# A Data-Driven Framework for Retail Inventory Optimization: Integrating Object-Centric Process Mining and Mathematical Models

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**Abstract.** Efficient inventory management is essential for retail companies, significantly impacting customer satisfaction and cost efficiency. However, managing related processes is highly complex due to the dynamic interaction of multiple object types along the supply chain (e.g. suppliers, customers, materials) and the reliance on diverse and fragmented information systems. Consequently, retail companies face challenges with inefficient inventory structures, including understock (loss of sales) and overstock (high capital commitment). This paper proposes an object-centric process mining approach to analyze process-related causes of inefficient inventory management. A novel Object-Centric Data Model (OCDM) is introduced, capturing key entities and interactions across inventory management-related processes. Unlike traditional models, the OCDM is enriched with established inventory metrics, enabling multi-perspective analyses that link process interactions to metrics such as *understock, healthy stock*, and *overstock*. This approach uncovers inventory management inefficiencies and their process-related root causes, delivering actionable insights. A case study at a leading European pet retailer demonstrates the approach's practical value in identifying bottlenecks and suggesting improvement actions, showcasing the potential for improved inventory control in retail settings.

**Keywords:** Inventory Management · Object-Centric Data Model · Process Mining

## 1 Introduction

Retail companies operate in a dynamic environment where efficient inventory management is crucial for balancing customer satisfaction (through product availability) and profitability (through cost minimization). Inventory management functions as the temporal bridge between customer orders and supplier replenishment [4, 34]. Core processes affecting inventory management are therefore Order-to-Cash (O2C) for sales and Purchase-to-Pay (P2P) for purchasing, both supported by diverse information systems, including Enterprise Resource Planning (ERP) systems and demand forecasting tools (see Figure 1).

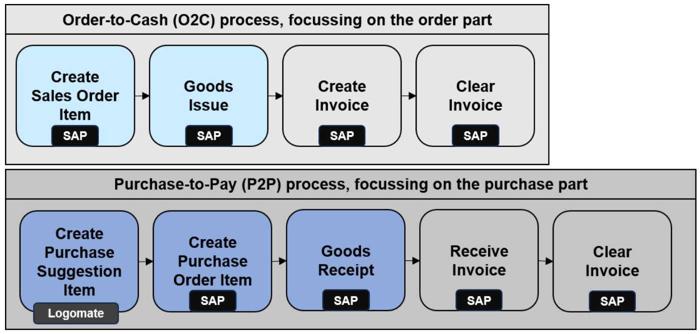


Fig. 1: Inventory management serves as the link between customer demand, managed through Order-to-Cash (O2C) processes, and purchasing activities, governed by Purchase-to-Pay (P2P) processes.

*Problem Statement and Research Motivation*: Efficient inventory management is critical for retail success but often hampered by the interplay of O2C and P2P processes. Diverse systems and suboptimal process executions can lead to understock (lost sales) or overstock (tied-up capital and storage costs) [4,23,34]. Traditional optimization models and ETL methodologies mainly provide static analysis, while advanced data analytics solutions primarily focus on improving demand forecasting models, lacking insights into the underlying process-related causes [32].

Process mining can reveal these causes by examining process flows [1,32]. Yet, standard methods struggle to capture the complex, multi-object nature of inventory management (e.g. suppliers, customers, materials) addresses this gap by incorporating these intertwined relationships [2]. By analyzing dynamic interactions and dependencies, OCPM helps identify root causes of understock and overstock, enabling a deeper understanding of process-driven inefficiencies.

This paper builds upon and extends the work presented in [17], where overstock issues in a P2P process were analyzed using object-centric process mining

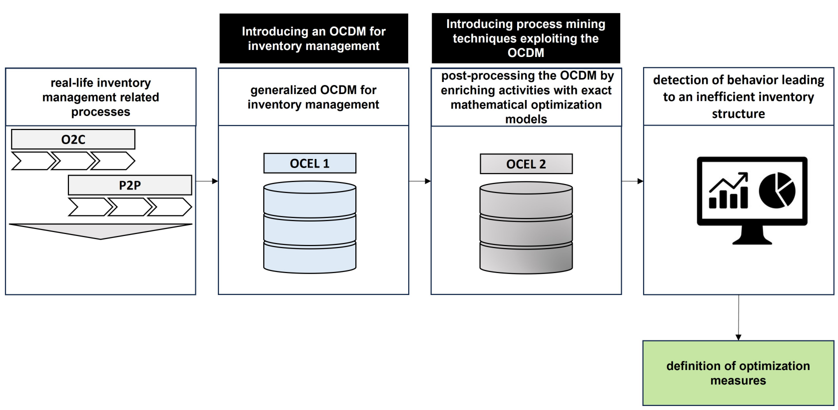


Fig. 2: Outline of the contributions of the paper.

in collaboration with a leading European pet retailer. While the previous study focused on identifying overstock patterns and proposing targeted improvements within P2P processes, this research broadens the scope to integrate both O2C and P2P processes, introducing a novel object-centric data model enriched with established inventory management metrics to address both understock and overstock inefficiencies comprehensively.

