Taylor & Francis
Taylor & Francis Group

Production & Manufacturing Research
An Open Access Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tpmr20

A continuous training approach for risk informed supplier selection and order allocation

Matteo Gabellini, Stephen Mak, Stefan Schoepf, Alexandra Brintrup & Alberto Regattieri

To cite this article: Matteo Gabellini, Stephen Mak, Stefan Schoepf, Alexandra Brintrup & Alberto Regattieri (2025) A continuous training approach for risk informed supplier selection and order allocation, Production & Manufacturing Research, 13:1, 2447035, DOI: 10.1080/21693277.2024.2447035

To link to this article: https://doi.org/10.1080/21693277.2024.2447035

Published online: 27 Dec 2024.

PRODUCTION & MANUFACTURING RESEARCH
2025, VOL. 13, NO. 1, 2447035
https://doi.org/10.1080/21693277.2024.2447035

A continuous training approach for risk informed supplier selection and order allocation

Matteo Gabellini[a], Stephen Mak[b], Stefan Schoepf[b], Alexandra Brintrup[b,c] and Alberto Regattieri[a]

[a]Department of Industrial Engineering, University of Bologna, Bologna, Italy; [b]Institute for Manufacturing, University of Cambridge, Cambridge, UK; [c]Data-Centric Engineering, The Alan Turing Institute, The British Library, London, UK

ABSTRACT
Supplier selection and order allocation, a longstanding challenge in supply chain management, has recently begun incorporating risk minimization alongside cost, reflecting growing interest in supply chain resilience and risk mitigation. In response, hybrid frameworks leveraging artificial intelligence and machine learning have emerged. However, current methods often lack mechanisms to update decisions over time and typically rely solely on demand forecasts. To address these gaps, this study introduces a new hybrid approach that integrates machine learning–based predictions of supplier delivery delays into a linear programming model for multiperiod supplier selection and order allocation. Additionally, the proposed method evaluates a continuous training strategy, wherein predictions and decisions are refreshed as new data become available. Empirical evidence from an automotive case study demonstrates that this approach reduces prediction errors and total costs more effectively than models without continuous training, albeit with increased order allocation instability.

ARTICLE HISTORY
Received 10 March 2024
Accepted 20 December 2024

KEYWORDS
Supplier selection; order allocation; machine learning; continuous training; supply chain risk management

1. Introduction

The Supplier Selection and Order Allocation (SSOA) problem has long captivated the attention of researchers in the field of supply chain management (Aissaoui et al., 2007; Aouadni et al., 2019). This problem is crucial because it involves two strategic decisions – selecting suppliers and allocating orders – that significantly influence a company's operational performance (Di Pasquale et al., 2020). In its multiperiod formulation, SSOA requires determining the optimal suppliers for specific components and subsequently allocating orders across multiple periods to maximize a given objective function.

Historically, research on SSOA has primarily focused on minimizing costs. This emphasis is well-founded, as material procurement accounts for over 80% of expenditures in manufacturing sectors (Jayaraman et al., 1999). However, as global supply chains have grown more complex, the need to mitigate risks in these systems

CONTACT Matteo Gabellini matteo.gabellini5@unibo.it Department of Industrial Engineering, University of Bologna, Viale del risorgimento 4, Bologna 61121, Italy

has become increasingly critical. Modern supply chains are vulnerable to disruptions and deviations, making risk management a central concern (Heckmann et al., 2015).

In response to these challenges, recent developments in artificial intelligence (AI) have offered new avenues for enhancing supply chain resilience. Machine learning (ML) and deep learning (DL) techniques are recognized for their potential to improve the accuracy of risk predictions, thereby playing a key role in mitigating supply chain vulnerabilities (Kassa et al., 2023). Nevertheless, it is important to recognize that not all AI models possess the decision-making capabilities required to address complex SSOA problems effectively. While supervised ML models excel at predicting future events, they are often limited in their ability to optimize decisions (Pournader et al., 2021). As a result, there is a growing consensus that hybrid frameworks integrating mathematical optimization and predictive ML models offer a more comprehensive solution (Baryannis et al., 2019).

Building on this insight, hybrid frameworks that combine ML with optimization techniques have been increasingly employed in the multiperiod SSOA context. These approaches enable proactive risk prediction and allow for dynamic supplier selection and order allocation based on these predictions (Cavalcante et al., 2019; Islam et al., 2021, 2022, 2024; Jafari-Raddani et al., 2023; Liu et al., 2023). Despite these advances, several critical aspects remain unexplored.

One such area is the role of supply chain learning in improving decision-making over time. The continuous acquisition and integration of new knowledge – referred to as continuous training in the AI community – has emerged as a promising avenue but remains underexplored in the context of supply chain management (Silvestre et al., 2023; Kreuzberger et al., 2023). Although the concept of updating data in multiperiod systems is not new, it has never been applied within the SSOA framework as evidenced by existing literature. The novelty of this study thus lies in the introduction of such an approach specifically for the SSOA problem. Additionally, this study is the first to empirically investigate the benefits of a continuous training mechanism in a real-world case study within the automotive sector, comparing its effectiveness against static approaches.

Another gap lies in the scope of predictions used in existing hybrid frameworks. Most studies have focused primarily on demand-related risks, overlooking other critical risks, such as supplier delivery delays, which are highly relevant in real-world scenarios (Niemi et al., 2020). The study by Cavalcante et al. (2019) is one of the few that considers supplier delivery delays within a hybrid SSOA framework. However, their approach models delivery delays using a binary classification system (risk/no risk), which fails to estimate the extent of delays. Additionally, their rule-based mechanism for solving the SSOA problem lacks the flexibility to incorporate standard supply chain constraints, such as supplier capacity limits, which could be better addressed using linear programming. Moreover, the absence of a continuous training mechanism in their approach limits the model's ability to adapt and improve over time. Given these gaps, this study proposes several key contributions:

- We introduce a hybrid approach that combines an ML-based prediction model for supplier delivery delays (formulated as a regression problem) with a linear programming model to solve the multiperiod SSOA problem.

- We develop a continuous training system that periodically updates the predictive model by integrating new data, thereby enhancing its accuracy over time.
- We provide empirical evidence of the effectiveness of the continuous learning approach through a real-world case study in the automotive sector, demonstrating the advantages of this dynamic approach over static methods.

The paper is structured as follows: Section 2 provides a comprehensive review of the relevant literature on the multiperiod SSOA problem. Section 3 describes the proposed methodology, detailing the constituent modules and the experimental design used to assess the performance of the approach against alternative benchmarks. Section 4 presents the results of these experiments, while Section 5 discusses the findings. Lastly, Section 6 offers conclusions.

2. Literature review

Various approaches have been employed to address risks in the multiperiod SSOA problem. One fundamental approach involves formulating mathematical models, typically in the form of linear programming, where risk parameters are expressed as deterministic rates, percentages, or numerical values.

For example, studies by Jolai et al. (2011) and Son & Van Hop (2021) represent risks deterministically using rates or percentages. Jolai et al. (2011) model supplier quality risk as the expected defect rate of purchased components, while Son & Van Hop (2021) quantify delivery delays and quality risks as percentages of on-time deliveries and product rejection rates, respectively. Similarly, Hamdan & Cheaitou (2017) and Hamdan et al. (2023) represent supplier disruption risk using the number of available suppliers per period.

In some cases, more complex risk aggregation techniques have been applied. Arabsheybani et al. (2018) integrate supplier delivery delays, costs, social risks, and quality risks into a single risk score using Failure Mode and Effect Analysis (FMEA). A similar approach has been adopted by Li et al. (2021) and Kaur & Prakash Singh (2021), who use the Best Worst Method (BWM) to calculate a consolidated risk number that encapsulates various supplier risks, including financial, production, cooperative, and service risks. Additionally, Almasi et al. (2021) model supplier cost risk using a single risk value.

Although these deterministic approaches allow for risk consideration in the multiperiod SSOA problem, they assume that precise risk values are known in advance, which is often unrealistic. To address this limitation, stochastic formulations have been proposed, introducing probabilistic scenarios to capture the uncertainty inherent in supply chains.

Sawik (2011) presented a stochastic model that considers local disruption, delivery delay, and quality risks, with scenario-dependent probabilities for disruptions and delays. Sawik (2013) extended this approach by differentiating between local and global supplier disruptions, and Sawik (2018) further developed this model by introducing stochastic delivery delay risks. Similarly, S. Hosseini et al. (2019) integrated stochastic local disruption and capacity risks, while Z. S. Hosseini et al. (2022) extended this to include stochastic demand and disruption risks. Babbar & Amin (2018) also addressed stochastic supplier cost and demand risks alongside deterministic quality and delivery risks.

While these stochastic models offer more realistic representations of uncertainties, they are often limited by the assumption of stationary risk distributions (Besbes et al., 2015). This assumption can be problematic when risks exhibit non-stationary behavior or temporal autocorrelation, which are common in real-world supply chains. To overcome this, predictive models have been introduced to dynamically forecast risks, which are then incorporated into optimization models to solve the multiperiod SSOA problem.

