Collaborative and Integrated Data-Driven Delay Prediction and Supplier Selection Optimization: A Case Study in a Furniture Industry

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Abstract

Optimizing supplier selections is an open ended problem, relevant to the operational performance of both individual companies and entire supply chains. Considering the prediction of future occurrences of delays in the optimization of supplier selections is still an under covered problem. Unlike existing literature, this article suggests a more collaborative and integrated workflow to improve the visibility and involvement of multiple stakeholders in the supplier selection decision-making processes. This is achieved through enhanced collaboration between multiple stakeholders (suppliers, customers, decision-makers from different departments, in addition to data sources from information systems), and better integration between data analysis and decision-making, through data-driven-machine-learning and optimization. The specificities of a French company in the furniture industry are considered. A workflow model is designed to support information sharing and to streamline knowledge and interactions between multiple stakeholders from different expertise domains. A Collaborative Predictive Optimization System (CPOS) is designed to classify expected occurrences of delays, to optimize order allocations, and to enable stakeholder collaboration. Delay prediction involves Decision Trees, Random Forests, and eXtreme Gradient Boosting (XGBoost). Supplier selection is solved using mathematical programming, while considering the classification of expected occurrences of delays. Stakeholder collaboration relies on information systems and uses prediction and optimization to support finding satisfactory agreements. The approach is validated using a real 3.5-year dataset, including 139 suppliers, 7,934 products and 89,080 purchase orders. A detailed experimentation, including sensitivity analysis, best-worst case analysis, and a larger scale analysis on company datasets, shows that the suggested approach enhances collaboration and achieves delay reduction and total procurement cost savings. Valuable managerial insights are collected, including the necessity to adopt digital technologies, to adapt company workflows, and to improve upstream negotiations and supplier commitments to yearly plannings.

Keywords: Supply chain, Data-driven Machine Learning, Delay classification, Supplier selection, Optimization

1. Introduction

It has been estimated that purchase/procurement costs represent 50% to 90% of the total cost of a manufactured product (De Boer et al., 2001). Therefore, the supplier selection problem (SSP) (Dickson, 1966) requires relevant management decisions to improve the overall performance and competitiveness of manufacturing companies (Mukherjee, 2017; Taherdoost and Brard, 2019). SSP have been widely studied in literature (Resende et al., 2021). It consists in assigning purchase orders to available suppliers, in such a way as to optimize one or several criteria (Memari et al., 2019) related to each supplier's capability and capacity to provide materials of varying types, qualities, quantities, costs, supply durations, supply chain risks, etc.

1.1. General Context

A significant factor in the selection process is the supplier's capability to deliver products and/or to provide services at the time agreed (Cavalcante et al., 2019). On-time supply enforces the adopted inventory and production strategies and expected plans and ensures cost reduction, compliance with deadlines and other contractual terms with customers (e.g., avoiding penalties due to delays), and ultimately, customer satisfaction (Steinberg et al., 2023). Inaccurate assumptions about supply durations may lead to bad supplier selections that cause delivery delays a posteriori, involving direct losses in terms of costs that can be measured, and indirect losses that can have greater long-term impacts and damage to the company's brand and image (Wani et al., 2022).

Unfortunately, existing approaches tend to tackle SSP according to "divide and conquer" strategies that lack overall efficiency and effectiveness, and that miss the added value of digitalization technologies. In most traditional approaches to SSP, the supplier selection process is usually compartmentalized into sequential steps (prediction, evaluation, ranking, selection, allocation, and order release). SSP is then solved through a series of local optimizations, where each local optimization does not necessarily take into account or use the outcomes of the previous steps (i.e. lack of integration). Some gap between academic research and industrial practice emphasizes this observation. For example, in academic research, data-driven (Li et al., 2022) and Machine Learning (Wani et al., 2022) approaches were successfully used to predict delays. However, these works stop at the prediction level and do not explain how predicted delays could be used in downstream supplier selection and order allocation decision-making. In industrial practice, a procurement module, integrated within an Enterprise Resource Planning (ERP) information system (Karlina et al., 2019), selects suppliers and assigns purchase orders to each supplier. The trend is to rely on ERP analytics (Jawad and Balázs, 2024), combined with human expertise, to process raw data and estimate various parameters, including delays. Estimated parameters are sent to the ERP procurement module, and some are handled by heuristic allocation rules and/or evaluation scores according to predefined criteria (Mondal et al., 2020). As the handling of estimated parameters often involves a human expert, supplier selection outcomes are often biased. The use of heuristics and rules leads to local optimal solutions, instead of global optimal ones if a more integrated optimization approach is considered within a streamlined process.

Moreover, the traditional supplier selection process is often based on the single perspective of the purchase/procurement department and does not consider the added value, interests, and/or potential contributions of several stakeholders involved in the decision-making processes: logistics and transportation, inventory and warehousing, production and sales/delivery. Decisions are made unilaterally by the purchase/procurement department based on its expertise, without sharing information on delays with other stakeholders, and without considering field/contextual appreciation or alternative solutions that could have been suggested by field experts and expertise domains other than the purchase/procurement department, if they were involved in the decision process. This lack of both visibility and collaboration can severely impact decision efficiency and effectiveness (Timonen and Vuori, 2018). The consideration of multiple perspectives enables information sharing with several stakeholders (suppliers, customers, decision makers from different departments), who are given the opportunity to express their viewpoints and provide feedback, suggestions and decision alternatives to influence and complement the decisions considered by the procurement department. In a digital era, where information and communication technologies contribute to a better integration of information management and decision-making processes, a better collaboration between stakeholders within a multiple perspective process enables taking full advantage of synergies between information systems, data analytics and optimization to achieve better performance.

1.2. Case study specificities

The furniture industry has a global market of US$766.20 billion in 2024, with a Compound Annual Growth Rate (CAGR) of 5.02% (Statista, 2024b). France is the seventh-largest market worldwide for furniture. In 2024, the revenue in the furniture market in France amounted to US$26.28 billion. It is projected that the market will experience a CAGR of 1.74% over the period 2024-2029 (Statista, 2024a). The French furniture market is fragmented, having a mix of small and major businesses. Some of the major global players currently dominate the French market. However, with technological advancement and product innovation, small to midsize enterprises (SMEs) are increasing their market shares by securing new contracts and tapping new markets (MordorIntelligence, 2024). It is in this SME context that the specificities of a French company are considered.

The company manufactures furniture in kits and deals with 139 suppliers to purchase 7,934 items. Each supplier has a finite capacity to deliver a given type of item within each procurement planning period. For each item, each supplier provides a price offer scale, where prices decrease in stages function of increasing ordered quantities. For each item, each supplier has a fixed delivery time (independent of ordered quantities) and predefined purchase costs representing the acquisition cost paid by the company to acquire the item (price offer scale includes purchase and transportation costs).

For safety and quality reasons, the company has an inventory management strategy, where purchase orders (PO) have to be received, and purchased items have to be stored in the warehouse for at least 10 days prior to being able to release them into production. Delays further than 10 days are exceptional (more than 90% of delays are less than 10 days, see section 3.2.1). When such delays occur, they are subject not only to case-by-case tight monitoring and follow up with suppliers, but also to important penalties, because they heavily disturb commitments to customers, logistics (transportation and warehousing), production plans, and quality requirements. At the end of each year, such exceptional delays are reviewed with the suppliers, and contractual arrangements are made to encourage anticipation and to strictly avoid their occurrence. However, delays of less than 10 days are more problematic to avoid, because less strict arrangements can be made with suppliers to control them, although they disturb production. Therefore, they have to be managed on the company side by looking for ways to anticipate the occurrence of such delays to better plan production, and better meet quality requirements. Delays of less than 10 days have fixed costs that are irrespective of time, such as administrative costs, mobilization/demobilization costs, and certain equipment and auxiliary material costs (Pricing Contractor Delay Costs). These delays and delay costs are due to several contextual causes (that are controllable on the company side), such as the type of ordered item, quantity, and day or week within which orders are placed. The same supplier may cause delays for one order in some contexts with certain attributes and be on time for a similar order in a different context with different attributes. Hence, for the company, it makes sense to predict whether or not a PO is likely to experience a delay of less than 10 days. The provision of such delay classification facilitates the implementation of proactive measures across diverse departments to mitigate the resultant impacts.

The company uses an Enterprise Resource Planning (ERP) system to manage its flows and processes. For each planning period, the ERP procurement module generates the material requirements in terms of purchase orders (PO). Each PO relates to a single item and determines the requested quantity and planned delivery date for that item. Each PO suggests a list of potential suppliers that have the capabilities to meet the quantity and delivery requirements of the item. The supplier selection is based on a priority rule, where a PO is assigned to the supplier who offers the lowest price for the stage of the requested PO quantity in the price offer scale.

The supplier selection decision is made through the ERP procurement module. It is validated unilaterally by the purchase department, and this validation is enacted without considering any feedback from other departments with respect to potential delivery delays that could stem from the decision made. This is problematic, because other departments, like the sales and the logistics (for outgoing customer deliveries) departments, may have several types of commitments that can be put into question due to bad supplier selection decisions. Also, other departments, like the logistics (for incoming supplier deliveries), inventory/warehouse management and production departments, may have previous or recent contextual and field experiences with the suppliers, and their appreciations could greatly influence the supplier selection decision. Thus, considering their appreciations before validating the decisions can better preserve the interests of the company.

1.3. Structure of the article

This article adopts a different approach to the SSP, both with respect to literature, and with respect to the current practice in the considered industry. The main contribution is to suggest a more collaborative and integrated workflow to improve the visibility and involvement of multiple stakeholders from multiple expertise domains in the decision-making processes. This is achieved through (i) the consideration of multiple perspectives from multiple stakeholders (suppliers, customers, decision makers from different departments, in addition to data sources from information systems), (ii) enhanced collaboration between stakeholders through an improved workflow, and (iii) better integration between data analysis and decision-making, through data driven-machine-learning and optimization.

Therefore, the remainder of this article is organized as follows. Section 2 reviews the literature related to several aspects of SSP and positions the contribution of this article. Section 3 describes the suggested methodology, workflow model, and the developed Collaborative Predictive-Optimization System (CPOS). Section 4 presents the numerical experiments on a real dataset, analyses sensitivity and best-worst case performance, and discusses results on different scales. Section 5 highlights the managerial insights of this work. Finally, section 6 summarizes and discusses the main findings and outlines insights as well as future research directions.

2. Related Work

In industrial practice, supplier selection is a task typically carried out by a procurement department (Taherdoost and Brard, 2019), where the procurement/purchase manager is the ultimate person and the only decision maker in command to validate supplier selections and order allocations. The importance of involving multiple internal and external stakeholders in SSP was highlighted in (Chai and Ngai, 2015). In (Xu et al., 2023), it was recognized that sharing information with suppliers improves the performance of the supplier selection process.

In existing SSP literature, indeed, some references addressed the topic of group decision-making by considering the opinions of multiple experts (Çalık, 2021; Banaeian et al., 2018; Boran et al., 2009). However, the decision-making process involves more than one expert, but from only one expertise domain (typically many experts from the procurement department), and does not consider the opinions of experts from many expertise domains (typically from different departments, other than the procurement department). This article particularly addresses this gap by considering a more collaborative approach that enables several experts from different expertise domains to express their opinions and provide their appreciation and feedback, and therefore be involved in the SSP decision-making process.

To select suppliers, several criteria can be considered separately or simultaneously, leading to a multi-criteria decision-making problem. Quality criteria include supplier failure rates, product quality indicators (Cabrita and Frade, 2016), warranty period, and reputation indicators (Stević et al., 2017). Financial criteria include purchase prices (Xia and Wu, 2007), transportation costs (Cabrita and Frade, 2016), and volume discounts (Stević et al., 2017). Sustainability concerns are reflected in economic, social, and environmental criteria (Azadnia et al., 2012; Jabbarzadeh et al., 2018; Liou et al., 2021). Finally, time-related criteria, such as delivery times, delivery delays (Haeri and Rezaei, 2019), on-time indicators (Thanaraksakul and Phruksaphanrat, 2009), and reliability indicators (Taherdoost and Brard, 2019) are being applied.

Several recent publications reviewed frameworks and suggested classifications of strategies, approaches and techniques to solve SSP (Saputro et al., 2022; Naqvi and Amin, 2021; Chai and Ngai, 2020; Aouadni et al., 2019). Fig. 1 synthesizes the main groups of SSP approaches and includes recent references, while being compliant with existing classifications.

Four major SS approaches categories can be distinguished : Multi-criteria Decision-Making (MCDM), Mathematical Programming (MP), Artificial Intelligence (AI) and Hybrid approaches. MCDM techniques are used to select the best option from a set of alternatives by taking into account multiple competing criteria. MP approaches are applied to solve well-structured SS problems that can be expressed mathematically. AI techniques have also been adopted according to four subcategories: (i) Metaheuristics for complex SS optimization problems by efficiently exploring large search spaces; (ii) Data driven and Machine Learning for pattern detection and prediction from big and unstructured data; (iii) Symbolic AI for SS problems by handling imprecise/subjective information through linguistic variables and fuzzy sets and/or by embedding human knowledge and reasoning; (iv) Hybrid AI where two or more techniques from these AI subcategories are jointly used. Finally, in the fourth category of Hybrid approaches, most works combine the main categories MCDM, MP and AI. Some other underexplored hybridizations are also proposed (Saputro et al., 2022). Within this category, each technique solves the different problem aspects for which it is most suitable.

This is particularly the case in this article, where the focus is on both the classification of expected occurrences of potential delays and the assignment of purchase orders to suppliers so as to minimize the total procurement costs. To handle large volume of unstructured data and extract dynamic features which influence delay predictions, data-driven approaches and machine learning algorithms are advocated due to their capability to identify trends, model complex relations, and predict future behaviors (Sutharssan et al., 2015; Olaoye and Potter, 2024). On the other hand, mathematical programming optimally solves well-structured optimization problems. This hybridization combines the predictive power of ML with the optimization capabilities of MP to enhance supplier selection decision-making.

2.1. Machine Learning and data analytics for SSP

In the literature, Machine Learning (ML) is mainly used for four different purposes in SSP.

- Clustering suppliers: in this category, the problem is to classify suppliers in order to put them into groups based on some criteria of similarity. Then, for each cluster/class/group, a different treatment is considered (Azadnia et al., 2012; Jabbarzadeh et al., 2018).
- Ranking suppliers: in this category, the problem is to find an ordering so that a list of available suppliers are prioritized according to some criteria of interest (Nepal and Yadav, 2015; Du et al., 2015; Tavana et al., 2016; Hosseini and Barker, 2016; Zhao et al., 2021).
- Ranking and selecting evaluation criteria: in this category, the problem is to set priorities among a set of available and competing criteria, in order to enable a downstream decision-making process, such as supplier ranking and/or supplier selection (Liou et al., 2021).
- Estimating unknown parameters: in this category, the problem is to quantify some parameters, such as risk factors (e.g., port congestion, price inflation, labor strikes, and supplier quality) (Nepal and Yadav, 2015) or product demand (Islam et al., 2022, 2024), and then use them in a downstream decision-making process.

