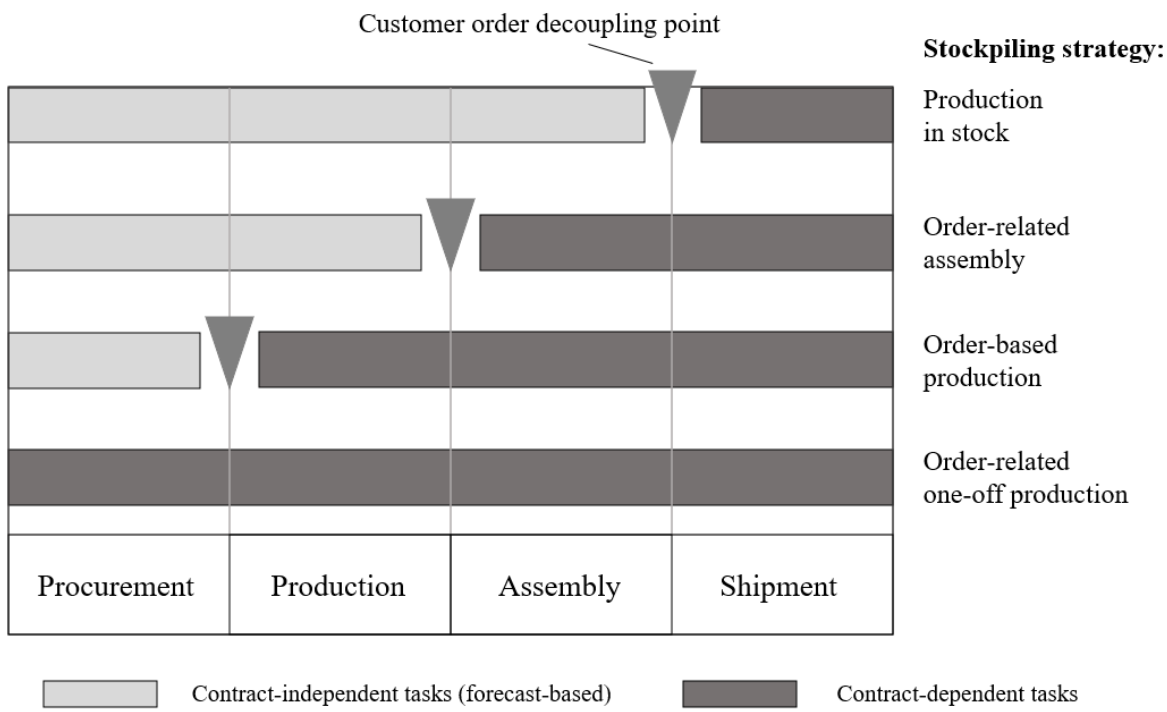

Figure 1: Inventory strategies (adapted from Wiendahl (2014)).

Demand forecasting can be performed using a variety of methods and technologies. Companies typically base their forecasts on internal historical data and, where appropriate, expert knowledge. Traditionally, each company in the same supply chain creates its own forecasts independently and without access to information from other parties. These forecasts are then used as the basis for ordering upstream goods. Forecasting methods can include both qualitative approaches (e.g., expert estimates, surveys) and quantitative techniques (e.g., moving average, exponential smoothing, or even neural networks) (Klingebiel and Feißner 2025).

This paper examines the supply network of a specific EMS provider. As mentioned earlier, in addition to procurement, the service provider's production planning also suffers from the volatility of the environment. In particular, machine scheduling is affected. Machine scheduling involves the assignment of orders or tasks to limited resources with the goal of optimizing defined objectives (Lee et al. 1997). There is an existing DES model of the machine scheduling at the studied EMS provider that will be used in this paper. The original model includes machines that handle goods in two stages. The machine scheduling is determined by sorting algorithms. In the old system, all goods are entered at the beginning of the simulation and then sorted according to priority rules. However, due to the dynamic and short-term nature of customer orders in the real world, new orders are introduced into the system, causing the prioritization of orders to change frequently. Because of the short order lead times, machine scheduling is often based solely on the Earliest Due Date (EDD) dispatching rule. EDD processes the orders with the least time remaining to the delivery date first. In addition, capacity is fixed in production planning. If many orders arrive within a short period of time, it is likely that not all of them will be completed in time for the delivery date.

4 SOLUTION APPROACH

The following section presents and compares two models based on different planning concepts, one representing traditional planning and the other a collaborative approach. Both models use DES, a method for modeling and analyzing systems in which state changes occur only at specific points in time, triggered by discrete events. The basic structure of both models is the same; the differences between them will be examined in a later section.

