

Multi-Criteria Optimization: A Satisfaction-Driven Supply Chain Optimization Approach

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ABSTRACT

Supplier selection and order quantity decisions are fundamental elements of decision-making within the context of supply chain management. Although extensive research exists on how to improve these decisions individually, limited attention has been given to their interdependent nature. Specifically, order quantity decisions are influenced by the chosen supplier, and supplier selection should take into account operational requirements for fulfilling future orders. This paper proposes a novel framework that integrates multi-criteria decision-making techniques with robust optimization, allowing for a robust way to deal with the trade-offs inherent to the decision-making process. This was achieved by solving both problems simultaneously, with the aim of achieving a robust and optimal satisfaction-driven decision under decision-dependent uncertainty.

KEYWORDS. Supply chain management. Robust optimization. Multi-criteria decision-making.

Paper topics Multiobjective optimization. Decision-dependent uncertainty. Satisfaction-driven optimization.

1. Introduction

Supply chain management (SCM) has become more complex and has drastically evolved in the last few years. Supply chain managers increasingly realize the complexity reflected in the trade-offs that are inherent to their decisions, and therefore, maximizing profit does not equate to the most satisfactory outcome.

The trade-offs vary from the classic interactions between cost and service level to more subtle issues such as the possibility of the bullwhip effect as a result of the mismatch between order placements and their suppliers' forecasts. Together with order-quantity decision making lies the challenge of supplier selection; managers must consider multiple trade-offs encompassing operational factors (e.g., cost, lead time, and quality control) and an increasing environmental concern, manifest in metrics such as carbon footprint [Igarashi et al., 2013].

Decision-making within the SCM domain is too complex to be accounted for by human expertise alone; Nevertheless, human expertise is still relevant since it is paramount in disruptive events not considered in the mathematical modeling. This motivates a full integration of human expertise to restructure the mathematical models utilized.

Therefore, the need for additional support is evident, combining methods based on distinguished areas of decision theory. On the one hand, the inherent trade-offs within the multitude of relevant variables call for multi-criteria decision-making. On the other hand, the domain is far too complex to be resolved without intensive computational support, and the active search for a robust set of data-driven solutions to provide ever-so-important resilience to supply chains.

However, the interdependent nature of order quantity and supplier selection decisions is still a challenge, affecting various operational factors. To ensure an optimal satisfaction solution, both should be approached simultaneously.

This paper aims to demonstrate the limitations and ill effects of using a single criterion as the objective function when faced with a typically multi-objective setting. We propose a framework to integrate supplier selection and order quantity decision-making to achieve maximum satisfaction by combining robust optimization and multi-criteria decision-making (MCDM), thus reaching the best robust satisfaction-driven solution.

The paper is structured as follows. A literature review section presents the necessary concepts applied in the proposal. Sections 3 and 4 detail the proposed framework and mathematical formulation, respectively. Section 5 presents the evaluation results using a benchmark scenario. Section 6 concludes with a discussion of the results and future work.

2. Literature Review

Robust optimization (RO) is capable of producing results irrespective of the true underlying distribution that generates the data. Therefore, it offers the advantage of computational tractability compared to alternative scenario generation methods. Another advantage is its independence from demand distribution assumptions, making the approach well-suited for inventory control applications under demand uncertainty [Goltsos et al., 2022].

However, classic RO models do not account for the inherent complexity and trade-offs present in supply chain management. These complexities can be better addressed by applying a stochastic programming model of uncertainty can be enhanced by integrating the interaction between optimization decisions and the information discovery process. This led to the application of a robust optimization technique called decision-dependent uncertainty.

