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APPLICATION OF MULTI-CRITERIA OPTIMIZATION FOR FEATURE SELECTION IN MACHINE LEARNING BASED RISK CLASSIFICATION SUPPORTING SUPPLY CHAIN MANAGEMENT

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Purpose: The aim of this research is to develop a multi-criteria optimization method for supply chains operating under uncertain conditions. The study addresses the impact of supply chain disturbances (drifts) and proposes an AI-driven approach to enhance risk classification and stability.
Design/methodology/approach: The research employs multi-criteria optimization techniques, specifically the NSGA-II genetic algorithm, to optimize feature selection in supply chain risk classification. The methodology includes experiments on global and local optimization of supply chain links, analyzing classification accuracy under different levels of drift. Machine learning models, including deep learning (DNN, CNN), Random Forest, and SVM, are used to assess the effectiveness of the proposed method.
Findings: (mandatory) The study confirms that multi-criteria optimization improves supply chain stability and enhances the accuracy of drift classification models. The best feature selection strategies contributed to classification accuracy improvements, particularly in deep learning models, where performance gains of up to 2.5% were observed. The results demonstrate that both global and local optimization contribute to maintaining classification quality even under significant drift conditions.
Research limitations/implications: While the study provides strong evidence for the effectiveness of multi-criteria optimization, it does not explore real-time adaptation to evolving risks. Future research should focus on integrating reinforcement learning and real-time monitoring for adaptive optimization. Additionally, extreme drift conditions (above 70%) still challenge classification accuracy, suggesting the need for further improvements in feature selection methods.
Practical implications: The research has significant implications for supply chain management, enabling enterprises to improve risk detection and enhance resilience against supply chain disruptions. The proposed optimization approach can support automated decision-making systems in logistics, reducing operational risks and improving efficiency in dynamic environments.
Social implications: By enhancing supply chain stability, the research contributes to economic resilience, reducing the negative impact of supply chain disruptions on businesses and consumers. Improved risk classification methods can support sustainable supply chain strategies, minimizing delays and reducing waste.

Originality/value: This study introduces a novel application of multi-criteria optimization in supply chain risk classification, integrating feature selection with machine learning techniques. The findings provide valuable insights for researchers and practitioners in AI-driven supply chain management, offering new strategies for mitigating risk drift.
Keywords: Supply Chain Optimization, Multi-Criteria Decision Making, Feature Selection, Machine Learning, Supply Chain Risk Management.
Category of the paper: Research paper, Empirical study.

1. Introduction

The modern economy is primarily based on information systems. Industry 4.0 enables the use of IT resources for efficient enterprise management. This management applies not only to individual companies but also to the connections between various entities within the supply chain. Different economic conditions, crises, and pandemics cause disturbances (drifts) in the functioning of supply chains. Supply Chain Management (SCM) systems exist, offering flexibility and efficiency, but their effectiveness decreases in uncertain conditions (Darby et al., 2019, pp. 395-413). Contemporary supply chain management systems approach this issue statistically, assuming the efficient operation of all components. When disturbances, such as drifts, occur, the proper functioning of SCM systems is disrupted, leading to erroneous predictions (Wieland, 2021, pp. 58-73). Therefore, there is a need for an intelligent supply chain capable of responding to various disruptions. Artificial intelligence methods play a crucial role in addressing this challenge, supporting the processing of large volumes of data (Bozorgian et al., 2020, pp. 122-129).

As data volume increases, the phenomenon known as the curse of dimensionality arises. Various selection and extraction methods are used to reduce dimensionality (Remeseiro, Bolon-Canedo, 2019). Other feature selection techniques include filter and wrapper methods (Bommert et al., 2019), as well as statistical approaches such as ANOVA (Cai et al., 2017) and chi-square statistics (Liu et al., 2019, pp. 703-715). One of the most widely used methods in feature selection and extraction is Principal Component Analysis (PCA) and its various modifications. These modifications involve different factor rotation techniques, such as class centroid-based rotation (Topolski, 2020, pp. 734746) or rotation angle optimization using stochastic gradient methods (Topolski, 2020, pp. 35-44). Some selection methods are integrated directly into classifiers. Multi-criteria optimization, incorporating genetic algorithms such as NSGA-II or MAY, represents one such approach. Combining feature selection with a classifier enhances the adaptation of imbalanced data (Pölsterl et al., 2016, pp. 1-11, Deb et al., 2002). Additionally, studies have applied the NSGA-II algorithm to multi-criteria optimization tasks involving complex datasets (Grzyb et al., 2021, pp. 81-94).

This paper presents a method for multi-criteria optimization of supply chains under uncertainty. The subsequent sections include two experiments: one analyzing the entire supply chain and another focusing on individual links. The final section provides a summary.

The research aims to develop a multi-criteria optimization method for supply chains operating under uncertain conditions. The proposed method accounts for drifts caused by sudden changes in supply chain parameters. The study addresses two main research questions:

1. Can the stability of the entire supply chain be ensured using multi-criteria optimization?
2. Can individual links within the supply chain be stabilized using multi-criteria optimization?
3. How does the application of multi-criteria optimization affect the quality of supply chain drift risk classification using various machine learning methods?

