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Towards efficient logistics through suitable negotiation strategies: the role of uncertainty

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Abstract: Uncertainty is a factor that affects many decision-making situations in practice. Supplier management and its flows in companies is no exception. This paper focusses on the choice of the most appropriate strategy towards suppliers in a company. This topic is unfairly neglected in the literature compared to other decisions related to suppliers, such as supplier selection or evaluation. For the sake of robustness, two different hybrid methods of multicriteria decision making, allowing managers to capture the uncertainty, are applied and compared. Namely, the AHP method together with Stochastic Multicriteria Acceptability Analysis (SMAA), and the fuzzy extension of the PROMETHEE method. The goal of this paper is twofold. First, the best strategy is explored with respect to time and uncertainty before the nomination of a supplier is done and after that. Second, it is pointed out how much oversimplifying and distorting the aggregation of opinions using the averaging operator can be. The results showed that examining individual evaluations helps better understand the impact of the uncertainty on the most suitable strategies towards suppliers, in comparison with the final ranking based on averaging individual opinions. The performed survey revealed that choosing the best strategy before nominating a supplier is more difficult than doing so after the nomination.

1 Introduction

Decision-making plays a vital role in numerous organizations and for individuals, who employ various approaches to evaluate its effects on the company, themselves, and the surroundings. The nature of decisions can depend significantly depending on the level of certainty or uncertainty faced by the decision-maker. Additionally, the framework within which decisions are made may evolve over time, resulting in circumstances that differ from those at present. By delving into a real-world scenario within the flows in logistics within the automotive sector, we explore how alterations in cost management can be impacted both before and after the selection of a supplier.

Numerous studies in the literature have examined supplier management and its flows, with a predominant focus on identifying optimal suppliers for inclusion in the portfolio [1], developing negotiation models to determine order quantities [2], or a combination of both [3]. In this study, we operate under the assumption that supplier selection has been completed and cannot be altered further. As precise price bids and quantities are not yet known, the model presented merely suggests a broad strategy to be implemented both before and after a supplier is designated.

Suggested strategies are tools, that could be implemented during negotiations process. The study [4] shows that the process preparation and information are essential during negotiation. In this paper, the most suitable strategy towards suppliers during negotiation process is investigated (before and after nomination of a supplier), and the impact of imprecise inputs on this strategy is carefully explored.

This paper builds on the contribution presented at the conference and published in its proceedings, see [5]. Unlike this work, this study is extended by the PROMETHEE analysis which enables one to understand the impact of the uncertainty in a more systemic and complex way. The basic structure of the introduced model has already been published in [5]. This paper uses extensive survey data collected from a car manufacturing company, previously utilized in [5]. Unlike that study, the main objective here is not to rank alternatives but rather to thoroughly investigate the influence of uncertainty on the issue at hand at the two considered moments – before the nomination of a supplier is done, and after this nomination. The uncertainty can impact the results in two ways: first, individual opinions may carry inherent uncertainty (all criteria in the model are nominal and subjective), and second, variability in opinions can also potentially impact the final recommendation.

In [5], the fuzzy-AHP method was used to find the best behaviour towards suppliers of a car manufacturer. This paper uses a different method. Namely, the Stochastic Multi-criteria Acceptability Analysis [6] and fuzzy-

PROMETHEE [7] are used. The motivation for this choice is that the optimal strategy obtained by Fuzzy-AHP in [5] was surprisingly unambiguous. SMAA (Stochastic Multicriteria Acceptability Analysis) together with the AHP (Analytical Hierarchy Process) method and a different way of capturing the uncertainty in fuzzy sets within Fuzzy-PROMETHEE will help us to explore whether this unambiguity was caused by the fact that the solution is really absolutely clear, or if it was brought by a simplifying aggregation operator which was used to aggregate individual opinions together.

The rest of the paper is organized as follows. Section 2 introduces the necessary methodological background of the used methods: AHP, SMAA and Fuzzy-PROMETHEE methods. Section 3 recalls the model taken over from [5]. The core part is Section 4, where the results of SMAA-AHP and fuzzy-PROMETHEE methods are provided, discussed and compared with the results of the Fuzzy-AHP method presented by [5].

2 Methodological background

If one has a decision problem where k criteria are used to assess n alternatives (where both sets are finite, discrete and 'reasonably' small), we talk about a multi-criteria decision-making problem (MCDM). Since many MCDM methods exist, one must be very careful when selecting the one for some particular real-life problem. The methods differ in many parameters: a way, how the final value of the alternatives is calculated, how a decision-maker evaluates parts of the model, suitability for some of all data types, ability to work in dynamic or uncertain environment, etc. For this study, we have decided for two different settings: (a) the combination of the AHP [8] and SMAA [6] and (b) fuzzy-PROMETHEE method. The reason for the first choice is straightforward. The AHP method is by far the most popular MCDM method all over the world (according to the number of records obtained when searching the name of the method in the Web of Science database), the input data from the decision-makers have been adapted to this method, and its fuzzy extension has already been used by [5], thus making the comparability of the results will be easier. However, group decision making with AHP usually works with the aggregation of opinions using some averaging function. On the other hand, SMAA allows us to consider all individual opinions without the necessity of using some simplifying aggregation operators such as the geometrical mean in [5]. In line with [6], SMAA is a highly suitable method when the robustness of the results is explored. As for the fuzzy-PROMETHEE, this method is built on a different logic than AHP and allows one to define the set of strengths and weaknesses of each alternative.