A delay occurs when the actual delivery date exceeds the planned delivery date (promised delivery date by the supplier) (Brintrup et al., 2020). As such, delays are unknown parameters that need to be estimated during the supplier selection process, and before releasing the purchase orders, in order to eventually make further arrangements for downstream logistics, warehousing, production, and delivery to customers.

To handle delays in SSP, researchers use metrics, such as on-time delivery rate (Islam et al., 2024), delivery delay rate (Jahangoshai Rezaee et al., 2017), or delivery lead-time (Pamucar et al., 2023), either in isolation or in conjunction with other criteria, such as costs. These metrics are not predicted, but calculated as ratios from historical data, and then used to make delay estimations. However, considering these metrics alone as criteria to select suppliers, without considering any contextual information, and without updating them dynamically when making decisions, can yield erroneous results. In fact, as the efficiency of suppliers depends on various dynamic factors, such as types of products, period of the year (e.g. seasonality), and pricing campaigns, a supplier who performed poorly in a period of the year that is unfavorable to him may not be selected in the following period, that might be more favorable to him, even if he outperforms all other suppliers. Therefore, predicting whether any delays will occur (classification problem), and estimating the duration of delays (regression problem) are important issues for which businesses are increasingly relying on data analytics to make more informed supplier selection decisions (Li et al., 2022).

Due to case study specificities, we are interested in delay classification approaches (predicting whether any delays will occur). Therefore, Table 1 shows the results of a literature review process that we conducted to find references related to delay classification. The review provides rationales for us to select the data analytics tools that are most promising and adapted to our case study. From Table 1, it appears that the most used ML models to predict supplier delays are decision trees, random forests, and XGBoost. From the analysis of the references in Table 1, it comes out that, although existing studies solve the delay classification problem, they do not address downstream challenges, neither to have collaborative approaches by sharing delay information among multiple stakeholders, nor to optimize supplier selections. Additionally, the prediction of supplier delays, with its two facets, classification and regression, remains under-explored in the furniture manufacturing industry.

Consequently, to the best of the author's knowledge, no previous work has addressed the specific problem considered in this article, which is the optimization of supplier selections while considering predictions on whether there will be supplier delays or not (classification problem).

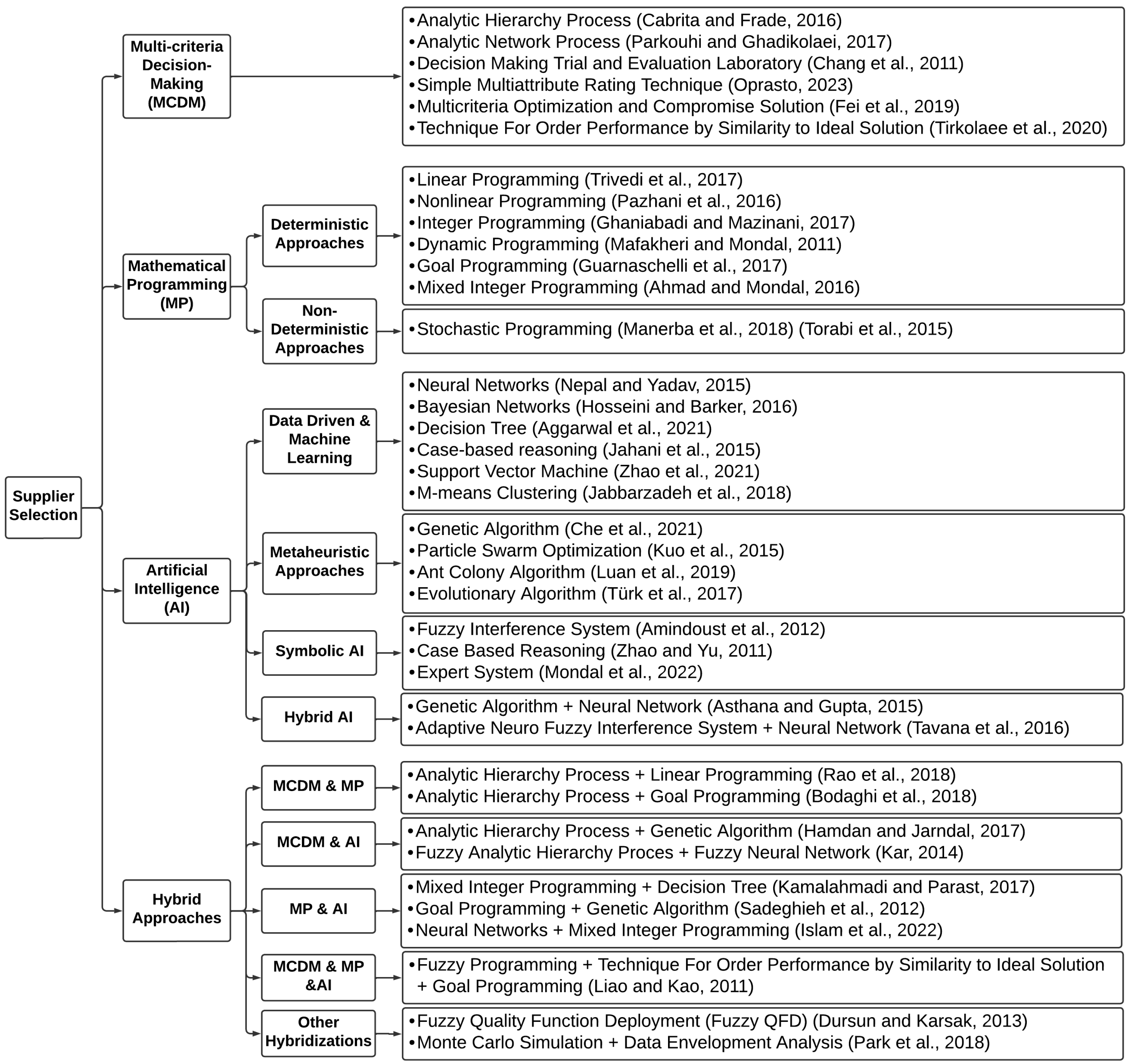

Figure 1: Supplier selection approaches with illustrative works

Table 1: Works dealing with supplier delay classification

Reference	**Algorithm**	**Evaluation Metrics**	**Dataset Source (Data Acquisition Period)**	**Field**	**Number of data records**	**Number of features**
(Bassiouni et al., 2024)	Softmax Classifier Random trees Random forest k-nearest neighbor Multi-layer perceptron SVM	Accuracy Recall Specificity Precision F1-score MCC FNR FPR	Public Website (3 years))	-	180,519	13
(Zheng et al., 2023)	Artificial Neural Network convolutional neural networks Logistic Regression Multi-layer perceptron	Accuracy Precision Recall F1-score	Real World (7 years)	Complex assets manufacturing	78,526	6
(Zaghdoudi et al., 2022)	Decision Tree Random Forest Naive Bayes	Accuracy Precision Recall F1-score	Real World (1 year)	Furniture manufacturing	22,389	6

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Reference	Algorithm	Evaluation Metrics	Dataset Source (Data Acquisition Period)	Field	Number of data records	Number of features
(Wani et al., 2022)	Decision Tree Random Forest Extra trees XGBoost Light GBM CatBoost Bagging	Accuracy Precision Recall F1-score	Public Website (3 years)	Oil & gas industry	180,000	26
(Sahoo et al., 2022)	Random Forest XGBoost Artificial Neural Network CatBoost Bagging Stacking	Accuracy Precision Recall F-score Specificity Error	Public Website (5 months)	Air cargo transport	56,802	36
(de Krom, 2021)	Logistic Regression SVM Random Forest Decision Tree XGBoost	Accuracy Precision Recall MCC	Real World (3 years)	Medical imaging instruments	68,807	21

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Table 1 – continued from previous page

Reference	Algorithm	Evaluation Metrics	Dataset Source (Data Acquisition Period)	Field	Number of data records	Number of features
(Brintrup et al., 2020)	Random Forest SVM Logistic Regression K-nearest neighbor	Precision Recall F-score	Real World (more than a year	Complex Asset manufacturing imaging	232,912	25
(Shahid, 2020)	Random Forest XGBoost	Accuracy Sensitivity Specificity Geometric Mean	Real World (5 months)	Air cargo transport	3,942	24
(Baryannis et al., 2019)	SVM Decision Tree	Accuracy F1-score Precision MCC	Real World (6 years)	Aerospace manufacturing	36,677	33

2.2. ERP supplier selection workflows

Enterprise Resource Planning (ERP) software is a cross-functional enterprise information system that streamlines and enhances a company's business processes and flows, promoting profitability and efficiency (Hadidi et al., 2020). ERP systems consist of several integrated modules that support business functions and processes, notably the supplier selection function of the procurement module. However, the supplier selection is usually based on predefined evaluation, ranking scores, and heuristic rules (Mondal et al., 2020).

In addition to their substantial role as a data warehouse (Steinberg et al., 2023), the capabilities of ERP systems are increasingly extended with intelligent modules based on machine learning and data analytics, to help users identify data patterns (Okanga and Groenewald, 2019) and better deal with unknown parameters (Babu and Sastry, 2014). The integration of data analytics in ERP systems is a pivotal catalyst for companies towards Industry 4.0 (Majstorovic et al., 2020) and digital transformation (Bodemer, 2023). It demonstrates efficiency in overcoming challenges inherent to ERPs (Yathiraju, 2022). Integrating data analytics into ERP systems enables companies to gain a competitive advantage, optimize operations, increase productivity, and drive informed decision-making (Jawad and Balázs, 2024; Bawa, 2023; Goundar et al., 2021). Commercial ERP systems use data analytics tools such as Epicor Data Analytics (Epicor, 2024a) and Forecast Pro (Epicor, 2024b) for Epicor ERP, S/4HANA (SAP, 2024b) and Analytics Cloud (SAP, 2024a) for SAP ERP, and AI Apps for Oracle ERP (Oracle, 2024). These tools enable data visualization and reporting but remain black boxes for users that cannot solve downstream optimization problems.

To the best of the author's knowledge, only one reference (Kohli, 2017) considered using ML with ERP to solve SSP. The author used decision trees and support vector machines (SVM) to rank a new supplier based on historical data of similar suppliers. The ERP serves as a data source for ML model training, and the outcomes of supplier rankings are subsequently fed back to the ERP system to support the order allocation process. Decisions are then made for each PO separately by expert judgment according to the best rank, leading to locally optimal decisions, and introducing potential bias into supplier selection outcomes.

2.3. Position and contributions

The literature review shows that

- Existing approaches are often based on the single perspective of the purchase/procurement department and do not consider the added value of several stakeholders from multiple expertise domains involved in the decision-making processes. In this article, a collaborative workflow is suggested to take advantage of feedback from all involved stakeholders (decision-makers from different departments in the company, suppliers, and customers). This is enabled through the use of industrial ERP systems as a backbone asset to integrate and streamline the supplier selection process, and to involve all interested/impacted stakeholders.

- Existing approaches tend to compartmentalize the supplier selection process and solve it through a series of local optimizations, which are mainly based on expert judgment, heuristics, and rules in industrial practice. In this article, a more integrated and streamlined supplier selection process is suggested to avoid local optima and improve supplier selection quality through an improved synergy between data analytics and machine learning for delay classification, and mathematical programming for optimization.

- To deal with delays, existing references determine time-related metrics that are not predicted, but calculated as ratios from historical data, and then used to make delay estimations. Calculations are made in a static way that does not consider any context or dynamics. This article focuses on delay predictions as a classification problem to predict whether there will be delays or not, based on data analytics and machine learning to account for historical context and dynamics. Classifications of expected occurrences of delays are then used in a mathematical programming optimization of supplier selections, to achieve an overall supplier selection optimization.

3. Methodology

This section designs a methodology to solve the limitations presented in the previous sections and develops a system to implement this methodology into the existing enterprise information systems and decision-making processes.

3.1. Workflow model

In order to enable collaboration between several stakeholders from different expertise domains (i.e. several decision-makers from different enterprise departments, in addition to suppliers and customers), and to have a more integrated and streamlined supplier selection process, a new Collaborative Predictive Optimization System (CPOS) architecture is suggested (see Fig. 2). The CPOS aims at (i) predicting whether there will be delays or not (classification of expected occurrences of delays), based on data analytics and machine learning to account for the historical context of previous purchase orders, and (ii) determining an order allocation plan to optimize purchase costs considering the classification of expected occurrences of delays. The CPOS enables the company to analyze data, identify patterns, classify expected occurrences of delays, and optimize collaboratively, not unilaterally, and globally (with mathematical programming), not locally (with rules and heuristics), the assignment of a set of purchase orders to suppliers. This is achieved through three main use cases, explained as follows.

3.1.1. Use case 1: prediction model training

The black arrows in Fig. 2 show the process of training the prediction models using historical data from the ERP. The learning outcomes of the training of the prediction models (e.g. hyper-parameters) are stored in the ERP to be reused.

3.1.2. Use case 2: CPOS decision support to supplier selection

The red arrows in Fig. 2 show the decision support process that CPOS provides to stakeholders to advise their decision-making. Purchase orders are created by the ERP system according to the production plan. These orders show available suppliers that meet the quantity and quality requirements. The generated purchase orders undergo classification of occurrences of delays and optimization of order allocations to suppliers. Classification and optimization results are submitted to stakeholders for approval.

3.1.3. Use case 3: Stakeholder collaboration

The blue arrows in Fig. 2 show the CPOS-supported collaboration process between stakeholders (decision-makers from different departments in the company, suppliers, and customers) until they reach an agreement and approve the supplier selection and order allocation plan. The classified expected delays, supplier selections, and order assignments are shared with stakeholders for approval or review.

For decision-makers from different expertise domains (i.e. different departments) in the company, having information in advance about expected late deliveries allows them to anticipate and propose new alternatives with revised parameters based on their expertise (Li et al., 2010). For example, they can suggest new suppliers (Chai et al., 2013; Chai and Ngai, 2020), adapt or outsource part of the production plans, revise (e.g., postpone, split) releases of production orders and prioritize resource dispatching (Singh et al., 2019). The ERP supports such collaboration by providing complementary information on available alternatives.

External stakeholders are also involved, as the new suggested workflow enables submitting new requests to suppliers and/or customers. In return, suppliers/customers can accept the proposals or suggest new alternatives. Available options and/or revised parameters are fed back to the CPOS. Feedback is assessed to determine at which step of decision support it should be taken into account. Interactions between the CPOS and stakeholders continue until some consensus is reached.