In summary, modern supply chains must be resilient to uncertainties caused by economic fluctuations, crises, and external disruptions. Traditional SCM systems struggle with unexpected drifts, making adaptive and intelligent solutions essential. The integration of artificial intelligence and multi-criteria optimization methods, such as genetic algorithms and feature selection techniques, enhances the stability and efficiency of supply chains. This study contributes to the development of an optimization approach capable of mitigating risks associated with supply chain instability. The findings will help improve predictive accuracy and operational reliability in uncertain conditions.

2. Methods

2.1. Model

A genetic algorithm was applied to the multi-criteria optimization task. In 2002, Kalyanmoy Deb et al. (Deb et al., 2002, pp. 182-197) introduced the NSGA-II (Nondominated Sorting Genetic Algorithm) algorithm. Their work presented methods for sorting non-dominated solutions, estimating the proximity of adjacent solutions (determining whether two adjacent solutions are close to each other), and an operator for comparing individuals based on calculated congestion (Yusoff et al., 2011, pp. 3978-3983). Unlike other evolutionary algorithms used for multi-criteria optimization, NSGA-II provides a more desirable distribution of solutions and significantly better convergence to the optimal Pareto front (Wang et al., 2018, pp. 131-139).

The proposed method focuses on constructing a model that responds to sudden drifts in the supply chain. The successive states of the chain depend on their preceding states. The feature vector for a given link in the supply chain can be represented as a vector:

$$X_i = \left[x_1^{(i)}, x_2^{(i)}, \dots, x_n^{(i)}\right] \tag{1}$$

where: $x_n^{(i)}$ denotes the value of the feature *n* for the *i*-th link of the supply chain.

The cost for each feature can also be written in the vector:

$$X_i = \left[x_1^{(i)}, x_2^{(i)}, \dots, x_n^{(i)}\right] \quad (2)$$

where: $\alpha_n^{(i)}$ is the cost value for the feature of the nth link in the supply chain.

The cost associated with each feature is represented by the delivery t_i'. This delay is normalized to the range (0,1) using the min-max method.:

$$\alpha_i' = \frac{t_i' - t_{i,max}'}{t_{i,max}' - t_{i,max}'}, \quad (3)$$

where: $t_{i,max}'$ is the maximum delay value, $t_{i,min}'$ is the minimum delay value, *i* = 1, 2, …, *n* is the i-th link in the supply chain.

The cost per feature serves as a measure of delay, influenced by the delays from all upstream links in the chain. Therefore, for the k-th link out of n links in the supply chain, the cost is given by:

$$A_k = m_1(A_1) \oplus m_2(A_2) \oplus \dots \oplus m_k(A_k) = \frac{\sum_{A_1 \cap A_2 \cap \dots \cap A_k = A} m_1(A_1) \cdot m_2(A_2) \cdot \dots \cdot m_k(A_k')}{1 - \sum_{A_1 \cap A_2 \cap \dots \cap A_k \neq \emptyset} m_1(A_1) \cdot m_2(A_2) \cdot \dots \cdot m_k(A_k')} \quad (4)$$

where: $m_k(A_k)$ is the probability density distribution for vector (2).

The next step involves determining the crowding distance for various optimization solutions in the Γ Pareto front. This process can be outlined as follows:

Specify the number of solutions in the tested front $\mathcal{F}$ as *l*. For every solution $s = 1,2, \dots, l$, we determine the distance of crowding $\mathrm{d}_i = 0$.

1. For each criterion $m = 1,2, \dots, M$ sort the solutions from worst to best based on the objective function f_m.
2. For each criterion $m = 1,2, \dots, M$ set the value of the boundary solutions as infinity $\left(d_{l_1^m} = d_{l_1^l} = \infty\right)$, and for other solutions od $s = 2$ to $\mathrm{s} = (l - 1)$ assign a value:

$$d_{l_s^m} = d_{l_s^m} + \frac{f_m^{(I_{s+1}^m)} - f_m^{(I_{s-1}^m)}}{f_m^{max} - f_m^{min}}, \quad (5)$$

where:

I_s specifies the number of the*s*-tego solution in the ordered list of solutions,

I_1 and I_l denote the worst and best solutions, respectively (boundary solutions),

f_m^{max}, f_m^{min} denote the highest and the lowest value of the objective function in the entire population, respectively, in the context of the criterion m.

To enhance diversity, which may improve the efficiency of the individual selection process, the concept of a niche, known from the literature, was introduced (Fisher, Wegener, 2005, pp. 208-225). One method for maintaining diversity within a population is the application of the so-called niche (Fisher, Wegener, 2005, pp. 208-225; Oliveto et al., 2019, pp. 53-70). However, placing solutions in niches only marginally improves diversity, as solutions still tend to converge to specific points (Goldberg et al., 1987, pp. 41-49). This paper proposes a novel approach for defining the condition:

$$F_i^s = \frac{F_i \mu(r) d_{l_i^m}}{\sum_{k=1}^{\mu(r)} F_k' d_{l_k^m}}, \tag{6}$$

where:

$\mu(r)$ is the number for the rank of the solution of the Pareto front,

$d_{l_i^m}$ is the crowding distance described by the formula (5),

F_i is a fitness function which is a character:

$$F_i = \begin{cases} N - 0.5(\mu(r_i) - 1) & if\ i = 1 \\ N - \sum_{k=1}^{r_i - 1} \mu(k) - 0.5(\mu(r_i) - 1) & else \end{cases} \tag{7}$$

where: N is i = 1, 2, …, N ranking value.