In order to keep the length of this paper acceptable, both methods will be outlined rather than completely described. An interested reader can look at many descriptions in the literature.

2.1 *Analytical Hierarchy Process (AHP)*

The AHP is based on pairwise comparisons using the Saaty's matrices, see [8]. The Saaty's matrix pair-wisely compares either the importance between two criteria, or the performance between two alternatives in terms of a given criterion. The matrix for weights' determination will be of size $k \times k$ and each of k matrices comparing the alternatives will be of size $n \times n$. Each Saaty's matrix must be reciprocal and its elements must belong to the Saaty's scale (the values from 2 to 9 to express the preferences in favour of an entity in a row over an entity in the column, and their reciprocals to express the opposite preference; 1 is used for equal preferences). Before the priorities are derived, each Saaty's matrix should be checked for the consistency, e.g., using the consistency ratio, see [8]. The weights w_i from the Saaty's matrix are calculated using Eq. 1, the utilities u_{ij}, revealing the performance of the j-th alternative in terms of the criterion i, would be analogical.

$$w_i = \frac{\prod_{j=1}^{k} s_{ij}}{\sum_{m=1}^{k} \prod_{j=1}^{k} s_{mj}} \tag{1}$$

The ranking is determined according to the value of total utilities of alternatives is calculated using Eq. 2.

$$U_i = \sum_{j=1}^{k} w_j \cdot u_{ij}, i = 1, \dots, n \tag{2}$$

2.2 *Stochastic Multicriteria Acceptability Analysis*

The SMAA method operates on the principle that it searches for the percentage of weights for which a given option is the best – this metric is referred to as the acceptability index and which weight vector is the centroid of the hyperplane of all weights where the given variant is the best. In cases where we have stochastic evaluations of options, we also obtain a confidence factor that tells us how likely it is that the weight vector, which is the centroid of the weight hyperplane that was best for a given variant, will actually turn out to be the best for that variant.

According to [6], the acceptability index a_i is calculated using the ratio of the volume of the weight vector W_i to the total volume of the weight vector W. Here, W represents the set of all possible weight vectors that meet the criteria of the user or the problem, and W_i is a subset of W that corresponds to the best variant. The function vol represents 'volume', or the measure of how much of the weight vector space the given subset W_i occupies compared to the total space W, see Eq. 3.

$$a_i = \frac{vol(W_i)}{vol(W)} \tag{3}$$

In the case of stochastic evaluations, we calculate a_i using the ratio with the expected value of the weight vector volume (Eq. 4).

$$a_i = \frac{E(vol(W_i(\gamma)))}{vol(W)} \quad (4)$$

The central weight vector for alternative i is defined as the expected centre of gravity and can be calculated as follows in deterministic case (Eq. 5) and stochastic case (Eq. 6).

$$w_i^c = \int_{W_i} w \,\mathrm{d}w / \int_{W_i} \mathrm{d}w \quad (5)$$

$$w_i^c = \int_{\gamma} f(\gamma) \left(\int_{W_i(\gamma)} w \, dw \int_{W_i(\gamma)} dw) \right) d\gamma \quad (6)$$

The confidence factor is obtained as the area of the probability distribution function for which it holds that for a random variable, the utility of variant i is greater than the utility of other variants, see (Eq. 7).

$$p_i^c = \int_{\gamma: u_i(\gamma, w_i^c) \geq u_k(\gamma_k, w_i^c)} f(\gamma) d\gamma, \quad (7)$$

where w_i^c is the central weight vector ~~in~~ for which the variant i is optimal.

For more detailed description of the SMAA method and its application in various fields, see [9]. For purposes of this work, the results of the integrals are calculated using Monte Carlo simulation for the sake of convenience.

2.3 Fuzzy PROMETHEE

The PROMETHEE ranking method, introduced by [10], has gained widespread popularity during the last decades, see the review paper by [11], or its particular application in logistics, see [12]. At its core, PROMETHEE ranking employs a preference function, which assigns a preference degree $P_i(a, b)$ to each pair of alternatives a, b with regard to each criterion i from the set of considered criteria. This preference degree is determined based on the difference in performance values between the alternatives compared with respect to the given criterion. Decision-makers have the flexibility to select from various types of preference functions, each with different configurations for individual criteria. The authors of [10] work with six predefined shapes of preference functions. Among the published applications, as reviewed by [11], the linear function type, with indifference and preference thresholds q and p, stands out as the most commonly utilized (see Figure 1). After comparing all pairs of alternatives across all criteria, the positive and negative flows of the alternative a are calculated using Eqs. 8 and 9.

$$\tilde{\phi}^+(a) = \frac{\oplus_{a \neq b}^{n} \oplus_{i=1}^{k} (w_i \odot \tilde{P}_i(a,b))}{n-1}, \text{for } \forall a. \quad (8)$$

$$\tilde{\phi}^-(a) = \frac{\oplus_{a \neq b}^{n} \oplus_{i=1}^{k} (w_i \odot \tilde{P}_i(b,a))}{n-1}, \text{for } \forall a, \quad (9)$$

where w_i represents the weight assigned to the i-th criterion, indicating its relative significance among the criteria, k indicates the number of criteria, n the number of alternatives.