*Research Questions*: This paper aims to address the limitations of existing approaches by investigating how the enrichment of state-of-the-art object-centric process mining techniques [2] with established inventory management exact mathematical optimization models [34] can be leveraged to optimize inventory management and gain a deeper understanding of process-related drivers for an inefficient inventory structure and define optimization measures. Specifically, we address the following research questions:

- **RQ1** How can we effectively model the complex interplay of objects and events within the O2C and P2P processes to facilitate a holistic, object-aware understanding of inventory management?
- **RQ2** How can we enrich the object-centric perspective with established inventory management exact mathematical optimization models (e.g. Min-Max method) to enable data-driven analysis of process inefficiencies leading to understock and overstock situations?
- **RQ3** What actionable insights can be derived from the application of OCPM to a real-life inventory management scenario, and how can these insights be used to improve existing practices?

*Contributions*:

- **C1** *OCDM for Inventory Management*: An Object-Centric Data Model (OCDM) that integrates data from diverse sources (e.g., ERP, forecasting) into a single object-centric event log (OCEL A, Fig. 2), enabling comprehensive inventory process analysis.
- **C2** *OCDM Enrichment with Inventory Metrics*: A method to enrich the OCDM with established inventory management exact mathematical optimization models (e.g., Min-Max method), producing OCEL B (Fig. 2) for deeper assessments of inventory efficiency and targeted optimization actions.
- **C3** *Real-Life Case Study*: A case study at a European pet retailer demonstrating how the OCDM and enrichment approach uncover process inefficiencies in demand forecasting and supplier management, informing concrete improvements.

The introduced Object-Centric Data Model (OCDM) (**C1**) and the enrichment with relevant inventory management exact mathematical optimization models (**C2**) are generalizable and reproducible across different scenarios and systems in the retail environment. This reduces the effort for retailers to define and implement their own object-centric process mining analyses, as the approach can be applied flexibly without extensive customization.

The rest of the paper is organized as follows. Section 2 covers related work on inventory management optimization. Section 3 outlines the metrics needed to understand the rest of the paper. Section 4 describes the proposed object-centric data model, the computation of metrics, and the post-processing operations. Section 5 presents an implementation based on simulated data for illustrative purposes. Section 6 details a case study conducted in a pet retailer company. Finally, Section 7 concludes the paper by discussing limitations and future work.

## 2 Related Work

Inventory management optimization techniques and tools have evolved significantly, yet existing approaches often fail to holistically connect data-driven decisions with the underlying processes that shape stock levels. While exact mathematical optimization models provide clear guidelines for optimal inventory structures, they often rely on idealized assumptions and static parameters that rarely hold in dynamic, real-world contexts [23,34]. In contrast, various approaches—from business process management techniques to lean management methods—offer qualitative insights into inefficiencies. ETL methodologies and advanced data analytics approaches concentrate on analyzing inventory structures and improving forecasting models. However, these approaches share a common limitation: the capability to systematically connect these insights to the precise causes manifest in event data and process executions.

Exact mathematical optimization models (e.g., ABC analysis [5, 23, 27, 33], Economic Order Quantity (EOQ) [13, 14, 28, 29], and the Min-Max method [5, 12, 29, 31]) are well-established for classifying inventory items, minimizing costs, and determining reorder thresholds. These models, however, often hinge on stable demand and constant lead times, assumptions that cannot capture the full complexity of modern supply chains [23,34]. The resulting gaps limit the explanatory power needed to diagnose why certain deviations—such as persistent understock or overstock—arise in practice.