Decision-dependent uncertainty (DDU) consists of a class of problems where decisions are optimized over a time horizon under uncertainty, and such decisions influence the time of information discovery for a subset of the uncertain parameters [Goel and Grossmann, 2006]. Therefore, it behaves as a robust optimization problem where a series of sequential decisions affect not only

one another but also the uncertainty of the next decision. Various SCM factors fall into this description, such as cash flow, manufacturing capacity, stock levels, logistics, and workforce, which are all inherently decision-dependent, while lead time uncertainty is dependent on supplier selection; despite this, DDU has rarely been used in SCM problems. [Peixoto et al., 2024]

From the rare uses of DDU within the supply chain literature, results on resilience were obtained in a supply chain design problem, where uncertainty was restricted by the decisions about the location of the facilities and their optimal capacity in the work of Zhao and You [2019]. Selecting resilience as the objective function, the formulation proved efficient in reducing the bullwhip effect. Peixoto et al. [2024] also demonstrated that by using a decision-dependent formulation and second-tier supplier communication, the bullwhip effect could be mitigated despite the poor decision-making of an intermediary agent along the supply chain.

Despite all its benefits, robust optimization has inherent limitations for the supply chain domain, due to the various trade-offs present. Any individual optimization criterion selected as the objective function, be it profit, cost, service level, resilience, or any other, becomes impossible to capture the impact of the trade-offs that would be seen as more aligned with the company's goals.

This is the main problem of applying mono-criteria decision-making techniques and sets of constraints for unacceptable outcomes; they lack and ability to consider the trade-offs among the remaining relevant factors. The supply chain management endeavor is concerned with multiple diverging aspects, and therefore, trade-offs are inherent to the nature of its decision-making. MCDM, however, is extremely effective in dealing with trade-offs [?].

Therefore, a multi-criteria approach is a solid candidate to assist as decision support for supply chain management decisions. Applying a multi-criteria approach consists of three basic steps: (1) The relevant criteria must be defined and weighted; (2) the input data on each criterion must be normalized, since the criteria may be in different scales such as cost and service level; and (3) the ranking algorithm must be defined, specifying the way to select the most satisfactory alternative. The ranking algorithms work by simply interpreting the data.

However, there are some limitations to this approach; despite generally being computationally efficient, MCDM methods themselves cannot create alternatives; this remains true even for more modern methods such as VIKOR, created to improve their robustness as more alternatives are included [Opricovic and Tzeng, 2004]. Nor can they integrate the consequences of certain choices, and how that interferes with the criteria, in other words, it depends on the information inputted, and cannot generate scenarios; therefore, the method cannot guarantee optimality in its satisfaction function.

MCDM methods are incapable of achieving a robust optimal satisfaction solution. Considering the trade-offs within SCM, MCDM methods are broadly applied in supplier selection problems, which are extremely relevant decisions within SCM, and multiple methods can be employed, as De Boer et al. [2001] shows. Linear Weighting Models are frequently employed, a method in which different criteria are assigned specific weights, with the highest weight representing the most critical factor (a characteristic of multi-criteria methods).[De Boer et al., 2001]

Satisfaction is employed by this paper using the same definition of satisfaction for MCDM methods, as a metric that determines preference between potential decision alternatives.

Green supply chain management (GSCM) is a topic with ever-growing importance in the field, and the work of Igarashi et al. [2013] was a relevant milestone for establishing green supplier selection, therefore implying green as a relevant criterion to be considered. Defining what 'green' means is paramount within an organization's overall strategy, since it identifies which aspects are of importance in the context of procurement, especially in supplier selection. Without a clear understanding of the implications of green criteria for supplier selection, managers may struggle to

effectively and persuasively convey these requirements to potential suppliers.

Decision support tools and methods have great importance, since poor decision-making can propagate the bullwhip effect [Wang and Disney, 2016], given that the consideration of environmental aspects further complicates supplier selection in the sense that more criteria must be evaluated and possibly traded off against each other [Igarashi et al., 2013]. A system capable of addressing the trade-offs between different business goals is of critical importance; this task, however, is far from trivial.

There is a need for integration of both qualitative and quantitative criteria, and the need for robustness in supply chain management. Procurement and innovation are critical factors to achieve green supply chain objectives such as the reduction of carbon emissions, as the research conducted by Stokke et al. [2022] showed. Note that the proposals of Stokke et al. [2022] and Igarashi et al. [2013] complement each other but are largely dependent on global understanding between organizations and the supply chain of their definitions and objectives for GSCM. Therefore, a decision support system capable of storing the definitions and metrics involved, dealing with the complexities of decision-making, and integrating supplier selection and order quantity decisions is a gap in the literature.