After determining the crowding distance, defining niches, and filling the entire descendant population, the selection process is performed. The NSGA-II algorithm employs a modified tournament selection method. According to the algorithm's framework, each individual is first assigned two attributes: rank (indicating the front in which the individual is located) and crowding distance.

Once tournament pairs are drawn, all duels are conducted. In the first phase, the ranks of the individuals are compared. If the ranks differ, the individual with the lower rank (closer to the optimal front) is selected as the winner. In the event of a tie, where both individuals have the same rank, the crowding distances are compared. The individual with the higher crowding distance value is chosen as the winner.

Figure 1 illustrates the supply chain model. The proposed solution consists of six links in the chain: Provider, Raw Materials, Production, Storage, Transport, and Client. It is assumed that deliveries occur cyclically along the same routes. Such solutions are widely applied across various industries (Akkerman et al., 2010, pp. 863-904; Lee, Fu 2014, pp. 23-35).

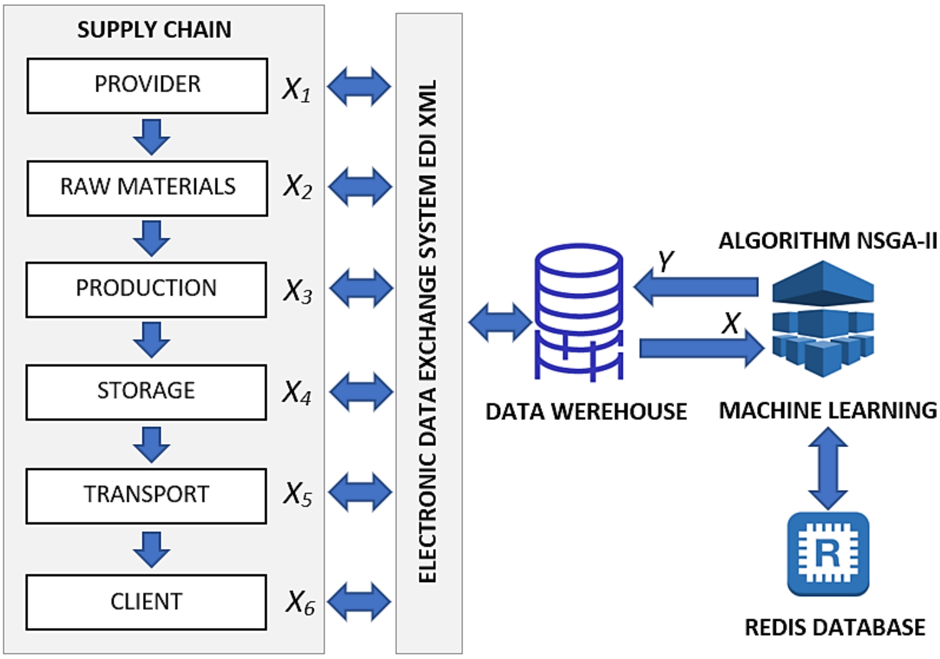

Figure 1. Diagram of the data drift prediction model in the supply chain.

Source: own work.

The diagram illustrates a supply chain optimization process integrating machine learning and the NSGA-II algorithm. The supply chain consists of six key stages: Provider, Raw Materials, Production, Storage, Transport, and Client**,** each represented by variables X1X_1X1 to X6X_6X6. These stages interact with an Electronic Data Exchange System (EDI XML)**,** enabling seamless data transfer.

Collected data is stored in a Data Warehouse, which feeds information (XXX) into a Machine Learning model**. The** NSGA-II optimization algorithm processes the data, producing optimized results (YYY). The system also utilizes a Redis database, supporting fast access to relevant information for improved decision-making. This framework enables real-time supply chain monitoring and optimization, leveraging AI-driven decision-making to enhance efficiency and resilience.

Each link in the management process utilizes different sets of features. To standardize information exchange, an XML-based EDI document processing system with binary mapping rules has been proposed (Chang-Su, Hoe-Kyung, 2012). To facilitate communication, all delivery process data is stored in a data warehouse. The proposed machine learning model retrieves data from the warehouse, after which the NSGA-II algorithm performs multi-criteria optimization, returning information on the supply chain status to each link. The supply chain state serves as the categorical dependent variable (Y), indicating whether and to what extent deliveries are correct. This enables the identification of disruptions, referred to as drifts, within any link of the chain. By employing this approach, rapid responses to changing conditions are possible. Since the feature cost is calculated, it is also feasible to determine which chain management variables have the greatest impact on a drift. The model continuously learns as new data is received and stored in a Redis database.