In line [7], the preference degrees are expressed with the triangular fuzzy number $\tilde{P} = (p_l, p_c, p_r)$ (denoted by tilde), see Figure 2. This fuzzy number captures the uncertainty by admitting that the corresponding variable can reach any value from some interval with the assigned value of the membership degree μ ($\mu \in (0; 1]$). This membership degree anwers the question to what extent some value belongs to the given set. The binary operators $\oplus$ and $\odot$ extends the classical binary operations of addition and multiplication for fuzzy sets, see Eqs. 10, and 11.

$$\tilde{P} \oplus \tilde{Q} = (p_l, p_c, p_r) \oplus (q_l, q_c, q_r) = (p_l + q_l, p_c + q_c, p_l + q_l) \quad (10)$$

$$\tilde{P} \odot k = (p_l, p_c, p_r) \odot k = (kp_l, kp_c, kp_l), k \in \mathbb{R}^+ \quad (11)$$

The fuzzy positive flow indicates to what extent the alternative surpasses, on average, the other alternatives. The other way around, the negative flow indicates the degree at which the alternative falls short, on average, compared to all other alternatives. To ensure a complete ranking of the alternatives, the positive and negative flows must be combined into net flows using (Eq. 12).

$$\tilde{\phi}(a) = \tilde{\phi}^+(a) \ominus \tilde{\phi}^-(a), \text{for } \forall a \quad (12)$$

where $\ominus$ stands for the fuzzy extension of classical subtraction given by Eq. 13.

$$\tilde{P} \ominus \tilde{Q} = (p_l, p_c, p_r) \ominus (q_l, q_c, q_r) = (p_l - q_r, p_c - q_c, p_r - q_l) \quad (13)$$

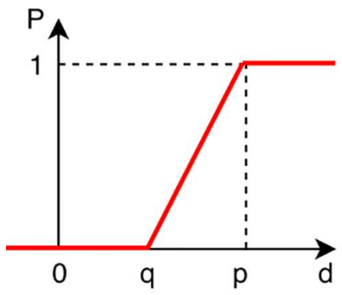


Figure 1 Linear preference function and preference degree

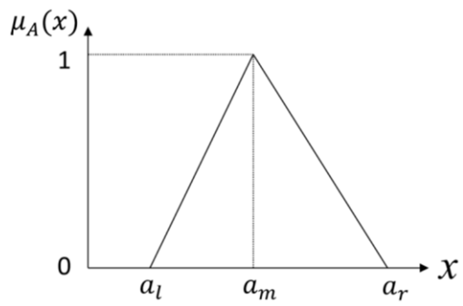


Figure 2 Triangular fuzzy number

3 Decision model

This section recalls the decision model introduced by [5]. The criteria and alternatives (strategies) have been expertly defined expertly based on the interviews conducted in the same car manufacturing company where the case study was performed. The selection of criteria is supported by [13] and [14], where the authors consider speed of process, complexity of process, and cost of processess in man-hours important factor for the evaluation. Despite the fact that the model has been proposed based on expert opinions from the automotive company, it does not use any criterion or strategy, which could not be reasonably expected in case of any industrial company.

3.1 Criteria

The following criteria for evaluations are considered:

- Speed of implementation,
- Complexity,
- Capacity effort,
- Setting of premises,
- Internal know-how,
- Output.

The speed of implementation is a very important factor in the selection of the tools. It is very important how fast each topic can be implemented in practice; how complex are the topics in the preparation and how much capacity must be used in terms of manpower and time. Furthermore, it is also very important whether premises can be set for the respective topic. For example, if premises are kept too coarse and generous in a change catalogue, the costs cannot be precisely defined. A precise and detailed definition of the premises also enables a detailed statement of costs for a specific measure. It is also important to ask whether the know-how is available internally. The employees and their experience are essential. Employees from development and purchasing can bring the topics into the lessons learnt tools. These topics have to be evaluated by the supplier. Finally, output is the last, also very important criterion. It can happen that everything can be implemented very fast, with low capacity and high know-how, but if the output is small or it brings little savings, the focus is usually placed on another topic. All six criteria are considered categorial (qualitative).

3.2 Alternatives

The alternatives in the presented model are three particular strategies which can be adopted by a company. These strategies can rarely be applied separately, but their combination with different ‘power’ is expected to be used:

- Change catalogue or pre-negotiation of possible changes in the future,
- Improvement of the technical requirements and specifications,
- A decrease in overhead and profit surcharge or a question of the ‘Surcharge calculation’ used by many OEMs, is future orientated.

The use of a change catalogue after nomination can be useful for example, to negotiate changes better and more effectively. A high-quality change catalogue is developed in close cooperation between the purchasing and development teams.

When specifying the details and quality of the specifications, the company can avoid many changes through the development of the product in the future, so that the change catalogue can be made redundant or at least greatly reduced in complexity.