Instead of modeling the complex supply network of the EMS provider with numerous customers and suppliers, we present a simplified supply chain. This chain consists of four actors connected by material and information flows.

- **Suppliers** are the first actor. They receive orders from the EMS provider and deliver materials. They are the source of the material flow and the sink of the information flow.
- The **EMS provider** receives materials from suppliers and customer orders from customers. By processing the materials according to customer orders, the EMS provider produces intermediate products that are then shipped to customers.
- The **customers** receive work-in-progress from the EMS provider and orders from retailers. By combining incoming orders and intermediate products, they produce a finished product that is then shipped to the retailers.
- The **retailers** receive the final products and thus represent the sink of the modeled supply chain. At the same time, they generate orders for customers and thus serve as the source of the information flow.

The material flow describes the movement of goods through the system and remains identical in both model variants. Materials are supplied by external suppliers to the EMS provider and are classified according to a characteristic known as the material family. Upon delivery, materials are stored in the EMS provider's inbound warehouse.

When a customer order arrives, the system checks for the availability of the required materials. If the necessary materials are in stock, they are released to the production line and processed further. If not, the order is marked as open and is queued for production once the materials become available. As previously described, the manufacturing process in the model is based on an established simulation model by Rolf et al. (2020). In the newly developed model variants, orders are scheduled daily for machine processing, using either the EDD or the Shortest Setup Time (SST) heuristic. SST is particularly relevant because machines must be reconfigured based on the sequence of orders. When consecutive orders require materials from the same material family, the setup time is significantly reduced. The SST rule therefore prioritizes orders in a sequence that minimizes machine setup time. By combining EDD and SST, the scheduling aims to achieve a balance between timely order fulfillment and efficient machine utilization.

Once manufacturing is complete, the semi-finished products are shipped to the respective customers and stored until further processing. To ensure traceability and to distinguish between products, each product is assigned a unique identifier. Upon receiving downstream orders, customers dispatch the relevant products to dealers. Similar to the material inspection performed by the EMS provider, customers verify whether the required semi-finished products are available in inventory. From the moment a product is retrieved from storage for shipment, it is classified as a finished product. This distinction is introduced to avoid ambiguity in subsequent analysis. For the sake of simplification, the customers' internal production steps are not modeled. Instead, it is assumed that finished products are immediately shipped to dealers and thereby exiting the system.

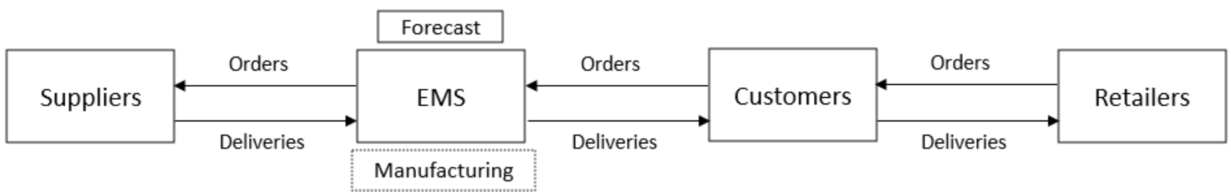

Figure 2: Basic structure of the supply chain.

In the information flow layer, data is either exchanged within a company or shared across organizational boundaries to support planning processes. The key data elements in both the traditional and collaborative model variants include customer orders, recorded material consumption, and generated demand forecasts. Orders originate from the retailers and are generated based on a stochastic distribution. The stochastic approach is used to examine the behavior of the models under varying demand intensities and different temporal intervals between order arrivals. A normal distribution is used. These orders are transmitted upstream through the supply chain. Each order is assigned two critical attributes:

1. **Job ID**: a unique identifier used to trace the product, applicable to both the final and intermediate products.
2. **Due date**: the required delivery date, which is determined by adding a normally distributed lead time to the order placement date. The maximum allowable lead time is referred to as period n.