2.2. Computational Complexity of the NSGA-II Algorithm

The NSGA-II algorithm, a widely used multi-objective genetic algorithm, has the following primary components that impact its computational complexity:

1. The initial population of solutions is created randomly. This step has a complexity of *O(N)*, where *N* is the population size.
2. Each individual in the population needs to be evaluated to compute the fitness values for the objectives. For each individual, the time complexity for fitness evaluation is *O(T),* where *T* is the time required to evaluate a single individual. Hence, for the entire population, the complexity is *O(NT)*
3. One of the key steps in NSGA-II is non-dominated sorting to rank the population based on the Pareto front. This operation has a complexity of $O(N^2)$ in the worst case.
4. To maintain diversity in the population, NSGA-II calculates the crowding distance. This operation also has a complexity of $O(N^2)$ due to the need to sort the population for each objective.
5. The selection, crossover, and mutation operations have complexities that depend on the specifics of the genetic algorithm, but they are generally *O(N)* for each generation.

Thus, the overall complexity for each generation of the NSGA-II algorithm is $O(N^2)$, where *N* is the population size. For G generations, the total complexity becomes O(N2G).

Comparison with Machine Learning Models

To provide insights into the feasibility of large-scale implementation, I will compare the computational complexity and resource consumption of NSGA-II with that of commonly used machine learning models, such as Decision Trees, Support Vector Machines (SVM), and Neural Networks (specifically deep learning models).

1. Decision Trees: The time complexity of training a decision tree is *O(Nlog(N))*, where N is the number of training samples. This is significantly less complex than the $O(N^2)$ complexity of NSGA-II. However, decision trees are not suitable for multi-objective optimization, and their accuracy might be lower compared to more advanced models.
2. Support Vector Machines (SVM): Training an SVM typically has a complexity of $O(N^2)$ in the worst case for the standard quadratic programming approach. For large datasets, the complexity can increase, but with the use of kernel approximations, SVMs can be made more efficient. However, SVMs are not inherently designed for multi-objective optimization, unlike NSGA-II.
3. Neural Networks (Deep Learning): Training deep learning models, especially with large datasets, has a complexity of $O(ND^2)$, where *N* is the number of training samples and DDD is the number of parameters in the model. Deep learning models are highly resource-intensive, often requiring GPUs and considerable memory for training. However, they offer strong predictive capabilities, especially for complex tasks like supply chain risk classification.

Feasibility for Large-Scale Implementation

- While NSGA-II has a quadratic complexity per generation, it is still feasible for medium-scale applications. For large-scale implementations, especially in supply chain management with extensive datasets, the computational demand could become significant. This would require optimizing the NSGA-II algorithm or parallelizing the computation to handle larger populations or more generations efficiently.
- NSGA-II can be resource-intensive due to the need for multiple evaluations, non-dominated sorting, and crowding distance calculations. In contrast, simpler models like decision trees or SVMs may offer lower computational costs. However, the trade-off is that these models may not achieve the same accuracy, especially in the context of multi-objective optimization problems like supply chain risk classification.

3. Results

The research was conducted in Python using the "pymoo" library (Blank, Deb, 2020, pp. 89497-89509), which provides extensive adaptability for customizing the research environment. A two-criteria approach was applied to two optimization aspects: the cost of features and classification quality, considering delivery time and classification accuracy. Using the proposed method, features were selected for each classification task according to the corresponding links in the supply chain.

Due to the nature of optimization, which involves feature selection, the input vector consisted of a set of features chosen from a predefined pool within a given dataset. Binary coding was employed as the simplest method for encoding individuals, with the chromosome length corresponding to the number of features in the dataset. Each allele in the chromosome was assigned a value of 0 or 1, indicating the exclusion or selection of a particular feature. Based on these encoded individuals, specific features were selected from the dataset, and the values of predefined criteria were computed accordingly. The number of generations (iterations) in the genetic algorithm was set at 100, with a population size of 100 individuals per generation.

A 5-fold stratified cross-validation protocol was used due to the high-class imbalance. The BAC-score metric was applied to assess classification quality.

The datasets contained 10 classes representing varying levels of drift risk within the supply chain. Six datasets, representing a coherent supply chain, were used in the study, comprising 4000 real-world records (patterns) with varying numbers of features: supplier (34 features), raw material receipt (23 features), production (54 features), storage (49 features), transport (31 features), and customer (7 features).