Predictive models have been integrated with prescriptive optimization models to address risks like demand (Islam et al., 2021; Islam et al., 2022; Liaqait et al., 2022; Jafari-Raddani et al., 2023; Islam et al., 2024) and supplier costs (Liu et al., 2023). Cavalcante et al. (2019) took a significant step by predicting supplier delivery delays within a hybrid SSOA framework. However, the approach proposed by Cavalcante et al. (2019) employs a binary classification model and relies on a rule-based decision system, which limits the precision and flexibility needed to handle more complex supply chain scenarios.

Despite these advancements, two critical gaps remain unaddressed. First, while demand risks have been extensively studied in hybrid SSOA frameworks, there has been limited exploration of supplier delivery delay risks, especially when formulated as a regression problem to predict the actual extent of delays. Second, none of the existing approaches incorporate continuous training mechanisms, which are essential for updating predictive models over time as new data becomes available (Kreuzberger et al., 2023). Continuous training allows models to adapt and improve, thereby enhancing decision-making in dynamic environments.

Table 1 provides a summary of the main studies investigating the multiperiod SSOA problem. Based on the identified gaps, this study seeks to extend the literature by proposing a novel approach that integrates supplier delivery delay predictions formulated as a regression problem into a Mixed-Integer Linear Programming (MILP) model. Additionally, we introduce a continuous training mechanism that periodically retrains the predictive model, enabling it to adapt to new supply chain information and improve predictive accuracy over time.

Table 1 clearly demonstrates that this study is the first to address supplier delivery delay risks in a hybrid SSOA framework using regression-based predictions, while also considering the impact of continuous training on model performance. By addressing these gaps, we aim to provide a more comprehensive solution for the multiperiod SSOA problem in complex supply chain environments.

3. Materials and methods

In this section, we first provide a qualitative overview of the problem to be solved. Subsequently, we present an overview of the proposed approach for addressing the problem. We then delve into a detailed examination of its constituent components. Finally, we outline the research methodology employed to empirically evaluate the proposed approach's performance compared to other benchmarks.

Table 1. Literature review summary.

Article	Products		Prescriptive approach	Predicted risks	Prediction type	Continuous training mechanism
	Single	Multiple				
Jolai et al. (2011)		X	MOMILP	-	-	-
Hamdan & Cheaitou (2017)	X		BOMILP	-	-	-
Arabsheybani et al. (2018)		X	MOMILP	-	-	-
Son & Van Hop (2021)		X	MILP	-	-	-
Li et al. (2021)		X	MOMILP	-	-	-
Kaur & Prakash Singh (2021)		X	MILP	-	-	-
Almasi et al. (2021)		X	MOMILP	-	-	-
Hamdan et al. (2023)	X		BOMILP	-	-	-
Sawik (2011)		X	SMILP	-	-	-
Sawik (2013)		X	SMILP	-	-	-
Sawik (2018)		X	SMOMILP	-	-	-
Babbar & Amin (2018)		X	SMILP	-	-	-
Z. S. Hosseini et al. (2019)	X		SBOMILP	-	-	-
Z. S. Hosseini et al. (2022)		X	SMILP	-	-	-
Islam et al. (2021)		X	MOMILP	D	R	-
Liaqait et al. (2022)		X	MOMILP	D	R	-
Islam et al. (2022)		X	MOMILP	D	R	-
Jafari-Raddani et al. (2023)		X	MOMILP	D	R	-
Islam et al. (2024)		X	MOMILP	D	R	-
Liu et al. (2023)		X	MOMILP	SC	R	-
Cavalcante et al. (2019)	X		RB	SDD	C	-
PROPOSED	**X**		**MILP**	**SDD**	**R**	**X**

MILP: Mixed Integer Linear Programming, BOMILP: Bi-Objective Mixed Integer Linear Programming, MOMILP: Multi-Objective Mixed Integer Linear Programming, SMILP: Stochastic Mixed Integer Linear Programming, SBOMILP: Stochastich Bi Objective Mixed Integer Linear Programming, SMOMILP: Stochastic Multi-Objective Mixed Integer Linear Programming, RB: Rule Based; SDD: Supplier Delivery Delay risk, SC: Supplier Cost, D: Demand risk, C: Classification, R: Regression.

3.1. Problem statement

In the multiperiod SSOA problem, decision-makers are tasked with identifying the optimal supplier or group of suppliers from which to order one or multiple components. Additionally, they must allocate the ordered quantities for each component among the selected suppliers over time to minimize a specified objective function.

Effectively solving this problem requires the ability to predict the potential future performance of suppliers accurately. Moreover, the capacity to update predictive models is essential to generate reliable forecasts in a continuously evolving environment.

This paper addresses the multiperiod SSOA for a single component that can be sourced from two suppliers. The future demand for the component is assumed to be known and fixed for a specific period due to planning activities. When assigning orders to suppliers, the objective is to minimize purchasing costs and costs associated with supplier non-punctual delivery. Late deliveries can result in stockout costs, while early deliveries can lead to holding costs. Supplier capacity must also be taken into account when allocating orders.

3.2. Framework of the proposed approach

This study proposes an integrated approach encompassing three distinct building blocks to effectively address the multiperiod SSOA problem outlined in Section 3.1 These building blocks include a predictive module, a prescriptive module, and a continuous training module. Figure 1 illustrates the proposed approach.

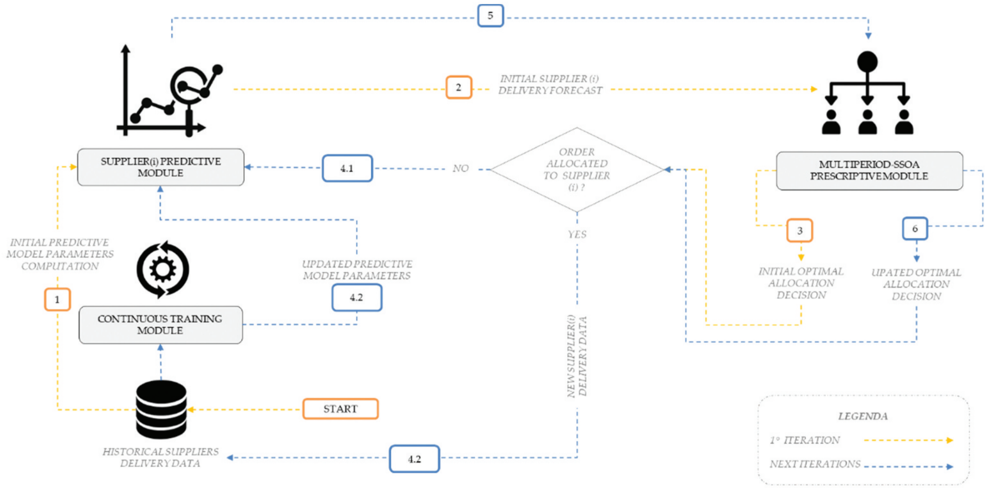

Figure 1. Proposed approach.

According to Figure 1, historical data on supplier deliveries are used to support the initial learning phase of the predictive module (step 1). Following this, the predictive module generates forecasts for the future performance of supplier deliveries, which are then used as input for the prescriptive module (step 2). In the prescriptive module, the multiperiod SSOA problem is addressed to produce optimal decisions regarding supplier selection and order allocation for future periods (step 3). These decisions lead to new orders being placed with either a subset or all of the suppliers. For those suppliers receiving orders, new data on delivery performance is collected as orders are fulfilled, and updated parameters for the predictive models are recalculated in the continuous training module (step 4.2). Conversely, if no orders are placed with a particular supplier, no data is collected and the predictive model parameters are not updated (step 4.1). With the updated predictive models, the predictive module then generates new forecasts for future orders (step 5). These forecasts are processed again by the prescriptive module, which provides revised decisions for the future periods of the SSOA problem (step 6). Steps 4.1, 4.2, 5, and 6 are repeated as time progresses.

3.2.1. Prescriptive module

A MILP model is proposed to formulate the prescriptive module. The model is constructed based on several key assumptions, outlined as follows:

- The demand for the components to be allocated among suppliers is predetermined and constant for the designated future period. These assumptions align with the typical rolling horizon production strategy, where demand is assumed to be fixed over a specific future horizon (Sahin et al., 2013).
- The unit purchasing cost varies among suppliers, and the total purchasing cost escalates linearly with the quantity ordered without any quantity discounts.

- The unit costs associated with untimely deliveries differ depending on whether the delivery is early or late. These costs are contingent on the components and remain consistent across suppliers. Additionally, the overall cost attributed to untimely deliveries increases linearly with the quantity delivered untimely and the amount of the delay/advance.
- The risk of untimely delivery from the supplier has been identified as the most significant risk among supply risks. Consequently, other risks, such as supplier quality risks, have not been considered, as their impact is deemed negligible. This assumption is in line with the empirical findings of Dias et al. (2020).
- Geopolitical and transportation risks are not explicitly modeled; however, their effects are implicitly considered in future forecasts related to supply risks. This is because the predictive models are trained using historical data on supplier delivery punctuality, which already reflects these risks.