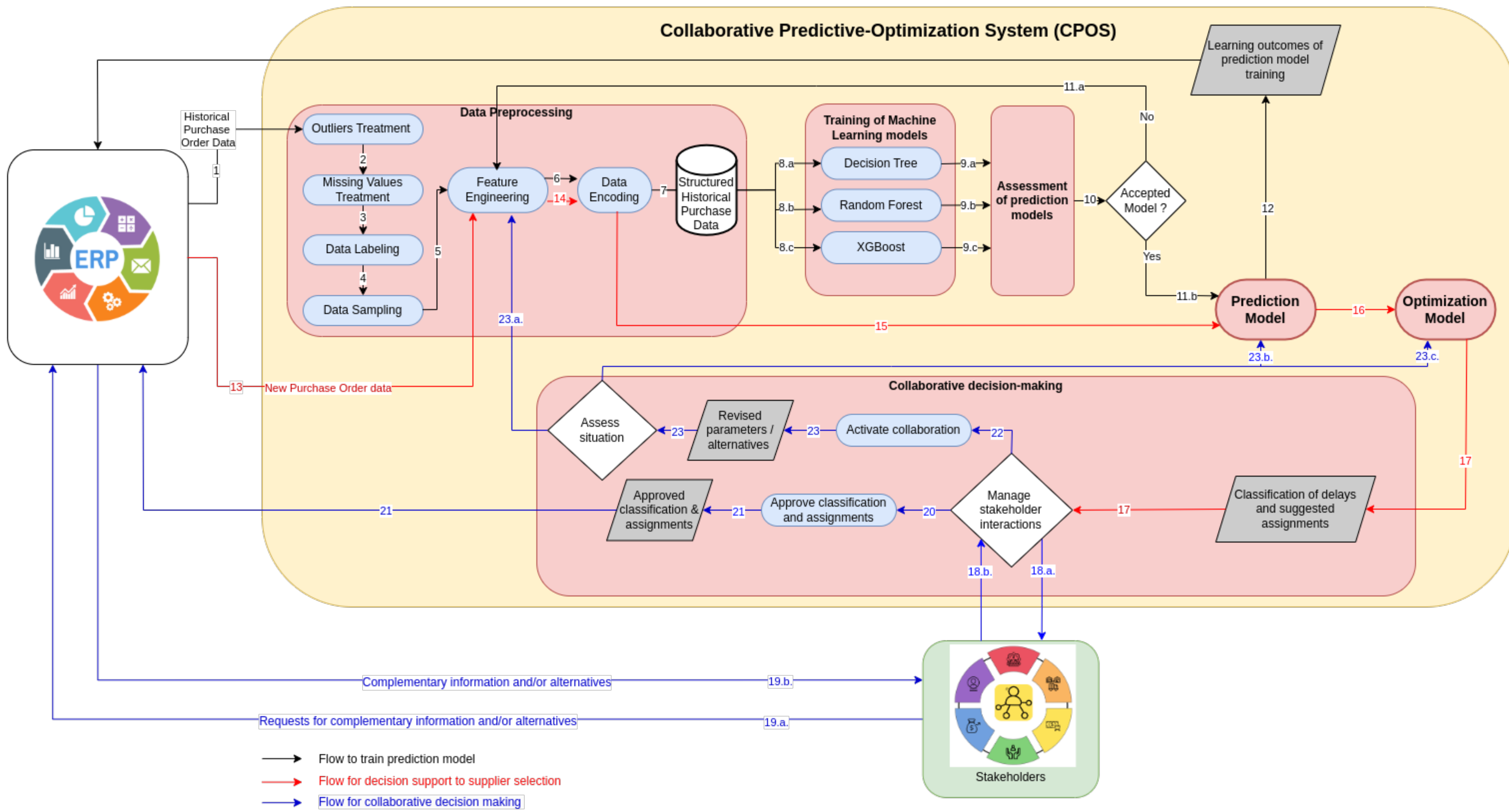


Figure 2: Architecture of the Collaborative Predictive Optimization System (CPOS)

Once the supplier selections and order allocations are approved, they are transmitted to the ERP procurement module, which will release purchase orders to suppliers (Pekša and Grabis, 2018) according to the approved plan. It is worth noting that the procurement department will play the role of coordinator in the suggested new workflow, for example, to plan meetings and discussions with stakeholders, to collect alternatives and suggestions, and to feed them as alternatives and/or revised parameters into the CPOS.

3.2. Collaborative Predictive-Optimization System

In addition to collaboration, which is mainly an interactive process (more details will be provided on this aspect in section 4.2.3), the CPOS is architectured around three main computational processes, which will be described in the following subsections: data preprocessing, prediction and optimization.

3.2.1. Data preprocessing

A three-and-a-half (3.5) year purchase history of the company is available, including data about released purchase orders, purchased items, suppliers, quantities, costs (planned and realized), and delivery dates (planned and realized). A 6-step data pre-processing pipeline is proposed to better understand the data and create a structured dataset to be processed by the machine learning algorithms.

(a) *Outliers handling*

In the period 2018 to 2021, the company placed 89,080 POs, among which 41,690 POs were subject to delays, thus late deliveries represent 46.8% of total deliveries. A preliminary analysis of these delays (see Fig. 3) shows that 94.4% of delays fall within the interval [-10;10] days. Delays that exceed 10 days are subject to penalties and to contractual terms with suppliers, who do all their possible to avoid them. Such delays are subject to dedicated procedures, and are considered as outliers so they are not considered in this article. Positive delays that are less than 10 days are more problematic, because they disturb production, cannot be handled by contractual terms, and have to be managed on the company side. Therefore, this article focuses mainly on the classification of released POs to determine whether or not there will be a late delivery of less than 10 days.

In addition, as illustrated in Fig. 4, the COVID-19 lockdown period of 2020 presents a significant drop in the number of deliveries, against an exceptional rise in the percentage of supply delays. The deliveries in the 2020 period are considered as outliers, and the orders related to this period are discarded.

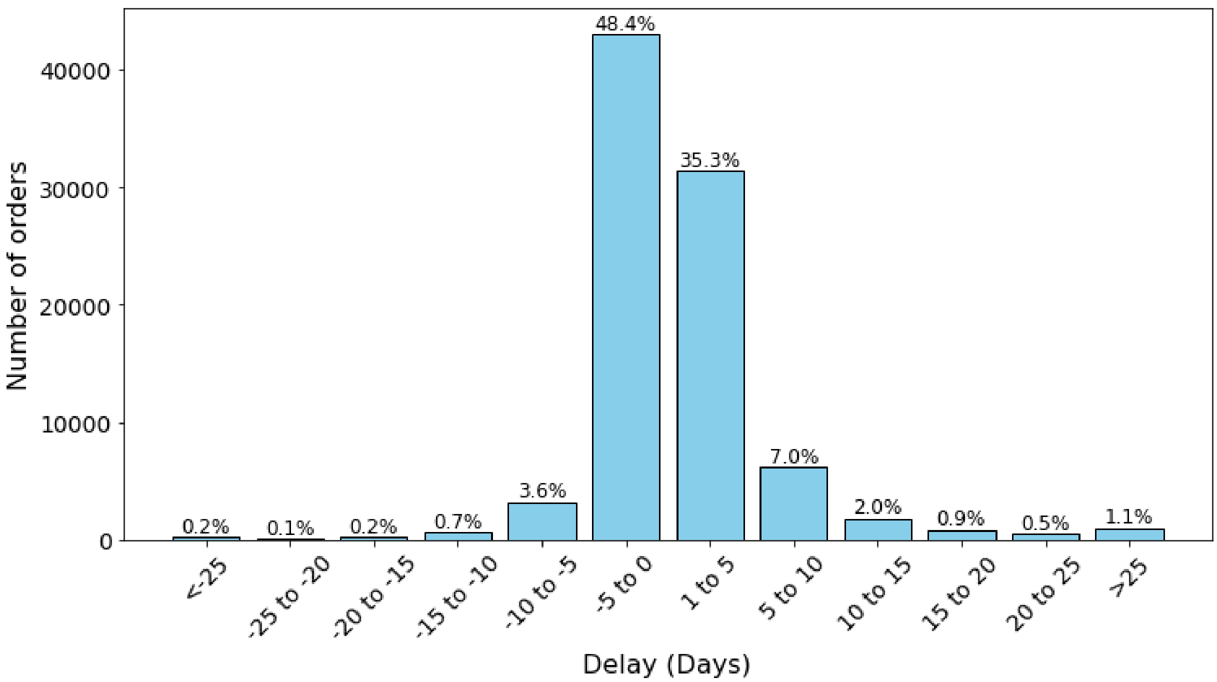


Figure 3: Distribution of delays per duration

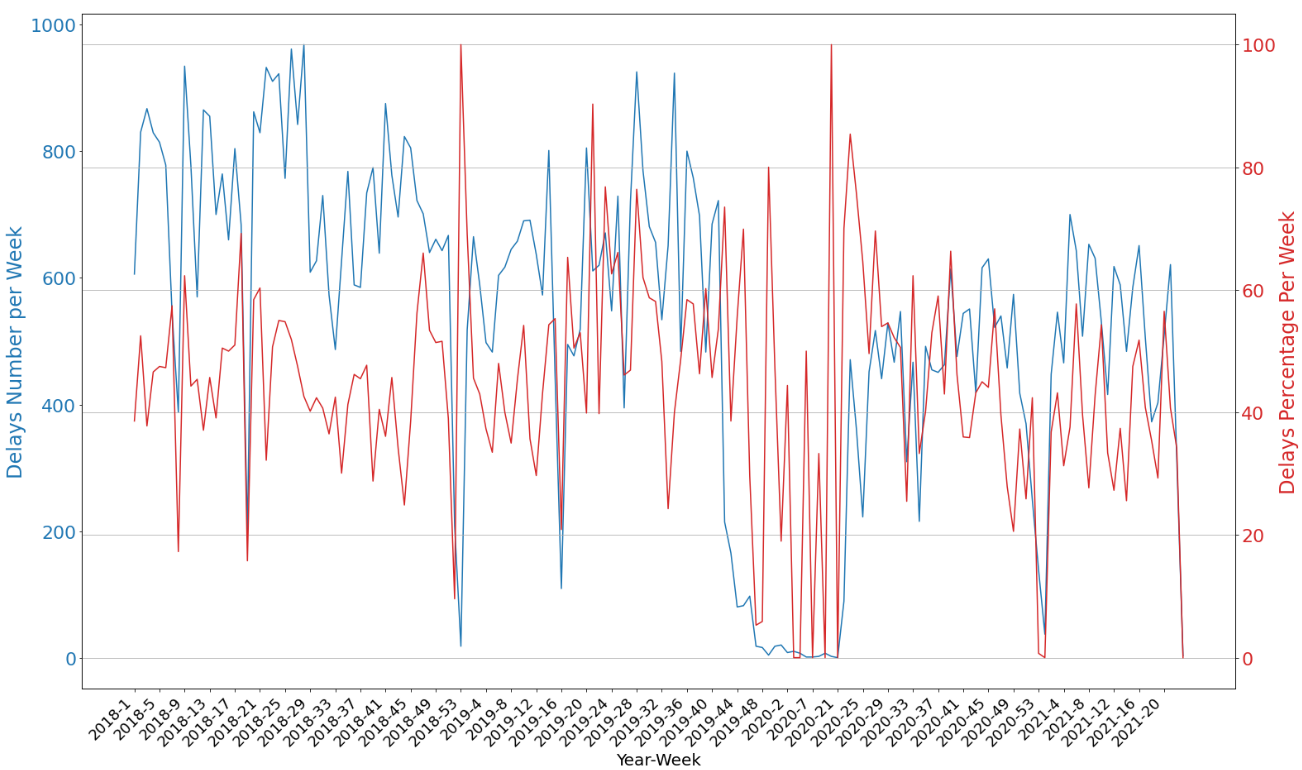


Figure 4: Number of delays (blue) and percentage of delays (red) during the period 2018 to 2021.

(b) *Missing values*

Missing data is a common problem in the data acquisition process (García et al., 2016). In our case, 239 instances with missing data were detected. As this number represents only 0.28% of the total number of observations, the instances with missing values were discarded.

(c) *Data labeling*

The instances are labeled so that they can be introduced to supervised learning algorithms. A binary feature is created to label the delay of each purchase order.

- 1: if the PO realized delivery date exceeds the planned delivery date by 1 to 10 days.
- 0: otherwise.

Such labeling enables classifying data into 2 classes: late and early deliveries.

(d) *Data sampling*

In the available dataset, early deliveries represent 56% of total deliveries. Therefore, there is an imbalance between the two labeling classes. Data imbalance leads to false training results in supervised learning applications (Brintrup et al., 2020). Therefore, a solution needs to be found to balance the data. Two different sampling techniques were tested to balance the two labeling classes.

- Random over-sampling (Mohammed et al., 2020) consists of randomly duplicating samples from the minority class until it has the same number of samples as the majority class.
- Entitled random under-sampling (Mohammed et al., 2020) consists of removing random samples from the majority class until the two classes become balanced.

After testing the two techniques, the random under-sampling technique is retained, as it gives better performances during the training process (see section 4.1.3).

(e) *Feature engineering*

Administrative data, such as the PO number or the person in charge of order release and follow-up, and features carrying the same information, such as the product ID and its name, have been removed. Then, for each PO in the available dataset, the week, the day of the month, and the day of the week of the planned delivery date have been added, since the number of delays shown in Fig. 4 is not uniform and depends strongly on these variables. Note that the end of the year always witnesses a high ratio of late deliveries. Additionally, after brainstorming sessions with the company's experts, it was decided to add the feature 'supply time' given by Eq. (1):

$$delay = Max(0; \textit{real delivery date - planned delivery date}) \quad (1)$$

This feature describes the level of flexibility given to a supplier, as a higher supply time means that the supplier has a sufficient margin to deliver the product.

(f) *Data encoding*

Categorical variables, representing the Supplier_ID and the Product_ID, are a challenge for machine learning algorithms, which typically operate on numerical data. Through the categorical encoding techniques, these alphanumeric variables are transformed into a numerical format that can be interpreted by tree-based models (Seger, 2018). The label encoding technique was used, by assigning a unique numerical label to each distinct category.

Table 2 details the selected features from the used dataset.

Table 2: Selected and created features from the available dataset

Feature	**Format**	**Description**
Supplier ID	Alpha Numeric	Unique supplier identifier
Product ID	Alpha Numeric	Unique code identifying the purchased product
Purchase_Cost	Float	The purchase cost of the order
Quantity	Float	The quantity of concerned product in the purchase order
Week	Integer	The week of the planned delivery date
Supply_Time	Integer	Difference between order date and planned delivery date
Day of the month	Integer	The day of the month of the planned delivery date
Day of the week	Integer	The day of the week of the planned delivery date
Delay	Binary	The status of the order, whether it is delayed or received on-time.

3.2.2. Prediction models

Three tree-based ML models, namely decision trees, random forests, and XGBoost, were developed to classify the occurrences of delays. These algorithms were selected because:

- They have shown interesting results in predicting delays in literature (see section 2.1 and table 1).
- They are able to handle numerical as well as categorical variables.
- They provide a feature importance analysis of predictions (Mirkouei et al., 2014).