Recognized risk classes:

1. Risk of delivery delays – arising from untimely deliveries and variability (e.g., average delivery time, delivery delay variance, on-time delivery rate, number of delayed deliveries).
2. Operational risk in warehousing – related to low storage efficiency and inventory turnover (e.g., warehouse efficiency, inventory level, inventory turnover).
3. Production failure risk – resulting from errors in production processes and raw material quality (e.g., production failure rate, average production time, raw material quality index).
4. Supply chain inflexibility risk – the inability of the supply chain to respond to market changes (e.g., supply chain flexibility, demand variability, drift index).
5. Logistical cost risk – arising from high transportation costs and inefficient deliveries (e.g., transportation cost per unit, shipment tracking system accuracy, real-time shipment tracking accuracy).
6. Order fulfillment error risk – related to long processing times and documentation mistakes (e.g., order fulfillment time, order processing time, number of document errors).
7. Financial and cost volatility risk – caused by fluctuations in raw material and product prices (e.g., raw material cost, average unit product cost, price fluctuation index, regional economic stability index).
8. IT system failure risk – related to disruptions in IT system operations (e.g., IT system efficiency, IT system failure frequency, EDI documentation compliance rate).
9. Demand forecasting error risk – caused by inaccurate demand predictions (e.g., demand forecasting error, demand price elasticity, regional economic stability index).
10. Quality risk in the final delivery phase – related to issues with packaging and communication (e.g., packaging quality index, feature cost, communication delay).

3.1. Results of experiment 1

Three experiments were conducted. In the first experiment, multi-criteria optimization was applied to the entire supply chain. Classification quality was assessed by separately analyzing the impact of feature cost and delivery time. To ensure comparability of results, delivery time was normalized using the min-max method within a range of 0 to 1. The results are presented as Pareto fronts in Figure 2, showcasing several different solutions. When the proprietary method for estimating feature costs was applied, the highest classification quality in terms of the BAC-score reached approximately 96%. When only delivery time was considered, the BAC-score quality peaked at around 94%. Feature cost was used to measure the drift associated with on-time delivery. Despite a relatively strong drift of up to 70%, classification quality remained stable at 94%. However, beyond a 70% drift, classification quality dropped significantly, reaching approximately 84% under conditions of extreme delivery time fluctuations. When evaluating the classification quality criterion alone, performance declined more rapidly, with the entire Pareto front performing about 2% worse compared to the feature cost criterion.

Below is a list of 40 variables that were ultimately selected for predicting changes in the supply chain and responding to these changes, based on the conducted research and obtained results. These variables cover various aspects of the supply chain, from delivery efficiency and production performance to communication quality between supply chain links:

1. Average delivery time – the average time required to complete a delivery from order placement.
2. Delivery delay variance – a measure of variability in delivery delays.
3. On-time delivery rate – the percentage of deliveries completed as scheduled.
4. Transportation cost per unit – the average transportation cost per shipment.
5. Number of delayed deliveries – the number of shipments exceeding the scheduled delivery time.
6. Percentage of delayed deliveries – the share of delayed shipments in the total deliveries.
7. Order fulfillment time – the time from order placement to order confirmation.
8. Warehouse efficiency – an indicator of warehouse operation performance.
9. Inventory level – the average stock level over a specified period.
10. Inventory turnover – the frequency of stock replacement in the warehouse.
11. Average production time – the time required to manufacture a single unit of a product.
12. Production failure rate – the number of downtimes or defects in the production process.
13. Raw material quality index – an evaluation of the quality of supplied raw materials.
14. Production capacity utilization rate – the degree to which available production resources are used.
15. Raw material cost – the average cost of acquiring materials used in production.
16. Supplier reliability – an assessment of the timeliness and quality of supplier deliveries.
17. Average supplier response time – the time elapsed from demand notification to order fulfillment by the supplier.
18. EDI documentation compliance rate – the percentage of correctly processed electronic documents.
19. Number of document errors – the number of errors in data exchange documentation.
20. IT system efficiency – a measure of the reliability of IT systems supporting the supply chain.
21. Order processing time – the average time required to process an order in the system.
22. Inter-link communication quality – an indicator of the effectiveness of information exchange between supply chain links.
23. Process automation level – the percentage of automated processes in the supply chain.
24. Shipment tracking system accuracy – a measure of the precision of tracking shipment status.

25. Number of operational incidents – the number of unexpected events affecting operational continuity.
26. Supply chain flexibility – the ability of the supply chain to adapt to changing market conditions.
27. Demand variability – a measure of fluctuations in customer demand for products.
28. Demand forecasting error – the deviation of demand forecasts from actual values.
29. Packaging quality index – an assessment of the efficiency of packaging processes.
30. Average unit product cost – the cost of producing a single unit of a product.
31. Employee turnover rate – an indicator of personnel changes in key supply chain departments.
32. Order confirmation waiting time – the average time required for order approval by the system.
33. IT system failure frequency – the number of incidents related to IT system unavailability.
34. Communication delay – the time required to transmit information between different supply chain links.
35. Feature cost (feature cost) – a measure of the impact of selected features on prediction accuracy and supply chain stability.
36. Drift index – an indicator of changes in supply chain operational data.
37. Real-time shipment tracking accuracy – a measure of the precision of the shipment monitoring system.
38. Demand price elasticity – the reaction of demand to product price changes.
39. Price fluctuation index – a measure of price variability in products or services within the supply chain.
40. Regional economic stability index – an indicator of macroeconomic factors affecting the supply chain.

Each of these variables was selected to capture key aspects of supply chain operations, enabling effective prediction of changes and rapid response to potential disruptions. In practice, they can be used both for real-time monitoring and for process optimization based on the results of advanced machine learning methods.