In parallel, traditional business management methods (e.g., process mapping, fishbone diagrams) and lean management approaches (e.g., Just-In-Time) highlight the value of understanding process-related factors [7,14,15,18,26]. However, these qualitative methods do not inherently exploit event data at scale, nor do they link inventory metrics directly to underlying process variations. Similarly, ETL methodologies centralize and standardize data for improved decision-making [11, 21], while advanced data analytics, AI, and ML approaches focus on demand forecasting models and anomaly detection [20, 24, 25, 30]. Though these tools improve accuracy and speed, they often operate as black boxes and remain detached from the actual process flows and their interdependencies, leaving practitioners without a clear path from insight to actionable process-oriented interventions.

Traditional process mining techniques have been applied to logistics and inventory management [3, 32], offering a complementary view by revealing how processes unfold and where inefficiencies occur. Yet these methods struggle to handle the multi-object nature of retail operations. The complexity lies in the interplay of various objects—suppliers, customers, materials—interacting through events spread across disparate systems. Recently, object-centric process mining (OCPM) has emerged as a powerful paradigm that incorporates multi-object event data [2]. While OCPM-based case studies for inventory management exist [17], they are not yet fully integrated with established inventory optimization models, nor do they systematically enrich process-level analyses with mathematical metrics.

This gap underscores why we have chosen our approach. By enriching OCPM with exact mathematical optimization models, we combine two complementary perspectives: the proven theoretical rigor of inventory metrics and the dynamic event-centric, object-aware lens of OCPM. The resulting synergy enables both to identify where a company's inventory structure diverges from optimal conditions and explain how these deviations originate from underlying process behaviors. In other words, we do not merely detect understock or overstock situations—we illuminate their root causes embedded in the company's operational processes, paving the way for targeted interventions and sustainable improvements.

## 3 Preliminaries

### 3.1 Inventory-Related Metrics and KPIs

Achieving an optimal balance between delivery service level, inventory costs, and capital commitment is crucial. Higher inventory ensures availability but increases costs, so finding an efficient, *normal* stock level is key [10, 23, 34].

We apply the classical formulas of the *Min-Max* method [5, 12, 29, 31], to simplify our approach. These methods use four main metrics calculated for each material (m):

*Economic Order Quantity (EOQ)* [28] minimizes total ordering and holding costs:

$$\mathrm{EOQ}_m = \sqrt{\frac{2D_mS}{H}},$$

where $D_m$ is demand, $S$ the fixed cost per order, and $H$ the holding cost.

*Safety Stock (SS)* [35] provides a buffer against variability:

$$\mathrm{SS}_m = z \times \sigma_m \times \sqrt{l_m},$$

with $z$ (service level), $\sigma_m$ (standard deviation of demand), and $l_m$ (lead time).

*Reorder Point (ROP)* [29] triggers replenishment:

$$\mathrm{ROP}_m = d_m \times l_m + \mathrm{SS}_m,$$

where $d_m$ is average demand.

*Maximum Stock Level (Max)* [29] limits excess stock:

$$\mathrm{Max}_m = \mathrm{EOQ}_m + \mathrm{SS}_m.$$

| Table | Description |
|---|---|
| **Sales Order Documents** | Sales Document Number |
| | Document Creation Date |
| | Customer Number |
| | Document Date in Document |
| | Sales Document Type |
| | Order Type |
| | Order Reason |
| **Sales Order Items** | Sales Document Number |
| | Item Number |
| | Material Number |
| | Plant |
| | Order Quantity |
| | Net Price |
| **Materials** | Material Number |
| | Material Type |
| | Industry Sector |
| | Material Group |
| | Valuation Class |
| | Gross Weight |
| | Net Weight |
| | Weight Unit |
| | Volume |
| | Volume Unit |
| | Transport Group |
| **Purchase Requisitions** | Client |
| | Purchase Document Number |
| | Item Number of Purchasing Document |
| | Purchase Requisition Number |
| | Purchase Requisition Item |
| | Purchase Requisition Date |
| | Document Type |
| | Purchasing Document Category |
| | Planned Delivery Time |
| | Latest Possible Goods Receipt |
| | Quantity |
| | Unit of Measure |