The third main strategy, when trying to reduce the costs of product development and its delivery, is a decrease in overhead and profit surcharges. Many OEMs use a surcharge calculation as a calculation basis. The calculation uses the bottom-up approach to calculate the cost components and then adds the overhead and profit surcharges as a percentage of the material and production costs. This is determined primarily during the nomination and is agreed with the supplier.

4 Case study

This section begins with the introduction of the input data. Then, the results obtained by [5] of the implementation of the fuzzy-AHP and fuzzy-PROMETHEE approach to the presented model. The core part of this section focusses on the results of the application of the hybrid AHP-SMAA and fuzzy-PROMETHEE method. The results of all three methods are carefully compared, and recommendations are provided.

4.1 Input data

In this paper, we present the implementation of the model on the data brought by the survey in a single car manufacturer. That is, 113 managers (out of approximately 500) from the fields of purchase and logistics have been asked (in the fall, 2022) to evaluate the importance of criteria and performance of the alternatives using the Saaty’s scale with the possibility to express their hesitance using the interval within the scale. All evaluations have had to be done twice – first for the period before nomination (before the contract is signed) and second after nomination.

As for the AHP-SMAA method, the evaluations were considered random variables with discrete empirical distribution. The probability of each grade on the Saaty's scale corresponds to the relative proportion between all decision-makers. For instance, if all 113 decision-makers chose in total 200 different values for some compared pairs of alternatives (note that each decision maker could select more values from the scale because of the uncertainty), and if the value 2 (a very weak preference in favour of the first evaluated alternative) occurs 20 times, its relative proportion is 0.1. In this way, each individual opinion is considered without loss of data.

As for fuzzy PROMETHEE, the input values were handled in a completely different way. Unlike the AHP-SMAA, not all opinions were preserved for the evaluation process. Namely, only the grades with at least 10% of the evaluations were kept, the rest was ignored as outliers (otherwise, the ranges were too wide, and almost all possible rankings could occur then). The fuzzy inputs for fuzzy-PROMETHEE were derived in the following way: the minimum and maximum of the 80% range were used to calculate the lower and upper bound of the triangular fuzzy number, the vertex of the triangle (with $\mu = 1$) is equal to the mode of the empirical distribution (i.e., the most frequently chosen value). Due to the same scale used for all criteria, an identical preference function was used for all criteria. Namely, the linear function with $q = 1$ and $p = 9$ was set (it means that the maximum preference on the Saaty's scale leads to the maximum value of the preference degree, the lowest possible value of preference (0.125) corresponds with the value 2 on the Saaty's scale and then, the preference degree increases by 0.125 with each grade.

4.2 Results

The authors of [5] applied the fuzzy AHP method to the same dataset and get an unambiguous ranking of the alternatives, see Figure 3 and Figure 4. In other words, the uncertainty does not impact the final ranking at all. This gives rise to the idea that the solution is absolutely robust and that no hesitance about the prioritization of the strategies seems to be justified.

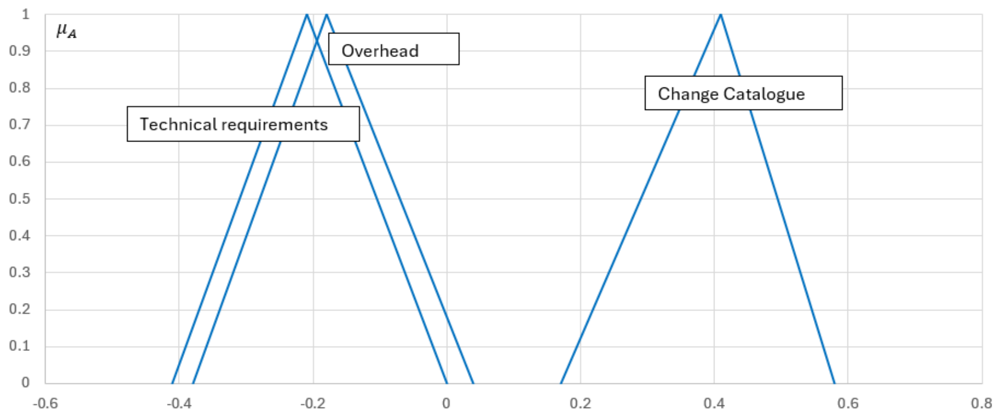


Figure 3 Final results of alternatives by fuzzy-AHP method before the nomination [Trumić and Zapletal (2023)]