The recipients of these orders fulfill the demand using available inventory and evaluate whether new reorder requests must be generated. To make this decision, they check whether the current stock level x is sufficient to cover future orders O within a specific planning horizon, without dropping below a predefined target stock level TS. Additionally, the number of open, unfulfilled reorder orders y is included in the evaluation to prevent repetitive reorder triggering, which could otherwise result in overstocking. However, the planning horizon considered in the models varies. In the traditional model, the horizon is defined as period z, which corresponds to the order lead time. This lead time is assumed to be constant across all products and is based on the average actual lead time observed for incoming orders to the EMS provider. Accordingly, the threshold condition for triggering a reorder in the traditional model is defined by the following expression:

$$x+y-\sum_{i=1}^{z} O_{t+i} < TS. \tag{1}$$

In the collaborative model, the period n is considered, which has already been defined as the maximum lead time. In contrast to the traditional model, which only considers the order lead time z, the EMS provider can now anticipate future demand over a longer period due to the information shared by its customers. Previously, the provider was limited to reacting to orders placed by its direct customers. Now, with access to the demand data from the customers of its customers, the provider can respond proactively to downstream demand. Therefore, the equation to calculate the threshold for reordering in the collaborative model is as follows:

$$x+y-\sum_{i=1}^{n} O_{t+i} < TS. \tag{2}$$

The algorithms are run once a week for each of the semi-finished products. The review is done on a rolling basis. When a reorder is triggered, it takes the job ID of the original order. In the traditional model, the due date of the order to the EMS provider is z periods in the future, starting from the order creation time. In the collaborative model, it is n periods in the future. In both models, customers place orders based on actual orders received. It is assumed that there is no need to forecast because the order lead times for semi-finished and finished products are short and can be nearly synchronized. This is where the traditional and collaborative models diverge significantly.

4.1 Traditional Model

To fulfill reorder requests, the EMS provider must manufacture semi-finished products using raw materials, which are consumed in the process. Since the procurement lead time for materials exceeds the order lead time, the EMS provider must initiate procurement based on a demand forecast rather than on actual demand. As previously described, this forecast, denoted as F, is generated by the EMS provider on a weekly basis for each material family. The forecast is derived from historical material consumption data MC, recorded over a defined time window of m weeks. In contrast to the reorder algorithms 1 and 2, which rely on future-oriented planning parameters, the forecast is based exclusively on past consumption patterns. The historical data used for the forecast is drawn from the preceding m weeks and reflects actual material usage. The corresponding equation for calculating the demand forecast is given by:

$$F_{t+n} = \frac{\sum_{i=t-m}^{t} MC_i}{m}. \tag{3}$$

The forecast uses the moving average, calculated as the sum of material consumption across m past weeks, divided by the number of weeks. The forecast is created for time $t+n$, where n is the planning horizon. The forecast is also updated in a rolling fashion. After the forecast is created, the EMS provider checks whether material procurement is necessary. Unlike the customers, who use actual future orders, the EMS provider uses the forecast as input. The equation to calculate the threshold to create a procurement order is therefore:

$$x+y-\sum_{i=1}^{n} F_{t+i} < TS. \tag{4}$$

Once a procurement order is placed, it is sent to the suppliers, thereby initiating the source of the material flow. No due date is assigned; instead, the arrival time depends on the procurement lead time, which is defined for each material family at the start of the simulation.

4.2 Collaborative Model

In the collaborative model, customers share all relevant information with the EMS provider in real time. This includes data on current inventory levels, open replenishment orders, and incoming orders from retailers. As soon as a customer receives a new order from a retailer, the order is recorded in a structured list, categorized by Job ID and Due Date. This early data exchange enables the EMS provider to incorporate downstream demand information into its planning processes at an earlier stage. Using this real-time order information, the EMS provider can translate final product orders into corresponding material procurement requirements. Each final product order is mapped to its associated material family via the Job ID. The EMS provider then applies the same procurement algorithm used in the traditional model. However, in contrast to the traditional model, which relies on demand forecasts, the collaborative model uses actual future orders—specifically, retailer orders communicated by customers. As a result, the EMS provider no longer depends on forecasted consumption but instead bases its procurement decisions on confirmed downstream demand, thereby increasing planning accuracy and responsiveness.

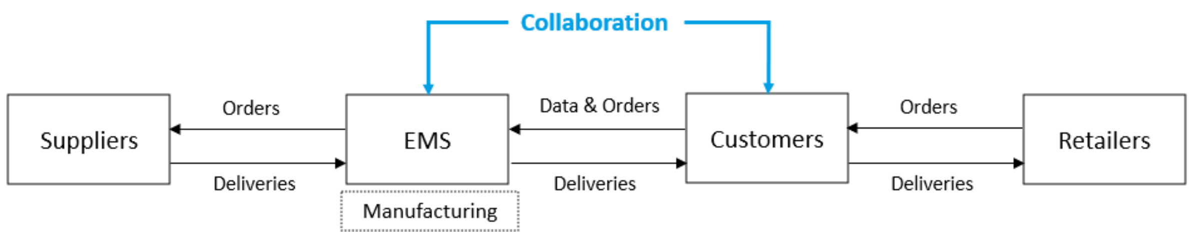

Figure 3: Structure of the collaborative supply chain.