| Table | Description |
|---|---|
| **Material Stocks** | Client |
| | Material Number |
| | Plant |
| | Storage Location |
| | Stock in quality inspection |
| | Stock in transfer |
| | Stock in posting |
| | Stock of material provided to vendor |
| | Blocked Stock |
| | Returns Stock |
| **Goods Receipts and Issues** | Client |
| | Purchase Document Number |
| | Line Item in Purchase Document |
| | Sequential Number of Account Assignment |
| | Movement Type (Goods Receipt, Goods Issue) |
| | Fiscal Year |
| | Document Number |
| | Accounting Document Line |
| | Material Number |
| | Plant |
| | Reference Document Number |
| | Document Date in Document |
| | Posting Date in the Document |
| | Date of the Posting in the Document |
| | Time of the Posting in the Document |
| | Quantity |
| **Sales Document Flows** | Client |
| | Sales Document |
| | Sales Document Item |
| | Sales Document |
| | Sales Document Item |
| | Document Category of Subsequent Document |
| | Document Category of Preceding Document |
| | Document Date |

| Table | Description |
|---|---|
| **Purchase Order Items** | Purchase Order Number |
| | Purchase Order Item Number |
| | Material Number |
| | Plant |
| | Quantity |
| | Change Date |
| | Net Price |
| **Purchase Order Documents** | Purchase Document Number |
| | Record Creation Date |
| | Account Number of Vendor |
| | Purchase Order Date |
| | Purchasing Document Category |
| | Purchasing Document Type |
| | Blocking Indicator |
| **Material Documents** | Client |
| | Material Document Number |
| | Material Document Year |
| | Line Item |
| | Material Number |
| | Plant |
| | Storage Location |
| | Vendor's Account Number |
| | Customer Number |
| | Movement Type (Goods Receipt, Issue) |
| | Receiving Plant |
| | Quantity |
| | Posting Date in the Document |
| **Order Suggestions** | Order Number |
| | Order Position |
| | Article Number |
| | Order Quantity |
| | Date |
| | Order Date |
| | Delivery Date |
| | Plant |

Fig. 3: List of tables considered from the relational data model.

*Overstock (OS)* occurs when inventory surpasses the max level at a certain point in time (t). However, mathematical definitions of overstock vary in the literature [6, 19, 22, 29]:

$$\text{Overstock}_{m,t} = \text{Inventory Level}_{m,t} - \text{Max}_m.$$

By applying these metrics, companies can maintain adequate service levels while controlling costs and avoiding excessive stock.

## 4 Approach (Data Extraction and Enrichment)

In this section, we start from the ERP database, applying the view (relational data model) described in Section 4.1 and extract a (single) object-centric event log (OCEL A) as described in Section 4.2. We then obtain in Section 4.3 a (single) "transformed" object-centric event log (OCEL B), in which the activities have been semantically enriched with inventory management exact mathematical optimization models (i.e. Min-Max method).

### 4.1 Relational Data Model

The relational data model presented in Figure 3 can be extracted from various ERP systems, including SAP ERP and Oracle EBS. This model includes several key tables such as *Sales Order Documents*, *Sales Order Items*, *Materials*, *Purchase Requisitions*, *Material Stocks*, *Goods Receipts and Issues*, *Sales Document Flows*, *Purchase Order Items*, *Purchase Order Documents*, *Material Documents*, and *Order Suggestions*. Each table captures specific aspects, facilitating the management of O2C and P2P processes.

### 4.2 Object-Centric Data Model and Event Log (C1)

The proposed OCDM (Tables 1 and 2) includes various object types and event types, also known as activities, essential for tracking and analyzing business processes in an ERP system.

Object types mapped in Table 1 include *materials* and *plants*, along with specific identifiers for *purchase* and *sales order items*, *customers*, and *suppliers*. These object types link to related event tables, ensuring comprehensive data integration across materials, sales, purchases, and inventory activities.

Event types are mapped in Table 2 to specific source tables and timestamp fields, detailing key actions such as *Create Purchase Requisitions*, *Sales Order Items*, and *Purchase Order Items*, as well as recording *Goods Receipts* and *Issues*. For instance, the creation of a purchase requisition is logged in the *Purchase Requisitions* table with the associated date, while goods receipts and issues are captured in the *Goods Receipts* and *Issues* table with their posting dates.

More in detail, we assume that, for a considered table, its rows can be mapped to events having a constant activity (for example "Goods Receipt" or "Create Purchase Order Item") and a timestamp given by the values of a single column of the table. We also assume that a table's row provides the connection of the corresponding event to all the relevant object types. Therefore, if the proposed extraction procedure was restricted to a single table, we would still be able to extract an object-centric event log containing a single activity.

Starting from the object-centric data model, we use the OCEL 2.0 Object-Centric Event Log standard [16] for the storage of the event data. The format is well-supported by object-centric process mining tools like pm4py[3] and OC-PM[4].