In accordance with these assumptions, the principal sets, parameters, decision variables, constraints, and components constituting the objective function to be minimized are enumerated below:

3.2.1.1. Sets.

- I = {1, . . ., i, . . ., M}: set of suppliers
- p = {1, . . ., t, . . .,T}: set of time period

3.2.1.2. Parameters.

- C_i^{period} maximum period capacity of supplier i
- Q_i^{period}: minimum order quantity from supplier i
- $c_i^{purchasing}$: unitary purchasing cost of supplier i
- c^{delay}: unitary cost related to the delivery in late of a components
- $c^{advance}$: unitary cost related to the delivery in advance of a components
- d_t: demand of the component that need to be ordered for day t
- $f_{itt'}^{delay}$: Amount of days of delays predicted from the *predictive module* updated at day t' for the amount of components ordered from supplier i for day t
- $f_{itt'}^{advance}$: Amount of days of advance predicted from the *predictive module* updated at day t' for the amount of components ordered from supplier i for day t

3.2.1.3. Decision variables.

- $Y_{itt'}$: Amount of quantity ordered from supplier i for day t based on forecast updated at day t'

3.2.1.4. Objective function.

$$Min \sum_{t'=0}^{T} \sum_{t'+1 \geq t > t'}^{T} \sum_{i=1}^{M} Y_{itt'} \left(c_i^{purchasing} + c^{delay} f_{itt'}^{delay} + c^{advance} f_{itt'}^{advance} \right) \quad (1)$$

In Equation (1), the objective function is thus to minimize the sum of purchasing costs and costs related to non-punctual delivery of suppliers. According to the objective function, the suppliers selected at each time step are thus those that allow for minimizing both the purchasing and the non-punctual delivery costs.

3.2.1.5. Constraints.

$$\sum_{t>t'}^{T} Y_{itt'} \leq \mathrm{C}_{\mathrm{i}}^{\mathrm{period}} - \sum_{t<t'}^{T} Y_{itt'} \quad i, \quad t' \tag{2}$$

$$Y_{itt'} \geq \mathrm{Q}_{\mathrm{i}}^{\mathrm{period}} \quad i, \quad t', \quad t \tag{3}$$

$$\sum_{i=1}^{M} Y_{itt'} = d_t \quad t, \quad t' \tag{4}$$

$$\sum_{t>t'}^{T} \sum_{i=1}^{M} Y_{it} = \sum_{t>t'}^{T} d_t \quad t, \quad t' \tag{5}$$

$$Y_{itt'} \geq 0, \quad i, \quad t, \quad t' \tag{6}$$

Equations (2) are devised to ensure that the maximum period capacity offered by each supplier remains within acceptable limits. Equations (3) guarantee that orders dispatched to suppliers surpass the minimum order quantity stipulated for each supplier. Equations (4) and (5) ensure the fulfillment of both daily and period demand for the component. Finally, Equations (6) mandate that orders dispatched to each supplier during each time period must exceed zero.

3.2.2. Predictive module

The aim of the predictive module is to provide the prescriptive module, forecasts about the value assumed by the parameters $f_{itt'}^{delay}$ and $f_{itt'}^{advance}$. These parameters represent respectively the predicted number of days in delay or in advance with which a specific component will be delivered from supplier i respect to the planned delivery date t based on forecast updated at day t'.

Although different options could have been adopted to build the predictive module, a ML model called Catboost was proposed for the predictive module. CatBoost is a non-linear gradient-boosting machine learning model that builds a series of decision trees sequentially, with each tree attempting to correct the errors made by the previous ones (Dorogush et al., 2018).

The decision to utilize CatBoost for the predictive module was made for several reasons. Firstly, while linear models are typically quicker to train (Hastie & Pregibon, 2017), non-linear machine learning models such as CatBoost excel at capturing complex relationships and patterns, particularly in large datasets (Mahmoudi, 2018; Strang et al., 2018). Secondly, gradient-boosting models offer higher explainability compared to non-linear black box models like neural networks or support vector machines (Burkart & Huber, 2021). Lastly, among gradient boosting algorithms, CatBoost, despite requiring longer training times than LightGBM, has demonstrated superior predictive performance when applied to tabular data (Dorogush et al., 2018). Given the complexity of the relationships in the dataset and the availability of ample tabular training data, CatBoost was deemed the most suitable choice for the predictive module.

In particular, in this study, i different CatBoost models, one for each supplier, have been adopted to compose the *predictive module*. The same strategy has been indeed adopted in Cavalcante et al. (2019), leading to good predictive results.

For each CatBoost model, the information related to the year, month, day of the month, and day of the week related to the delivery date has been adopted as independent variables to predict the amount of delay or advance related to the specific delivery.

The output $f_{itt'}$ produced by each Catboost model contained in the predictive module thus consists of a real number representing the number of days of delays if positive, or the number of days of advance if negative with which a supplier i is supposed to deliver a specific component for a delivery date t. These forecasts have been thus adopted to generate the values of the parameters $f_{itt'}^{delay}$ and $f_{itt'}^{advance}$ according to Figure 2.

In summary, the predictive module thus consists of multiple CatBoost models, with one model for each supplier. Each CatBoost model predicts the number of days a specific supplier will deliver an order either ahead of schedule or delayed. These predictions are based on the historical relationship learned from past delivery records between the supplier's punctuality and the temporal features of the delivery date, including the year, month, day of the month, and day of the week.

3.2.3. Continuous training mechanisms

The continuous training mechanism developed in this study addresses the need for regularly updating machine learning models as new data becomes available, ensuring that predictions remain accurate and pertinent over time. This is particularly crucial in dynamic environments such as supply chain management, where supplier performance can exhibit significant variability across multiple periods.

In the context of the multiperiod SSOA problem, the continuous training mechanism functions as follows: after each supplier completes an order, new data on delivery performance is collected. This data is subsequently used to retrain the predictive module, which is responsible for forecasting future supplier delivery delays. Specifically, this study employs the full retraining of the CatBoost model associated with each supplier whenever new performance data is acquired. The updated model then generates revised predictions, which are integrated into the prescriptive module to refine supplier selection and order allocation decisions for subsequent periods.

The decision to implement full retraining, as opposed to incremental model updates, is grounded in the practicalities of our specific application. Although various techniques exist to incrementally update machine learning models without full retraining, such methods often introduce additional complexity and require a deep understanding of the model's internal mechanics, potentially leading to increased implementation costs.

T	0	1	2	3	4	….	T
f_{it}	-3	4	0	2	-1	…	6
f_{it}^{delay}	0	4	0	2	0	…	6
$f_{it}^{advance}$	3	0	0	0	1	…	0

Figure 2. Construction of forecasting parameters.

Moreover, incremental learning approaches can be vulnerable to model degradation if not meticulously managed, particularly when dealing with non-stationary data.

In this study, the computational cost associated with retraining the CatBoost model is manageable, making full retraining a straightforward and reliable choice. This approach minimizes the need for specialized knowledge in model management and avoids potential risks linked to incremental updates. By fully retraining the model, we ensure that the most recent data is effectively incorporated, allowing the model to consistently reflect the latest supplier behavior. This method is particularly well-suited to scenarios such as ours, where the frequency of new data acquisition is moderate, and the computational infrastructure supports regular retraining without significant strain on resources.

In summary, the continuous training mechanism proposed in this study is specifically tailored to maintain accurate predictions by leveraging full retraining of the predictive model. This approach not only ensures that the model remains aligned with the most recent supplier performance data but also offers a practical and accessible solution for managing supplier risks in multiperiod SSOA problems.

3.3. Research methodology

This section presents the research methodology employed to empirically investigate the performance of the proposed approach compared to other benchmarks. Specifically, a mixed research approach involving case study research and experimental design has been adopted. Section 3.3.1 outlines the case study and the associated collected data, while Section 3.3.2 delineates the experimental design.

3.3.1. Case study data collection

A real case study within the automotive sector has been chosen to assess the efficacy of the proposed approach. The automotive industry was selected due to its significant economic impact. Moreover, the widespread adoption of multiple sourcing as a risk management strategy in this sector underscores the importance of optimal decision-making in multiperiod SSOA. Specifically, the study focuses on 34 different components for which a dual sourcing strategy was implemented between 1 January 2021, and 31 December 2023. Table 2 provides a summary of the key data associated with the components under consideration. In particular, for each component, the number of purchasing orders sent to suppliers, the mean and the standard deviation of the demand related to each component and the mean and the standard deviation of the delivery performance of suppliers are reported. Moreover, the holding and the shortage cost related respectively to early or late delivery have been expressed as a percentage of the purchasing cost, while the period capacity of suppliers has been expressed as a percentage of the demand.

3.3.2. Experimental design

Utilizing the data acquired from the case study outlined in Section 3.3.1, an experimental framework was devised to thoroughly evaluate the effectiveness of the proposed approach in contrast to other benchmarks. Section 3.2.1.1 delineates the benchmarks against which the proposed approach was assessed. Subsequently, Section 3.2.1.2 enumerates the metrics chosen for comparative analysis. Finally,

Table 2. Case study data.