The algorithm is therefore similar to the threshold in (2) used by customers in the collaborative model. However, the EMS provider applies it to the material families rather than to the intermediate products. Similarly, no due date is generated; instead, the delivery time depends on the lead time of the material family. The differences of the two models can also be seen in Table 1.

Table 1: Comparison of traditional and collaborative models.

Aspect	Traditional Model	Collaborative Model
Information flow	Internal only; no real-time exchange	Real-time data sharing across companies
Data basis for procurement	Forecast based on historical material consumption	Actual customer orders from retailers
Forecasting method	Weekly forecast $F = \frac{1}{m}\sum_{i=1}^{m} MC_i$	No forecast required
Order mapping	Based on historical consumption patterns	Based on Job ID of actual customer orders
Inventory visibility	No access to customer inventory data	Full access to customer inventory and open orders
Responsiveness	Limited, dependent on outdated data	High, based on real-time demand signals

5 EXPERIMENTS AND ANALYSIS

To evaluate the performance of both models, two key objective variables are analyzed: average inventory and service level. First, the average inventory over time is examined. This metric reflects the mean number of units stored within a given time period and serves as an indicator of capital tied up in inventory, as well as of storage costs (Chopra and Meindl 2016). A lower average inventory implies reduced inventory holding costs and improved capital efficiency. Consequently, minimizing this value is desirable. Second, the service level is assessed. This variable represents the proportion of customer orders that are fulfilled on time and is defined as the complement of the late delivery rate (Chopra and Meindl 2016). A high service level signifies strong delivery performance and customer satisfaction. Failure to meet promised delivery dates often results in penalty costs or a loss of customer trust. Therefore, the objective is to maximize the service level.

Although both metrics are positively correlated, i.e., a higher inventory level tends to improve the service level-they also create a trade-off. Increasing inventory improves responsiveness but comes at the cost of higher holding expenses. Thus, the central challenge lies in balancing the two conflicting objectives: minimizing inventory while maintaining a sufficiently high service level. To ensure that both collaboration partners, the EMS provider and its customers, benefit from the system, average inventory and service level are considered separately for each. This results in four output variables in total. The central research question addressed by the experiments is: How low can inventory levels be reduced without allowing service levels to drop below an acceptable threshold? This threshold is set at 95% for all service levels in both models. In practice, this requirement is implemented via a soft constraint: if any service level falls below the 95% threshold, a penalty value C is added to the objective function, significantly degrading the solution value V so that it is no longer considered optimal. The resulting objective function is defined as follows:

$$minV = a * AVGM + b * AVGIP + C. \tag{5}$$

The objective function incorporates a weighted combination of two inventory-related metrics: the average inventory of raw materials $AVGM$ held by the EMS provider, and the average inventory of intermediate products $AVGIP$ stored by the customers. These two components are weighted using factors a and b, respectively, where the weights are determined based on the relative contribution each inventory type would make to the total cost if considered in isolation. The goal of the experiments is to identify combinations of input variables that yield the lowest solution value under the given constraints. Due to the stochastic nature of the system, each input configuration is evaluated over multiple iterations to account for variability in outcomes.

To explore the input space efficiently, a genetic algorithm is employed. This metaheuristic iteratively evolves the population of input combinations by preserving and recombining those with favorable solution values. Small, random modifications (mutations) are introduced in each generation to avoid local optima. The algorithm terminates once further improvements in solution quality fall below a predefined threshold over several generations, indicating convergence. The best solutions, evaluated across all iterations, are averaged for the four key output variables in both model variants (traditional and collaborative). We then compare the results to assess the relative performance of the two models. To account for different operating conditions and stress levels in the system, the experiments are conducted under six distinct scenarios, following the approach of Gansterer (2015). By varying the mean and the standard deviation of the normal distribution that mimics the ordering behavior of the retailers, the frequency and intervals between dealer order arrivals are adjusted:

- Scenario 1: High demand from retailers, mild stochastic fluctuations
- Scenario 2: High demand from retailers, no stochastic fluctuations
- Scenario 3: High demand from retailers, strong stochastic fluctuations
- Scenario 4: Low demand with mild stochastic fluctuations

- Scenario 5: Low demand with no stochastic fluctuations
- Scenario 6: Low demand with strong stochastic fluctuations

The targeted service level of 95% was achieved in all analyzed scenarios. Therefore, this target value is not explicitly considered in the further comparison of the planning models. Table 2 compares the minimal average inventory levels of the two planning approaches. The lower value is presented as an absolute figure, while the higher value is shown as a percentage deviation from the better one.