3. Proposal

The introduction and literature review sections outlined the necessity to integrate the decisions of supplier selection and order quantity, since order quantity solutions are dependent on the lead time and cost derived from the supplier selection decision, while the supplier selection decision is dependent on the order quantity, since capacity is a constraint. All that considered, there is also a problem of overall satisfaction, the interdependent nature of decisions makes it hard to optimize for any single criterion as optimal solutions in one lens may hinder the performance in other aspects, this is also true considering sequential decision-making, the optimal decision for supplier in isolation won't necessarily imply on the best overall solution.

Therefore, a proper solution demands a robust response from multi-criteria methods that they cannot provide due to their inability to generate scenarios. Robustness in decision-making is critical for supply chain resilience as it considers the potential scenarios of crisis described in the lower end of the distribution of events provided to it by the process of RO.

However, during the RO process, it is typically impossible to deal with trade-offs, as normalization becomes impossible given the undetermined state of the variables during solution. To put it in another way, since the maximum and minimum values that the criterion will assume are dependent on the demand scenario, the objective function could not use these values for normalization, as there is an indeterminate state, not to mention the possibility of having division by zero.

Our proposal aims to address these limitations by solving the multi-criteria problem inside the optimizer objective function, by estimating the maximum and minimum values of each criterion in auxiliary problems, thus allowing for the normalization of the outcomes described for the overall satisfaction-driven objective. Therefore, creating a robust satisfaction-driven optimal decision since the scenario generation can provide the much-needed robustness to MCDM, while the MCDM-like structure of the objective function will give the means necessary to deal with trade-offs. The framework can be outlined by 5 main steps:

1. Uncertainty estimation: a forecasting model is used to estimate the expected demand for each time period;
2. Criteria weighting: this step is paramount, since it is the information that will govern the behavior of the objective function and reflect the strategic goals of the company or supply chain. There is a great concern with consistency for this step, as it involves human interaction. To

mitigate this inconsistency, it is highly recommended to use the Best Worst Method (BWM) as it possesses an internal consistency rating and has proven to be more reliable than AHP [Rezaei, 2015] and, for that reason, was the method used in this paper. There are potential alternative solutions for this step, such as using fuzzy weights or using rank-based algorithms, despite of the method employed in a real-world case, the decision suggestion generated by the final step should always be revised, as there is a risk of dissonance between the true preferences of the user and how the method translated it into the scale;

3. Split into sub-problems: this step is the basis for the normalization. Essentially, based on the criteria and constraints, it is important to determine the maximum and minimum values to be estimated in the sub-problems. Certain aspects of this step can be quite useful to save time in the estimation process, for instance, if there is a cash-flow constraint that determines that profit should always be above a specific level, this constraint can be used as a workaround to calculate the minimal cost and minimal service level, since they will both be capped by the profit constraint.

Another interesting aspect to save on computational time is to use the direct dependence between the demand and certain criteria, for instance, carbon footprint, cost, profit, and service level are always dependent on the demand, and since those attributes are dependent on a known and relatively small set of suppliers the maximum values for each criteria can be extracted from the same extreme point of the distribution uncertainty of the demand, multiplied by the criteria reflected by the attribute of the most significant supplier.

For example, to calculate the highest possible carbon footprint, one could use an extreme point of the demand multiplied by the highest carbon footprint among the suppliers. The same can be said for cost, while profit can be obtained by applying the same logic; however, by aiming for the supplier with the lowest ordering cost.

4. Solve sub-problems: after attempting to reduce as much as possible the required sub-problems in step 3, the solution of the remaining minimum and maximum points must be calculated so they can be used to normalize the data for the weights of the objective function;
5. Determine the optimal satisfaction-driven solution: the final step consists of determining the optimal satisfaction-driven solution for the integrated order quantity and supplier selection problems.