The models take as inputs the purchase orders, where each purchase order PO_i is characterized by the 8 preprocessed features in Table 2. The models are trained to perform a binary classification (de Krom, 2021) of outcome $\beta_{i,j}$ to predict whether order PO_i will be delayed or not if it is assigned to supplier S_j.

- $\beta_{i,j} = 1$ if order PO_i will experience a delay in the interval [1;10] days if PO_i is assigned to supplier S_j
- $\beta_{i,j} = 0$ otherwise.

(a) *Decision Tree*

A Decision Tree (DT) is a classification model presented as a tree structure (Ferreira and Vasilyev, 2015). To train the DT model, the entire dataset containing the 8 selected features (Table 2) and their corresponding labels (on-time or delayed) are taken as inputs. The algorithm selects the feature that best divides the data into distinct classes. The split is done by calculating the Gini impurity measure for each feature (Daniya et al., 2020) and selecting the one that gives the lowest Gini measure (Eq. (2)):

$$Gini = 1 - \sum_{i=1}^{A} pr_i \tag{2}$$

with:

A is the number of classes. A=2.

pr_i is the probability of selecting an item from class i.

After deciding which feature is the best, the algorithm splits the data based on the selected feature. Thus, the nodes of the tree represent tests on a specific variable from the training features, branches correspond to the results of the tests, and leaf nodes represent the PO class. The splitting process is repeated recursively until one of two stopping criteria is met: the depth of the tree or the number of leaf nodes reaches a predefined maximum number.

(b) *Random Forest*

A random forest is a machine-learning algorithm, which is based on an assembly of a predefined number Nmax of independent decision trees (Parmar et al., 2019). Training a random forest starts by creating a random subset of the training dataset for every decision tree to capture the data variability. This process is done using the bootstrap aggregating technique (Bagging) (Breiman, 1996). It consists of selecting data samples randomly from a population with replacement. For each tree, a random subset of the feature set is used to add diversity to trees (Breiman, 2001). Each individual decision tree is grown, as explained in subsection 3.2.2(a), using the Gini impurity measure (Eq. (2)) and the maximum depth as a stopping criterion.

The decision trees are grown and used for the classification of new purchase orders. To achieve this, the features of a new PO are introduced into each tree to make a prediction, and the final decision of the Random Forest is given by the majority voting technique (Fawagreh et al., 2014).

(c) *eXtreme Gradient Boosting*

eXtreme Gradient Boosting (XGBoost) is an ensemble learning algorithm that has achieved good performances in various predictive modeling tasks (Chen and Guestrin, 2016). It is specifically designed to optimize model performance by iteratively combining the predictions of multiple decision trees. XGBoost uses a boosting technique instead of bagging.

The boosting technique starts by creating an initial tree and training it using the same process detailed in subsection 3.2.2(a). Based on the results obtained from this first model, weights are given to misclassified instances. Then, a second tree is built to attempt to correct the errors present in the first model. It is trained using the weighted data obtained in the first stage. This procedure continues and models are added until the number of trees reaches a predefined number Nmax. The correction is performed by calculating the gradient (Friedman, 2001) and using a learning rate. Unlike the Random Forest model, the trees created by the XGBoost model are highly dependent. The prediction of delay for a new PO is a weighted linear combination of the predictions provided by all tree models.

(d) *Evaluation metrics*

The outputs from the prediction models are categorized into four distinct classes:

- True Positive (TP): represents instances where delays are accurately predicted;
- True Negative (TN): represents instances where on-time deliveries are correctly predicted;
- False Positive (FP): represents instances where on-time deliveries are erroneously classified as delays;
- False Negative (FN): represents instances where delays are inaccurately classified as on-time deliveries.

The evaluation metrics, presented in Table 3, were used to evaluate the performances of the prediction models.

Table 3: Classification evaluation metrics

Evaluation Metric	Formula	Interpretation
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Assess how well each prediction model performs overall in predicting the two class labels.
Precision	TP / (TP + FP)	Determine how many of the predicted delays turned out to be true delays.
Recall	TP / (TP + FN)	Determine how many effective delays are predicted correctly.
F1-score	(2 x Recall x Precision) / (Recall + Precision)	Determine how well a prediction model manages both false positives and false negatives.

3.3. Optimization model

A Supplier Selection Optimization Model (SSOM) given by an integer linear programming model is developed to assign all suggested purchase orders to potential suppliers so as to minimize the total purchase and delay costs. Let us consider the following notations:

- PO_i: Purchase Order i (i= 1, 2, . . . , n).
- N: Set of all purchase orders indexes N= 1,2,. . . , n.
- S_j: Supplier j (j=1, . . . , m).
- P_k: Product type k (k=1, . . . , l).
- V_k: Set of purchase order indexes of the product type k.
- Q_i: Quantity of product in purchase order i.
- $Cap_{j,k}$: Maximum capacity of supplier j to deliver product type k.
- $Cu_{i,j}$: Product unit purchase cost of the purchase order i by the supplier j.
- Cs_i: Product unit delay cost of the purchase order i.
- $\beta_{i,j}$: Predicted delay of PO_i by supplier j.

- $\beta_{i,j} = 1$, if order PO_i will experience a delay in the interval [1..10] days if PO_i is assigned to supplier S_j
- $\beta_{i,j} = 0$ otherwise

- C_t: Total procurement cost.
- $X_{i,j}$: decision variable
  - $X_{i,j} = 1$, if PO_i is assigned to supplier S_j
  - $X_{i,j} = 0$ otherwise
- C_p : Total purchase cost given by Eq. (3)

$$C_p = \sum_{i=1}^{n}\sum_{j=1}^{m}(Q_i \cdot Cu_{i,j}) \cdot X_{i,j} \tag{3}$$

- C_d : Total delay cost given by Eq. (4)

$$C_d = \sum_{i=1}^{n}\sum_{j=1}^{m}(\beta_{i,j} \cdot Q_i \cdot Cs_i) \cdot X_{i,j} \tag{4}$$

- C_t : Total procurement cost

Then, the SSOM is given by the following mathematical programming model:

Objective function:

$$Minimize\, C_t = \sum_{i=1}^{n}\sum_{j=1}^{m}(Q_i \cdot Cu_{i,j} + \beta_{i,j} \cdot Q_i \cdot Cs_i) \cdot X_{i,j} \tag{5}$$

Subject to the following constraints:

$$\sum_{j=1}^{m} X_{i,j} = 1; \;\; i = 1, 2, ..., n \tag{6}$$

$$\sum_{i \in V_k} Q_i \cdot X_{i,j} \leq Cap_{j,k};\ k = 1, 2, ..., l;\ j = 1, 2, ..., m \tag{7}$$

$$X_{i,j} \in \{0, 1\};\ i = 1, 2, ..., n;\ j = 1, 2, ..., m \tag{8}$$

The objective is to minimize the total procurement cost (Eq.(5)) given by the sum of the purchase costs Cp (Eq.(3)) and delay costs Cd (Eq.(4)). Eq.(6) ensures that each order is assigned to only one supplier. Eq.(7) specifies that the total quantity delivered of each product type does not exceed the supplier's capacity. Finally, Eq.(8) imposes the binarity condition on the decision variables.

4. Experiments and validation

In this section, the prediction models are first trained, and then the CPOS performance is evaluated on real case studies.

4.1. Prediction results and analysis

The prediction models are trained, and their performance is evaluated based on the metrics introduced in Table 3. The importance of the features is evaluated to determine which features are most impactful on predictive analytics.

4.1.1. Test and training datasets

The complete dataset includes 89,080 (planned and realized) purchase orders over the period 2018 to 2021. After data preprocessing (see section 3.2.1), the preprocessed dataset (84,041 purchase order) was divided into two subsets using the stratification technique (Liberty et al., 2016) to ensure that the class distribution in each subset matches the class distribution in the original dataset:

- A testing set, constituting 20% of the preprocessed dataset (17,816 of POs)
- A training set, comprising 80% of the preprocessed dataset (71,264 of POs)

4.1.2. Hyperparameters of prediction models

The Python programming language, and the Pandas, Numpy, and Sklearn libraries were used to process data and perform ML predictive analysis. The training process was conducted on a computer with Intel(R) Core(TM) i5-8350U CPU at 1.70GHz and 16GO of RAM. In order to fine-tune the hyperparameters of the prediction models, the grid search algorithm (Lerman, 1980) was used to explore possible combinations of hyperparameters, evaluate each combination using the accuracy metric, and select the best-performing combination. Table 4 shows the obtained hyperparameters for each prediction model.

Table 4: Machine learning model hyperparameters

Model	**Decision Tree**	**Random Forest**	**eXtreme Gradient Boosting**
Parameters	- Tree depth: 30 - Max leaf nodes: 500 - Split quality measure: Gini impurity - Split strategy: Best	- Number of trees: 300 - Maximum depth: 30 - Split quality measure: Gini impurity	- Number of trees: 300 - Maximum depth: 30 - Learning rate = 0.1

4.1.3. Selection of a predictive model

Prediction models were trained and validated using cross-validation on the training set. The testing dataset was kept separate and was used only after model training to evaluate the training (using the evaluation metrics) and validate performance. During training, the 10-fold cross-validation (Wong and Yeh, 2019) was used to evaluate the overfitting of the models on the training dataset. The training dataset was split into ten equal folds and the model was trained using nine folds, while the last fold was used to test the training. This process was repeated 10 times. For each iteration, a different fold was used to test the training. Finally, the model cross-validation score was calculated as the average of the ten accuracies measured in the testing folds.

Table 5 shows that obtained metrics are above 88% for all metrics for all three algorithms. The decision tree model presents the lowest results for all metrics. On the other hand, the ensemble algorithms perform better, given their ability to reduce learning bias, generalize training results, and improve robustness. The XGBoost model achieves the highest results, with an improvement of 1% over the random forest model and 2% over the decision tree model. In terms of precision, more than 91% of the predicted delays are effective delays, compared to 90.21% for random forest and 89.37% for decision tree. For the recall metric, the XGBoost model achieves a score of 93.52%, meaning that more than 93% of true positive delays were detected. It is worth noting that the cross-validation scores closely match the accuracy on the testing sets, indicating that all models are not overfitting.

In the particular case of XGBoost, Table 6 shows that random under sampling enables reaching a high cross validation score of 0.9285, which confirms that the XGBoost model is not overfitting. Hence, the model is able to generalize on new data and to predict supplier delays. Its results can be transmitted to the downstream optimization model and used with high confidence. Accordingly, the XGBoost is selected

Table 5: Evaluation of prediction model performances

Algorithm	**10-folds cross validation score on the training dataset**	**Evaluation metrics scores on the testing dataset**			
		Accuracy	**Precision**	**Recall**	**F1-score**
Decision Tree Model	0.9005	0.8900	0.8937	0.8871	0.8904
Random Forest Model	0.9213	0.9162	0.9021	0.9351	0.9183
XGBoost Model	0.9285	0.9243	0.9163	0.9352	0.9257

Table 6: Results of different sampling techniques for XGBoost model

Sampling technique	10-folds cross-validation score	Accuracy
No sampling	0.7195	0.9264
Random oversampling	0.7712	0.9341
Random undersampling	0.9285	0.9243

to be used for the remainder of the study.

4.1.4. Feature importance analysis

A feature importance analysis is conducted to determine the significant factors that most influence delays using the XGBoost model. Whereas in its current practice, the company did not consider the day of the week and the supply time as influential or important features, Fig 5 shows that they are indeed the most influential features, since they impact by 60.66% the final predictions. Identifying the importance of such parameters would help the company pay more attention to them, and improve its processes accordingly. The supplier, the ordered product, the week, and the day of the month of the planned delivery date are also of great importance, since they impact by 31.41% the final predictions. These results show that the proposed engineered features have an impact of 77.17% on provided decisions. It is, therefore, strongly recommended, to consider those variables to predict late deliveries.

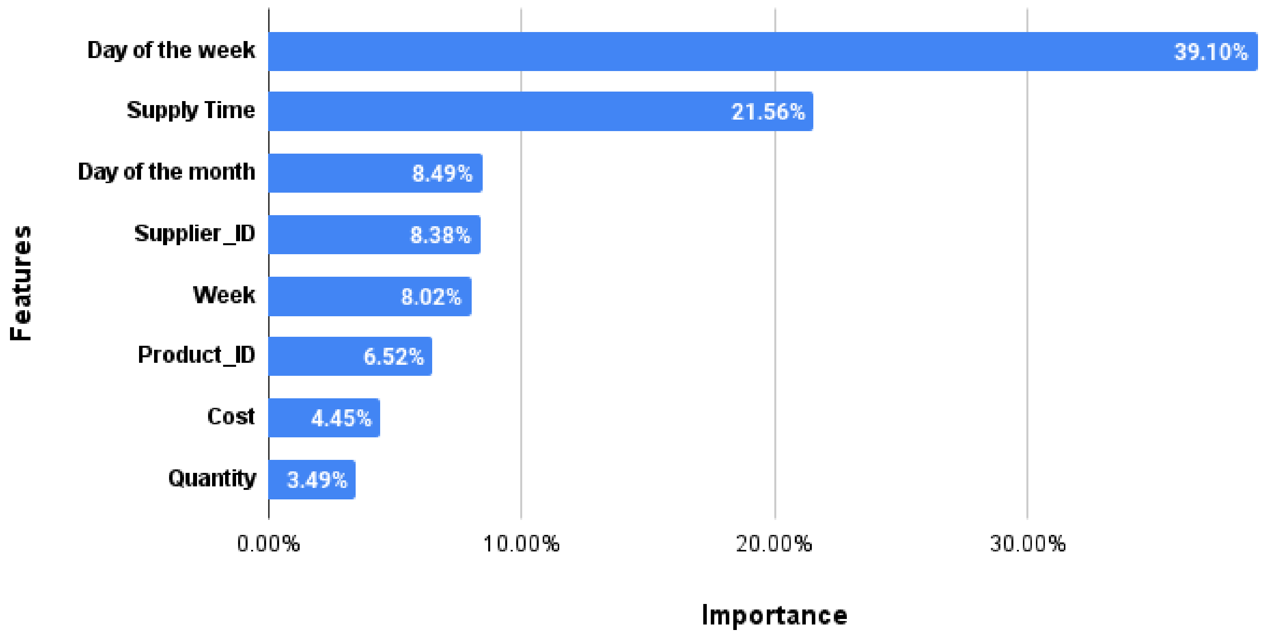


Figure 5: Feature importance analysis for XGBoost model

4.2. Optimization of supplier selection

The company practice is based on weekly plannings, where production and procurement plans are established at the end of the current week for the next coming week. The company is hardly willing to change this practice. Consequently, experimentation and validation of the suggested approach involved an analysis of available data to determine typical profiles of production and procurement work weeks in terms of typical numbers of suppliers, products, purchase orders and quantities. These profiles determine the size and scale of the numerical analysis. Five case studies were established, involving six suppliers, five products and varying in purchase order products, suppliers and periods. This allows assessing the suggested methodology and system performance under different conditions. First, the case studies are introduced. Then, the predictive optimization system (POS) to support decision-making is assessed without collaboration. Finally, the collaborative predictive optimization system (CPOS) is assessed, where collaboration occurs based on decision support from the predictive optimization system.