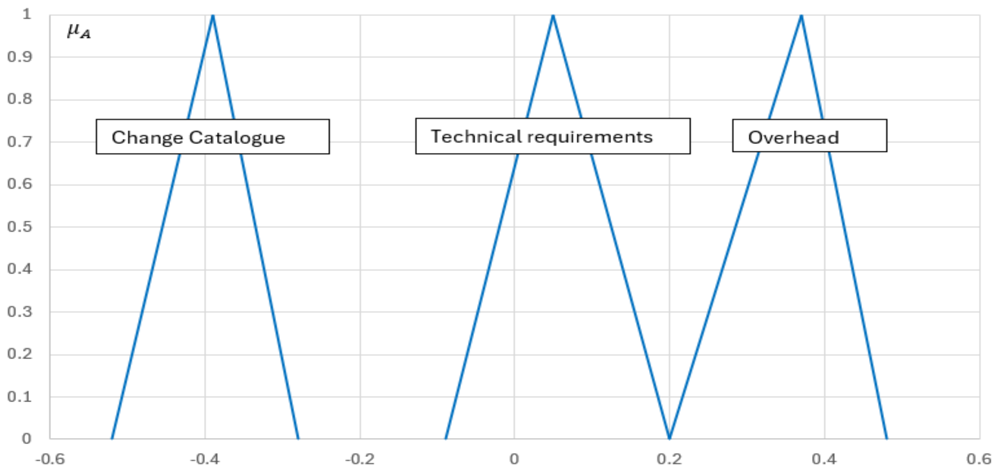


Figure 4 Final results of alternatives by fuzzy-AHP method after the nomination [Trumić and Zapletal (2023)]

In the lead-up to the supplier decision before nomination, it is crucial to prioritize the development of a cost catalogue, while defining highly detailed technical specifications is of lesser importance. This is reasonable because negotiating the list of changes with the best conditions is only possible before the contract is signed. Good prices for future changes after signing a contract cannot be expected. The reason why these future changes should be negotiated before the contract is signed is the better power position of purchasing and the leverage to be able to place the order with another supplier.

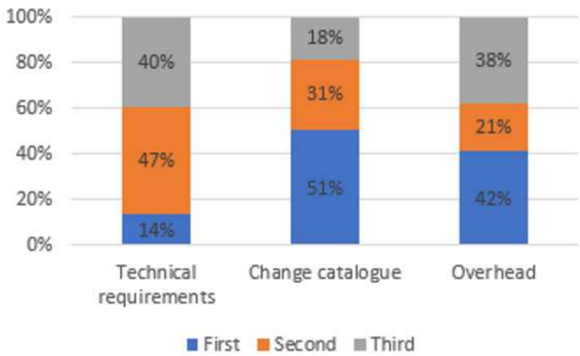
For the period after nomination, the ranking obtained by [5] is also unambiguous, but differs substantially. The most important tool is the overhead, followed by the technical requirements and the catalogue of changes. After the nomination, the lever towards the suppliers is gone and purchasing loses its position of power. For this reason, the prioritization of the change catalogue slipped to third place after a nomination, which is also understandable, because negotiating the change costs after the nomination makes little sense.

However, these results were based on the aggregation of the individual uncertain opinions using the (fuzzy-) geometric mean, and as for any other use of an aggregation operator, a part of information is potentially lost.

4.2.1 Results of AHP-SMAA method

Now, let us have a look at the results of the AHP-SMAA analysis. Unlike the fuzzy AHP, no evaluations by the decision-makers were lost by their aggregation. This means that the method reflects all assessments, even extremely outlying ones. Such an approach checks very well to what extent the final ranking is stable and unambiguous.

The results of the application of the AHP-SMAA method are shown in Figure 5. Namely the acceptability indices for all three positions of the strategies before and after the nomination are provided there. For the situation after nomination, the results are not so surprising. Althought each strategy can potentially be ranked at all positions, 3% of the cases are omittable for both, the first position of 'Change catalogue' and the last position of 'Overhead'. These results were expected in light of knowledge of the previous fuzzy AHP results. The results before nomination are much more interesting. It can be seen that the most frequent individual ranking need not necessarily correspond with the aggregated ranking. Technical requirements are ranked in almost 50% as the second one, however, according to aggregated results, this alternative is clearly the last one. 'Overhead' was ranked using the aggregated opinion as clearly second, but the AHP-SMAA analysis revealed that this position is the least frequent at all. The results indicated how much simplifying the aggregation can be, despite the included uncertainty. The results pointed out how unwise would be to focus only on the 'winning' strategy and ignore the remaining two strategies.



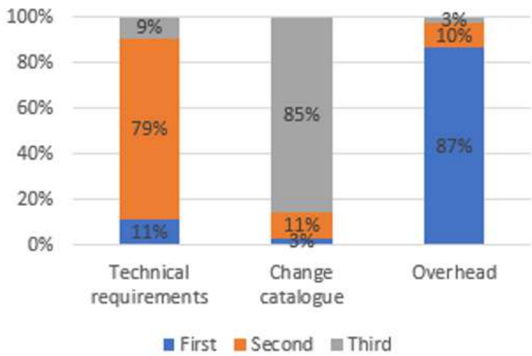


Figure 5 Final results of alternatives before (left) and after (right) the nomination

Table 1 Central weight vector for the results before nomination

Top ranked/criterion	Speed	Complexity	Capacity	Premises	Know-how	Output
Change catalogue	0.32	0.20	0.09	0.05	0.07	0.27
Technical requirements	0.29	0.22	0.12	0.06	0.08	0.23
Overhead	0.30	0.19	0.13	0.06	0.07	0.26

Since the ranking of the strategies before the nomination is by far more ambiguous, the central weight vector for this situation was calculated, see the results in Table 1. The weights in this table represent the mean value of the weights when one of the strategies is ranked the first. This analysis reveals to what extent the first position depends on the weights of the criteria. It can be seen that the average weights of some criteria are the same or very similar, regardless of the winning strategy (premises, know-how). On the other hand, the mean weights differ significantly (the statistical significance has been checked using the Mann-Whitney test in IBM SPSS statistics at 5% level of significance) in case of speed (the highest priority if change catalogue wins), complexity (the highest priority if technical requirements win), and output (the highest priority is assigned to this criterion if change catalogue or overhead are ranked the first).