The proposed solution addresses some challenges that emerge when the solution to the problems is attempted sequentially or in isolation. The first challenge is the weighting of the criteria since some criteria are either not applicable to one decision or represent different aspects. For instance, when considering ordering from two suppliers the comparison is between the ordering cost of the different suppliers, supposedly \$50 and \$60 per unit.

However, when addressing the element of cost for the order quantity problem the comparison is between the cost of all potential solutions estimated and other elements are considered such as stocking costs, carbon footprint linked to each supplier, not to mention the constraints linked to lead time and capacity. Therefore, despite MCDM techniques having ample use in supplier selection, since they cannot consider the operational consequences, they may hinder overall performance.

To address this challenge, it is important to apply a decision-dependent approach, by understanding that the overall cost has as one of its factors the ordering cost. This implies that the weight of cost must be considered as the overall evaluation of its importance, not isolated. In other words, the relative importance of cost changes if considered isolated in the solution of each

problem; Therefore, an overall approach should be applied and then normalized for the individual solutions.

This shift in importance, considering the problems in isolation, makes it critical to define the weights in a global lens, since there is no way to guarantee consistency between all subsets of criterion as not necessarily it would be maintained considering that best and worst criteria may not be part of the decision-specific relevant criterion subset (i.e. the isolated supplier selection and order quantity decisions)

One final challenge was addressed: The risk of the normalized value being too small, and therefore rounded to zero by the optimizer. This would result in an error during the robust optimization. The scenarios generated are multiplied by their probability of occurrence; if the weight of a given criterion is too small and the scenario considered unlikely, the multiplication may result in a rounding to zero by the solver.

This is solved with the basic concept of robust optimization: Big-M. Big-M is a numerical value that represents a near-infinite difference in scale. Therefore, a Big-M will multiply each normalized criterion, preventing it from being rounded down to zero. Since it is the same value, the proportionality given by the weights of the criteria is still maintained.

4. Formulation

The formulation of the problem, described in Figure 1, contemplates a production planning problem for thirty-six months. The formulation uses three main parameters: i (the index denoting the supplier, from 1 to I), t (the time period, from one to T , being 36 for this particular case), and j (the delivery type). As represented in lines 3, 4, and 5), delivery types are categorized into preferential or regular clients. They are used to represent decision-dependent uncertainty, similarly to the concept of fractional delivery applied in Peixoto et al. [2024].

The DDU exists within a time period t because of the concept of fractional delivery. There are two decisions for each time period. The first refers to the fraction of the delivery designated for preferential clients, which implies a shorter time, as shown by $Conv_{Time}^{max[1]} \leq Conv_{Time}^{max[2]}$. The available conversion time for the initial delivery is shorter. The second delivery relates to the rest of the demand that may be met, i.e., regular clients without preferred status. The DDU relation is described in equation 34 as the demand uncertainty of the second delivery decision is affected by the order decision of the preferential client delivery. Constraint 35 was used to limit the capacity of suppliers.

Another parameter used is α that denotes the specific criteria within the set of criteria K being evaluated, associated with it is its criteria weight W_α . It is important to note that the weights attributed will already take the objective of each criterion into account; therefore, negative criteria (such as cost and carbon footprint) will have negative weights to reflect their criterion type. $k_{[\alpha,t]}^{max}$ and $k_{[\alpha,t]}^{min}$ are calculated by the sub-problems of the maximum or minimum optimization of the α criteria in question, as section 3 outlined.

Therefore, the objective function as described by equation 1 aims to maximize the sum of the satisfaction for all criteria, during all delivery types j in periods t , considering all potential suppliers i and their inherent attributes, pondered by the likelihood of each generated scenario.

There are three decision variables, as shown in line 2: (i) how much to order from a given supplier at a given delivery type and time period; (ii) how much to manufacture at a given delivery type and time period; and (iii) how much finished product to store between time periods. This is illustrated in lines 10, 11, and 12 to maximize the satisfaction of the criteria cost, profit, on-time delivery, service level, and carbon footprint, as denoted by line 6.

The demand is stochastic and assumed to be normal, as described in lines 8 and 9. Some constants and their descriptions can be found in lines 13 to 16, 19, and 21, with them and the

definition for stocking cost described by line 17 and equation 24 all the criteria can be defined.

