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Research Article

An Integrated PIPRECIA and COPRAS Method under Fuzzy Environment: A Case of Truck Tractor Selection

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ABSTRACT

Selecting the right truck tractor is critical for logistics companies involved in road freight transportation. Determining the criteria that are effective in the selection of truck tractors and then evaluating the alternatives are the main objectives of this study. In this context, a hybrid Multi-Criteria Decision-Making model composed of Fuzzy PIPRECIA (F-PIPRECIA) and Fuzzy COPRAS (F-COPRAS) methods is proposed to be used in the selection of truck tractors. In the related literature, no studies that applied F-PIPRECIA and F-COPRAS together to determine the best truck tractor have been published yet. In this regard, this study is thought to contribute to the literature in terms of the methods used and the application of truck tractor selection. Moreover, the findings of this study will pave the way for those who conduct academic studies and the authorities of companies involved in road transport in the logistics sector.

Keywords: Truck Tractor Selection, F-PIPRECIA, F-COPRAS, Multi-Criteria Decision-Making

1. Introduction

Road transportation is one of the most important branches of the logistic sector. Parallel to the development and growth, the products and services offered by other industries that provide inputs to the logistic industry have also diversified significantly, developed, and become more complex in response to the sector's needs. The importance of factors such as efficiency and economy has grown for the increasingly complex logistics business processes. It has become an unavoidable requirement for every decision to be one step ahead in a sector with intense competition to contribute to these factors positively. Strategic issues are confronting road transport companies operating in the logistics sector. The truck tractor selection problem is one of the decision-making problems. An essential investment for businesses, and the appropriate selection of truck tractors, which comprise the cost item, is critical to the company's success. A poor decision may result in high costs and inefficient business operations. Numerous companies in the market manufacture and sell truck tractors. When it comes to brands from other countries, there are a plethora of options. Companies must make the most appropriate decision to make the most suitable choice by taking into account their specific working conditions and situations. However, various criteria must be considered and evaluated concurrently to make an informed decision. This situation adds difficulty to the case. The current study will examine the essential criteria for the truck tractor selection problem and their importance in decision-making.

In this study, the truck tractor selection problem is handled comprehensively. Firstly, the most important criteria in this selection problem are investigated and put forth by the experts and then confirmed by the similar studies published in the literature. Secondly, integrated multi-criteria decision-making (MCDM) model under a fuzzy environment is implemented to the selection problem of truck tractors for the first time to the best of our knowledge. The F-PIPRECIA method, a relatively new MCDM method, is used to determine the importance of eight different criteria in selecting truck tractors. The eight alternatives are evaluated using the F-COPRAS method. Furthermore, a comprehensive sensitivity analysis is conducted to reveal the effect of changing criteria weights, reverse rank and alternative sets.

The reason to apply PIPRECIA is that this method is one of the relatively novel MCDMs in the literature and allows researchers to handle the problem without ranking. Moreover, the PIPRECIA method stands out as it offers the opportunity to evaluate with fewer comparisons compared to other pairwise comparison-based methods. On the other hand, the COPRAS method is preferred because of its ratio-based principle. The examined problem is handled in a fuzzy environment due to the nature of the truck tractor selection problem. It is thought to be more accurate to carry out operations with fuzzy numbers due to the definition sets of the criteria included in the study. For this reason, the effect of these criteria in a fuzzy environment will reflect the reality more. The literature review and methodology sections discuss further explanations for the defense to prefer PIPRECIA and COPRAS under a fuzzy environment.

The remaining of the study is structured as a literature review, the methodology of F-PIPRECIA and F-COPRAS, the case study, the sensitivity analysis, and the conclusion sections, respectively.

2. Literature Review

The literature has been reviewed in terms of three perspectives. Recent studies about F-PIPRECIA, F-COPRAS, and the studies about truck tractors are summarized, respectively.

Authors	The focus of the study	Solution methodology
Stevic et al. (2018)	Evaluation of SWOT elements for the application of barcode technology	F-PIPRECIA
Đalić et al. (2020)	Selection of green supplier	F-PIPRECIA–interval rough SAW
Vesković et al. (2020)	Evaluation of criteria to select a reach stacker	F-PIPRECIA
Marković et al. (2020)	Evaluation of banks' performances	F-PIPRECIA, CRITIC, and I-distance
Stanković et al. (2020)	Evaluation of risks in road traffic	F-PIPRECIA, fuzzy MARCOS, fuzzy SAW, and fuzzy TOPSIS
Tomašević et al. (2020)	Evaluation of criteria for computing systems	F-PIPRECIA
Blagojević et al. (2020)	Evaluation of safety in rail traffic	F-PIPRECIA and Data Envelopment Analysis
Blagojević et al. (2021)	Evaluation of safety at railway crossings	F-PIPRECIA and Fuzzy MARCOS
Puška et al. (2021)	Selection of suppliers for agricultural pharmacies	Interval-valued F-PIPRECIA and Interval-valued fuzzy MABAC
Nedeljković et al. (2021)	Selection of rapeseed oils	F-PIPRECIA -Fuzzy MABAC

Table 1. Literature Review of F-PIPRECIA

After introducing the PIPRECIA method, its extensions and application studies have rapidly been brought into the literature. According to Table 1, it is seen that PIPRECIA was applied in integration with different methods, especially in 2020. Subjects such as supplier selection, system, and performance evaluation have been studied primarily.