Part ID	Mean demand [pcs]	Std dev demand	N Orders	Mean delivery delay S1 [days]	Mean delivery delay S2 [days]	Std dev Delivery delay S1	Std dev delivery delay S2	Overall capacity S1 [%]	Overall capacity S2 [%]	Holding Cost [%]	Shortage Cost [%]	Purch. cost S1 [euro]	Purch. cost S2 [euro]
1	464,5	384,3	137	−4,5	10,4	46,8	40,9	14,6%	85,9%	136,5%	3,8%	3342,4	3465,8
2	350,0	220,4	57	0,5	5,2	43,2	45,1	35,5%	88,7%	88,8%	194,8%	3421,9	3443,5
3	280,8	92,9	123	8,6	10,5	20,0	16,4	83,8%	53,3%	49,4%	8,0%	2669,5	2636,4
4	749,8	70,4	57	0,9	0,5	43,6	19,6	13,8%	87,5%	29,9%	131,8%	2219,7	2189,9
5	365,1	206,4	123	17,5	−8,9	36,6	40,7	83,8%	77,9%	49,4%	189,0%	4290,1	4215,2
6	577,9	405,0	123	10,9	4,0	26,4	40,6	98,8%	34,3%	51,5%	197,5%	3342,4	3465,8
7	729,3	18,9	123	19,0	25,1	25,1	36,2	83,8%	50,9%	153,8%	8,0%	1949,9	1966,0
8	399,9	89,4	123	12,9	−0,3	31,2	24,6	78,7%	83,3%	162,5%	48,6%	3694,2	3782,8
9	286,6	113,9	123	−0,5	2,7	35,3	41,5	98,8%	28,1%	153,8%	8,0%	1949,9	1960,1
10	331,4	277,9	123	−2,9	9,1	42,9	24,6	98,8%	65,0%	19,4%	3,8%	3342,4	3465,8
11	362,2	271,0	57	−5,8	8,6	39,3	23,0	35,5%	94,9%	162,5%	197,5%	3421,9	3443,5
12	510,3	77,6	57	7,4	5,1	26,7	40,2	76,2%	63,8%	19,4%	131,8%	2219,7	2189,9
13	599,8	111,7	123	1,7	1,9	38,5	28,2	98,8%	92,5%	49,4%	197,5%	327,6	321,8
14	281,0	92,3	123	−0,7	−2,6	18,6	19,2	14,6%	85,4%	134,2%	3,8%	3342,4	3359,9
15	690,0	20,7	57	8,2	−0,1	40,3	34,1	35,5%	67,0%	98,4%	178,3%	629,4	632,1
16	633,4	76,9	137	1,9	10,6	39,5	44,2	14,6%	88,0%	136,5%	3,8%	3342,4	3465,8
17	523,0	86,6	123	16,6	12,6	19,7	44,7	35,5%	71,2%	153,8%	121,5%	788,0	774,2
18	255,4	119,7	123	12,7	−5,4	19,3	23,5	98,8%	66,4%	153,8%	8,0%	1949,9	1960,1
19	399,9	89,1	123	9,7	−11,7	42,3	26,1	5,0%	98,4%	136,5%	3,8%	3342,4	3465,8
20	237,2	75,2	123	14,6	20,6	30,6	38,6	78,7%	21,5%	162,5%	131,8%	3694,2	3782,8
22	367,7	204,0	57	−8,9	3,3	34,4	21,1	35,5%	82,6%	98,4%	74,1%	2219,7	2230,5
22	862,8	122,6	57	−4,5	10,4	20,1	43,7	49,2%	66,1%	98,4%	93,0%	1949,9	1918,9
23	516,9	465,3	57	−5,2	5,0	38,6	23,6	5,0%	96,5%	153,8%	8,0%	2669,5	2636,4
24	752,7	44,1	123	−2,0	8,2	35,6	41,5	13,8%	93,0%	69,1%	8,0%	422,1	427,0
25	367,1	205,1	57	18,8	10,4	38,7	40,8	35,5%	94,9%	88,8%	3,8%	3421,9	3443,5
26	566,3	42,8	57	15,1	15,4	15,8	25,1	35,5%	70,2%	162,5%	197,5%	3421,9	3443,5
27	326,4	155,1	123	−2,5	23,6	15,3	31,1	14,6%	99,8%	136,5%	3,8%	3342,4	3490,9
28	281,3	92,6	137	0,5	16,7	22,2	26,6	14,6%	89,0%	141,6%	3,8%	3416,2	3542,3
29	457,1	286,3	123	16,6	16,0	20,7	37,0	83,8%	19,0%	49,4%	189,0%	4666,9	4778,9
30	407,0	304,0	57	17,0	18,5	27,3	39,8	35,5%	87,5%	162,5%	197,5%	788,0	792,9
31	776,8	206,2	123	−2,6	−2,6	34,6	38,4	78,7%	85,8%	162,5%	48,6%	3694,2	3782,8
32	484,6	227,1	123	−5,3	4,2	43,4	24,7	14,6%	95,7%	98,4%	3,8%	2669,5	2788,2
33	658,8	88,4	57	20,3	19,0	25,9	41,1	35,5%	95,4%	141,6%	121,5%	4742,9	4949,0
34	635,7	262,3	57	−5,2	−7,0	24,5	37,1	35,5%	91,7%	88,8%	74,1%	2219,7	2230,5

Section 3.3.2.3 elucidates the experimental configurations employed for each evaluation.

3.3.2.1. Investigated benchmarks. Two distinct benchmark approaches have been employed to evaluate the efficacy of the proposed approach: the Horacle approach and the Static approach.

In the Horacle approach, future values of the parameters f_{it}^{delay} and $f_{it}^{advance}$ are presumed to be precisely known. Consequently, decisions derived from this approach represent the optimal allocation of orders to suppliers, with the objective function's value serving as a lower bound for other methodologies.

On the other hand, the Static approach serves as a comparative benchmark to assess the benefits of the continuous training mechanism implemented in the predictive module. Unlike the proposed approach, the Static approach does not incorporate a continuous training mechanism. Here, the forecast related to the supplier delivery performance is not updated, and thus, the initial decisions regarding order allocation to suppliers for the entire planning period remain unchanged, regardless of any new delivery punctuality data collected subsequently.

3.3.2.2. Evaluation metrics. Three distinct groups of metrics have been utilized to assess the proposed approach's performance compared to the benchmarks outlined in Section 3.2.1.1.

First, the difference in the predictive accuracy reported by the proposed approach and by the Static approach in estimating the number of days of delay or advance with which suppliers will deliver components was evaluated. This assessment was conducted using Mean Absolute Error (MAE), and the Root Mean Squared Error (RMSE), calculated according to the following equations:

$$\Delta_{(proposed,static)}^{MAE} = \frac{MAE_{proposed} - MAE_{static}}{MAE_{static}} \tag{7}$$

$$\Delta_{(proposed,static)}^{RMSE} = \frac{RMSE_{proposed} - RMSE_{static}}{RMSE_{static}} \tag{8}$$

Where the MAE and the RMSE have computed according to the following equations:

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |Y_t - \hat{Y}_t| \tag{9}$$

$$RMSE = \frac{1}{N}\sqrt{\sum_{t=1}^{N} (Y_t - \hat{Y}_t)^2} \tag{10}$$

Here, Y_t is the true historical value of the delivery delay or advance recorded at time t for a specific component, $\hat{Y}_t$ is the value predicted, and N is number of time periods considered in the test set.

Furthermore, six additional custom metrics were designed to represent respectively the cost difference reported from the proposed approach against the cost reported by the Static and by the cost reported by the Horacle approach:

$$\Delta^{PURCHASING\ COST}_{(proposed,horacle)} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{M}\left(Y^{proposed}_{it} c^{purchasing}_{i} - Y^{horacle}_{it} c^{purchasing}_{i}\right)}{\sum_{t=1}^{T}\sum_{i=1}^{M} Y^{horacle}_{it} c^{purchasing}_{i}} \tag{11}$$

$$\Delta^{DELIVERY\ COST}_{(proposed,horacle)} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{M}\left(Y^{proposed}_{it} - Y^{horacle}_{it}\right)\left(c^{delay} true^{delay}_{it} + c^{advance} true^{advance}_{it}\right)}{\sum_{t=1}^{T}\sum_{i=1}^{M} Y^{horacle}_{it}\left(c^{delay} true^{delay}_{it} + c^{advance} true^{advance}_{it}\right)} \tag{12}$$

$$\Delta^{OVERALL\ COST}_{(proposed,horacle)} = \Delta^{PURCHASING\ COST}_{(proposed,horacle)} + \Delta^{DELIVERY\ COST}_{(proposed,horacle)} \tag{13}$$

$$\Delta^{PURCHASING\ COST}_{(proposed,static)} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{M}\left(Y^{proposed}_{it} c^{purchasing}_{i} - Y^{static}_{it} c^{purchasing}_{i}\right)}{\sum_{t=1}^{T}\sum_{i=1}^{M} Y^{static}_{it} c^{purchasing}_{i}} \tag{14}$$

$$\Delta^{DELIVERY\ COST}_{(proposed,static)} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{M}\left(Y^{proposed}_{it} - Y^{static}_{it}\right)\left(c^{delay} true^{delay}_{it} + c^{advance} true^{advance}_{it}\right)}{\sum_{t=1}^{T}\sum_{i=1}^{M} Y^{static}_{it}\left(c^{delay} true^{delay}_{it} + c^{advance} true^{advance}_{it}\right)} \tag{15}$$

$$\Delta^{OVERALL\ COST}_{(proposed,static)} = \Delta^{PURCHASING\ COST}_{(proposed,static)} + \Delta^{DELIVERY\ COST}_{(proposed,static)} \tag{16}$$

Here, $Y^{proposed}_{it}$ represent the optimal quantity to allocate to a specific supplier i for a specific period t according to the proposed approach, while Y^{static}_{it} and $Y^{horacle}_{it}$ respectively represent the optimal quantity identified using the Static and the Horacle approach. The parameters $true^{delay}_{it}$ and $true^{advance}_{it}$ represent instead the true delivery punctuality reported by supplier i in period t. These values can be higher or lower than the predicted values reported in the parameters $f^{delay}_{itt'}$ and $f^{advance}_{itt'}$. Lastly, c^{delay}, $c^{advance}$, $c^{purchasing}$ respectively represent the unitary shortage cost related to a late delivery, the unitary holding cost related to an advanced delivery and the unitary purchasing cost.