Cost, $k_{[C,j,t,\omega]}$ is defined by the quantity ordered from each supplier multiplied by their ordering cost $C_{[i,j,t]}$ of the supplier for the given delivery type and period of time, plus the number of units delivered (i.e selected to be converted) times the conversion cost, and the stocking cost, as shown in equation 23. The carbon footprint criteria, $k_{[CFP,j,t,\omega]}$ is similar to cost as it is defined by the quantity ordered times the carbon footprint of the supplier and the number of units to be delivered times de carbon footprint emitted in their manufacturing as demonstrated by equation 28. Profit, denoted by $k_{[P,j,t,\omega]}$, is defined by the number of units delivered times the sale price minus the cost, as shown in equation 25. All the definitions stand for all suppliers, delivery types, time periods, and scenarios.

The criteria of service level and on-time delivery are unique in the sense that they are, by their very definition, normalized, since they would already be within a scale between zero and one. However, since the cashflow constraint exists, they still need to be normalized, as delivering zero units is no longer an option. Their definition is similar, being respectively, the quantity manufactured to be delivered in both delivery types of each time period and the stocked units divided by total demand for the time period; and the stocked units plus the units manufactured to be delivered in the first delivery type of a given time period divided by the preferential client rate of the demand. Both are shown in equations 27 and 26, respectively. It is also important to note that the criteria are capped and cannot exceed the value of 1, which helps avoid an incentive for overproduction as the response of the objective function.

The remaining equations are auxiliary constraints for the problem, such as equation 29 that determines how much of what was ordered from a given supplier can be converted into final products, considering the quality control of each supplier; equation 30 sets the time limits for manufacturing; equation 31 defines the stock transitivity between periods; equation 32 sets the starting stock as zero for the first period. Equation 33 forces non-negativity upon the decision variables.

Therefore, the proposed experiment involves two major steps. First, a performance analysis of the proposed integrated and satisfaction-driven solution compared to the profit-driven solution, which evidences the effectiveness of the MCO in achieving optimal robust satisfaction. This implies that the use of profit as a satisfaction proxy constrains the solutions in a potentially negative manner. The second step compares the sequentially constrained solutions, i.e, solutions that order only from the preferred supplier. These solutions will be evaluated as the classic profit-driven and the satisfaction-driven variation.

In summary, the results section aims to illustrate the main points discussed for the motivation of the proposed formulation, that is, the inappropriate effects of having the decisions made sequentially instead of integrated, and the gain of satisfaction when compared to classic profit-driven optimization. The sequential approach was defined by the constraint of ordering from the most preferred supplier selected purely from an MCDM method. Consequently, to maintain consistency, whichever method is used for this ranking will be used to rank the overall satisfaction of the solutions. For this specific case, supplier 2 was considered the most preferable when considered in isolation, therefore, the sequential solution was constrained to order only from supplier 2.

Figure 1: Mathematical formulation

$$\max \sum_{\alpha} (W_{\alpha} * ((\sum_{\omega} IP(\omega) * (\sum_{t=1}^T (\sum_{j=1}^J k_{[\alpha,j,t,\omega]}))) - k_{[\alpha]}^{min}) / (k_{[\alpha]}^{max} - k_{[\alpha]}^{min})); \quad (1)$$

$$S_{[i,j,t,\omega]}; Z_{[j,t,\omega]}; Zr_{[t-1,\omega]}; \quad (2)$$

$$i \in [1, \dots, I]; \text{ Where } I \text{ is the number of suppliers}; \quad (3)$$

$$j \in [1, \dots, J]; \text{ Where } J \text{ is the number of delivery types}; \quad (4)$$

$$t \in [1, \dots, T]; \text{ Where } T \text{ is the number of time periods}; \quad (5)$$

$$\alpha \in [P, C, OTD, SL, CFP]; \text{ Where } \alpha \text{ is the criteria being evaluated}; \quad (6)$$

