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Research on Multi-source Demand Perception and Inventory-Capacity Co-optimization of Sales and Operation Planning in Discrete Manufacturing Enterprises

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Abstract: Given the changes in the demand environment, delivery risks and extended supply chains of modern manufacturing enterprises, the previous model of sales and operations planning has shown several defects, such as scattered data, slow forecasting and departmental misalignment. Based on the EU enterprise digital technology application statistics in 2025, this paper proposes a multi-source big data-driven framework for collaborative sales and operations planning by means of secondary data analysis, standardised modelling and process design. The five kinds of models in this study are: demand perception, dynamic weight updates, inventory balancing, multi-objective cost optimisation and service-level risk constraints. The four levels of the implementation plan are data governance, collaborative planning, decision optimisation and closed-loop execution. Based on the statistics, large enterprises significantly outperform the average enterprise in terms of ERP, business intelligence, cloud computing, data analytics and artificial intelligence applications, and the adoption rates of data analytics vary substantially among different countries. Therefore, to optimise the supply chain, we do not need a single algorithm that replaces human labour; rather, we should establish a unified data semantics, cross-departmental constraint negotiation, and an interpretable rolling decision-making mechanism.

1. Research Background of Collaborative Optimization of Sales and Operations Planning in Discrete Manufacturing Enterprises

The world's supply chain has moved away from a relatively stable linear model to a multi-node, highly interconnected and prone-to-disruption network system. A manufacturing enterprise produces a large number of organised and unorganised data during sales forecasting, procurement planning, capacity allocation, inventory replenishment and logistics scheduling. The above data are generally distributed among ERP, MES, WMS, TMS, CRM and other external market platforms, and it is difficult to establish a unified, timely and intuitive planning foundation. The old method of sales and operations planning usually issues only monthly summaries, and thus it cannot promptly identify changes in orders, supply problems or shifts in sales channels. Therefore, the forecasting errors will be magnified at each link in the procurement, production and inventory stages.

Based on the above research, it has been determined that the effective application of big data analysis in supply chain planning depends on the alignment of data sources, analysis methods and specific planning activities, and simply adding more data does not guarantee better results [1]. Therefore, this paper takes the sales and operating plan scenario of manufacturing enterprises as its research object, explores how multiple sources of data can be converted into cross-departmental collaborative plans, and finally introduces business decision optimisation. The main content of this paper is as follows: First, based on actual statistical data, analyze the deficiency in enterprise digital technology adoption. Second, propose a collaborative framework consisting of the data layer, analysis layer, planning layer and execution layer. Third, build five editable core models. Fourth, establish a data governance and organisation mechanism that can be rolled out in stages.

2. Current Status of Enterprise Digital Technology Adoption and Cross-Departmental Supply Chain Planning Collaboration

2.1 Differences in Enterprise Adoption of ERP Cloud Platforms and Data Analytics Technologies

Supply chain big data usually includes order, price, promotion, customer behaviour, inventory, equipment status, supplier delivery, transportation route and weather/macro market data. The more abundant the data sources, the more urgently master data unification, time-granularity alignment and business-scope extension are required. Research on absorption capacity has shown that a company's ability to convert external knowledge into procurement and supply chain decisions is related to the organization's capability to identify, absorb and apply data-knowledge [2]. Therefore, when building a big data platform, one must pay attention to data quality rules, permissions, lineage and responsible persons in the governance system, not only storage and computation.