Table 1: Object types and related tables.

| **Object Type** | **Description** | **Related Tables** | **Essential Attributes** |
|---|---|---|---|
| MAT | Material Number | Materials, Sales Order Items, Goods Receipts and Issues, Purchase Requisitions, Purchase Order Items, Material Documents | Stock Level, Material type, Material Group, Transport Group, Weight, Volume |
| PLA | Plant | Sales Order Items, Material Stocks, Purchase Requisitions, Goods Receipts and Issues, Purchase Order Items, Material Documents | |
| PO_ITEM | Purchase Document and Item Number | Purchase Order Items, Purchase Orders, Goods Receipts and Issues | Category, Type, Quantity, Price |
| SO_ITEM | Sales Order and Item Number | Sales Order Items, Sales Orders, Sales Document Flows | Document Type, Order Type, Quantity, Price |
| CUSTOMER | Customer Number | Sales Orders, Material Documents | |
| SUPPLIER | Supplier Number | Purchase Orders, Material Documents | |

[3]https://pm4py.fit.fraunhofer.de
[4]https://www.ocpm.info/

Table 2: Activities with related object types, source tables, and timestamp field.

| Activity | Object Types | Source Event Table | Timestamp Field |
|---|---|---|---|
| Create Purchase Requisition | PO_ITEM, MAT, PLA, MAT_PLA | Purchase Requisitions | Purchase Requisition Date |
| Create Purchase Suggestion Item | PO_ITEM, MAT, PLA, MAT_PLA | Order Suggestions | Date |
| Create Purchase Order Item | PO_ITEM, MAT, PLA, MAT_PLA, SUPPLIER | Purchase Order Items | Purchase Order Date |
| Goods Receipt | PO_ITEM, MAT, PLA, MAT_PLA, SUPPLIER | Goods Receipts and Issues | Date of the Posting |
| Create Sales Order Item | SO_ITEM, MAT, PLA, MAT_PLA, CUSTOMER | Sales Order Items | Sales Order Date |
| Goods Issue | PO_ITEM, MAT, PLA, MAT_PLA, CUSTOMER | Goods Receipts and Issues | Date of the Posting |

Each event, at the item level, is associated with at most one object per object type. The event log includes events/objects along with their attributes and event-to-object relationships essential for object-centric process mining. An important note is that each event of the proposed OCEL corresponds to an activity at the item level, so it is related to at most an object per object type. In principle, this allows for storing the object-centric event log in columnar databases for more performant querying and processing.

### 4.3 Computation of the Relevant Metrics (C2)

After storing the relevant information in an OCEL 2.0 event log, we can compute the relevant metrics of the *Min-Max* method. To calculate the *Economic Order Quantity* (*$EOQ_m$)*, we compute $D_m$ measuring the customer demand in each time unit (e.g. one month) by summing the amounts issued in events with the activity *Goods Issue*. $S$ is the fixed cost per order. $H$ is the holding cost per unit per year. In our case study, we used fixed values provided by the pet retail company. For $S$ we used 100€ and for $H$ 0.1€. To calculate the *Safety Stock* ($SS_m$), we compute the z-score $z$ corresponding to the desired service level. For example, a service level of 99% indicates a 99% probability that demand will be fulfilled without stock-outs during the lead time. For the standard deviation of demand $\sigma_m$, we measure the customer demand in each time unit, and computed the average and standard deviation of this demand. The lead time, $l_m$, is defined as the average time passed between the event with *Create Purchase Order Item* and the corresponding *Goods Receipt*.

To calculate the *Reorder Point* ($ROP_m$), we compute $d_m$, $l_m$, and $SS_m$ as described. For the *Maximum Stock level* ($Max_m$), we compute the $EOQ_m$ and $SS_m$ as reported. To calculate $Overstock_{m,t}$, we use the *Inventory Level*$_{m,t}$ given in the OCDM and compute the $Max_m$ as described.