Authors	The focus of the study	Solution methodology
Zarbakhshnia et al. (2018)	Evaluation of third-party reverse logistics provider	F-COPRAS
Khorasani (2018)	Evaluation of green supplier	Fuzzy AHP and F-COPRAS
Garg et al. (2019)	Selection of e-learning websites	F-COPRAS
Tolga & Durak (2019)	Evaluation of air cargo projects	F-COPRAS
Dhiman & Deb (2020)	Evaluation of hybrid wind farms	Fuzzy TOPSIS and F-COPRAS
Ansari et al. (2020)	Evaluation of risk solutions for sustainable remanufacturing supply chain	Fuzzy SWARA and F-COPRAS
Alkan & Albayrak (2020)	Evaluation of renewable energy sources	F-COPRAS and Fuzzy MULTIMOORA
Roozbahani et al. (2020)	Evaluation of water transfer projects	Grey COPRAS and F-COPRAS
Shaikh et al. (2020)	Selection of braking system material for automobiles	F-COPRAS
Hasheminezhad et al. (2021)	Evaluations of risks in train accidents	F-COPRAS and Fuzzy DEMATEL
Başaran & Çakir (2021)	Evaluation of food safety and halal food criteria	F-COPRAS

Table 2. Literature Review of F-COPRAS

F-COPRAS studies published in the literature are given in Table 2. It is seen that F-COPRAS has been integrated with more traditional MCDM methods or applied alone. This issue shows that Fuzzy COPRAS is one of the MCDM methods that can be used with more up-to-date methods. However, when we look at the application areas, it is seen that it is frequently used in the logistics sector and supplier selection issues. Therefore, the integration of COPRAS with PIPRECIA will contribute to the logistics literature.

Authors	The focus of the study	Solution methodology
Baykasoglu (2010)	Selection of truck	ELECTRE
Baykasoglu et al. (2011)		EVEN-SWAP
Baykasoglu et al. (2013)		Fuzzy DEMATEL and Fuzzy hierarchical TOPSIS
Baykasoglu & Golcuk (2014)		Fuzzy Integral
de Sousa Junior et al. (2014)	Selection of highway truck	Weighted Product Model ELECTRE I PROMETHEE II
Chan et al. (2016)	Supply Chain Optimization involving truck selection	Heuristic Method
Chakraborty & Prasad (2016)	Selection of industrial truck	Quality Function Deployment based Approach (QFD)
Doğan et al. (2017)	Selection of truck in the logistics industry	COPRAS-G
Görçün (2019)	Selection of towing vehicles	AHP, Entropy, and TOPSIS

Table 3. Literature Review of Trucks

Studies focused on the trucks are given in Table 3. In order to show the diversity of the methods used in the studies, the literature has been discussed in a broader time frame. Since the truck concept contains many types, the selection of trucks used in different areas has been applied with various methods.

The fact that the PIPRECIA method has not been applied in the logistics sector and the COPRAS method has not been used by integrating recently proposed MCDM methods shows the contribution that this study will make to the literature. For these reasons, there is still a gap in the literature, and therefore studies that comprehensively address truck selection and offer objective evaluations are required. It is thought that this study will fill these gaps and contribute to the literature.

3. Methodology

In this study, we applied integrated PIPRECIA and COPRAS methods under a fuzzy environment for the case of truck tractor selection problem. The reasons to choose these two MCDM methods lay in their advantages and suitability for the problem.

PIPRECIA proposed by Stanujkić et al. (2017) is developed as an extension of SWARA method proposed by Kersuliene et al. (2010). Although SWARA has the advantage of providing less comparison compared to AHP developed by Saaty (1980), it has a drawback in handling real-world problems under group decisions (Stanujkić et al., 2017, 119). Moreover, SWARA may limit decision-makers in their evaluations since it requires sorting criteria by considering their expected importance (Stanujkić et al., 2021, 2). The PIPRECIA method has been brought to the literature by eliminating these disadvantages. As stated by Stanujkić et al. (2021), PIPRECIA does not require pre-rank criteria; instead, it allows the relative significance to be less than, equal to, or greater than the significance value of the previous criterion. In addition, proposing PIPRECIA method as an extension of SWARA method eliminates the difficulty in handling real-world group decision-making problems (Stanujkić et al., 2017, 119). Also, as mentioned in the literature review section, there is a gap in the literature of studies that applied PIPRECIA method.