4.2.1. Presentation of the case studies

The case studies cover 5 to 30 purchase orders placed at different periods of the year. Table 7 shows the involved products, suppliers and purchase orders for each case study.

Table 8 shows supplier capacities, unit purchase costs and delay costs collected from the ERP system.

Table 7: Details of the case studies

Case study number	**Number of purchase orders**	**Suppliers involved**	**Products involved**	**Period of the year**
1	5	S1, S2, S3	P1, P2	11th week of the year
2	8	S1, S2, S3	P1, P2	10th week of the year
3	15	S1, S2, S3, S4	P1, P2, P3	29th week of the year
4	20	S1, S2, S3, S4, S5	P1, P2, P3, P4	23th week of the year
5	30	S1, S2, S3, S4, S5, S6	P1, P2, P3, P4, P5	41th week of the year

Table 8: Capacities and costs per supplier

	Supplier capacity per product						**Unit purchase cost (€) per product**						**Unit delay cost (€) per product**
Supplier	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**Any supplier**
P1	450	300	300	250	350	200	3.2	3	3	3	3.1	3.2	3.2
P2	350	250	300	200	300	200	2.4	2.6	2.5	2.5	2.4	2.4	3
P3	350	300	300	250	250	150	2	2.2	2	2	2.1	2	2.8
P4	400	200	300	200	100	150	3	2.8	3	3	2.8	2.9	2.9
P5	450	250	350	400	300	250	2.7	2.8	2.9	2.8	2.7	2.9	3.1

For each product P_k, the maximum quantity *QMax(Sj, Pk)* that supplier S_j can deliver in a procurement planning period is given by Eq. (9):

$$QMax(S_j, P_k) = Min(Cap_{j,k} \ ; \ \textit{Total demand of } P_k) \tag{9}$$

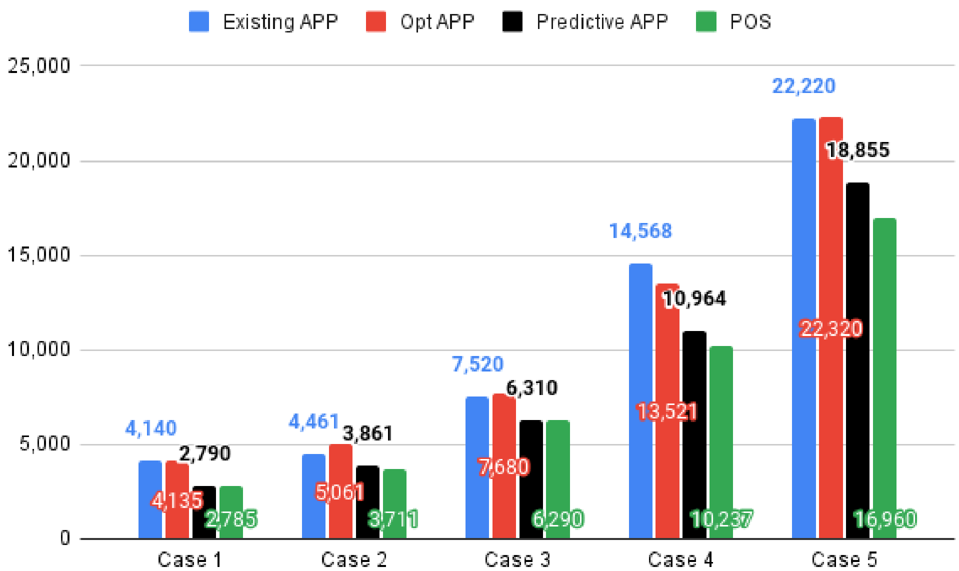
4.2.2. Predictive optimization of supplier selection

An analysis is conducted to compare four approaches on the five suggested case studies. The total procurement costs and number of delays for each case study and each approach are illustrated in Fig. 6:

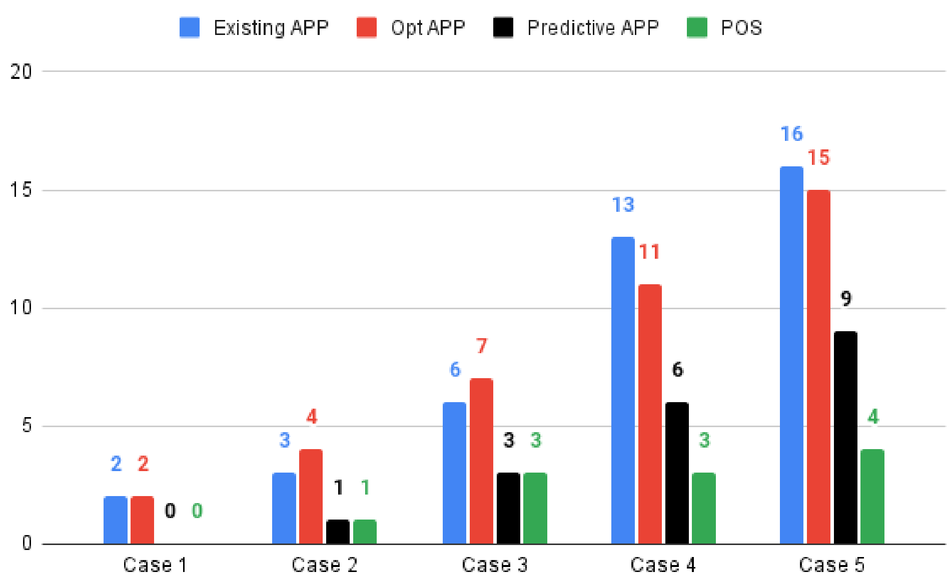
- Approach 1 (which results are shown under the label "**Existing APP**" in Fig. 6): the existing approach of the company, which relies on the ERP classical procurement module to assign orders to suppliers based on the minimum purchase cost heuristic rule, not considering the predicted delays;

- Approach 2 (which results are shown under the label "**Opt APP**" in Fig. 6): the optimization approach, in which orders are assigned to suppliers using the suggested linear programming model, but without considering the predicted delays;
- Approach 3 (which results are shown under the label "**Predictive APP**" in Fig. 6): an improved version of the company approach, which relies on the ERP procurement module to assign orders to suppliers based on the minimum cost heuristic rule, where cost includes both purchase and delay costs;
- Approach 4 (which results are shown under the label "**POS**" in Fig. 6): The predictive optimization approach, where the decision support process combining prediction and optimization is applied, but without collaboration (i.e. the red colored process in Fig. 2).;

In Fig. 6, the POS approach outperforms all other approaches in reducing the total procurement costs for all cases. The difference in total procurement costs between the POS and the Existing APP varies between 16.36% (case 3) and 32.73% (case 1). The results show that using an optimization model based only on costs and supplier capacities does not systematically reduce the total procurement costs. For cases 2, 3, and 5, using the linear programming model (Opt APP) resulted in an increase in the total procurement costs compared to the Predictive APP and POS. By considering supplier delays, the Predictive APP approach becomes more efficient than the Opt APP in terms of the resulting number of delays and the procurement costs. However, by combining the mathematical optimization model with the predicted delays (POS), the number of delays decreases up to 100% in case 1. It should be noted that the minimum reduction of number of delays is 50% recorded in case 3. In other words, in the worst scenario, the use of the POS helps avoid at least half of the delays, with a 16.36% reduction in total costs.
Case 4 and case 5 show that, even for procurement plans with a high number of purchase orders and higher involved suppliers and products, the POS succeeded in reducing total costs by 29.73% (case 4) and 23.67% (case 5).



(a) Total procurement costs (€)



(b) Number of delays

Figure 6: Performance assessment of the case studies.

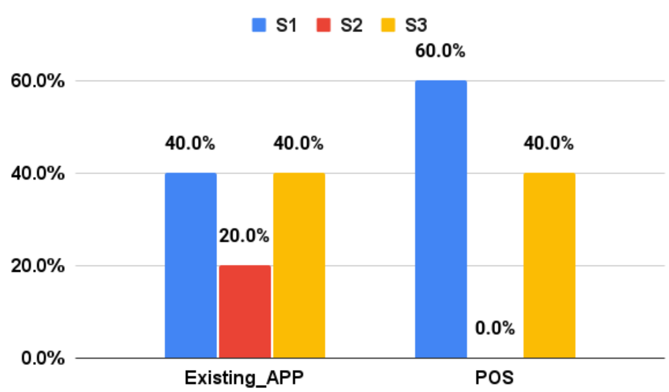
To further illustrate the proposed POS approach, cases 1 and 2 are discussed in more detail. As the two cases involve a close number of purchase orders, which are released in two successive weeks, to order the same products from the same suppliers, the prediction of delays is almost the same (see Table 9).The supplier selection obtained by POS and existing approaches are presented in Table 10.

The distributions of order allocations to suppliers obtained with the company's existing approach (Existing APP) versus the POS approach are presented in Fig. 7.

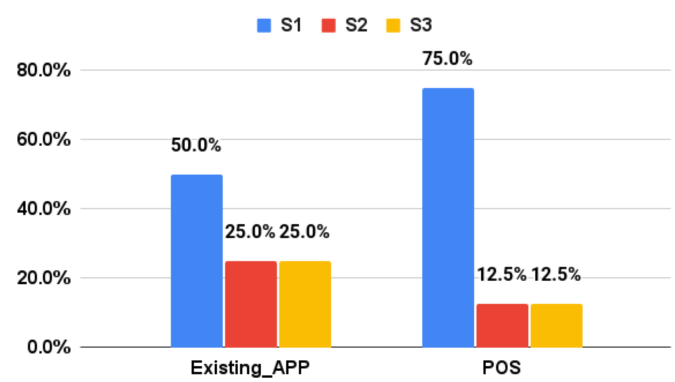
Table 9: Predicted occurrences of delays for case 1 and case 2

	Case 1							
	PO1	**PO2**	**PO3**	**PO4**	**PO5**			
S1	(0)	(0)	(0)	(0)	(0)			
S2	(1)	(0)	(0)	(1)	(0)			
S3	(1)	(0)	(0)	(1)	(0)			
	Case 2							
	PO1	**PO2**	**PO3**	**PO4**	**PO5**	**PO6**	**PO7**	**PO8**
S1	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
S2	(1)	(1)	(0)	(1)	(0)	(0)	(0)	(1)
S3	(1)	(1)	(0)	(1)	(0)	(0)	(0)	(1)

(0): On-time order, (1): Delayed order



(a) Case1



(b) Case2

Figure 7: Distributions of order allocations to suppliers with the existing approach Vs. the POS approach

Table 10: Supplier selection with POS, and existing approaches for case 1 and case 2

Case 1			**Case 2**		
Purchase order (Product, Quantity)	**Existing APP**	**POS**	**Purchase order (Product, Quantity)**	**Existing APP**	**POS**
PO1 (P1,200)	S2(1)	S1(0)	**PO1 (P1,150)**	S2(1)	S2(1)
PO2 (P2,100)	S1(0)	S3(0)	**PO2 (P1,100)**	S2(1)	S1(0)
PO3 (P2,150)	S1(0)	S3(0)	**PO3 (P2,100)**	S1(0)	S1(0)
PO4 (P1,250)	S3(1)	S1(0)	**PO4 (P1,150)**	S3(1)	S1(0)
PO5 (P2,300)	S3(0)	S1(0)	**PO5 (P2,90)**	S1(0)	S1(0)
			PO6 (P2,150)	S1(0)	S1(0)
			PO7 (P2,210)	S3(0)	S3(0)
			PO8 (P1,200)	S1(0)	S1(0)

(0): On-time order, (1): Delayed order

Comparing POS to Existing APP on both case 1 and case 2, Figure 7 shows that the number of orders allocated to supplier S1 is greater than the number of orders allocated to supplier S2 in both cases. The number of orders allocated to supplier S3 remains unchanged in case 1, whereas it decreases in case 2.

To explain these results, it is worth noticing that supplier S1 is known from historical data to process all orders in the same way in general, and prediction model training tends to confirm predictions that this supplier will not be late for new orders. For supplier S2, the Existing APP maintains approximately the same proportion (around 20%) of allocations in both cases, as this supplier offers the lowest purchase cost for product P1. This is no longer valid using the POS approach to allocate orders to supplier S2, where the selection of supplier S2 is no more systematic (0% order allocations in case 1 compared to 12.5% order allocations in case 2), and this despite S2 being the cheapest supplier for product P1. This is due to the fact that the POS predicts delays with supplier S2, and tends to allocate less orders to reduce delay costs and therefore better optimize total cost. It is also worth noticing that for case 1, supplier S3 is considered better than supplier S2, since supplier S3 was allocated 40% of purchase orders compared to 0% for supplier S2 using POS. This observation is no longer valid in case 2, where S2 and S3 are considered similar with 12.5% of order allocations each using POS. Thus, by not focusing solely on the purchase cost aspect, and taking into account delay considerations, the POS is able to make more balanced decisions, which is better adapted to the context of the case study. The obtained results highlight that the large streams of data stored in the ERP, which exceed human capabilities to fully grasp them without the support of digital technologies, are better exploited and valued using predictive analytics to extract actionable information and to make suitable tradeoffs.

4.2.3. Collaborative predictive optimization

As illustrated in section 4.2.2, the POS approach allows minimizing procurement costs and reducing the number of delays, given the characteristics of the suppliers and the predicted delays. In some cases, zero delay costs and zero delays cannot be achieved, and this is where the importance of a collaborative approach is recognized. Based on the proposed workflow model given in Fig. 2, the POS outcomes are shared with stakeholders, who can consider different alternatives, as illustrated in Fig. 8, to prevent delays and reduce their inconveniences.