$$W_{\alpha} \text{ is the weight of the criteria being evaluated}; \quad (7)$$

$$\xi_{[\omega,t]} \text{ is the demand for the scenario } \omega \text{ during time period } t \quad (8)$$

$$\omega \text{ is the scenario extracted from the demand } \xi_{[\omega,t]} \text{ described by mean } \mu_t \text{ and variance } \sigma_t; \quad (9)$$

$$S_{[i,j,t]} \text{ is the order made from the supplier } i \text{ during the delivery type } j \text{ of time period } t; \quad (10)$$

$$Z_{[j,t]} \text{ is the quantity of product delivered during the delivery type } j \text{ of time period } t; \quad (11)$$

$$Zr_{[t-1]} \text{ is the quantity of product remaining from time period } t-1 \text{ (Make to stock)}; \quad (12)$$

$$Conv_C \text{ is the financial cost spent to convert raw material into a finished product} \quad (13)$$

$$Conv_{CFP} \text{ is the carbon footprint emitted to convert raw material into a finished product}; \quad (14)$$

$$Conv_{Time} \text{ is the time spent in days to convert raw materials into finished products}; \quad (15)$$

$$Conv_{Time}^{max[j]} \text{ is the limit of time in days to convert raw materials of type } j; \quad (16)$$

$$SC \text{ is the unitary stocking cost for one period of time, from } t-1 \text{ to } t; \quad (17)$$

$$PCR \text{ is the Preferred Client Rate, the } \% \text{ of the demand belonging to preferred clients}; \quad (18)$$

$$Q_i \text{ is the quality control of each supplier } i \quad (19)$$

$$q \text{ is the sale price.} \quad (20)$$

$$CFC \text{ is the value for the cashflow constraint of all decision types and times}; \quad (21)$$

$$\text{subject to} \quad (22)$$

$$k_{[C,j,t,\omega]} = \sum_{i=1}^I (S_{[i,j,t,\omega]} * C_{[i,j,t]}) + Conv_C * Z_{[j,t,\omega]} + SC * Zr_{[t-1,\omega]}; \forall j, t, \omega \in \Omega \quad (23)$$

$$SC = 0.05 * C_{[i,j,t-1]}; \forall t, \omega \in \Omega \quad (24)$$

$$k_{[P,j,t,\omega]} = Z_{[j,t,\omega]} * q - k_{[C,j,t,\omega]} \geq CFC; \forall j, t, \omega \in \Omega \quad (25)$$

$$0 \leq k_{[OTD,j,\omega,t]} = (Z_{[j,t,\omega]} + Zr_{[t-1,\omega]}) / (\xi_{[\omega,t]} * PCR) \leq 1; \forall j, t, \omega \in \Omega | j = 1 \quad (26)$$

$$0 \leq k_{[SL,j,\omega,t]} = (Z_{[j,t,\omega]} Z_{[j+1,t,\omega]} + Zr_{[t-1,\omega]}) / (\xi_{[\omega,t]}) \leq 1; \forall j, t, \omega \in \Omega | j = 1 \quad (27)$$

$$k_{[CFP,j,t,\omega]} = Conv_{CFP} * Z_{[j,t,\omega]} + \sum_{i=1}^I S_{[i,j,t,\omega]} * CFP_{[i,j,t]}; \forall j, t, \omega \in \Omega \quad (28)$$

$$Z_{[j,t,\omega]} \leq \sum_{i=1}^I Q_i * S_{[i,j,t,\omega]}; \forall j, t, \omega \in \Omega \quad (29)$$

$$Z_{[j,t,\omega]} * Conv_{Time} \leq Conv_{Time}^{max[j]}; \forall j, t, \omega \in \Omega \quad (30)$$

$$0 \leq Zr_{[t-1,\omega]} \leq Z_{[j,t-1,\omega]} - \xi_{[\omega,t-1]}; \forall j, t, \omega \in \Omega \quad (31)$$

$$Zr_{[t-1,\omega]} = 0; \forall j, t, \omega \in \Omega | t = 1; \quad (32)$$

$$0 \leq S_{[i,j,t,\omega]}, Z_{[j,t,\omega]}, Zr_{[t-1,\omega]}; \forall i, j, t, \omega \in \Omega \quad (33)$$

$$Z_{[j,t,\omega]} \leq \xi_{[\omega,t]} - Z_{[j-1,t,\omega]}; \forall j, t, \omega \in \Omega | j \geq 2 \quad (34)$$

$$S_{[i,j,t,\omega]} \leq \bar{S}_{[i,j,t,\omega]}; \forall i, j, t, \omega \in \Omega; \text{ Where } \bar{S}_{[i,j,t,\omega]} \text{ is the capacity of each supplier} \quad (35)$$