Table 1. Use of Order, Inventory, Supply Chain, Logistics and External Data in Sales Operations Planning

Data Domain	Typical Fields	Planning Role	Quality Rule
Demand	Orders, price, promotion, search index	Demand sensing and forecast revision	Time alignment and duplicate removal
Inventory	On-hand, in-transit, safety stock, ageing	Replenishment and shortage control	SKU-location consistency
Supply	Capacity, yield, lead time, supplier status	Allocation and capacity reservation	Supplier master-data validation
Logistics	Route, freight rate, delay, node congestion	Transport planning and delivery promise	Event timestamp integrity
External	Weather, policy, commodity price, sentiment	Scenario adjustment and risk warning	Source credibility scoring

Table 1 analysis: The table divides the multi-source data into categories of demand, inventory, supply, logistics and external environment, and links them to demand perception, replenishment, capacity, transportation and risk warning activities. Therefore, the value of the data needs to be realised by planning its use clearly, and quality rules are set for different kinds of data to prevent model bias caused by inconsistencies in the same SKU, location or time.

Although artificial intelligence and big data analysis have been applied to enhance the resilience of supply chains, some deficiencies remain in the research, such as scattered technology topics, disjointed business scenarios and weak organisational implementation [3]. The Scope of the Digital Infrastructure in enterprises also varies considerably from place to place. By 2025, the proportion of large EU enterprises that have adopted ERP, business intelligence, pay-as-you-go cloud computing, data analytics and artificial intelligence will be much higher than at the overall enterprise level.

Figure 1. Adoption Rate of Five Types of Digital Technologies by EU Enterprises and Large Enterprises in 2025

Data source: Eurostat, Digital Economy and Society Statistics—Enterprises, data codes isoc_eb_iip, isoc_cicce_use, isoc_eb_das, and isoc_eb_ai.

As shown in Figure 1, large enterprises have an ERP adoption rate of 88.71% and a data analysis adoption rate of 78.84%; both are significantly higher than the general EU enterprise adoption rates of 46.45% and 33.02%, respectively, and the gap in artificial intelligence adoption rates is also relatively large. As shown in the above results, the resource barrier for large-scale data-driven collaborative initiatives is relatively high; therefore, SMEs can reduce construction costs by using cloud platforms, standardised interfaces, modular models, etc.

2.2 Mechanism for Resolving Conflicts and Negotiations Regarding Sales, Production, Procurement, and Financial Objectives

The old planning system generally has the sales department put forward high-demand plans, the production department requires a stable production schedule, the purchasing department seeks bulk discounts, and the finance department manages working capital. The Goals of the different departments are not aligned. Research on the risks of technology adoption shows that data security, system compatibility, talent shortage, uncertainty of return on investment, and organisational resistance can all hinder the spread of analytical technologies in the supply chain [4]. Therefore, through the spread of a single forecast figure, collaborative planning cannot be achieved; instead, negotiable constraints, traceable versions, and explainable reasons for modification must be generated.

Research in data ethics has found that errors in analysis or out-of-bounds use of data can harm supplier-customer relationships and create new governance risks for technological efficiency [5].

Therefore, the data source, model version, reason for human intervention and the final responsible party need to be recorded in the planning process, and a decision path of "machine suggestion - business review - authorised execution" should be established.

2.3 The Evolution of Supply Chain Analysis from Visualization to Predictive Optimization

The impact of big data analytics on innovation performance varies according to the cycle of technology and business, so different rhythms of data investment are needed at different stages of development [6]. For manufacturing enterprises, the first need is to solve the unification and visualisation of master data; in the middle stage, prediction and anomaly detection models can be built; and finally, cross-node optimisation and intelligent decision-making will be realised. Research on industry barriers has found that there is a hierarchical transmission relationship among strategic cognition, data foundation, organisational resources and methodological capabilities, and thus, algorithms cannot break through the systemic bottleneck at a single point [7].