Following these definitions $\Delta^{PURCHASINGCOST}_{(proposed,horacle)}$, $\Delta^{DELIVERYCOST}_{(proposed,horacle)}$, $\Delta^{OVERALLCOST}_{(proposed,horacle)}$ thus respectively represent the difference between the purchasing cost, the delivery cost and the overall cost originated following the decision resulting from the proposed approach on the one hand, and the decisions instead originated following the Horacle approach on the other hand. In particular, the difference has been expressed as percentage of the cost reported from the Horacle approach. Similarly $\Delta^{PURCHASINGCOST}_{(proposed,static)}$, $\Delta^{DELIVERYCOST}_{(proposed,static)}$, $\Delta^{OVERALLCOST}_{(proposed,static)}$ express the difference between the cost originated from the proposed approach and from the Static approach with respect to the cost reported by the Static approach.

Finally, a third metric to monitor the Order Allocation Instability (OAI) produced by the proposed approach in each timestep t for each supplier i has been considered. Indeed, the allocation decision in the proposed approach can deviate from the initial one (i.e.

those adopted in the Static approach) every time new delivery performance data are gathered.

$$OAI_{it}^{approach} = \frac{Y_{it}^{static} - Y_{it}^{proposed}}{\sum_{t=1}^{T} Y_{it}^{static}} \tag{17}$$

Equation (17) thus allows to compute the difference between the quantity initially allocated to supplier i for a period t from the Static approach and the revised quantity instead proposed by the proposed approach for the same period. Moreover it allows to express this difference with respect to the overall quantity initially allocated to that supplier. For instance, a value of $OAI_{it}^{approach}$ equal to 30 for a supplier to which 100 units have been initially allocated in total indicates that the proposed approach leads to a revision of the quantity allocated to that supplier in the specific considered period of 30 additional units.

3.3.2.3. Experimental setup. The experimental setup remained consistent across all 34 components outlined in Section 3.3.1 Specifically, the historical data pertaining to the delivery performance reported by each supplier for the respective component was divided into two consecutive subsets, as illustrated in Figure 3.

The two subsets, referred to as the training set (comprising 80% of the historical data) and the test set (containing the remaining data), were utilized to achieve distinct objectives.

The training set facilitated the initial learning phase of the ML models constituting the predictive module. During this phase, the ML models learned the relationship between the selected features and the label to predict, namely the number of days between the planned delivery date and the actual delivery date. The hyperparameters utilized for the ML models are detailed in Table 3.

The test set, on the other hand, served a different purpose. It was used to simulate the decisions generated by the prescriptive module progressively, update the predictive module whenever new delivery data were acquired, and compute the values of the evaluation metrics across the entire period covered by the test set.

4. Results

The results obtained from the experiments outlined in Section 3.3.2 are presented in this section. First, the results related to the cost difference indicators and the predictive accuracy results are presented. Then, the results pertaining to the planning instability of the proposed approach are reported.

The boxplot shown in Figure 4 reports the mean values that the three monitored cost difference metrics (Δ *PURCHASING COST*, Δ *DELIVERY COST* and Δ*OVERALL COST*) assumed in the experiments related to the 34 investigated components.

As depicted in the chart, the mean difference observed between the approaches in terms of overall cost indicates a 69.3% increase with the proposed approach compared to the Horacle approach. However, there is a mean reduction of 34.0% in overall cost compared to the Static approach. Similarly, in terms of the mean difference in delivery cost, the proposed approach shows a 94.8 % increase compared to the Horacle approach

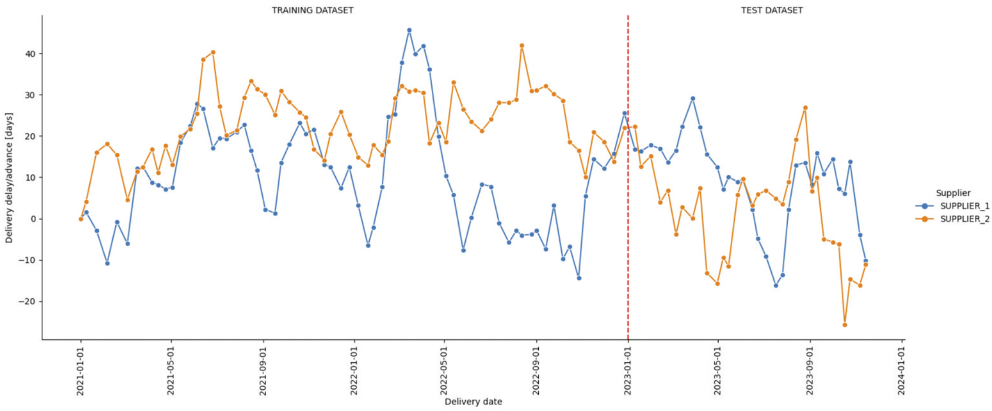

Figure 3. Temporal splitting of historical data related to the delivery performance reported by each supplier for a specific component.

Table 3. Hyperparameters of CatBoost model.

Hyperparameters	Hyperparameters value
Iterations	100
Learning rate	0.03
Loss function	RMSE
Deep of trees	6

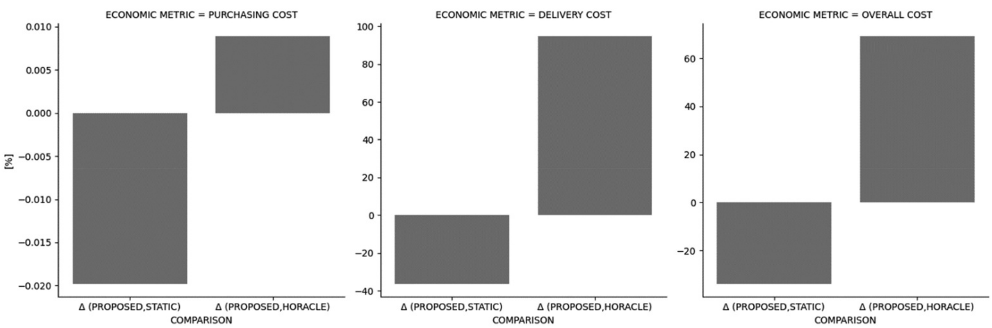

Figure 4. Mean cost difference reported between the proposed approach and the static approach and between the proposed approach and the Horacle approach.

and a 36.5 % decrease compared to the Static approach. No relevant mean difference is observed in terms of purchasing cost. The charts thus illustrate a consistent trend of the proposed approach in reducing overall costs compared to the Static approach, particularly by minimizing expenses associated with supplier delivery performance.

Results related to the predictive accuracy are instead reported in Figure 5. Here, the plot reports the mean accuracy error difference reported between the proposed approach and the Static approach computed according to Section 3.2.1.2.

The charts illustrate a mean tendency of the proposed approach to produce slightly better forecast when considering the error difference for one of the two suppliers

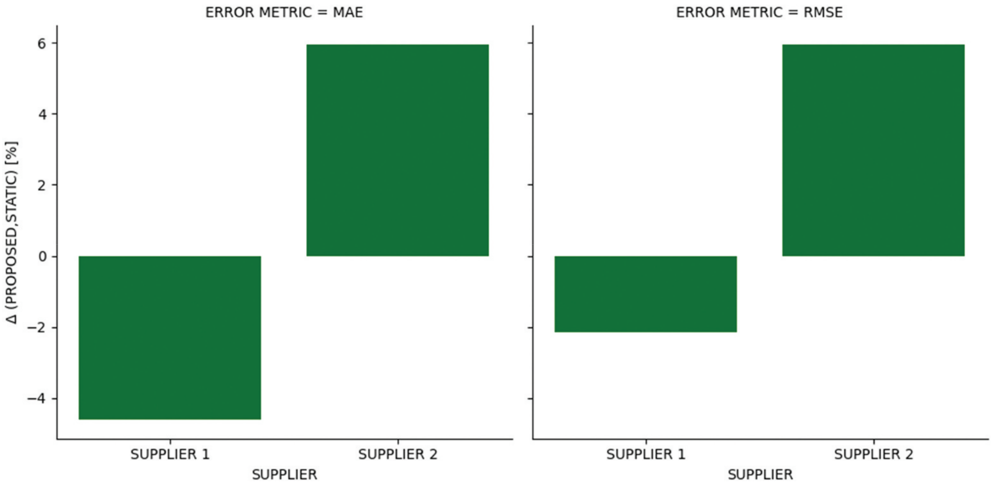

Figure 5. Mean accuracy error difference reported between the proposed approach and the static approach.

compared to the Static approach. Indeed, a mean reduction of prediction errors of 4.6 % and 2.2 % has been observed, respectively, in terms of MAE and RMSE for supplier 1. However, when considering the other supplier the adoption of the proposed approach reveals an asymmetric performance difference. Indeed, while the proposed approach leads to a median tendency for the first supplier to reduce the prediction error compared to the Static approach, this tendency is inverted for the second supplier, where an increase of the prediction error of 5.9 % in terms of MAE and RMSE is observed.