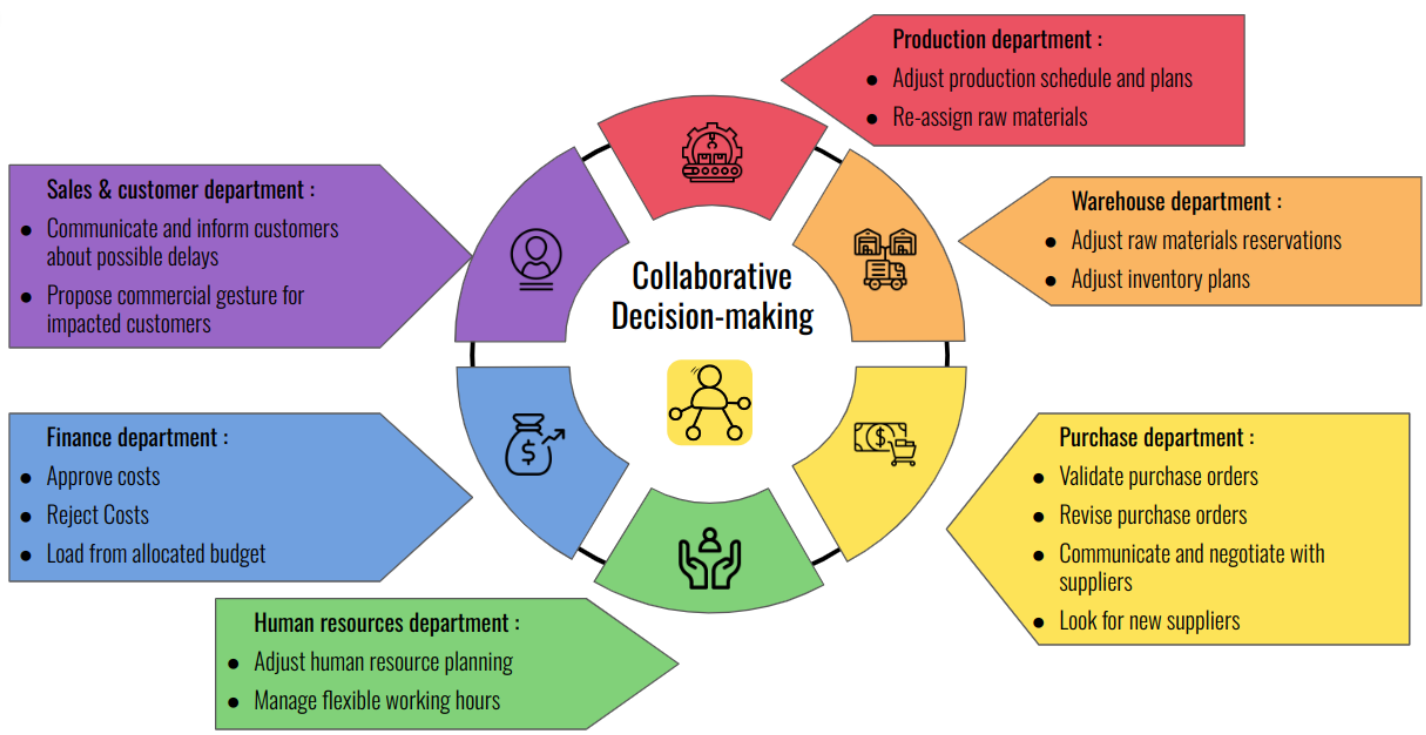


Figure 8: Examples of proactive actions to manage delays

The final decision is made collaboratively among involved stakeholders. In Table 11, a comparison is made between on the one hand the POS approach (without collaboration, i.e. only the red arrows process in Fig. 2), and on the other hand a collaborative approach (CPOS), which involves collaboration between stakeholders after the results of a POS approach are presented to them (i.e. processes with both red and blue arrows in Fig. 2). Examples of alternatives applied to the case studies and their consequences are presented in Table 11.

Case 1 generated an allocation without delay costs using the POS. Thus, decision-makers can validate the resulting order allocations without downstream intervention. However, for the remaining cases, the available alternatives allowed a further reduction of the number of delays and total procurement costs. In case 2, by intervening at the purchasing department level and negotiating with the supplier who was predicted to be late, a new allocation is proposed with zero predicted delays. In addition, in case 3, re-assigning raw materials by the production department allowed to mitigate delay costs of product P3 and, therefore, further decrease procurement costs proposed by the POS. This emphasizes that proactive measures are robust to delays without incurring any extra costs.

The results show that collaboration between several stakeholders results in a reduction of up to 20% in procurement costs.

Table 11: Alternatives from multiple stakeholders applied to the case studies and their consequences

Case	Applied actions	Consequences		C_p (€)	C_d (€)	C_t (€)	N_{Delays}	Upgrade in C_t(%)
Case 1	-	-	POS	2,785	0	2,785	0	-
			CPOS	2,785	0	2,785	0	
Case 2	Communicate and negotiate with Supplier S2 [Purchase department & Supplier]	Avoid delays of S2 for product P1	POS	3,231	480	3,711	1	12.93
			CPOS	3,231	0	3,231	0	
Case 3	Reasign raw materials [Production department]	Delays of P3 will not have delay costs	POS	5,030	1,260	6,290	3	20.03
			CPOS	5,030	0	5,030	3	
Case 4	Communicate and inform customers about possible delays [Sales department & Client]	1. Delays of P2 and P3 will not have delay costs	POS	8,652	1,585	10,237	3	6.35
		2. commercial discount to customer: 500 € added to the delay cost	CPOS	8,652	935	9,587	3	
Case 5	1. Communicate and negotiate with S4 [Purchase department & Supplier]	1. An increase in S4 capacities to deliver P1 (+200), P4 (+100), P5 (+200)	POS	14,960	2,000	16,960	4	11.56
	2. Adjust raw materials reservations [Warehouse department]	2. Delays of P2 will not have delay costs	CPOS	15,000	0	15,000	1	

C_p: Purchase cost

C_d: Delay cost

C_t: Total procurement cost

N_{Delays}: Numbers of delays

-: Nothing to report

4.3. Sensitivity analysis

The suggested CPOS system combines ML based delay prediction with linear programming to optimize order allocations. The linear programming technique ensures the optimality of the solution. However, since the accuracy of the upstream prediction model is 92%, false predictions can be generated with a probability of 8% and subsequently distort the optimization process. An analysis of the prediction results shows that the false-negative rate (a delay predicted incorrectly as an on-time delivery) is 3%. A margin of error of 3% represents, at most, a delay that was not predicted. In cases 1 and 2, as this translates to half a delay ("half occurrence of a delay" does not make sense), half occurrences are replaced with full occurrences. Therefore, the prediction results are adjusted accordingly, assuming that supplier forecasts for on-time deliveries may be erroneous, resulting in the conversion of every (0) to a (1) to encompass all potential scenarios. Then, to perform the sensitivity analysis, the worst, best and median cases were retained in terms of total procurement costs (C_t).

For each case study, the deviation of total procurement costs of the POS and CPOS are calculated using Eq. (10).

$$Dev(\%) = \frac{C_t^d - C_t}{C_t} \cdot 100 \tag{10}$$

with:

C_t: Total procurement costs of the initial obtained solution (Table 11)

C_t^d: Total procurement costs with added delays to the initial obtained solution

Eq. (11) presents the difference between the number of delays (N_{Delays}) given by the initial obtained solution (Table 11) and the number of delays given by the disturbed initial solution with added delays (N_{Delays}^d):

$$Delay_{variation} = N_{Delays}^d - N_{Delays} \tag{11}$$

Table 12 illustrates the results of the sensitivity analysis for the POS and CPOS when applying the same alternatives from stakeholders for each case study.

The results show that, even for the worst cases, the variation in total procurement costs does not exceed 10.22%. These results confirm the objective of the sensitivity analysis, where it is proved that for each case study (typical procurement week), the initial solution remains robust even if some disturbances, due to prediction errors, occur.

Table 12: Results of the sensitivity analysis

		POS			CPOS		
		$Delay_{variation}$	C_t(€)	$Dev(\%)$	$Delay_{variation}$	C_t(€)	$Dev(\%)$
Case 1	Minimum deviation	0	2,785	0	0	2,785	0
	Median deviation	0	2,785	0	0	2,785	0
	Maximum deviation	0	2,840	1.98	0	2,840	1.98
Case 2	Minimum deviation	0	3,711	0	0	3,231	0
	Median deviation	0	3,732	0.57	0	3,252	0.65
	Maximum deviation	0	3,770	1.59	0	3,280	1.52
Case 3	Minimum deviation	0	6,290	0	0	5,030	0
	Median deviation	0	6,350	0.95	0	5,090	1.19
	Maximum deviation	1	6,740	7.15	1	5,480	8.94
Case 4	Minimum deviation	0	10,287	0.49	0	9,637	0.52
	Median deviation	2	10,824	5.73	2	10,174	6.12
	Maximum deviation	2	11,217	9.57	2	10,567	10.22
Case 5	Minimum deviation	1	17,380	2.48	1	15,380	2.53
	Median deviation	1	17,760	4.72	1	15,760	5.07
	Maximum deviation	2	18,350	8.20	2	16,350	8.26

Ct: Total procurement costs

4.4. Best-Worst case analysis

The prediction model can generate up to 8% false predictions 4.1.3, with 5% being false positives (incorrectly predicting on-time deliveries as delays) and 3% being false negatives (incorrectly predicting delays as on-time deliveries). The sensitivity analysis emphasized a pessimistic scenario, where the predicted number of delays was rounded up to a greater number to account for fractional delays. To provide a more balanced assessment and account for decision-maker attitude, a best-worst case analysis is performed across three scenarios. In the **Pessimistic Scenario**, 3% of predicted on-time deliveries are considered as delays, converting each predicted on-time delivery (0) to a delay (1). In the **Optimistic Scenario**, 5% of predicted delays are considered as on-time deliveries, converting each delay prediction (1) to an on-time delivery (0). In the **Neutral Scenario**, 8% of predictions are randomly flipped, altering both on-time and delayed delivery predictions (with respect to false positive and false negative rates). These scenarios are applied to each case study, with the minimum, median, and maximum deviations recorded. The deviations in total procurement costs (Eq. (10)) and the number of delays (Eq. (11)) are analyzed considering additional measures, namely the mean measure (Eq. (12) (Kiely et al., 2011) and its deviation (Eq. (13) and the min-max range measure (Eq. (14) (Kiely et al., 2011) and its deviation from the minimal case (Eq. (15)).

$$Mean = \frac{\sum_{b=1}^{Na} C_{t,b}^{d}}{Na} \tag{12}$$

$$DevM(\%) = \frac{Mean - C_t}{C_t} \cdot 100 \tag{13}$$

$$Range = \underset{Na}{Max}(C_{t,b}^{d}) - \underset{Na}{Min}(C_{t,b}^{d}) \tag{14}$$

$$DevR(\%) = \frac{Range - \underset{Na}{Min}(C_{t,b}^{d})}{\underset{Na}{Min}(C_{t,b}^{d})} \cdot 100 \tag{15}$$

with:

C_t: Total procurement costs of the initial obtained solution (Table 11)

$C_{t,b}^{d}$: Total procurement costs of alternative b (b=1,...,Na)

Na : Number of alternatives.

As presented in Table 13, an increase in delays (pessimistic scenario) consistently results in higher total purchase costs, ranging from 0% to 9.57% across various case studies. Conversely, the optimistic scenario predicts substantial cost reductions between 2.56% and 15.58%. The neutral scenario, which represents a more balanced approach, results in cost deviations that can either increase or decrease, reflecting a more realistic assessment of prediction uncertainty. The mean deviation across all case studies ranges from -5.07% to 2.06%, suggesting that the initial allocation yields balanced outcomes with potential minor gains or losses due to prediction errors. This is further illustrated in Fig.9, which shows box plots of total procurement costs for case study 4 across different scenarios, indicating that the initial allocation falls between the first and third quartiles of possible costs and is close to the mean cost for the neutral scenario. Hence, the generated solution was selected, as it provides benefits when deliveries are on time and the maximum deviation is within acceptable limits. The optimistic scenario can be opted for, assuming fewer delays, but this choice entails greater deviations if false positive predictions occur, as the maximum range is 26.93%. Alternatively, the pessimistic scenario, which anticipates more delays than predicted, leads to higher procurement costs and unnecessary collaborative actions that could be avoided. This confirms that the POS generated allocation balances the costs associated with prediction uncertainties.

Table 13: Best-Worst case analysis results

		Pessimistic Scenario		Optimistic Scenario		Neutral Scenario		$Mean$ (€)	$DevM$ (%)	$Range$ (€)	$DevR$ (%)
		C_t (€)	Dev (%)	C_t (€)	Dev (%)	C_t (€)	Dev (%)				
Case 1 (5 PO)	Min	2,785	0	2,735	-1.8	2,735	-1.8	2,781	-0.14	105	3.84
	Med	2,810	0.9	2,735	-1.8	2,785	0				
	Max	2,840	1.97	2,735	-1.8	2,840	1.97				
Case 2 (8 PO)	Min	3,711	0	3,201	-13.74	3,201	-13.74	3,523	-5.07	569	17.78
	Med	3,732	0.67	3,201	-13.74	3,711	0				
	Max	3,770	1.59	3,201	-13.74	3,770	1.59				
Case 3 (15 PO)	Min	6,290	0	5,310	-15.58	5,310	-15.58	6,116.36	-2.76	1,430	26.93
	Med	6,350	0.95	5,590	-11.13	6,290	-0.48				
	Max	6,740	7.15	6,290	0	6,740	7.15				
Case 4 (20 PO)	Min	10,287	0.49	9,527	-6.94	9,577	-6.45	10,298.85	0.60	1,690	17.74
	Med	10,797	5.47	9,792	-4.35	10,312	0.73				
	Max	11,217	9.57	10,207	-0.29	11,187	9.28				
Case 5 (30 PO)	Min	17,380	2.48	16,310	-3.83	16,510	-2.65	17,308.63	2.06	2,040	12.51
	Med	17,800	4.95	16,525	-2.56	17,320	2.12				
	Max	18,350	8.2	16,920	-0.24	18,310	7.96				

Min: Minimum deviation, Med: Median deviation, Max: Maximum deviation

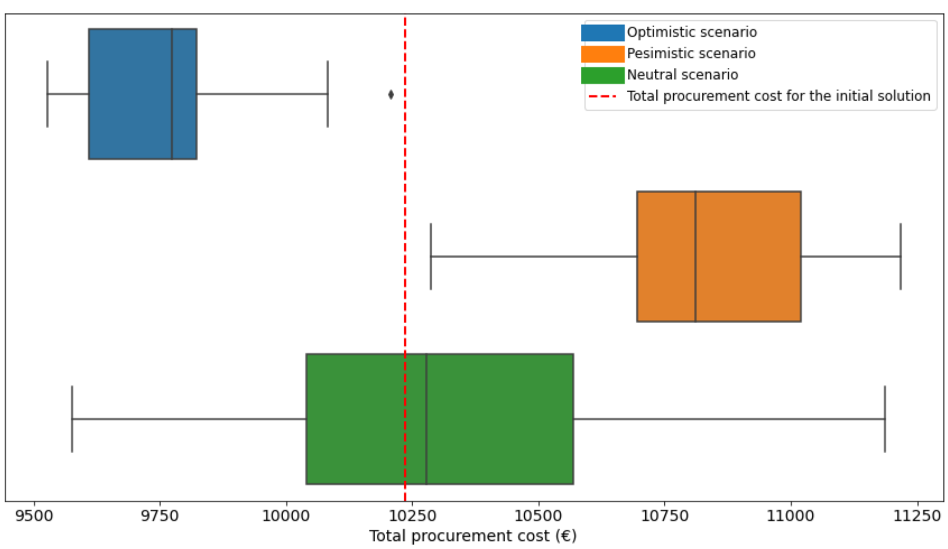


Figure 9: Box Plot of total procurement costs for case study 4 with different scenarios

4.5. Larger scale application

In the conducted experiments, the largest number of purchase orders (POs) within a single case study is 30. With respect to the used dataset, this represents the upper limit of POs per week that can be incorporated into a case study involving multiple suppliers and products. In this section, a synthetic case study was constructed in order to evaluate the approach on a larger scale. This is achieved by aggregating purchase orders over four procurement weeks, specifically those involving the same suppliers and products as in case study 5 (cases details presented in Table 14). The aggregated purchase orders are then consolidated into a single procurement plan consisting of 110 POs. To simulate a month's worth of orders, the capacities of the suppliers are multiplied by a factor of four. The results of the large-scale experiments are presented in Table 15.