As an example calculation, we compute the proposed metrics for a single material of the pet retailer, a *toy for dogs* from the 'non-food' category, as follows:

– *Economic Order Quantity (EOQ)*:

$$\mathrm{EOQ}_m = \sqrt{\frac{2D_mS}{H}}$$

Table 3: Performed transformation of the original activities. For simplicity, situations in which the stock fall to 0 are identified by 0 instead of *Understock*.

| **Activity** | **Stock Before** | **Stock After** | **ROP** | **EOQ** | **Transformed Activity** | **Assessment** |
|---|---|---|---|---|---|---|
| Goods Receipt | < SS | < SS | | | Goods Receipt (Understock to Understock) | Negative |
| | < SS | ≥ SS, < OS | | | Goods Receipt (Understock to Normal) | Positive |
| | < SS | ≥ OS | | | Goods Receipt (Understock to Overstock) | Negative |
| | ≥ SS, < OS | ≥ SS, < OS | | | Goods Receipt (Normal to Normal) | Positive |
| | ≥ SS, < OS | ≥ OS | | | Goods Receipt (Normal to Overstock) | Negative |
| | ≥ OS | ≥ OS | | | Goods Receipt (Overstock to Overstock) | Negative |
| Goods Issue | < SS | < SS | | | Goods Issue (Understock to Understock) | Negative |
| | ≥ SS, < OS | < SS | | | Goods Issue (Normal to Understock) | Negative |
| | ≥ SS, < OS | ≥ SS, < OS | | | Goods Issue (Normal to Normal) | Positive |
| | ≥ OS | ≥ SS, < OS | | | Goods Issue (Overstock to Normal) | Positive |
| | ≥ OS | ≥ OS | | | Goods Issue (Overstock to Overstock) | Positive |
| Create Purchase Order Item | < SS | | ≤ | ≤ | Create Purchase Order Item (Understock) (<= EOQ) | Uncertain |
| | ≥ SS, < OS | | ≤ | ≤ | Create Purchase Order Item (Normal, ≤ ROP) (<= EOQ) | Uncertain |
| | ≥ SS, < OS | | > | ≤ | Create Purchase Order Item (Normal, > ROP) (<= EOQ) | Uncertain |
| | ≥ OS | | > | ≤ | Create Purchase Order Item (Overstock) (<= EOQ) | Negative |
| | < SS | | ≤ | > | Create Purchase Order Item (Understock) (> EOQ) | Uncertain |
| | ≥ SS, < OS | | ≤ | > | Create Purchase Order Item (Normal, ≤ ROP) (> EOQ) | Uncertain |
| | ≥ SS, < OS | | > | > | Create Purchase Order Item (Normal, > ROP) (> EOQ) | Uncertain |
| | ≥ OS | | > | > | Create Purchase Order Item (Overstock) (> EOQ) | Negative |
| Create Purchase Suggestion Item | < SS | | ≤ | ≤ | Create Purchase Suggestion Item (Understock) (<= EOQ) | Uncertain |
| | ≥ SS, < OS | | ≤ | ≤ | Create Purchase Suggestion Item (Normal, ≤ ROP) (<= EOQ) | Uncertain |
| | ≥ SS, < OS | | > | ≤ | Create Purchase Suggestion Item (Normal, > ROP) (<= EOQ) | Uncertain |
| | ≥ OS | | > | ≤ | Create Purchase Suggestion Item (Overstock) (<= EOQ) | Negative |
| | < SS | | ≤ | > | Create Purchase Suggestion Item (Understock) (> EOQ) | Uncertain |
| | ≥ SS, < OS | | ≤ | > | Create Purchase Suggestion Item (Normal, ≤ ROP) (> EOQ) | Uncertain |
| | ≥ SS, < OS | | > | > | Create Purchase Suggestion Item (Normal, > ROP) (> EOQ) | Uncertain |
| | ≥ OS | | > | > | Create Purchase Suggestion Item (Overstock) (> EOQ) | Negative |
| Create Sales Order Item | ≤ SS | ≤ SS | | | Create Sales Order Item (Understock to Understock) | Negative |
| | ≥ SS, < OS | ≤ SS | | | Create Sales Order Item (Normal to Understock) | Negative |
| | > SS | ≤ SS | | | Create Sales Order Item (Overstock to Understock) | Negative |
| | ≥ SS, < OS | ≥ SS, < OS | | | Create Sales Order Item (Normal to Normal) | Positive |
| | ≥ OS | ≥ SS, < OS | | | Create Sales Order Item (Overstock to Normal) | Positive |
| | ≥ OS | ≥ OS | | | Create Sales Order Item (Overstock to Overstock) | Positive |

with $D_m = 281$ [packaging units], $S = 100$ €, $H = 0.1$ €.
Thus,

$$EOQ_m = \sqrt{\frac{2 \times 281 \times 100}{0.1}} = 750 \text{ [packaging units]}.$$