Lastly, the distribution of the values of the OAI metric reported over the planning period for each of the 34 investigated components is reported separately for each supplier in Figure 6.

The chart reveals that a significant variability of the mean value of the OAI metric can be observed between components and suppliers. Indeed, looking at component 31, the proposed approach led to a value of the OAI metric that for the first supplier can reach up to 18.8 %. However, for the same component the OAI only reach −3.1% for the second supplier. A complex pattern of the OAI metrics can thus be evinced from the case study.

However, considering the general mean tendency for both suppliers, a moderate value of the OAI metric can be observed. For the first supplier, the mean OAI indeed corresponds to 1.5 %, while a value of 0.03 % can be observed for the second supplier.

5. Discussions

The findings of our study thus underscore the benefits of adopting a continuous training mechanism, which aligns with existing literature across various domains that emphasize the advantages of continuous training systems (Peláez-Rodríguez et al., 2024). Concurrently, our results also shed light on a notable aspect: the presence of a certain degree of planning instability when decision-making relies on revised forecasts. This

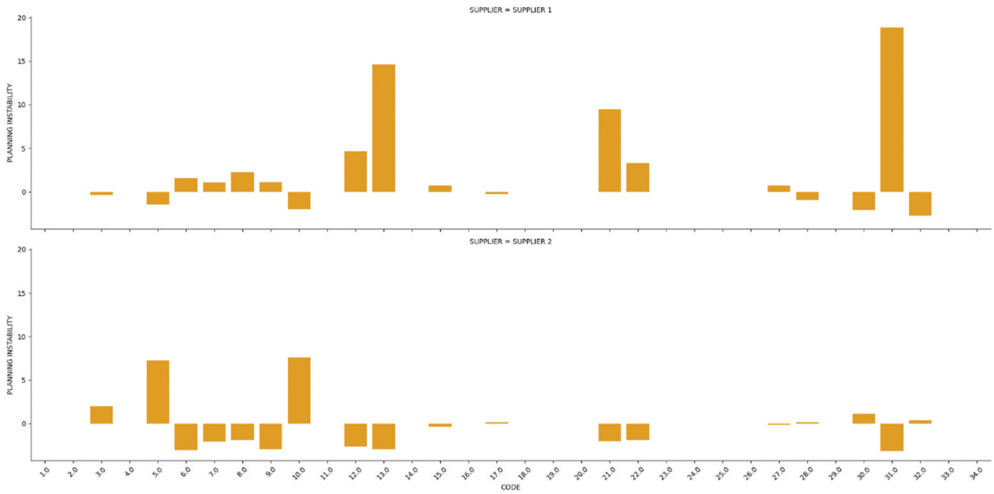

Figure 6. Mean values for the order allocation instability metric reported over the planning periods for each of the 34 components investigated in the case study.

echoes observations from broader studies focused on supply chain management, particularly those examining the challenges associated with rolling horizon planning models (Sahin et al., 2013).

These findings have significant practical implications. First, the observed increase in order instability highlights the necessity when solving the multiperiod SSOA problem to integrate the proposed approach with additional practices for its effective implementation in industrial settings. Key measures include establishing flexible contracts with suppliers to accommodate variability in order quantities and enhancing collaboration and communication with suppliers to better anticipate and respond to changes in order volumes. These measures are essential to mitigate the negative impacts of increased order instability, which, if not properly managed, can disrupt supplier production schedules and strain supplier relationships.

Secondly, it has to be noticed that while the adoption of continuous training mechanisms can improve economic performance, it also entails additional computational requirements and expertise. Therefore, the establishment of multidisciplinary teams with expertise in various domains is a prerequisite for the effective solution of the multiperiod SSOA problem. Specifically, machine learning experts are crucial for training, validating, and deploying machine learning models. Operations research skills are necessary for formulating and solving linear programming problems and integrating them with machine learning outputs. Data engineering proficiency in building and maintaining continuous data acquisition systems and software development competence for developing scalable and maintainable software systems are also indispensable. For this reason, the economic benefits reported in this study must be balanced with implementation and maintenance costs. These costs should include investments in high-performance computing resources, licensing fees for advanced software tools and frameworks, and expenses related to hiring and training specialized staff in machine learning, operations research, and data engineering. Moreover, the costs associated with integrating the new system into existing workflows should be considered. In conclusion, this consideration thus implies that to effectively solve the multiperiod SSOA problem in various industries or supply chain contexts, practitioners should begin with gathering relevant historical supplier data, ensuring data quality and completeness. Afterward, machine learning models to predict supplier performances should be built and integrated with linear programming optimization models. Following this, it is crucial to implement a system for continuous training and updating of the machine learning models using new data. A phased implementation in a controlled environment, coupled with extensive testing, is recommended and before full-scale deployment, it is essential to estimate implementation costs and compare them with the simulated costs in the proposed system. Finally, a robust training and change management process should be established to support the transition.

6. Conclusions

In response to the critical need for precise supplier selection and order allocation decisions in today's volatile supply chain landscape, this study addresses the imperative for a hybrid framework merging ML and optimization models to manage supply chain risks effectively. By leveraging ML models to predict supplier delivery delays in a regression format, our approach thus guarantees to proactively deal with risks of supplier nonpunctual deliveries. Indeed, predictions related to supplier delivery punctuality are provided as inputs to a MILP model, enabling the resolution of a single product multiperiod SSOA problem considering delivery delay risks. Moreover, a continuous training mechanism, which allows the retraining of ML predictive models every time new data are collected, has been introduced to deal with information accuracy risks (Tang & Nurmaya Musa, 2011). Indeed, as time evolves, new supplier delivery punctuality data are collected, and avoiding considering this additional data to formulate new predictions could lead to the risk of generating inaccurate information.

The performance of the proposed approach has been scrutinized through comparison with two alternative methodologies: a Static approach, which lacks a continuous training mechanism, and a Horacle approach, which assumes perfect foresight regarding supplier delivery performance. Three distinct sets of metrics have been employed to assess the efficacy of our approach. These metrics encompass the accuracy of predictions, the economic ramifications of allocation decisions, and the stability of order allocation plans, all evaluated within the context of a real-world case study within the automotive sector. In particular, this study focuses on 34 distinct components subject to a dual-sourcing strategy, providing a comprehensive and practical evaluation framework.

The results of our study reveal a consistent trend wherein the proposed approach, incorporating continual learning, achieves a reduction in prediction errors compared to the Static approach. Moreover, the heightened accuracy attained by our proposed method translates into a median substantial decrease of 34.0 % in the overall economic costs associated with allocation decisions, as compared to the Static approach. This cost reduction primarily stems from decreased expenses related to supplier delivery performance. Moreover, when compared to the lower bound represented by the Horacle approach the median overall cost increase has been observed to be 69.3 %. However, it is important to note that these benefits come with a trade-off: the proposed approach introduces a certain level of order allocation instability, which, depending on the supplier and component, can vary significantly with complex patterns.

The findings of this study suggest several managerial implications. A continuous training mechanism ensures that predictive models remain aligned with the most recent supplier performance data, empowering supply chain managers to dynamically adapt their decision-making processes in response to evolving supplier reliability. By leveraging the proposed framework, managers can proactively mitigate risks by reallocating orders to suppliers based on updated predictions, thereby enhancing supply chain resilience and ensuring operational continuity even in the face of unforeseen disruptions. However, the observed planning instability necessitates the adoption of complementary strategies to facilitate the practical implementation of such a dynamic framework. Flexible contracts with suppliers are essential to accommodate variability in order quantities, reducing the likelihood of supply chain bottlenecks. Strengthening communication with suppliers to anticipate changes in order volumes and fostering collaboration to address fluctuations in demand can also mitigate the adverse effects of order instability, such as production schedule disruptions and strained supplier relationships. In implementing the proposed approach, managers should consider that deploying such a system requires significant investment in multidisciplinary expertise and infrastructure. Machine learning experts are necessary for model training and validation, operations research specialists for formulating and solving optimization problems, data engineers for designing continuous data acquisition systems, and software developers for creating scalable and maintainable software platforms. Managers should evaluate the costs associated with implementing the proposed system, including investments in computing infrastructure, licensing fees for advanced tools, and the training of specialized personnel. These expenditures should be weighed against the demonstrated economic benefits to ensure a positive return on investment. A phased implementation approach is recommended, starting with controlled pilot projects to test and refine the system before scaling it across broader operations. This strategy reduces the risks associated with large-scale deployment and enables thorough testing of the system's effectiveness in real-world settings.