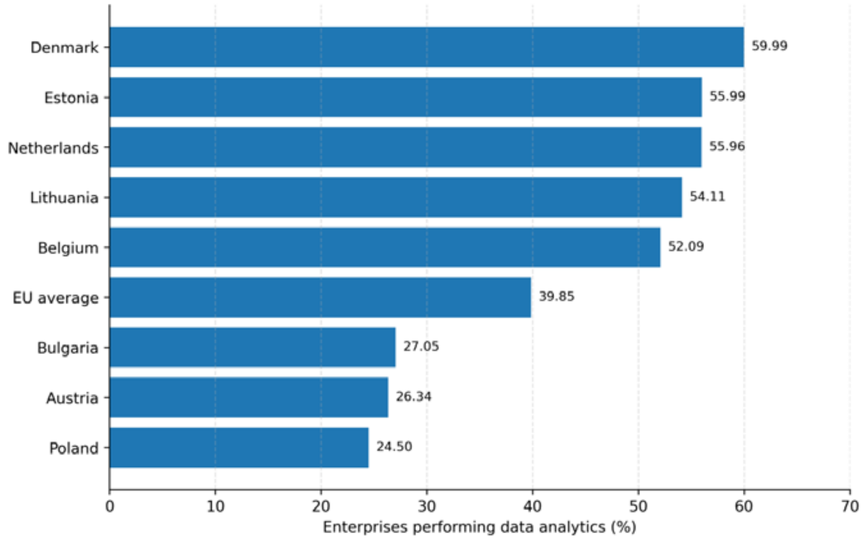

Figure 2. Differences in the Adoption Rate of Corporate Data Analytics in the Eight EU Member States by 2025.

Data source: Eurostat, Data analysis by enterprise size class, data code isoc_eb_das.

As shown in Figure 2, the data analysis adoption rates in Denmark, Estonia, the Netherlands, Lithuania and Belgium all exceed 52%, whereas those in Bulgaria, Austria and Poland are below 28%; thus, the highest and lowest rates differ by 35.49 percentage points. Therefore, the lack of this feature is likely due to insufficient digital infrastructure, a shortage of talent, and an unsupportive institutional environment, rather than only an internal algorithm.

3. Three types of obstacles to the execution of data forecasting in sales and operations planning

3.1 Conflicts between coding granularity and timeliness of order, inventory, capacity, and delivery date data.

The problem of manufacturing enterprises is not a lack of data, but rather inconsistencies in the coding, hierarchy and update time of order, inventory, capacity and delivery date data. For example, the same material may have different codes in the purchasing, production and warehousing systems;

sales forecasts are aggregated weekly, production schedules are implemented daily, and there is no closed-loop mechanism connecting supplier-committed delivery dates with actual delivery events. These differences make it difficult to stabilise the model's input, and thus the forecast results cannot be directly applied to business decisions.

3.2 Disconnect between demand forecasting and constraints on batch production capacity, inventory, and logistics.

Most enterprises still focus on a single goal of forecasting accuracy and ignore the combined effect of forecasting errors on inventory, production capacity and service level. Even if the models improve the short-term forecasting accuracy, these forecasts are still not feasible for implementation without considering constraints such as planning freeze periods, minimum order quantities, changeover times and logistics windows. Human experience often outweighs the model's output in the end, and thus there is a loss of trust in the model and business operations.

3.3 Conflict between cost-service resilience objectives and insufficient explanation of optimization results

The Goals of Supply-Chain Decisions Differ: reduce inventory to prevent stockouts, achieve a high-service-level requirement with rapid delivery, and strengthen the network of suppliers by expanding coverage at the expense of scale economies. Research on resilience has moved from prediction to prescription and now integrates algorithm-driven recommendations with scenarios, constraints and organisational choices [8]. However, many enterprises lack standardised weighting rules and risk boundaries, and the different departments have thus achieved local optima according to their own indicators.

Table 2: Analysis Methods and Cross-departmental Action Mapping for Five Types of Obstacles to Sales Operations Planning.