5. Results

For this section, two things are relevant to be clarified: First, all the results displayed refer to the actual performance of the solutions analyzed, not the expected values of the presented solutions, reflected in the objective function. Second, the data used for the demand time series belonged to the M5 forecasting dataset [Makridakis et al., 2022], which contains various Walmart time series for various products; the time series used was *FOODS3WI3*, that is, the aggregation of the food items of category 3 of the Wisconsin state for the third supermarket, the period used was the last 276 weeks, 240 for training of the SARIMA model used to generate the forecasts and the remaining 36 for testing, i.e to be integrated to the optimizer.

We tested variations with two ranking algorithms, TOPSIS [NÄdÄban et al., 2016] and VIKOR [Opricovic and Tzeng, 2004] and their fuzzy formulations. For the fuzzy weights and performance of the criteria, a $\pm 5\%$ variation was applied for almost all of them, with the only exception being for OTD, since it could not be higher than 1 the variation was of 1% around 99%, considering all outcomes for the OTD criterion were the same, this criteria should not influence the choice. It is important to note that when evaluating the suppliers in isolation, both VIKOR and TOPSIS selected Supplier 2 as the most satisfactory option. The supplier attributes are described in Table 1, and the results are displayed in Table 2.

For the evaluation, the following metrics were used: Sale price $q=200$; Conversion time=0.06 days; Carbon footprint emitted during conversion=15; Conversion cost=40; Time constraint for conversion on the first and second deliveries (preferential and regular) were 5, and 25 days respectively; The criteria Weights used were: 16% for profit, 15% for cost, 16% for carbon footprint, 26% for service level and 27% On-time delivery. Additional information can be obtained from Table 1.

Attribute	Supplier 1	Supplier 2	Supplier 3	Criterion Type
Unitary cost	50	60	70	Minimization
Unitary carbon footprint of each supplier i	150	115	60	Minimization
Delivery capacity of each supplier i for decision type j	3000	2600	1500	Maximization
Lead Time in days	2	4	1	Minimization
Lead Time Variance in days	1	0.2	2	Minimization
Quality Control	90%	97%	93%	Maximization

Table 1: Supplier attributes.

Objective function:	Profit-driven	Satisfaction-Driven	Profit-Driven	Satisfaction-Driven
Solution type:	Sequential	Sequential	Integrated	Integrated
Profit	172,363	175,430	209,452	175,104
Cost	199,845	189,095	186,158	221,181
CFP	257,326	244,340	360,989	177,524
SL	0.93	0.97	0.92	0.98
OTD	1	1	1	1
Satisfaction (TOPSIS):	0.51	0.58	0.24	0.79
Satisfaction (VIKOR):	-	-	#4	#1
Satisfaction (Fuzzy TOPSIS):	0.29	0.3627	0.351	0.7414
Satisfaction (Fuzzy VIKOR):	#4	#3	#2	#1

Table 2: Performance of each variation of the objective function and solution type.

To analyze the results, solutions were categorized into two categories: Objective Function and Solution Type. The objective function refers to the objective of the optimization model, being driven by satisfaction (i.e. the formulation proposed by this paper) or by profit. The solution type distinguishes whether the problem is solved sequentially (i.e., the typical practice of evaluating the suppliers by an MCDM algorithm, and constraining the optimization problem to only order from the most satisfactory supplier) or integrated (without this constraint, as in the proposed formulation).