From a practical application perspective, the proposed approach is particularly applicable in industries characterized by complex and dynamic supply chains. In the automotive sector, as demonstrated in the proposed case study, the ability to dynamically adjust order quantities and supplier selection ensures continuity in production despite supply disruptions, mitigating risks of stockouts and production line halts while reducing economic losses. Similarly, electronics manufacturing, where supplier lead times are critical, can benefit from real-time updates to supplier delivery performance forecasts, enabling manufacturers to meet volatile demand cycles and avoid costly penalties or delays in product launches. The framework is also relevant for the energy and utility sectors, where managing supplier risks for power grids and renewable energy projects ensures timely delivery of critical components, reducing potential delays in infrastructure deployment. These applications demonstrate the versatility of the proposed approach across industries where supply chain risks and lead time variability pose significant operational challenges.

However, the obtained results must be interpreted within the context of several limitations. Firstly, the analysis focused solely on a single product multiperiod SSOA setting. Thus, the findings may not be directly applicable to multiproducts multiperiods settings. Additionally, supplier delivery delay has been assumed to be the most impactful risk source. Therefore, the results of the proposed approach should be considered generalizable to settings where similar assumptions hold. Furthermore, no exploration versus exploitation strategy of suppliers was incorporated in the prescriptive module for the multiperiod SSOA problem. Indeed, in the proposed approach, orders were allocated to suppliers based on their predicted future delivery delay profile at the time of decision-making. Consequently, if a specific supplier had the worst profile for a given date, the model might propose not to assign any orders to them for that date. However, avoiding orders to certain suppliers prevents the acquisition of new data, potentially leading to missed predictions and decision changes. Lastly, the study only examined a single case study, limiting the generalizability of the findings.

Considering these limitations, future research could expand the proposed approach to multiperiod multiproduct settings. This expansion would entail addressing the challenges associated with larger machine-learning models and exploring more computationally efficient strategies for the continuous training process. Additionally, future studies could focus on predicting multiple risks, such as quality (Chongwatpol, 2015; Gabellini, Calabrese, et al., 2023; Liu & Xiong, 2015), partial shipment (Banerjee et al., 2001; Dawande et al., 2006; Gabellini, Calabrese, Civolani, et al., 2024), and demand (Babai et al., 2022; Feizabadi, 2022; Gabellini et al., 2022), by employing univariate or multivariate models that leverage multiple data sources (Bodendorf et al., 2023; Gabellini, Civolani, et al., 2023, 2024; Gonçalves et al., 2021). Furthermore, nonlinear formulations that account for the interaction between ordered quantity and delivery performance could represent another promising area of development. Such efforts might involve integrating heuristic approaches with machine learning models to solve nonlinear MILP problems (Gabellini, Calabrese, Regattieri, et al., 2024; Lombardi et al., 2017). Furthermore, different risks may have varying levels of prediction accuracy, and acquiring new data may impact the prediction error differently for each risk. Therefore, balancing the benefit of data acquisition with its associated costs, such as order emission, would be crucial. Exploring supplier exploration versus exploitation strategies when considering different risks would present an intriguing research direction.

Moreover, investigating the tradeoff between planning instability costs and purchasing and delivery performance costs could provide valuable insights. Lastly, while the proposed approach allows for the generation of future risk predictions, future research could explore a stochastic optimization framework where scenarios are directly generated from stochastic forecasts. This approach would enable the consideration of non-deterministic predictions and offer a more robust solution to address uncertainties in supply chain management.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Alexandra Brintrup http://orcid.org/0000-0002-4189-2434

References

Aissaoui, N., Haouari, M., & Hassini, E. (2007). Supplier selection and order lot sizing modeling: A review. Computers and Operations Research, 34(12), 3516–3540. https://doi.org/10.1016/j.cor.2006.01.016

Almasi, M., Khoshfetrat, S., & Galankashi, M. R. (2021). Sustainable Supplier Selection and Order Allocation under Risk and Inflation Condition. IEEE Transactions on Engineering Management, 68(3), 823–837. https://doi.org/10.1109/TEM.2019.2903176

Aouadni, S., Aouadni, I., & Rebaï, A. (2019). A systematic review on supplier selection and order allocation problems. Journal of Industrial Engineering International, 15, 267–289. https://doi.org/10.1007/s40092-019-00334-y

Arabsheybani, A., Paydar, M. M., & Safaei, A. S. (2018). An integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection considering quantity discounts and supplier's risk. Journal of Cleaner Production, 190, 577–591. https://doi.org/10.1016/j.jclepro.2018.04.167

Babai, M. Z., Boylan, J. E., & Rostami-Tabar, B. (2022). Demand forecasting in supply chains: A review of aggregation and hierarchical approaches. *International Journal of Production Research*, *60*(1), 324–348. https://doi.org/10.1080/00207543.2021.2005268

Babbar, C., & Amin, S. H. (2018). A multi-objective mathematical model integrating environmental concerns for supplier selection and order allocation based on fuzzy QFD in beverages industry. Expert Systems with Applications, 92, 27–38. https://doi.org/10.1016/j.eswa.2017.09.041

Banerjee, S., Banerjee, A., Banerjee, A., Burton, J., & Bistline, W. (2001). Controlled partial shipments in two-echelon supply chain networks: A simulation study. *International Journal of Production Economics*, *71*(1–3), 91–100. https://doi.org/10.1016/S0925-5273(00)00108-0

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. In International Journal of Production Research (Vol. 57, Issue 7, pp. 2179–2202). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2018.1530476

Besbes, O., Gur, Y., & Zeevi, A. (2015). Non-stationary stochastic optimization. Operations Research, 63(5), 1227–1244. https://doi.org/10.1287/opre.2015.1408

Bodendorf, F., Sauter, M., & Franke, J. (2023). A mixed methods approach to analyze and predict supply disruptions by combining causal inference and deep learning. *International Journal of Production Economics*, *256*, 108708. https://doi.org/10.1016/j.ijpe.2022.108708

Burkart, N., & Huber, M. F. (2021). A survey on the explainability of supervised machine learning. *The Journal of Artificial Intelligence Research*, *70*, 245–317. https://doi.org/10.1613/jair.1.12228

Cavalcante, I. M., Frazzon, E. M., Forcellini, F. A., & 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. https://doi.org/10.1016/j.ijinfomgt.2019.03.004

Chongwatpol, J. (2015). Prognostic analysis of defects in manufacturing. *Industrial Management & Data Systems*, *115*(1), 64–87. https://doi.org/10.1108/IMDS-05-2014-0158

Dawande, M., Gavirneni, S., & Tayur, S. (2006). Effective heuristics for multiproduct partial shipment models. *Operations Research*, *54*(2), 337–352. https://doi.org/10.1287/opre.1050.0263

Dias, G. C., Hernandez, C. T., & de Oliveira, U. R. (2020). Supply chain risk management and risk ranking in the automotive industry. *Gestao e Producao*, *27*(1). https://doi.org/10.1590/0104-530X3800-20

Di Pasquale, V., Nenni, M. E., & Riemma, S. (2020). Order allocation in purchasing management: a review of state-of-the-art studies from a supply chain perspective. In International Journal of Production Research (Vol. 58, Issue 15, pp. 4741–4766). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2020.1751338

Dorogush, A. V., Ershov, V., & Gulin, A. (2018). *CatBoost: Gradient boosting with categorical features support*. http://arxiv.org/abs/1810.11363

Feizabadi, J. (2022). Machine learning demand forecasting and supply chain performance. *International Journal of Logistics: Research & Applications*, *25*(2), 119–142. https://doi.org/10.1080/13675567.2020.1803246

Gabellini, M., Calabrese, F., Civolani, L., Regattieri, A., & Galizia, F. G. (2023). *A predictive data-driven approach for supply chain quality risks in the automotive sector. Proceedings of the Summer School Francesco Turco*. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85193746650&partnerID=40&md5=c52a7125ed7e170e4791ac09d49067aa

Gabellini, M., Calabrese, F., Civolani, L., Regattieri, A., & Mora, C. (2024). A data-driven approach to predict supply chain risk due to suppliers' partial shipments. In S. G. Scholz, R. J. Howlett, & R. Setchi (Eds.), *Smart innovation, systems and technologies* (Vol. 377, pp. 227–237). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-981-99-8159-5_20

Gabellini, M., Calabrese, F., Regattieri, A., & Ferrari, E. (2022). *Multivariate multi-output LSTM for time series forecasting with intermittent demand patterns. Proceedings of the Summer School Francesco Turco*. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85176726507&partnerID=40&md5=57a91bccffa761dad0e449d27de71820