Table 2: Results of the comparison.

	Ø Inventory EMS-provider		Ø Inventory customers	
Scenario	Traditional	Collaborative	Traditional	Collaborative
1	+74%	15.49	1.46	+26%
2	+64%	16.48	1.46	+26%
3	+74%	15.51	1.46	+26%
4	+56%	15.14	+18%	1.35
5	+56%	15.11	+13%	1.35
6	+75%	15.16	+15%	1.35

In all scenarios, the use of collaborative planning led to a significant reduction in the average inventory levels of the EMS provider. Traditional planning resulted in average inventories that were 56% to 75% higher compared to the collaborative approach. This difference is particularly pronounced in Scenarios 3 and 6, where retailer orders are generated at irregular intervals. In such cases, collaborative planning clearly proves to be the superior alternative for the EMS provider. From the provider's perspective, collaboration thus represents an attractive measure for inventory reduction.

For the customers of the EMS provider, however, the picture is more differentiated. Only in Scenarios 4 to 6, which are characterized by relatively low end-customer demand, does collaborative planning also lead to lower inventory levels on the customer side. The inventory levels for traditional planning are 13% to 18% higher than with collaborative planning. In scenarios with high end-customer demand, however, collaborative planning results in up to 26% higher inventory levels for customers compared to the traditional approach.

It can therefore be concluded that customers have no immediate incentive to engage in collaboration with the EMS provider. The additional effort required is only offset by inventory reductions in specific scenarios. However, given the substantial benefits of collaboration for the EMS provider, it would be reasonable for the provider to offer additional incentives-such as guaranteed service levels, improved delivery conditions, or shared IT infrastructure—to encourage customer participation. Such measures could create a win-win situation.

The results clearly demonstrate that collaborative planning is an effective tool for reducing inventory levels and improving planning efficiency—particularly for the EMS provider, but under certain conditions also for its customers. Companies in comparable settings should therefore evaluate whether significant supply chain potential can be unlocked through the structured exchange of demand and planning data.

6 CONCLUSION AND OUTLOOK

In summary, the collaborative planning approach offers EMS providers a significant improvement over traditional planning methods. Instead of relying on self-created forecasts, current customer inventory and order data is used as the basis for procurement and production planning. This enables the optimization of the objective variables considered - service level and average inventory. Different scenarios were tested to observe how these variables behave. In all cases, the collaborative model allows the EMS provider to reduce average inventory while maintaining the desired service level. This is particularly beneficial when the per-unit cost of holding inventory is high (Kamalapur and Lyth 2014), which is the case in the EMS industry. Therefore, EMS providers should strongly consider collaborating with their customers.

The foundation of collaborative planning is information sharing. In the case discussed in this paper, the EMS provider uses data from its customers. However, since customers are often reluctant to share sensitive business information, so they need to be incentivized to do so. The comparison of the models shows that collaborative planning provides overall better solutions in only three of the six scenarios considered. The dynamic demand situation described at the beginning is either the third or sixth scenario, which massively reduces the inventory level for the EMS-provider. As a result, the incentive for customers to collaborate may be lacking in some cases, but the EMS-provider should definitely push for the usage of information sharing and incentivize the customers in some other way. However, it is important to assess whether the effort required to initiate collaboration is justified. Costs associated with IT system integration, as well as the effort and time required to acquire partners, must be considered. It may make more sense to work with key customers, especially if the customer base is large.

In addition, the value of involving suppliers in the collaboration should be explored. This could lead to better coordination between supply chain actors and an improved procurement situation for EMS providers. The use of artificial intelligence to optimize the structure of supply chain processes should also be explored. Artificial intelligence has significant potential, especially for complex supply network structures and multi-partner collaborations. Finally, the feasibility of more efficient data exchange and transparency of material and information flows within the supply network could be explored using new tools such as the Digital Twins method.

REFERENCES

Auerbach, T., F. Bauhoff, M. Beckers, D. Behnen, C. Brecher, T. Brosze, *et al*. 2011. “Selbstoptimierende Produktionssysteme”. In *Integrative Produktionstechnik für Hochlohnländer*, edited by C. Brecher, 747–1057. Berlin, Heidelberg: Springer https://doi.org/10.1007/978-3-642-20693-1_6.