– *Safety Stock (SS)*:

$$\mathrm{SS}_m = z \times \sigma_m \times \sqrt{l_m}$$

For a 99% service level, $z = 2.326$. Given $\sigma_m = 97$ [packaging units] and $l_m = 1.0$ [month]:

$$SS_m = 2.326 \times 97 \times \sqrt{1.0} = 226 \text{ [packaging units]}.$$

– *Reorder Point (ROP)*:

$$\mathrm{ROP}_m = d_m \times l_m + \mathrm{SS}_m$$

$$ROP_m = 281 \times 1.0 + 226 = 507 \text{ [packaging units]}.$$

- *Maximum Stock Level (Max)*:

$$\mathrm{Max}_m = \mathrm{EOQ}_m + \mathrm{SS}_m = 750 + 226 = 976 \text{ [packaging units]}.$$

- *Overstock (OS)*:
  If Inventory $\mathrm{Level}_{m,t} = 3017$, then

$$\mathrm{Overstock}_{m,t} = \text{Inventory Level}_{m,t} - \mathrm{Max}_m = 3017 - 976 = 2041 \text{ [packaging units]}.$$

To optimize the O2C and P2P processes, we transformed the activities of the object-centric event log by examining *Safety Stock (SS)*, *Overstock (OS)*, *Reorder Point (ROP)*, and *Economic Order Quantity (EOQ)*. The transformation represented in Table 3 is necessary to enable the analysis of patterns in the related systems, highlighting how different states and thresholds impact operations. By categorizing activities based on inventory levels before and after executing the events, we could systematically evaluate the process behavior leading to positive (normal stock, reduction of understock or overstock), uncertain (risk of understock or overstock), and negative (understock or overstock) situations, and identify process-related causes. For example, when processing a goods receipt, we assessed if the stock before the event was *below SS*, *between SS and Max, i.e. Normal Stock*, or above *Max, i.e. Overstock*. This classification helped identify understock, normal stock, and overstock scenarios. Similarly, goods issue events were analyzed based on their impact on stock levels, revealing patterns in stock depletion.

## 5 Simulated OCDM and Implementation

Due to confidentiality, the original data and implementation cannot be disclosed. Instead, we provide a public repository[5] containing scripts to simulate and store

Table 4: Case study: simplified extract of the original object-centric event log (OCEL A) alongside the transformed activities (OCEL B). Both event logs are available at `https://zenodo.org/records/13347782`. We assume that for the material $M001$, $SS = 91$ and $OS = 150$.

| Original Activity | Transformed Activity | Material | Supplier | Customer | PO Item | Quantity | Stock Before | Stock After |
|---|---|---|---|---|---|---|---|---|
| Goods Issue | Goods Issue (Normal to Normal) | M001 | | C001 | | 2 | 100 | 98 |
| Goods Issue | Goods Issue (Normal to Normal) | M001 | | C002 | | 3 | 98 | 95 |
| Create Purchase Suggestion Item | Create Purchase Suggestion Item (Normal, > ROP) (> EOQ) | M001 | S001 | | | 100 | 95 | 95 |
| Create Purchase Order Item | Create Purchase Order Item (Normal, > ROP) (> EOQ) | M001 | S001 | | PO1 | 100 | 95 | 95 |
| Goods Issue | Goods Issue (Normal to Understock) | M001 | | C003 | | 5 | 95 | 90 |
| Goods Receipt | Goods Receipt (Understock to Normal) | M001 | S001 | | PO1 | 50 | 90 | 140 |
| Goods Receipt | Goods Receipt (Normal to Overstock) | M001 | S001 | | PO1 | 50 | 140 | 190 |
| Goods Issue | Goods Issue (Overstock to Overstock) | M001 | | C001 | | 10 | 190 | 180 |

[5] `https://github.com/fit-alessandro-berti/inventory-management-simulation`

Table 5: Case study: classes of materials based on their stock level.

| Material Stock | Percentage |
|---|---|
| Always normal | 70.0 % |
| Understock (no Overstock) | 14.7 % |
| Overstock (no Understock) | 11.6 % |
| Understock and Overstock | 3.7 % |

Table 6: Case study: main activities in the proposed OCDM. Colors indicate effect on stock: positive, uncertain, negative.

| Transformed Activity | Occurrences |
|---|---|
| Goods Issue (Normal to Normal) | 381.307 |
| Goods Issue (Overstock to Overstock) | 68.059 |
| Create Sales Order Item (Normal to Normal) | 30.526 |
| Create Purchase Suggestion Item (Normal, >ROP) (>EOQ) | 2.512 |
| Goods Receipt (Normal to Normal) | 2.370 |
| Create Purchase Order Item (Normal, >ROP) (>EOQ) | 2.216 |
| Create Purchase Suggestion Item (Overstock, <= EOQ) | 703 |
| Goods Receipt (Overstock to Overstock) | 658 |

inventory data following the OCDM described in Section 4. These scripts generate synthetic data mimicking key inventory management entities and demonstrate how to extract an OCEL (A) from the relational model, linking events, objects, and timestamps as in Table 2.