4.2.2 Results of Fuzzy-PROMETHEE method

Now, let us focus on the results of the fuzzy PROMETHEE method, see Figure 6 and Figure 7. The results before the nomination closely align with the AHP-SMAA findings, indicating a less clear ranking compared to fuzzy-AHP. The strategy that should be prioritized the most is, as well as the one that showed the original results of fuzzy-AHP, 'Change catalogue'. The remaining two strategies are more or less equally suitable. After the nomination, the alternative ranking matches that of fuzzy AHP. However, there is a reduction in the gap between the leading 'Overhead' and the second-place 'Technical requirements'. The removal of the outliers for the fuzzy-PROMETHEE did not substantially impact the final ranking. Moreover, for managers, the resulting fuzzy flows are easy to interpret when compared with the acceptability indices in SMAA.

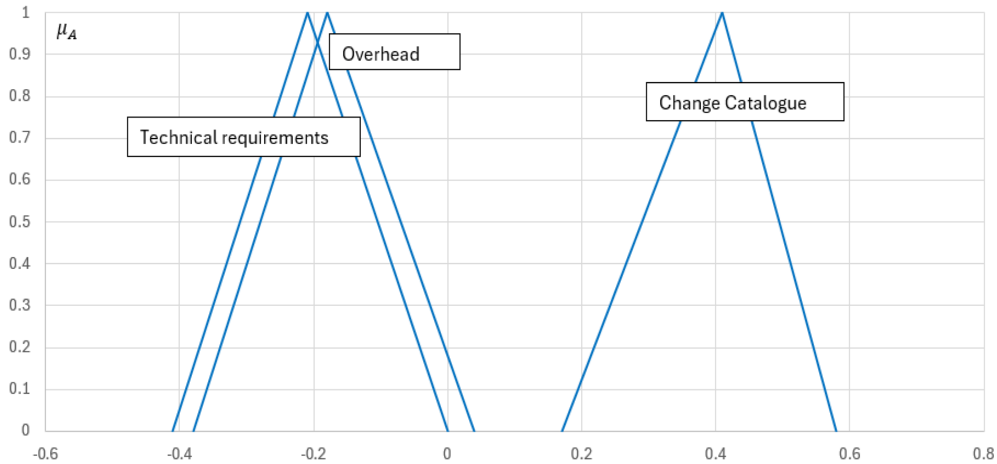


Figure 6 Final result of alternatives by fuzzy-PROMETHEE method before the nomination [Trumić and Zapletal (2023)]

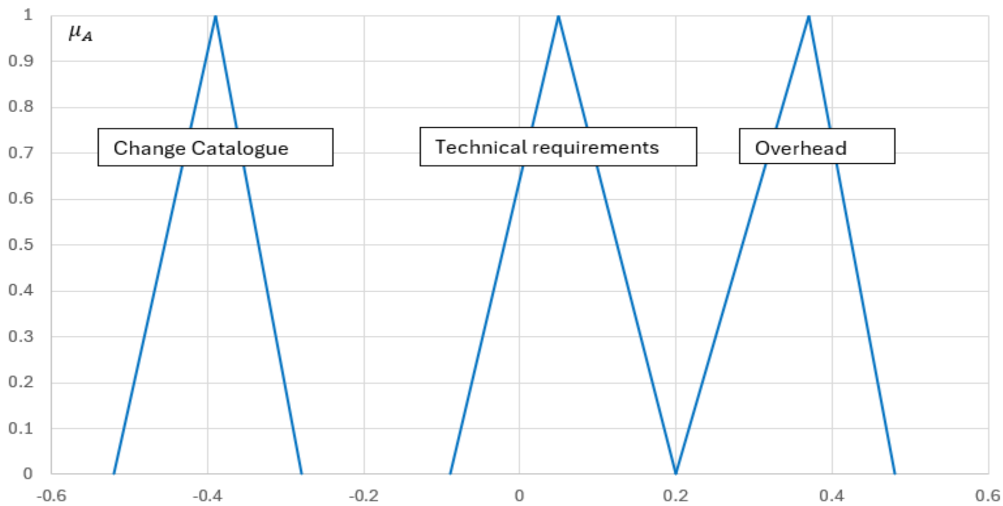


Figure 7 Final result of alternatives by fuzzy-PROMETHEE method after the nomination [Trumić and Zapletal (2023)]

One significant advantage of PROMETHEE is its capability to break down the net flow values, see Eq. (12). Essentially, the net flow can be decomposed into individual contributions of criteria. This means that the net flow can be seen as the sum of contributions from each criterion separately. If a criterion's individual contribution to the net flow is negative, it indicates that the alternative is weaker in that criterion compared to others, on average, thereby reducing the total net flow (such a criterion can be seen as a disadvantage of the alternative). On the contrary, if the individual contribution is positive, it signifies the strength in that criterion, boosting the total net flow. These individual criterion contributions are illustrated in Figure 8 and Figure 9.