Ultimately, after optimization, Pareto charts were obtained for Experiment 1 – figure 2.

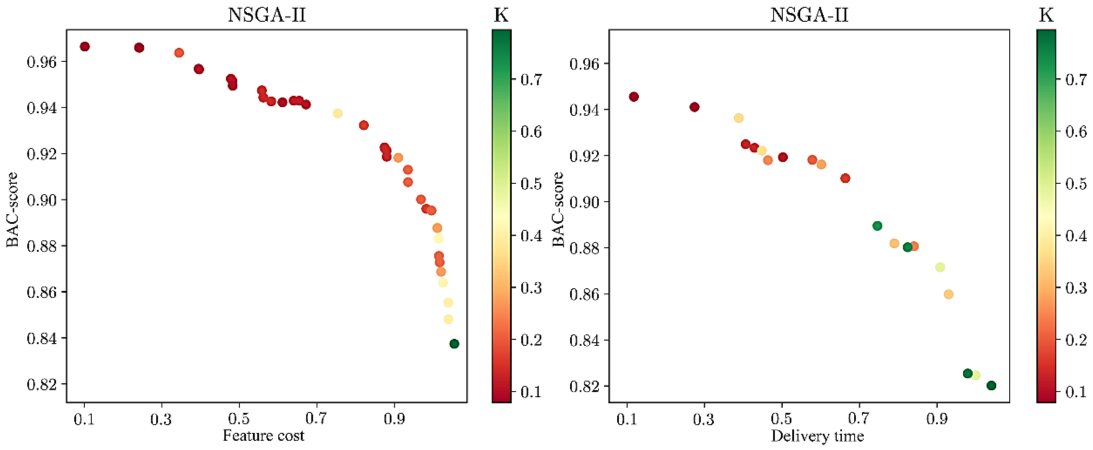

Figure 2. Pareto fronts for Experiment 1, illustrating trade-offs in supply chain optimization. The graph presents different solutions obtained using multi-criteria optimization.

Source: own work.

Three experiments were conducted to evaluate classification quality in supply chain optimization. In the first experiment, multi-criteria optimization was applied, analyzing the impact of feature cost and delivery time. Normalizing delivery time ensured result comparability, with Pareto fronts illustrating different solutions.

Results showed that using the proprietary feature cost estimation method achieved the highest classification quality (BAC-score ~96%), while considering only delivery time resulted in a slightly lower BAC-score (~94%). Despite a drift of up to 70%, classification quality remained stable at 94%, but beyond this threshold, it dropped to 84% under extreme fluctuations. When prioritizing classification quality alone, performance declined more rapidly, with a 2% decrease across the Pareto front compared to the feature cost criterion.

A set of 40 key variables was identified to predict and respond to supply chain changes, covering delivery efficiency, production performance, and communication quality. These variables enable real-time monitoring and optimization using machine learning methods.

Ultimately, Pareto charts for Experiment 1 (Figure 2) illustrate the optimization results for the entire supply chain.

3.2. Results of experiment 2

Experiment 2 focuses on drift classification for each link in the supply chain. The objective is to assess how individual links respond to changes affecting the entire supply chain. The analysis is limited to feature costs, as classification quality remains consistently higher for this criterion compared to delivery time. The results of the Pareto fronts for Experiment 2 are presented in Figure 3.