Planning Issue	Root Cause	Analytics Method	Collaborative Action	KPI
Forecast bias	Fragmented demand signals	Ensemble forecasting	Joint forecast review	MAPE and bias
Excess inventory	Static safety stock	Probabilistic inventory model	Parameter approval	Inventory days
Capacity conflict	Independent functional targets	Constraint optimization	Capacity negotiation	Utilization and backlog
Delivery delay	Weak event visibility	Anomaly detection	Exception escalation	On-time delivery
Supplier risk	Single-source dependence	Risk scoring and scenario analysis	Allocation adjustment	Supply continuity

Table 2 Analysis: The table shows five typical problems and their corresponding predictive integrations, probabilistic inventories, constraint optimisations, anomaly detections and risk scores, along with cross-departmental actions and indicators. As shown in the mapping, only by adding a joint review, parameter approval, capacity negotiation and anomaly escalation mechanism can the algorithm be transformed into an executable collaborative plan rather than just an analytical tool.

4. Multi-source demand perception and inventory-capacity collaborative decision-making optimization framework

4.1 Integrated Data Architecture of Lake Warehouse Semantic Layer and Planning Workbench

The five levels of the architecture for the enterprise are: Data Lakehouse - Indicator Semantic Layer - Analysis Service - Planning Workbench - Execution Feedback. The data lake warehouse collects internal transaction data, equipment information, logistics data and external data; the indicator semantic layer normalises SKU, customer, supplier, location, time and version attributes; the analysis service provides prediction, classification, optimisation and scenario simulation functions; the planning workbench supports joint review by sales, operations, procurement and finance; and the execution feedback writes back actual order, output, arrival and delivery results to the model. The function of big data analysis capability in supply chain resilience is often to provide visibility and flexibility; thus, visualised event flow and rapid replanning should be the focus of the platform [9].

4.2 Dynamically Weighted Demand Forecasting Based on Integrated Order and Promotion Channel Signals

Demand forecasting should not rely on a single historical sales volume, but should integrate orders, prices, promotions, channel search, customer behavior, and macroeconomic variables. Let the product be p, the time be t, and the data source or forecaster be s, then the integrated forecast can be expressed as:

$$\widehat{D}_{p,t}=\sum_{s=1}^{S} w_s\, f_s\left(X_{s,t}\right), \quad \sum_{s=1}^{S} w_s=1 \tag{1}$$

In equation (1), $\widehat{D}_{p,t}$represents the predicted demand for the product $p$at a given time point t, $f_s(\cdot)$represents $s$the prediction function of the i-th data source or model, $X_{s,t}$represents the input feature, and $w_s$represents the weight. The sum of the weights equals 1 to ensure the interpretability of the fusion result.

Given the change in the structure of demand, weights can be updated dynamically based on errors over a rolling window.

$$w_{s,t}=\frac{\exp\left(-\lambda E_{s,t}\right)}{\sum_{r=1}^{S}\exp\left(-\lambda E_{r,t}\right)} \tag{2}$$

In equation (2), $E_{s,t}$represents $s$the prediction error of the model in the nearest window, $\lambda$and is the error sensitivity coefficient. The smaller the error, the higher the model weight; when promotion, season or channel structure changes, the system can automatically adjust the importance of different signals. Comparative studies of machine learning show that incorporating prediction accuracy, implementation cost and sustainability indicators into model selection is more conducive to business implementation [10].

4.3 Multi-objective optimization of inventory shortage transportation and plan change costs

Collaborative planning should incorporate inventory, stockout, transportation, and plan change costs into a unified objective. Let the inventory cost during the decision-making period be *x* C^{inv}, the stockout cost be *y C^{short}*, the transportation cost be *f* C^{trans}, and the plan change cost be *v* C^{chg}, then the comprehensive objective function is:

$$\min Z=\alpha C^{inv}+\beta C^{short}+\gamma C^{trans}+\delta C^{chg} \quad (3)$$

In equation (3), α, β, γ and δ are weights jointly confirmed by sales, operations, procurement, and finance. By comparing different weight combinations through scenario simulation, the trade-offs between service level, cost, and stability can be identified, avoiding the dominance of a single department's indicator in overall decision-making.