Gabellini, M., Calabrese, F., Regattieri, A., Loske, D., & Klumpp, M. (2024). A hybrid approach integrating genetic algorithm and machine learning to solve the order picking batch assignment problem considering learning and fatigue of pickers. *Computers & Industrial Engineering*, *191*, 110175. https://doi.org/10.1016/j.cie.2024.110175

Gabellini, M., Civolani, L., Calabrese, F., & Bortolini, M. (2024). A deep learning approach to predict supply chain delivery delay risk based on macroeconomic indicators: A case study in the automotive sector. *Applied Sciences (Switzerland)*, *14*(11), 4688. https://doi.org/10.3390/app14114688

Gabellini, M., Civolani, L., Regattieri, A., & Calabrese, F. (2023). A data model for predictive supply chain risk management. *Lecture Notes in Mechanical Engineering*, 365–372. https://doi.org/10.1007/978-3-031-34821-1_40

Gonçalves, J. N. C., Cortez, P., Carvalho, M. S., & Frazão, N. M. (2021). A multivariate approach for multi-step demand forecasting in assembly industries: Empirical evidence from an automotive supply chain. *Decision Support Systems*, *142*, 142. https://doi.org/10.1016/j.dss.2020.113452

Hamdan, S., & Cheaitou, A. (2017). Dynamic green supplier selection and order allocation with quantity discounts and varying supplier availability. Computers and Industrial Engineering, 110, 573–589. https://doi.org/10.1016/j.cie.2017.03.028

Hamdan, S., Cheaitou, A., Shikhli, A., & Alsyouf, I. (2023). Comprehensive quantity discount model for dynamic green supplier selection and order allocation. Computers and Operations Research, 160. https://doi.org/10.1016/j.cor.2023.106372

Hastie, T. J., & Pregibon, D. (2017). Generalized linear models. *Statistical Models in S*. https://doi.org/10.1201/9780203738535

Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk - Definition, measure and modeling. In Omega (United Kingdom) (Vol. 52, pp. 119–132). Elsevier Ltd. https://doi.org/10.1016/j.omega.2014.10.004

Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M. D., Barker, K., & Khaled, A. Al. (2019). Resilient supplier selection and optimal order allocation under disruption risks. International Journal of Production Economics, 213, 124–137. https://doi.org/10.1016/j.ijpe.2019.03.018

Hosseini, Z. S., Flapper, S. D., & Pirayesh, M. (2022). Sustainable supplier selection and order allocation under demand, supplier availability and supplier grading uncertainties. Computers and Industrial Engineering, 165. https://doi.org/10.1016/j.cie.2021.107811

Islam, S., Amin, S. H., & Wardley, L. J. (2021). Machine learning and optimization models for supplier selection and order allocation planning. International Journal of Production Economics, 242. https://doi.org/10.1016/j.ijpe.2021.108315

Islam, S., Amin, S. H., & Wardley, L. J. (2022). Supplier selection and order allocation planning using predictive analytics and multi-objective programming. Computers and Industrial Engineering, 174. https://doi.org/10.1016/j.cie.2022.108825

Islam, S., Amin, S. H., & 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. https://doi.org/10.1016/j.eswa.2023.121121

Jafari-Raddani, M. H., Asgarabad, H. C., Aghsami, A., & Jolai, F. (2023). A Hybrid Approach to Sustainable Supplier Selection and Order Allocation Considering Quality Policies and Demand Forecasting: A Real-Life Case Study. Process Integration and Optimization for Sustainability. https://doi.org/10.1007/s41660-023-00350-x

Jayaraman, V., Srivastava, R., & Benton, W. C. (1999). Supplier selection and order quantity allocation: A comprehensive model. Journal of Supply Chain Management, 35(1), 50–58. https://doi.org/10.1111/j.1745-493X.1999.tb00237.x

Jolai, F., Yazdian, S. A., Shahanaghi, K., & Azari Khojasteh, M. (2011). Integrating fuzzy TOPSIS and multi-period goal programming for purchasing multiple products from multiple suppliers. Journal of Purchasing and Supply Management, 17(1), 42–53. https://doi.org/10.1016/J.PURSUP.2010.06.004

Kassa, A., Kitaw, D., Stache, U., Beshah, B., & Degefu, G. (2023). Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research. Computers and Industrial Engineering, 186. https://doi.org/10.1016/j.cie.2023.109714

Kaur, H., & Prakash Singh, S. (2021). Multi-stage hybrid model for supplier selection and order allocation considering disruption risks and disruptive technologies. International Journal of Production Economics, 231. https://doi.org/10.1016/j.ijpe.2020.107830

Kreuzberger, D., Kuhl, N., & Hirschl, S. (2023). Machine Learning Operations (MLOps): Overview, Definition, and Architecture. IEEE Access, 11, 31866–31879. https://doi.org/10.1109/ACCESS.2023.3262138

Li, F., Wu, C. H., Zhou, L., Xu, G., Liu, Y., & Tsai, S. B. (2021). A model integrating environmental concerns and supply risks for dynamic sustainable supplier selection and order allocation. Soft Computing, 25(1), 535–549. https://doi.org/10.1007/s00500-020-05165-3

Liaqait, R. A., Warsi, S. S., Agha, M. H., Zahid, T., & Becker, T. (2022). A multi-criteria decision framework for sustainable supplier selection and order allocation using multi-objective optimization and fuzzy approach. *Engineering Optimization*, *54*(6), 928–948. https://doi.org/10.1080/0305215X.2021.1901898

Liu, C. H., & Xiong, W. (2015). Modelling and simulation of quality risk forecasting in a supply chain. *International Journal of Simulation Modelling*, *14*(2), 359–370. https://doi.org/10.2507/IJSIMM14(2)CO10

Liu, Y., Yang, C., Huang, K., Gui, W., & Hu, S. (2023). A Systematic Procurement Supply Chain Optimization Technique Based on Industrial Internet of Things and Application. IEEE Internet of Things Journal, 10(8), 7272–7292. https://doi.org/10.1109/JIOT.2022.3228736

Lombardi, M., Milano, M., & Bartolini, A. (2017). Empirical decision model learning. *Artificial Intelligence*, *244*, 343–367. https://doi.org/10.1016/j.artint.2016.01.005

Mahmoudi, M. R. (2018). On comparing two dependent linear and nonlinear regression models. *Journal of Testing and Evaluation*, *47*(1), 449–458. https://doi.org/10.1520/JTE20170461

Niemi, T., Hameri, A. P., Kolesnyk, P., & Appelqvist, P. (2020). What is the value of delivering on time? Journal of Advances in Management Research, 17(4), 473–503. https://doi.org/10.1108/JAMR-12-2019-0218

Peláez-Rodríguez, C., Torres-López, R., Pérez-Aracil, J., López-Laguna, N., Sánchez-Rodríguez, S., & Salcedo-Sanz, S. (2024). An explainable machine learning approach for hospital emergency department visits forecasting using continuous training and multi-model regression. *Computer Methods and Programs in Biomedicine*, *245*, 108033. https://doi.org/10.1016/j.cmpb.2024.108033

Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. International Journal of Production Economics, 241, 108250. https://doi.org/10.1016/j.ijpe.2021.108250

Sahin, F., Narayanan, A., & Robinson, E. P. (2013). Rolling horizon planning in supply chains: Review, implications and directions for future research. *International Journal of Production Research*, *51*(18), 5413–5436. https://doi.org/10.1080/00207543.2013.775523

Sawik, T. (2011). Selection of a dynamic supply portfolio in make-to-order environment withrisks. Computers and Operations Research, 38(4), 782–796. https://doi.org/10.1016/j.cor.2010.09.011

Sawik, T. (2013). Integrated selection of suppliers and scheduling of customer orders in the presence of supply chain disruption risks. International Journal of Production Research, 51 (23–24), 7006–7022. https://doi.org/10.1080/00207543.2013.852702

Sawik, T. (2018). Selection of a dynamic supply portfolio under delay and disruption risks. International Journal of Production Research, 56(1–2), 760–782. https://doi.org/10.1080/00207543.2017.1401238

Silvestre, B. S., Gong, Y., Bessant, J., & Blome, C. (2023). From supply chain learning to the learning supply chain: drivers, processes, complexity, trade-offs and challenges. International Journal of Operations & Production Management, 43(8), 1177–1194. https://doi.org/10.1108/IJOPM-04-2023-0318

Son, N. H., & Van Hop, N. (2021). A hybrid meta-heuristics approach for supplier selection and order allocation problem for supplying risks of recyclable raw materials. International Journal of Industrial Engineering Computations, 12(2), 177–190. https://doi.org/10.5267/j.ijiec.2020.12.001

Strang, B., van der Putten, P., van Rijn, J. N., & Hutter, F. (2018). Don't rule out simple models prematurely: A large scale benchmark comparing linear and non-linear classifiers in OpenML. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11191*, 303–315. https://doi.org/10.1007/978-3-030-01768-2_25

Tang, O., & Nurmaya Musa, S. (2011). Identifying risk issues and research advancements in supply chain risk management. *International Journal of Production Economics*, *133*(1), 25–34. https://doi.org/10.1016/j.ijpe.2010.06.013