There are some noteworthy findings:

- For all MCDM evaluation methods, the proposed solution remained the most satisfactory, even when fuzzy weights were introduced.
- VIKOR could not rank the sequential alternatives, which is understandable as TOPSIS evaluates them as the most similar alternatives for satisfaction level.
- There is a shift in the rankings when the fuzzy weights are introduced. Considering the difficulty of accurately reflecting a decision-maker's preference, the fuzzy weights provide a more robust evaluation. Therefore, the results indicate that the current way (sequentially and profit-driven) that decisions are made for the supply chain context may lead to the least satisfactory outcomes.
- As expected, the sequential solutions are extremely similar since they can only order from the same supplier.
- The integrated profit-driven solution indeed attained the highest profit, as the only supplier ordered was 1, having the lowest ordering cost.
- The performance in profit of both sequential solutions and the proposed integrated satisfaction-driven solution was extremely similar; however, there is a significant reduction in the carbon footprint made feasible by having a cost trade-off combining orders from suppliers 2 and 3.
- There is a clear increase in the level of service for satisfaction-driven solutions compared to those with a profit-driven objective function.

6. Conclusion and Future work

This paper proposed a novel way to combine MCDM and RO techniques to integrate the trade-off analysis capabilities of MCDM with the scenario generation and robustness of RO. One of the focal points was to analyze the interdependent nature of supplier selection and order quantity decisions. In that regard, benefits were detected when considering the integrated approach in place of the typical sequential decision-making process. Thus, the proposal of a satisfaction-driven robust optimizer was developed, which may be further incorporated into a full decision support system.

The proposal's effectiveness was assessed by conducting an experiment using a multi-supplier, continuous, multi-period decision-dependent uncertainty scenario.

The work presented limitations, such as testing for a single time series. As a strategy to mitigate this, fuzzy approaches were applied regarding outcomes and weights to increase the robustness of the results. The use of a Big-M was a consequence of the current formulation, to avoid the risk of the optimizer rounding down results to zero, since the normalized criterion and the probability of a given scenario are multiplied by one another.

The paper takes a simplified view of purchasing, as the items are treated generically. Specific characteristics of products ordered, such as expiration dates and storage specifications, could be interesting developments for future research.

The proposal integrated several knowledge areas, since factors regarding robust optimization, mathematical modeling, multi-criteria decision-making, and supply chain management are paramount to the proposal. Navigating these different areas of knowledge is a challenge, as there is a risk of overly simplifying some aspects of a given field, and of misinterpretations due to the existence of different conceptualizations of the same term in different contexts. An example of this problem is the concept of satisfaction, understood by the SCM community as the supplier/customer satisfaction level and its impact on the preferred partner status, something widely different from the conceptualization used in MCDM (employed in this paper).

As a matter of fact, this constitutes a gap in the literature, as the proper linking of this information in a computationally actionable system would be of great importance for effective decision support systems. This is the typical problem that can be solved by using ontologies. One example of a somewhat similar situation was addressed in the work of Peixoto et al. [2025], which proposed a well-founded ontology to precisely define the concepts of cognitive biases and time series forecasting, and their impact on decision-making, and showed how this semantic artifact may be encapsulated into a fully automated anchoring bias detection system.

How to control for the bullwhip effect in a multi-supplier supply chain is a current gap within the literature, since according to Wang and Disney [2016], the bullwhip effect is measured by the variance between the original demand and order quantity time series is the most applicable metric. After quick consideration, the measurement is found to be inappropriate for multi-supplier cases, as the difference in variance of each supplier is not reflected in the difference in variance of the total order and the original demand.

For future work, some interesting potential developments are: (1) test the approach for different time series, including at the SKU level, that are frequently intermittent; (2) expand the problem for multiple decision-makers, allowing for the first-tier suppliers to make decisions; (3) analyze the effects of integrated satisfaction-driven agents against conventional sequential profit-driven agents; (4) create an ontology to integrate the concepts originating from the domains of optimization, multi-criteria decision-making and supply chain management to address ambiguities, provide refined decision support and make the mathematical modeling more adherent to reality; (5) study how the bullwhip effect could be better measured and mitigated in the multi-agent problem.

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