Chatfield, D. C., J. G. Kim, and T. P. Harrison. 2004. “The Bullwhip Effect — Impact of Stochastic Lead Time, Information Quality, and Information Sharing: A Simulation Study”. *Production and Operations Management Society* 13(4):340–353 https://doi.org/10.1111/j.1937-5956.2004.tb00222.x.

Chopra, S., and P. Meindl. 2016. *Supply Chain Management: Strategy, Planning, and Operation*. Sixth ed. Boston: Pearson.

Gansterer, M. 2015. “Aggregate Planning and Forecasting in Make-to-Order Production Systems”. *International Journal of Production Economics* 170:521–528 https://doi.org/10.1016/j.ijpe.2015.06.001.

Ivanov, D. 2017. “Simulation-Based Ripple Effect Modelling in the Supply Chain”. *International Journal of Production Research* 55:2083–2101 https://doi.org/10.1080/00207543.2016.1275873.

Kamalapur, R., and D. Lyth. 2014. “Benefits of CPFR Collaboration Strategy under Different Inventory Holding and Backorder Penalty Costs”. *International Journal of Business and Management* 9(10) https://doi.org/10.5539/ijbm.v9n10p1.

Klingebiel, K., and F. Feißner. 2025. “Absatz- und Allokationsplanung”. In *Handbuch Logistik*, edited by Furmans, Kilger, Tempelmeier, Hompel, and Schmidt, 1–13. Berlin, Heidelberg: Springer.

Kück, M. 2024. *Selbination: Ein hybrides Meta-Lernverfahren zur automatischen Selektion und Kombination geeigneter Prognosemodelle für die Produktionsplanung*. First ed. Wiesbaden: Springer Fachmedien and Imprint Springer Vieweg https://doi.org/10.1007/978-3-658-45605-4.

Lee, C.-Y., L. Lei, and M. Pinedo. 1997. “Current Trends in Deterministic Scheduling”. *Annals of Operations Research* 70:1–41 https://doi.org/10.1023/A:1018909801944.

Poppe, R. 2017. *Kooperationsplattformen für das Supply Chain Management*. Wiesbaden: Springer Fachmedien https://doi.org/10.1007/978-3-658-16369-3.

Rolf, B., T. Reggelin, A. Nahhas, S. Lang, and M. Müller. 2020. “Assigning Dispatching Rules Using a Genetic Algorithm to Solve a Hybrid Flow Shop Scheduling Problem”. *Procedia Manufacturing* 42:442–449 https://doi.org/https://doi.org/10.1016/j.promfg.2020.02.051.

Schönsleben, P. 2020. *Integrales Logistikmanagement*. Berlin, Heidelberg: Springer https://doi.org/10.1007/978-3-662-60673-5.

Singh, H., R. K. Garg, and A. Sachdeva. 2018. “Supply Chain Collaboration: A State-of-the-Art Literature Review”. *Uncertain Supply Chain Management* 6(2):149–180 https://doi.org/10.5267/j.uscm.2017.8.002.

Skjoett-Larsen, T., C. Thernøe, and C. Andresen. 2003. “Supply Chain Collaboration: Theoretical Perspectives and Empirical Evidence”. *International Journal of Physical Distribution & Logistics Management* 33(6):531–549 https://doi.org/10.1108/09600030310492788.

Småros, J., J.-M. Lehtonen, P. Appelqvist, and J. Holmström. 2003. "The Impact of Increasing Demand Visibility on Production and Inventory Control Efficiency". *International Journal of Physical Distribution & Logistics Management* 33(4):336–354 https://doi.org/10.1108/09600030310478801.

Valverde, R., and R. G. Saadé. 2015. "The Effect of E-Supply Chain Management Systems in the North American Electronic Manufacturing Services Industry". *Journal of Theoretical and Applied Electronic Commerce Research* 10(1):79–98 https://doi.org/10.4067/S0718-18762015000100007.

Wiendahl, H. P. 2014. *Betriebsorganisation für Ingenieure*. Seventh ed. München: Hanser.

Winzker, M. 2023. *Elektronik für Entscheider: Grundwissen für Wirtschaft und Technik: mit Aufgaben und Lösungen sowie Anwendungsbeispielen*. Third ed. Wiesbaden, Heidelberg: Springer Vieweg.

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