Table 14: Cases details for large-scale analysis

	Procurement week	**Number of PO**	**Suppliers involved**	**Products involved**
Case 1	41th week	30	S1,S2,S3,S4,S5,S6	P1,P2,P3,P4,P5
Case 2	42th week	27	S1,S2,S3,S4,S5,S6	P1,P2,P3,P4,P5
Case 3	44th week	24	S1,S2,S3,S4,S5,S6	P1,P2,P3,P4,P5
Case 4	45th week	29	S1,S2,S3,S4,S5,S6	P1,P2,P3,P4,P5

Table 15 demonstrates that, for a relatively large number of purchase orders, the proposed POS significantly reduces total purchase costs and the number of delays compared to existing optimization and predictive approaches. Furthermore, by implementing three actions collaboratively, the number of delays was reduced by 75%, resulting in an allocation without delay costs. It should also be noted that the execution time of the optimization module remains low, around 1 second, which means that the suggested approach is scalable with respect to the considered company size and operational requirements.

Table 15: Large-scale case study results with different approaches

	C_p (€)	C_d (€)	C_t (€)	N_{Delays}
Existing APP	54,915	30,830	86,745	59
Opt APP	54,850	30,040	84,890	57
Predictive APP	56,190	5,765	61,955	14
POS	56,260	3,500	59,760	8
CPOS	56,300	0	56,300	2
CPOS Applied Actions	1- Communicate and negotiate with S1 2- Communicate and negotiate with S4 3- Adjust raw materials reservations **Consequences** 1- An increase in S1 capacities to deliver P3 (+200), P5 (+300) 2- An increase in S4 capacities to deliver P1 (+350), P4 (+200), P5 (+400) 3- Delays of P2 will not have delay costs			

5. Managerial insights

The "experimentation and validation" section was conducted within the company, with approval and iterative and incremental improvements from company experts. The outcome is an operational system that has acceptance and brings value to users. This study supports the company, similar manufacturers and similar industrial sectors, in restructuring their conventional supplier selection process to take better advantage of the collaboration and integration offered by digitalization technologies and trends. The outcomes of the experimentation and validation section highlight the managerial and functional implications of the proposed framework. A summary of these implications is as follows:

- The feature importance analysis (section 4.1.4) sheds light on influential features that were not paid attention to, and not considered, in company practice before this study, although they impact decision-making significantly. Combined awareness of these features (including the day of the week and the supply time), and of delay predictions, impacts future decisions about when to release purchase orders, and how to select suppliers based on the flexibility they need to avoid delays.

- As a corollary, the previous insight, as well as the best-worst case (section 4.4) and larger scale (section 4.5) analyses influence strategic relations with suppliers and customers. The suggested methodology (workflow) and system (CPOS) influence strategic, long-term relations with suppliers, through improved negotiation of annual reviews of performance, and contractual terms and conditions. They influence operational settings, like safety storage levels, inventory replenishment strategies, downstream warehouse management (e.g. mobilization of necessary and sufficient logistics workforce), and production planning and control, for example through advised decision-making with respect to the choice of planning horizons and production order releases. On the customer side, being aware of potential delays can improve the quality of commitments to customers in terms of negotiated quantities and delivery conditions.

- In the large-scale analysis, it is important to note that the suggested approach is scalable with respect to company operational requirements, because it was able to adapt to consolidating orders and extending the planning horizon. Although this consolidation contributes to reducing costs and delays, such an approach may not always be feasible due to constraints such as suppliers' capacities, storage locations, storage costs, and the risks of spoilage. Therefore, companies must seek an optimal compromise that balances these factors. The suggested approach provides decision support tools to reach advised agreements when negotiating quantities and discussing annual procurement plans with suppliers.

- The suggested study offers a sound basis to roadmap strategic digital transformation projects. Whereas the current trend is to endow ERP systems with extra layers to enable them perform data analytics, without necessarily linking data analytics to decision-making, the suggested methodology and system go a step further by streamlining data analytics to optimization and collaborative decision-making processes. Such empowerment is a step forward towards the virtual enterprise paradigm, where several stakeholders and interested parties in different geographical locations (like suppliers and customers), and different functional affiliations and responsibilities (like different departments), interact to achieve common business goals (for instance, just in time deliveries).

6. Conclusions

This article addressed some aspects of the supplier selection problem that are not well covered both in literature and industrial practice. Two main limitations were addressed, namely (i) the unilateral, single perspective of the purchase/procurement department, who usually does not consider the added value of involving several stakeholders from multiple expertise domains (decision makers from different departments, suppliers, and customers) in the decision-making processes, and does not consider collaboration to solve the supplier selection and order allocation problem; (ii) the under use of digitalization technologies, such as enterprise information systems, data analytics and optimization, to streamline the supplier selection and order allocation decision-making processes.

To deal with these limitations, a collaborative workflow was developed to take advantage of feedback and alternatives from all involved stakeholders. The workflow relies on industrial ERP systems as a backbone asset to integrate and streamline the supplier selection process. The workflow also involves a collaborative predictive optimization system (CPOS) that was developed to coordinate knowledge and interactions between several stakeholders from multiple expertise domains. The CPOS uses data from industrial ERP systems to predict occurrences of delays, based on data analytics and machine learning to account for historical context and dynamics. Classifications of occurrences of delays are then used in a mathematical programming optimization of supplier selections, to achieve an overall supplier selection optimization.

To assess performance and validate the CPOS, the specificities of a French company in the furniture industry were considered. The company is facing supplier selection problems under capacity constraints, and is suffering from a significant number of supplier delays. An experimental numerical assessment shows that delays are tied to dynamic factors, like order release and delivery dates, product and purchase costs, and that evaluating delays with metrics that do not take these dynamic factors into account can yield unsatisfactory results. The integration of predictive analytics into ERP systems improves results, but not enough compared to the proposed predictive-optimization approach, in which the mathematical model capitalizes on the predictive module outcomes to achieve a global optimal allocation. The collaborative decision-making process further improves results, allowing significant cost savings, delays reduction and realistic solutions with well-designed and practical budgets.

As managerial insights, the outcomes of this research help managers better understand, explain and deal with delays to find optimal decisions and improve operational performance. Data analytics, information sharing and collaborative decision-making with all impacted stakeholders promote collective efforts to prevent and actively mitigate the negative consequences of possible delays. Instead of traditionally fragmented architecture and compartmentalized processes, where only the purchase department deals with the selection of suppliers, the suggested approach and system promote more transparent, effective and efficient (material, information and financial) flows across all involved processes and actors, thus consolidating the foundations for a successful digital transformation.

To the best of the authors' knowledge, no previous work has investigated the above-mentioned limitations using a data-driven, collaborative, predictive-optimization approach. Our findings can be leveraged by other companies facing similar challenges. The modular and flexible architecture of the proposed methodology and system enable for an easy implementation of different possible extensions for other industrial case studies, unknown/uncertain parameters and/or various objectives to be handled separately or simultaneously.

Future research directions to improve this work, to overcome some of its limitations, and to deal with problems that are challenging both scientific research and industrial practice include considering solving the prediction problem as multiple regression problems, where the duration of delays, the variable costs of delays, and eventually other quantifiable supply chain risks are predicted and proactively considered in the supplier selection process. Fuzzy logic can be considered to better deal with uncertainty and ambiguity in data. Multi-agent systems can be considered to automate and support the collaboration process. Knowledge based systems can be considered to reuse knowledge about similar previous supplier selections and order allocations.

References

Aggarwal, I., Gunreddy, N., and Rajan, A. J. (2021). A hybrid supplier selection approach using machine learning and data envelopment analysis. In *2021 Innovations in Power and Advanced Computing Technologies (i-PACT)*, pages 1–5. IEEE.

Ahmad, M. T. and Mondal, S. (2016). Dynamic supplier selection model under two-echelon supply network. *Expert Systems with Applications*, 65:255–270.

Amindoust, A., Ahmed, S., Saghafinia, A., and Bahreininejad, A. (2012). Sustainable supplier selection: A ranking model based on fuzzy inference system. *Applied soft computing*, 12(6):1668–1677.

Aouadni, S., Aouadni, I., and Rebaï, A. (2019). A systematic review on supplier selection and order allocation problems. *Journal of industrial engineering international*, 15:267–289.

Asthana, N. and Gupta, M. (2015). Supplier selection using artificial neural network and genetic algorithm. *International Journal of Indian Culture and Business Management*, 11(4):457–472.

Azadnia, A. H., Saman, M. Z. M., Wong, K. Y., Ghadimi, P., and Zakuan, N. (2012). Sustainable supplier selection based on self-organizing map neural network and multi criteria decision making approaches. *Procedia-Social and Behavioral Sciences*, 65:879–884.

Babu, M. P. and Sastry, S. H. (2014). Big data and predictive analytics in erp systems for automating decision making process. In *2014 IEEE 5th international conference on software engineering and service science*, pages 259–262. IEEE.

Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I. E., and Omid, M. (2018). Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. *Computers & Operations Research*, 89:337–347.

Baryannis, G., Dani, S., and Antoniou, G. (2019). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. *Future Generation Computer Systems*, 101:993–1004.

Bassiouni, M. M., Chakrabortty, R. K., Sallam, K. M., and Hussain, O. K. (2024). Deep learning approaches to identify order status in a complex supply chain. *Expert Systems with Applications*, 250:123947.

Bawa, S. S. (2023). How business can use erp and ai to become intelligent enterprise. *vol*, 8:8–11.

Bodaghi, G., Jolai, F., and Rabbani, M. (2018). An integrated weighted fuzzy multi-objective model for supplier selection and order scheduling in a supply chain. *International Journal of Production Research*, 56(10):3590–3614.

Bodemer, O. (2023). Revolutionizing enterprise resource planning: Integrating java and ai to propel web-based erp systems into the future. *Authorea Preprints*.

Boran, F. E., Genç, S., Kurt, M., and Akay, D. (2009). A multi-criteria intuitionistic fuzzy group decision making for supplier selection with topsis method. *Expert systems with applications*, 36(8):11363–11368.

Breiman, L. (1996). Bagging predictors. *Machine learning*, 24:123–140.

Breiman, L. (2001). Random forests. *Machine learning*, 45:5–32.

Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., and McFarlane, D. (2020). Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research*, 58(11):3330–3341.

Cabrita, M. D. R. and Frade, R. (2016). Supplier selection approach: integrating analytic hierarchy process and supplier risk analysis. *International Journal of Business and Systems Research*, 10(2-4):238–261.

Çalık, A. (2021). A novel pythagorean fuzzy ahp and fuzzy topsis methodology for green supplier selection in the industry 4.0 era. *Soft Computing*, 25(3):2253–2265.

Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., and Ivanov, D. (2019). A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing. *International Journal of Information Management*, 49:86–97.

Chai, J., Liu, J. N., and Ngai, E. W. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert systems with applications*, 40(10):3872–3885.

Chai, J. and Ngai, E. W. (2015). Multi-perspective strategic supplier selection in uncertain environments. *International Journal of Production Economics*, 166:215–225.

Chai, J. and Ngai, E. W. (2020). Decision-making techniques in supplier selection: Recent accomplishments and what lies ahead. *Expert Systems with Applications*, 140:112903.

Chang, B., Chang, C.-W., and Wu, C.-H. (2011). Fuzzy dematel method for developing supplier selection criteria. *Expert systems with Applications*, 38(3):1850–1858.

Che, Z., Chiang, T.-A., and Lin, T.-T. (2021). A multi-objective genetic algorithm for assembly planning and supplier selection with capacity constraints. *Applied Soft Computing*, 101:107030.

Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794.

Daniya, T., Geetha, M., and Kumar, K. S. (2020). Classification and regression trees with gini index. *Advances in Mathematics: Scientific Journal*, 9(10):8237–8247.

De Boer, L., Labro, E., and Morlacchi, P. (2001). A review of methods supporting supplier selection. *European journal of purchasing & supply management*, 7(2):75–89.

de Krom, B. (2021). Supplier disruption prediction using machine learning in production environments.

Dickson, G. W. (1966). An analysis of vendor selection systems and decisions. *Journal of purchasing*, 2(1):5–17.

Du, B., Guo, S., Huang, X., Li, Y., and Guo, J. (2015). A pareto supplier selection algorithm for minimum the life cycle cost of complex product system. *Expert Systems with Applications*, 42(9):4253–4264.

Dursun, M. and Karsak, E. E. (2013). A qfd-based fuzzy mcdm approach for supplier selection. *Applied Mathematical Modelling*, 37(8):5864–5875.

Epicor (2024a). Epicor data analytics. https://www.epicor.com/en/products/business-intelligence-software/epicor-data-analytics. Accessed February 29, 2024.

Epicor (2024b). Forecast pro. https://www.epicor.com/en/partners/alliance-isv-partner/forecast-pro. Accessed February 29, 2024.

Fawagreh, K., Gaber, M. M., and Elyan, E. (2014). Random forests: from early developments to recent advancements. *Systems Science & Control Engineering: An Open Access Journal*, 2(1):602–609.

Fei, L., Deng, Y., and Hu, Y. (2019). Ds-vikor: A new multi-criteria decision-making method for supplier selection. *International Journal of Fuzzy Systems*, 21:157–175.

Ferreira, D. R. and Vasilyev, E. (2015). Using logical decision trees to discover the cause of process delays from event logs. *Computers in Industry*, 70:194–207.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of statistics*, pages 1189–1232.

García, S., Ramírez-Gallego, S., Luengo, J., Benítez, J. M., and Herrera, F. (2016). Big data preprocessing: methods and prospects. *Big Data Analytics*, 1(1):1–22.

Ghaniabadi, M. and Mazinani, A. (2017). Dynamic lot sizing with multiple suppliers, backlogging and quantity discounts. *Computers & Industrial Engineering*, 110:67–74.

Goundar, S., Nayyar, A., Maharaj, M., Ratnam, K., and Prasad, S. (2021). How artificial intelligence is transforming the erp systems. *Enterprise systems and technological convergence: Research and practice*, 85.

Guarnaschelli, A., Bearzotti, L., and Montt, C. (2017). An approach to export process management in a wood product enterprise. *International Journal of Production Economics*, 190:88–95.

Hadidi, M., Al-Rashdan, M., Hadidi, S., and SOUBHI, Y. (2020). Comparison between cloud erp and traditional erp. *Journal of Critical Reviews*, 7(3):140–142.