When looking at Figure 8, we can see unicriterion net flows before supplier nomination. The alternative of creating a change catalogue has no got any significant weaknesses and has three important strengths. It is relatively fast to create a change catalogue and it provides a good performance in premises and outputs. The alternative of improving technical requirements has advantage, that it is not a complex task, but on the other hand, it is not easily specified at this stage, and it would not make a large difference in outcomes. The remaining alternative (Overhead) has two main weaknesses: it takes a lot of time to negotiate overheads and it is difficult to know overheads before the production starts.

When looking at the structure of the net flows at the period after the nomination (Figure 9) four criteria are the most driving (the size of their columns is the greatest). ‘Change catalogue’ is the most preferred strategy because of its outstanding performance in outputs, premisses and speed (the contribution of all these three criteria to the net flow is more or less the same). The strategy of ‘Overhead’ is mainly undermined by poor performance in complexity (it is too high) and related slow speed.

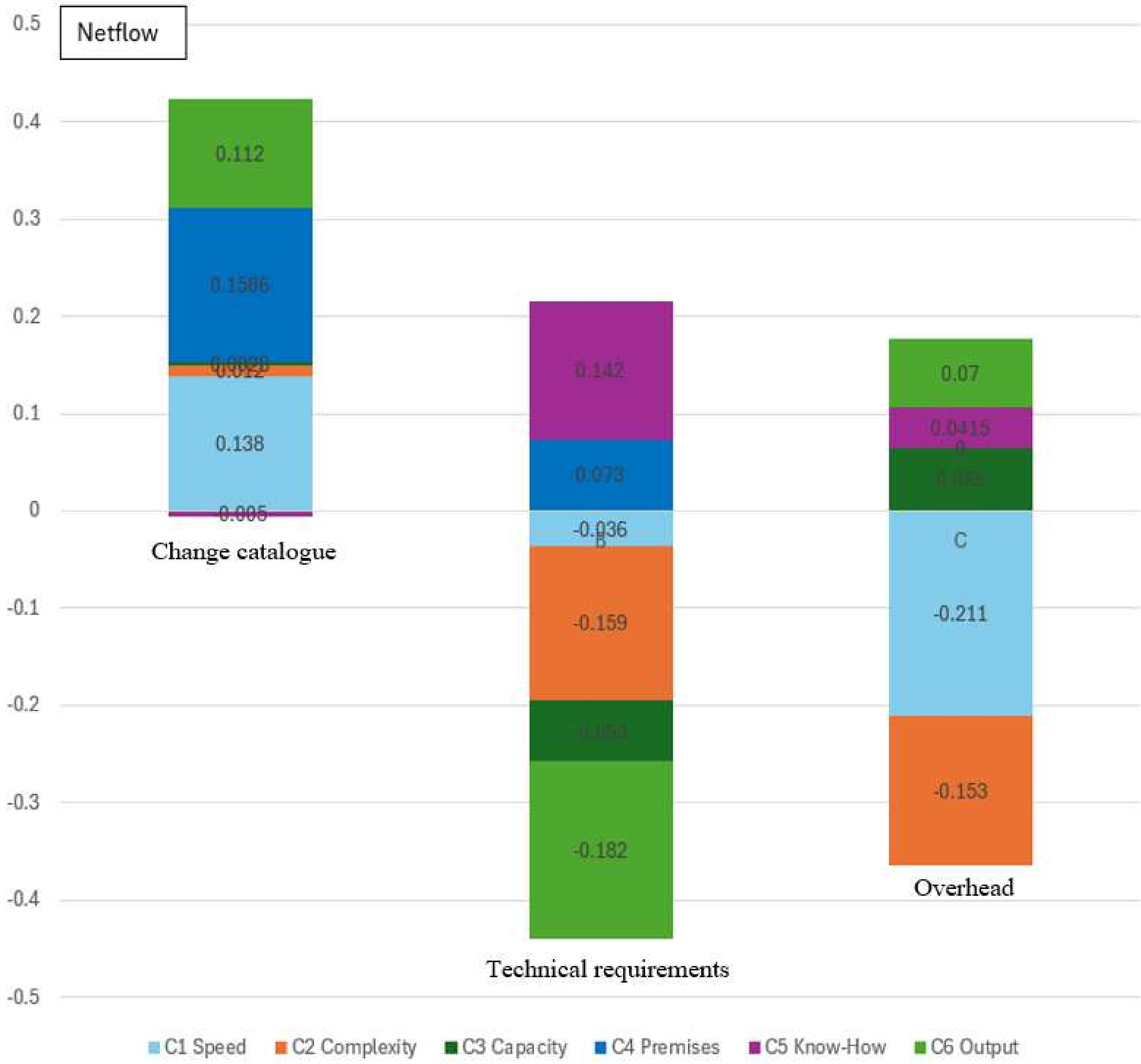


Figure 8 Results from fuzzy-PROMETHEE before the nomination

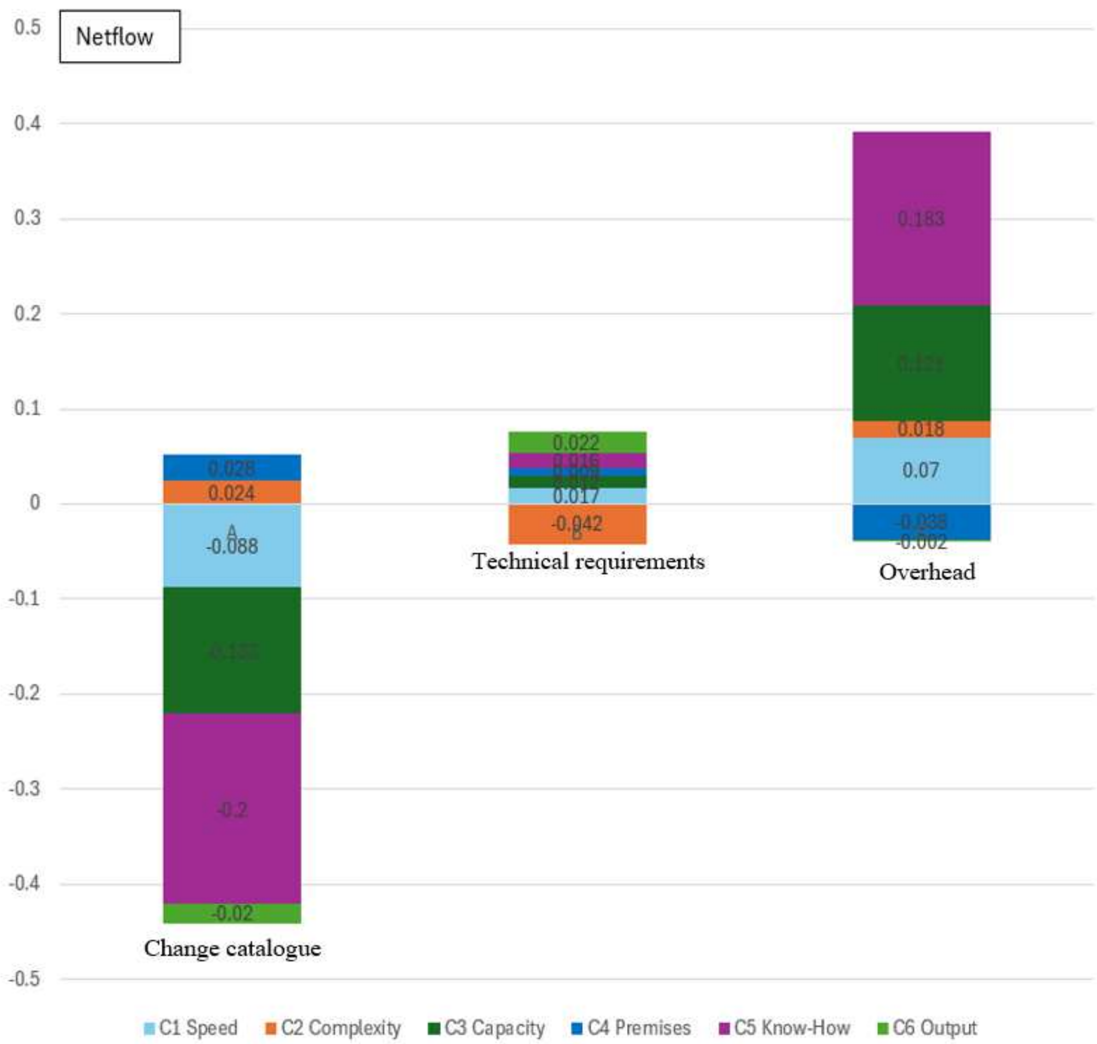


Figure 9 Results from fuzzy-PROMETHEE after the nomination

5 Conclusions

In this paper, an optimal strategy of a company towards its suppliers was explored for the periods before and after the nomination of a supplier is done. The model introduced by [5] has been solved using a completely different approach to investigate the impact of uncertainty on the results. Rather than aggregating individual opinions to derive a single outcome, every individual opinion was taken into account, including the hesitations of the participants. The findings showed that meanwhile aggregated rankings may appear clear and straightforward, analyzing individual evaluations could potentially reveal a completely different perspective. The research demonstrated that, based on survey data, selecting the best strategy before supplier nomination is more challenging compared to the post-nomination scenario. A drawback of detailed results is their complexity in interpretation compared to aggregated results. If the proportions for alternatives are closely similar, a supplementary analysis becomes necessary. For example, segmentation of individuals to understand the variability of the ranking or exploration of the weight values of the average criteria weights for each ranking could be beneficial. The main limitation of this study is that the conclusions are made based on the survey conducted in a single company, despite the fact that the company is a key player on the market, and that a significant number of expert opinions were collected. Above that, the model does not consider the dependencies between evaluation criteria at all, which can potentially be simplifying too. Future research will focus on verifing the results using further datasets. Then, an impact of other factors, that are not considered in this study, can be explored, like different type of products (or their parts), or the aforementioned dependencies between the criteria.

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