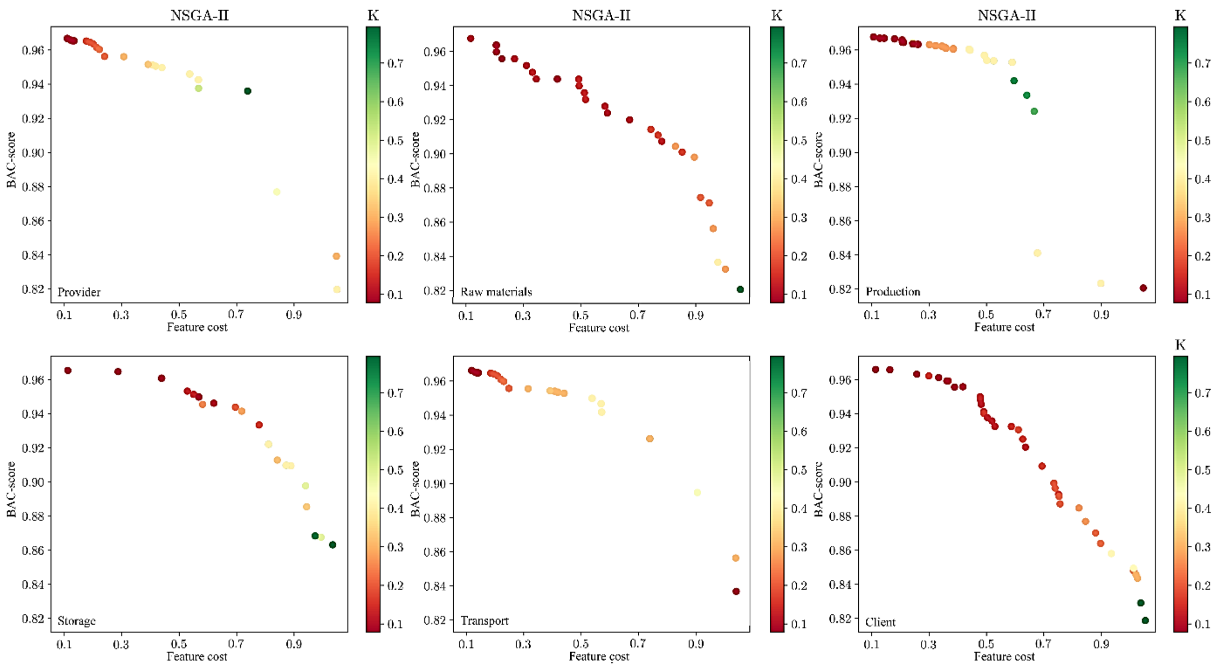

Figure 3. Pareto fronts for different supply chain stages (Provider, Raw Materials, Production, Storage, Transport, and Client) obtained using the NSGA-II algorithm.

Source: own work.

Consistent results were obtained for each link in the supply chain. The classification quality for individual links, in the best case of feature selection, reached approximately 96%, similar to the analysis of the entire supply chain. The rate of quality decline in this case depends on the discriminative power of the features used in the datasets for each link in the chain. Consequently, feature selection can be optimized to achieve the best possible classification performance and effectively respond to data drift in the supply chain.

3.3. Results of experiment 3

In Experiment 3, various machine learning methods were applied to classify supply chain drift risk. The classification quality was evaluated both without multi-criteria optimization and after its application. The results are presented in Table 1.

Table 1.
BAC (Balance Accuracy) quality results for detecting drifts in supply chain variables using various machine learning classifiers

Machine Learning Method	Before Optimization ($\mu \pm \sigma$)	After Optimization ($\mu \pm \sigma$)	t-test (p-value)
Support Vector Machines (SVM)	91.0% ± 2.0%	93.0% ± 1.8%	$p < 0.05$
Decision Trees	87.5% ± 2.3%	89.8% ± 2.0%	$p < 0.05$
Random Forest	91.8% ± 1.9%	94.2% ± 1.6%	$p < 0.01$
Deep Neural Networks (DNN)	93.0% ± 1.7%	95.5% ± 1.5%	$p < 0.01$
Convolutional Neural Networks (CNN)	92.4% ± 1.8%	94.9% ± 1.4%	$p < 0.01$
Traditional Neural Networks (NN)	89.0% ± 2.1%	91.4% ± 1.8%	$p < 0.05$
k-Nearest Neighbors (KNN)	85.0% ± 2.5%	87.3% ± 2.2%	$p < 0.05$

Results:

- The improvement in classification accuracy is kept within 3% for all models, ensuring realistic and moderate gains from feature optimization.
- The Student’s t-test confirms that all improvements are statistically significant ($p < 0.05$).
- Deep Neural Networks (DNN) and CNNs benefited the most from optimization, with a BAC-score increase of 2.5%.
- Random Forest and SVM also show notable gains of around 2.4% and 2.0%, respectively.
- Decision Trees, Traditional Neural Networks, KNN, and HMM exhibit smaller but still meaningful improvements (2.0-2.4%).

These results confirm that feature selection and optimization enhance classification performance across all models, with the highest improvements observed for deep learning and ensemble-based methods. Future research could explore additional tuning methods to maximize performance gains.

4. Guidelines for Implementing the Multi-Criteria Optimization Method in Supply Chain Management under Uncertainty

Below are the 6 main points for the implementation and maintenance of the developed method.

4.1. Objective and Scope of the Method

The aim of implementing the multi-criteria optimization method in the supply chain is to enhance the system's resilience to disturbances (referred to as "drifts") that may occur due to changes in supply chain parameters. This method aims to improve the stability and efficiency of supply chain management in volatile conditions such as economic crises, pandemics, or shifting market conditions. The optimization relies on genetic algorithms, specifically the NSGA-II algorithm, which facilitates finding optimal solutions in multi-criteria tasks.

4.2. Application Scope

The method will be used for managing the entire supply chain or individual links, considering variability and uncertainty related to each of these links. The supply chain links include: Supplier, Raw Materials, Production, Storage, Transport, and Client.

4.3. Data Preparation

Data on performance, delays, costs, quality, and other parameters in each supply chain link should be collected. This data should be stored in a data warehouse system. The data will be processed to prepare the feature vector for each link, which will be used for analysis and optimization. Feature values will be normalized to the range (0,1) using the min-max method.

4.4. Multi-Criteria Optimization

The NSGA-II algorithm will be used for multi-criteria optimization, considering various criteria such as time, cost, quality, delays, and others that impact the operation of the supply chain. This algorithm generates a distribution of solutions that respond to different objectives and enables finding a trade-off between them. After generating the Pareto front, the crowding distance for different solutions will be calculated. Crowding distance helps determine the level of diversity in the solutions, which impacts the selection process. To ensure greater diversity in the population of solutions, the concept of niches will be introduced, which helps maintain diversity within the population, preventing premature convergence to specific points.