The repository also includes a post-processing script for OCEL A that enriches events with the metrics described in Section 4.3, producing OCEL B and reflecting the transformations in Table 3.

This simulated environment enables researchers and practitioners to experiment with the proposed techniques, deepening their understanding of the methodology and its applicability across various scenarios.

## 6 Case Study (C3)

We performed a case study with a leading European pet retailer. The pet retailer has a strong online and offline presence, achieving sales exceeding 4 billion euros in 2023. The company is confronted with inventory management challenges (see Table 5) in the seven-digit range and sees the potential of object-centric process mining to address these issues effectively.

The retailer's main goals included addressing key inventory management challenges: *maintaining optimal stock levels*, *reducing stock-outs and overstock*, and *improving the replenishment process*. Ensuring accurate *demand forecasting* was also critical to align stock levels with market demand, reduce costs, and increase supply chain responsiveness. The pet retailer uses SAP ERP for sales (O2C) and purchase orders (P2P), supplemented by Logomate for forecasting and replenishment (see Figure 1). SAP tracks processes from procurement to sale. Logomate enhances management through data analytics and predictive modeling using historical and real-time data.

### 6.1 Main Results

**Activities Analysis:** We transformed the activities as defined in Table 3. Using the *Min-Max* method, we assessed the behavior in the processes and differentiated between positive (normal stock, reduction of understock or overstock), uncertain (risk of understock or overstock), and negative (understock or overstock) situations. As shown in Table 4, the original activities (OCEL A) are listed alongside their transformed counterparts (OCEL B). The transformations highlight when purchase orders and other actions deviate from the optimal reorder point or economic order quantity, leading to imbalances. For instance, we observe that orders are sometimes placed too early or too late, disrupting the desired stock levels. In some cases, the demand forecasting system suggests placing orders beyond the computed Reorder Point and at quantities exceeding the Economic Order Quantity, pushing the material into understock (as the stock is not replenished in time) and eventually overstock (as we receive more materials than needed). We further note instances of goods receipt events when the material was already in an overstock situation, exacerbating excessive inventory levels. This behavior can result in unnecessary holding costs and inefficiencies. The overall impact for all considered materials is summarized in Table 6 (the number of occurrences is approximated for confidentiality reasons).

**Other Analyses:** We considered applying traditional object-centric process mining analyses, such as the analysis of the control flow using object-centric DFGs [8] and the analysis of interactions between objects [9]. The control-flow analysis was not suitable, as the intertwining of the O2C and P2P processes leads to a quadratic number of flows between different activities. However, by studying interactions between objects, we observed that materials connected to several customers often contain understock, while materials connected to several suppliers are less prone to understock.

### 6.2 Process Improvements

Based on the findings, we suggested revising demand forecasting models to incorporate the number of customers and suppliers per material as standalone factors. The company should also enhance calculations of *Safety Stock*, *Reorder Points*, and *Economic Order Quantities* in Logomate and SAP to better align inventory with demand, reducing under- and overstock. Additionally, avoiding orders for materials already in overstock and adjusting supplier agreements on minimum order quantities and truck capacity can mitigate oversupply and holding costs.

## 7 Conclusion and Future Work

This paper proposed an integrated approach to optimize inventory management in retail by combining object-centric process mining with established exact mathematical optimization models.

**RQ1** was addressed by introducing an Object-Centric Data Model (OCDM) that holistically captures the interplay of objects and events within O2C and P2P processes.

**RQ2** was answered by enriching the OCDM with established inventory management exact mathematical optimization models, enabling data-driven analyses to pinpoint process-related drivers of inventory inefficiencies.

**RQ3** was investigated through a case study at a European pet retailer, where the approach identified root causes of under- and overstock and informed actionable improvements, including refining demand forecasting and supplier management practices.

Future work includes integrating advanced data analytics and exploring applications beyond retail, further demonstrating the potential of integrating object-centric process mining and mathematical models for inventory optimization.

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