Haeri, S. A. S. and Rezaei, J. (2019). A grey-based green supplier selection model for uncertain environments. *Journal of cleaner production*, 221:768–784.

Hamdan, S. and Jarndal, A. (2017). A two stage green supplier selection and order allocation using ahp and multi-objective genetic algorithm optimization. In *2017 7th International Conference on Modeling, Simulation, and Applied Optimization (ICMSAO)*, pages 1–6. IEEE.

Hosseini, S. and Barker, K. (2016). A bayesian network model for resilience-based supplier selection. *International Journal of Production Economics*, 180:68–87.

Islam, S., Amin, S. H., and Wardley, L. J. (2022). Supplier selection and order allocation planning using predictive analytics and multi-objective programming. *Computers & Industrial Engineering*, 174:108825.

Islam, S., Amin, S. H., and Wardley, L. J. (2024). A supplier selection & order allocation planning framework by integrating deep learning, principal component analysis, and optimization techniques. *Expert Systems with Applications*, 235:121121.

Jabbarzadeh, A., Fahimnia, B., and Sabouhi, F. (2018). Resilient and sustainable supply chain design: sustainability analysis under disruption risks. *International Journal of Production Research*, 56(17):5945–5968.

Jahangoshai Rezaee, M., Yousefi, S., and Hayati, J. (2017). A multi-objective model for closed-loop supply chain optimization and efficient supplier selection in a competitive environment considering quantity discount policy. *Journal of Industrial Engineering International*, 13:199–213.

Jahani, A., Azmi Murad, M. A., bin Sulaiman, M. N., and Selamat, M. H. (2015). An agent-based supplier selection framework: Fuzzy case-based reasoning perspective. *Strategic Outsourcing: An International Journal*, 8(2/3):180–205.

Jawad, Z. N. and Balázs, V. (2024). Machine learning-driven optimization of enterprise resource planning (erp) systems: a comprehensive review. *Beni-Suef University Journal of Basic and Applied Sciences*, 13(1):4.

Kamalahmadi, M. and Parast, M. M. (2017). An assessment of supply chain disruption mitigation strategies. *International Journal of Production Economics*, 184:210–230.

Kar, A. K. (2014). Revisiting the supplier selection problem: An integrated approach for group decision support. *Expert systems with applications*, 41(6):2762–2771.

Karlina, O., Ridwan, A. Y., and Fajrillah, A. A. N. (2019). Designing green procurement system based on enterprise resources planning for the rubber processing industry. In *2019 International Conference on Electrical Engineering and Informatics (ICEEI)*, pages 608–613. IEEE.

Kiely, B. E., Soon, Y. Y., Tattersall, M. H., and Stockler, M. R. (2011). How long have i got? estimating typical, best-case, and worst-case scenarios for patients starting first-line chemotherapy for metastatic breast cancer: a systematic review of recent randomized trials. *Journal of Clinical Oncology*, 29(4):456–463.

Kohli, M. (2017). Supplier evaluation model on sap erp application using machine learning algorithms. *International Journal of Engineering & Technology*, 7(2.28):306–311.

Kuo, R., Pai, C., Lin, R., and Chu, H. (2015). The integration of association rule mining and artificial immune network for supplier selection and order quantity allocation. *Applied Mathematics and Computation*, 250:958–972.

Lerman, P. (1980). Fitting segmented regression models by grid search. *Journal of the Royal Statistical Society Series C: Applied Statistics*, 29(1):77–84.

Li, C., Chen, Y., and Shang, Y. (2022). A review of industrial big data for decision making in intelligent manufacturing. *Engineering Science and Technology, an International Journal*, 29:101021.

Li, Y., Kramer, M., Beulens, A. J., and van der Vorst, J. G. (2010). A framework for early warning and proactive control systems in food supply chain networks. *Computers in Industry*, 61(9):852–862.

Liao, C.-N. and Kao, H.-P. (2011). An integrated fuzzy topsis and mcgp approach to supplier selection in supply chain management. *Expert Systems with Applications*, 38(9):10803–10811.

Liberty, E., Lang, K., and Shmakov, K. (2016). Stratified sampling meets machine learning. In *International conference on machine learning*, pages 2320–2329. PMLR.

Liou, J. J., Chang, M.-H., Lo, H.-W., and Hsu, M.-H. (2021). Application of an mcdm model with data mining techniques for green supplier evaluation and selection. *Applied Soft Computing*, 109:107534.

Luan, J., Yao, Z., Zhao, F., and Song, X. (2019). A novel method to solve supplier selection problem: Hybrid algorithm of genetic algorithm and ant colony optimization. *Mathematics and Computers in Simulation*, 156:294–309.

Mafakheri, F., Breton, M., and Ghoniem, A. (2011). Supplier selection-order allocation: A two-stage multiple criteria dynamic programming approach. *International Journal of Production Economics*, 132(1):52–57.

Majstorovic, V., Stojadinovic, S., Lalic, B., and Marjanovic, U. (2020). Erp in industry 4.0 context. In *IFIP International Conference on Advances in Production Management Systems*, pages 287–294. Springer.

Manerba, D., Mansini, R., and Perboli, G. (2018). The capacitated supplier selection problem with total quantity discount policy and activation costs under uncertainty. *International journal of production economics*, 198:119–132.

Memari, A., Dargi, A., Jokar, M. R. A., Ahmad, R., and Rahim, A. R. A. (2019). Sustainable supplier selection: A multi-criteria intuitionistic fuzzy topsis method. *Journal of manufacturing systems*, 50:9–24.

Mirkouei, A., Haapala, K. R., et al. (2014). Integration of machine learning and mathematical programming methods into the biomass feedstock supplier selection process. In *Proceedings of the 24th International Conference on Flexible Automation and Intelligent Manufacturing*, pages 20–23. DEStech Publications, Inc.

Mohammed, R., Rawashdeh, J., and Abdullah, M. (2020). Machine learning with oversampling and undersampling techniques: overview study and experimental results. In *2020 11th international conference on information and communication systems (ICICS)*, pages 243–248. IEEE.

Mondal, K. C., Nandy, B. D., and Baidya, A. (2020). Fact-based expert system for supplier selection with erp data. *Algorithms in Machine Learning Paradigms*, pages 43–55.

MordorIntelligence (2024). France furniture market size share analysis - growth trends forecasts (2024 - 2029). https://www.mordorintelligence.com/industry-reports/france-furniture-market. Accessed June 11, 2024.

Mukherjee, K. (2017). Supplier selection: An mcda-based approach. 88. Springer.

Naqvi, M. A. and Amin, S. H. (2021). Supplier selection and order allocation: a literature review. *Journal of Data, Information and Management*, 3(2):125–139.

Nepal, B. and Yadav, O. P. (2015). Bayesian belief network-based framework for sourcing risk analysis during supplier selection. *International Journal of Production Research*, 53(20):6114–6135.

Okanga, B. and Groenewald, D. (2019). Optimising enterprise resource planning system to leverage a firm's absorptive and adaptive capabilities. *South African Journal of Information Management*, 21(1):1–15.

Olaoye, F. and Potter, K. (2024). The power of data-driven decision making: Effective leaders leverage data to identify areas of strength and weakness within their schools.

Oprasto, R. R. (2023). Decision support system for selecting the best raw material supplier using simple multi attribute rating method technique. *Jurnal Ilmiah Computer Science*, 2(1):10–18.

Oracle (2024). Fusion ai for oracle financials. https://www.oracle.com/erp/ai-financials/. Accessed February 29, 2024.

Pamucar, D., Torkayesh, A. E., and Biswas, S. (2023). Supplier selection in healthcare supply chain management during the covid-19 pandemic: a novel fuzzy rough decision-making approach. *Annals of Operations Research*, 328(1):977–1019.

Park, S., Ok, C., and Ha, C. (2018). A stochastic simulation-based holistic evaluation approach with dea for vendor selection. *Computers & Operations Research*, 100:368–378.

Parkouhi, S. V. and Ghadikolaei, A. S. (2017). A resilience approach for supplier selection: Using fuzzy analytic network process and grey vikor techniques. *Journal of Cleaner Production*, 161:431–451.

Parmar, A., Katariya, R., and Patel, V. (2019). A review on random forest: An ensemble classifier. In *International conference on intelligent data communication technologies and internet of things (ICICI) 2018*, pages 758–763. Springer.

Pazhani, S., Ventura, J. A., and Mendoza, A. (2016). A serial inventory system with supplier selection and order quantity allocation considering transportation costs. *Applied Mathematical Modelling*, 40(1):612–634.

Pekša, J. and Grabis, J. (2018). Integration of decision-making components in erp systems. In *Proceedings of the 20th International Conference on Enterprise Information Systems*, volume 1, pages 183–189.

Rao, M. S., Rao, V. K., et al. (2018). Supplier selection and order allocation in supply chain. *Materials Today: Proceedings*, 5(5):12161–12173.

Resende, C. H., Geraldes, C. A., and Junior, F. R. L. (2021). Decision models for supplier selection in industry 4.0 era: A systematic literature review. *Procedia Manufacturing*, 55:492–499.

Sadeghieh, A., Dehghanbaghi, M., Dabbaghi, A., and Barak, S. (2012). A genetic algorithm based grey goal programming (g3) approach for parts supplier evaluation and selection. *International Journal of Production Research*, 50(16):4612–4630.

Sahoo, R., Pasayat, A. K., Bhowmick, B., Fernandes, K., and Tiwari, M. K. (2022). A hybrid ensemble learning-based prediction model to minimise delay in air cargo transport using bagging and stacking. *International Journal of Production Research*, 60(2):644–660.

SAP (2024a). Sap analytics cloud. https://www.sap.com/france/products/technology-platform/cloud-analytics.html. Accessed February 29, 2024.

SAP (2024b). Sap s/4hana cloud public edition. https://www.sap.com/france/products/erp/s4hana.html. Accessed February 29, 2024.

Saputro, T. E., Figueira, G., and Almada-Lobo, B. (2022). A comprehensive framework and literature review of supplier selection under different purchasing strategies. *Computers & Industrial Engineering*, 167:108010.

Seger, C. (2018). An investigation of categorical variable encoding techniques in machine learning: binary versus one-hot and feature hashing.

Shahid, S. (2020). *Predicting Delays In Delivery Process Using Machine Learning-Based Approach*. PhD thesis, Purdue University Graduate School.

Singh, R. K., Modgil, S., and Acharya, P. (2019). Assessment of supply chain flexibility using system dynamics modeling. *Global Journal of Flexible Systems Management*, 20:39–63.

Statista (2024a). Furniture - france. https://www.statista.com/outlook/cmo/furniture/france. Accessed June 11, 2024.

Statista (2024b). Furniture - worldwide. https://www.statista.com/outlook/cmo/furniture/worldwide. Accessed February 29, 2024.

Steinberg, F., Burggräf, P., Wagner, J., Heinbach, B., Saßmannshausen, T., and Brintrup, A. (2023). A novel machine learning model for predicting late supplier deliveries of low-volume-high-variety products with application in a german machinery industry. *Supply Chain Analytics*, 1:100003.

Stević, Ž., Tanackov, I., Vasiljević, M., and Rikalović, A. (2017). Supplier evaluation criteria: Ahp rough approach. In *XVII International Scientific Conference on Industrial Systems*, pages 298–303.

Sutharssan, T., Stoyanov, S., Bailey, C., and Yin, C. (2015). Prognostic and health management for engineering systems: a review of the data-driven approach and algorithms. *The Journal of engineering*, 2015(7):215–222.

Taherdoost, H. and Brard, A. (2019). Analyzing the process of supplier selection criteria and methods. *Procedia Manufacturing*, 32:1024–1034.

Tavana, M., Fallahpour, A., Di Caprio, D., and Santos-Arteaga, F. J. (2016). A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection. *Expert Systems with Applications*, 61:129–144.

Thanaraksakul, W. and Phruksaphanrat, B. (2009). Supplier evaluation framework based on balanced scorecard with integrated corporate social responsibility perspective. In *Proceedings of the International MultiConference of Engineers and Computer Scientists*, volume 2, pages 18–20.

Timonen, H. and Vuori, J. (2018). Visibility of work: how digitalization changes the workplace. In *Proceedings of the 51st Hawai'i International Conference on System Sciences, Hilton Waikoloa Willage, Big Island, January 2–6, 2018*. Hawai'i International Conference on System Sciences.

Tirkolaee, E. B., Mardani, A., Dashtian, Z., Soltani, M., and Weber, G.-W. (2020). A novel hybrid method using fuzzy decision making and multi-objective programming for sustainable-reliable supplier selection in two-echelon supply chain design. *Journal of cleaner production*, 250:119517.

Torabi, S., Baghersad, M., and Mansouri, S. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation research part e: logistics and transportation review*, 79:22–48.

Trivedi, A., Chauhan, A., Singh, S. P., and Kaur, H. (2017). A multi-objective integer linear program to integrate supplier selection and order allocation with market demand in a supply chain. *International Journal of Procurement Management*, 10(3):335–359.

Türk, S., Özcan, E., and John, R. (2017). Multi-objective optimisation in inventory planning with supplier selection. *Expert Systems with Applications*, 78:51–63.

Wani, D., Singh, R., Khanapuri, V. B., and Tiwari, M. K. (2022). Delay prediction to mitigate e-commerce supplier disruptions using voting mechanism. *IFAC-PapersOnLine*, 55(10):731–736.

Wong, T.-T. and Yeh, P.-Y. (2019). Reliable accuracy estimates from k-fold cross validation. *IEEE Transactions on Knowledge and Data Engineering*, 32(8):1586–1594.

Xia, W. and Wu, Z. (2007). Supplier selection with multiple criteria in volume discount environments. *Omega*, 35(5):494–504.

Xu, H., Liu, X., and Huang, H. (2023). Information sharing and order allocation rule in dual-sourcing. *Omega*, 114:102741.

Yathiraju, N. (2022). Investigating the use of an artificial intelligence model in an erp cloud-based system. *International Journal of Electrical, Electronics and Computers*, 7(2):1–26.

Zaghdoudi, M. A., Hajri-Gabouj, S., Varnier, C., Zerhouni, N., and Ghezail, F. (2022). Predictive analysis methodology for industrial systems: Application in supplier delays prediction. In *2022 IEEE Information Technologies & Smart Industrial Systems (ITSIS)*, pages 1–6. IEEE.

Zhao, K. and Yu, X. (2011). A case based reasoning approach on supplier selection in petroleum enterprises. *Expert Systems with Applications*, 38(6):6839–6847.

Zhao, L., Qi, W., and Zhu, M. (2021). A study of supplier selection method based on svm for weighting expert evaluation. *Discrete Dynamics in Nature and Society*, 2021:1–11.

Zheng, G., Kong, L., and Brintrup, A. (2023). Federated machine learning for privacy preserving, collective supply chain risk prediction. *International Journal of Production Research*, 61(23):8115–8132.