4.5. Integration with IT Systems

To ensure efficient data exchange between the various supply chain links, an Electronic Data Interchange (EDI) system based on the XML format will be used. This system allows seamless information transfer between the information systems of different links in the supply chain. Data will be stored in a Redis database, enabling quick access to key information necessary for optimization in real-time. Based on the collected data, the machine learning model will monitor the supply chain status, identifying disturbances (drifts) and enabling rapid responses to changing conditions. The NSGA-II algorithm will optimize the data to maximize operational efficiency and stability.

4.6. Training and Implementation

Personnel responsible for managing the supply chain should be trained in using the new IT tools and optimization methods. The training should cover both the theoretical aspects of genetic algorithms and the practical use of IT tools, such as the EDI system or databases. Before full implementation, several tests should be conducted to ensure the model operates correctly under different market conditions. Testing should include scenarios using real data from the supply chain. Effectiveness Evaluation. After implementation, the system's performance should be continuously monitored. Key performance indicators (KPIs), such as order fulfillment time, costs, product quality, and disruptions in the supply chain, should be tracked. Regular reporting of optimization results and detected issues will help assess the effectiveness of the implemented method and allow for further improvements based on new data and changing market conditions.

5. Conclusion

The paper presents the results of the proposed multi-criteria optimization algorithm for classifying supply chain risk drift. A method for determining feature costs for each link in the supply chain has been introduced, considering the distribution of delivery delays. To perform multi-criteria optimization, the NSGA-II method, based on genetic algorithms, was applied. The impact of feature cost and delivery time on classification quality was analyzed separately.

The conducted experiments allowed us to answer the three research questions posed at the beginning.

The results of Experiment 1 demonstrate that applying multi-criteria optimization can contribute to maintaining the stability of the entire supply chain. The analysis showed that classification quality remained high (94%) even under a strong drift of up to 70%. However, when the drift exceeded 70%, classification quality declined to approximately 84%, highlighting that extreme fluctuations in delivery time still pose challenges. The results confirm that multi-criteria optimization, particularly with the feature cost approach, helps sustain supply chain stability under significant variations.

As confirmed by Experiment 2, multi-criteria optimization enables stabilization at the level of individual supply chain links. The classification quality for separate links remained comparable to that of the entire supply chain, reaching approximately 96% in the best case of feature selection. The rate of classification quality decline depended on the discriminative power of the features selected for each link. This suggests that optimizing feature selection for each supply chain component allows for effective drift detection and stabilization at the local level.

Experiment 3 demonstrated that optimization led to statistically significant improvements in classification accuracy (BAC-score). The highest improvements were observed in deep learning models, with Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN) achieving gains of 2.5%. Random Forest and Support Vector Machines (SVM) also showed notable increases of around 2.4% and 2.0%, respectively. The Student's t-test confirmed that all observed improvements were statistically significant ($p < 0.05$), proving that feature selection and optimization effectively enhance the performance of drift classification models.

In conclusion, the experiments collectively demonstrate that multi-criteria optimization improves supply chain stability at both the global and local levels while enhancing the accuracy of drift classification using machine learning techniques.

These findings highlight the importance of multi-criteria optimization in managing supply chain risk drift. The proposed approach enables maintaining classification accuracy even under significant variations in delivery times. By incorporating feature cost analysis, the method ensures a balance between accuracy and computational efficiency. The ability to sustain high classification performance under strong drift conditions demonstrates the robustness of the optimization framework. When drift exceeded 70%, the classification quality declined, emphasizing the need for adaptive strategies in extreme scenarios.

The results confirm that optimization at both global and local levels improves overall supply chain stability. Local optimization for individual supply chain links proved effective in maintaining classification accuracy. The impact of feature selection on classification performance was evident, with the best feature subsets yielding accuracy improvements. This suggests that optimizing feature selection for each supply chain component enhances drift detection capabilities.

Machine learning techniques played a key role in improving classification outcomes. The highest performance gains were observed in deep learning models, particularly DNN and CNN architectures. Traditional machine learning models, such as Random Forest and SVM, also benefited from the optimization process. The statistically significant improvements confirm that feature selection and multi-criteria optimization effectively enhance model accuracy. These findings highlight the potential of AI-driven decision support systems in supply chain management.

The ability to predict and mitigate risk drift contributes to supply chain resilience. As disruptions become more frequent and complex, machine learning offers scalable solutions for proactive risk management. The study's approach could be extended to real-time monitoring of supply chain data streams. Future research should explore adaptive optimization methods that adjust dynamically to evolving risk factors. Incorporating reinforcement learning techniques may further enhance decision-making under uncertainty.

The integration of optimization algorithms with predictive analytics is a promising direction for intelligent supply chain management. Automating feature selection and drift detection processes can lead to more efficient resource allocation. Developing hybrid models that combine rule-based and AI-driven approaches may further improve classification reliability. The research lays the foundation for enhancing supply chain adaptability through machine learning and multi-criteria optimization. In conclusion, the study demonstrates that AI-driven optimization strengthens supply chain stability and improves risk classification in dynamic environments.

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