Multi-node inventory and order flow need to maintain a basic balance:

$$I_{i,t}=I_{i,t-1}+Q_{i,t}+R_{i,t}-D_{i,t}-B_{i,t} \quad (4)$$

In equation (4), $I_{i,t}$ is the ending inventory at the node i at time point t, $Q_{i,t}$ is the purchase or production replenishment quantity, $R_{i,t}$ is the transfer-in quantity, $D_{i,t}$ is the actual demand, $B_{i,t}$ and is the stockout or backlog disposal quantity. This constraint ensures that the planning results are executable at the material flow level and can be used to identify imbalances in cross-warehouse transfers and replenishment schemes.

Limit the scope of demand uncertainty and set a service-level objective constraint.

$$\Pr\left(I_{t-1}+\sum_{i=1}^{n} x_{i,t} \geq D_t\right) \geq 1-\varepsilon \quad (5)$$

In equation (5), $x_{i,t}$ represents i the supply quantity of the source ε during the cycle , t and represents the allowable stockout probability. Enterprises can set differentiated risk thresholds based on product value, customer level, and life cycle to ensure higher service guarantees for high-value or critical products, rather than using a uniform safety stock for all SKUs [[11-20].

4.4 Closed-loop execution of weekly re-planning and monthly sales operations meetings

Model outputs will be included in the management process via weekly rolling plans and monthly sales and operations meetings. A weekly mechanism will respond to changes in demand and supply and delivery problems; a monthly mechanism will coordinate the capacity, inventory, cash and profit of all departments. The three retained versions of the system are the baseline plan, the optimised plan and the manually adjusted plan, along with the reasons for each. For high-impact decisions, the contribution of key variables, constraint conflicts and sensitivity analysis results should be shown to help managers understand "why adjust", rather than accepting a single figure.

Table 3. Five-Stage Implementation Roadmap for Data Governance and Feedback Learning in Manufacturing Enterprises.

Stage	Core Task	Data Scope	Decision Output	Governance Gate
Foundation	Master-data and metric alignment	ERP, WMS, MES, CRM	Trusted planning dataset	Data-owner approval
Visibility	Event integration and dashboards	Orders, inventory, logistics	Exception list and alerts	Quality threshold
Intelligence	Forecasting and risk scoring	Internal and external signals	Scenario forecast	Model validation
Optimization	Multi-objective planning	Cost, capacity, service, risk	Executable plan	Cross-functional sign-off
Learning	Feedback and parameter update	Actual execution results	Updated weights and rules	Post-action review

Table 3 analysis: The implementation roadmap gradually moves from basic governance to visualisation, intelligent analysis, optimised decision-making and feedback learning, and does not directly apply complex algorithms by enterprises before data standards are normalised. At all times, a government department or organisation should be in charge of managing the quality of the data and models [21-25].

5. Research findings and implementation implications of multi-source data-driven sales and operations plan optimization

This paper studies the cooperation between sales and operations planning in manufacturing enterprises, investigates the actual foundation, main problems and implementation paths of big data-driven supply chain planning and business decision optimisation. Actual statistics show that enterprise size and the digital environment in a certain area affect the level of adoption for ERP, cloud computing, data analysis and artificial intelligence; therefore, technological application should be conducted in coordination with organisational capacity and governance. The framework presented in this paper connects forecasting, planning and execution in a closed-loop manner via multi-source demand fusion, dynamic weighting, multi-objective costing, inventory balancing and opportunity constraints.

The main results of this study are as follows: First, the problem of supply chain collaborative optimisation is mainly one of data semantics and accountability mechanisms, and only secondarily an algorithmic issue; Second, demand forecasting should be integrated into rolling plans along with inventory, capacity, transportation and risk constraints; Third, the optimisation results must be interpretable, negotiable and retain human authorisation; Fourth, SMEs can lower the implementation threshold through cloud platforms, standardised data interfaces and phased construction. This paper will use publicly available data and standardised models. In the future, one can add order, inventory and delivery data from manufacturing enterprises for multi-industry comparison and model ablation and verification of actual operating performance [26-30].

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