On the other hand, COPRAS method developed by Zavadskas et al. (1994) attracts attention in two reasons. The first one is related to its working procedure. It mainly provides reliable and accurate solutions by handling every aspect of criteria to determine the best alternative according to the ratios (Amoozad Mahdiraji et al., 2018, 10). The second reason is the gap in the application literature of COPRAS. As stated in the literature review section, it is seen that COPRAS method has been integrated with traditional MCDM methods. However, demonstrating the usability of the COPRAS method with recently proposed methods will enable us to benefit from the advantages of the COPRAS.

In addition to applying MCDM methods traditionally, scholars tend to prefer fuzzy environments to avoid biased results. Although there are several fuzzy sets (i.e., Classical Fuzzy Sets (Zadeh, 1965), Intuitionistic Fuzzy Sets (Atanassov, 1983), Neutrosophic Sets (Smarandache, 1999), Plithogenic Fuzzy Sets (Smarandache, 2017)) used in MCDM problems, this study applies PIPRECIA and COPRAS methods under a classic fuzzy environment. Solving MCDM problems with fuzzy sets makes the decision environment more accurate (Ulutaş et al., 2021, 1229). In other words, using fuzzy sets in MCDM problems eliminates the unreliability, ambiguity of the information gathered from decision-makers (Stanujkić et al., 2021, 2). Although different concepts are introduced to remove uncertainty with each fuzzy extension, the use of appropriate fuzzy sets according to the structure of the data of the problem is another point that should be given importance. Therefore, the examined problem is handled in a classical fuzzy environment because of the nature of the truck tractor selection problem. Due to the content and data of the issue discussed in the study, it is thought that operating with fuzzy numbers will satisfy the need to eliminate ambiguity.

In the following, the detailed procedures OF F-PIPRECIA and F-COPRAS methods are explained. While the criteria weights are calculated with the help of F-PIPRECIA, the evaluations of the alternatives are conducted by the F-COPRAS method.

3.1. Fuzzy PIPRECIA (Fuzzy PIvot Pairwise RElative Criteria Importance Assessment)

F-PIPRECIA is one of the MCDM methods to determine criteria weights. F-PIPRECIA procedure is as follows (Stevic et al., 2018, 7-9).

In the first phase of F-PIPRECIA method, the criteria are determined.

$$j: criterion; j = 1,2,3, \dots, n$$

In the second phase of F-PIPRECIA method, the decision-makers (DMs) evaluate the criteria. The fuzzy evaluation scale can be seen in Table 4.

$$l: triangular\ fuzzy\ number\ lower\ limit\ value$$

$$m: triangular\ fuzzy\ number\ the\ most\ promising\ value$$

$$u: triangular\ fuzzy\ number\ upper\ limit\ value$$

If criterion *j* is more important than criterion *(j+1)*			**If criterion *j* is less important than criterion *(j+1)***		
l	m	u	l	m	u
1.000	1.000	1.050	0.667	1.000	1.000
1.100	1.150	1.200	0.500	0.667	1.000
1.200	1.300	1.350	0.400	0.500	0.667
1.300	1.450	1.500	0.333	0.400	0.500
1.400	1.600	1.650	0.286	0.333	0.400
1.500	1.750	1.800	0.250	0.286	0.333
1.600	1.900	1.950	0.222	0.250	0.286

Table 4. Fuzzy Scale of F-PIPRECIA

The relative importance of criteria can be seen in Equation 1.

$$d: decision\ maker; d = 1,2,3, \dots, D$$

$\tilde{s}_{jld}: relative\ importance\ lower\ limit\ value\ according\ to\ decision\ maker\ r$

$\tilde{s}_{jmd}: relative\ importance\ the\ most\ promising\ value\ according\ to\ decision\ maker\ r$

$\tilde{s}_{jud}: relative\ importance\ upper\ limit\ value\ according\ to\ decision\ maker\ r$

$\tilde{s}_{jr}: relative\ importance\ according\ to\ decision\ maker\ r$

$$\tilde{s}_{jd} = \left(\tilde{s}_{jld}; \tilde{s}_{jmd}; \tilde{s}_{jud}\right) \quad (1)$$

The structure of relative importance can be seen in Equation 2.

$$\tilde{s}_{jd} = \begin{cases} Criterion\ j\ is\ more\ important\ than\ criterion\ (j-1) \Rightarrow \tilde{s}_{jd} > \tilde{1} \\ importance\ of\ criterion\ j = importance\ of\ criterion\ (j-1) \Rightarrow \tilde{s}_{jd} = \tilde{1} \\ Criterion\ (j-1)\ is\ more\ important\ than\ criterion\ j \Rightarrow \tilde{s}_{jd} < \tilde{1} \end{cases} \quad (2)$$

The opinions of the DMs are integrated by using Equations 3, 4, and 5.

$\tilde{s}_{jl}: relative\ importance\ lower\ limit\ value$

$\tilde{s}_{jm}: relative\ importance\ the\ most\ promising\ value$

$\tilde{s}_{ju}: relative\ importance\ upper\ limit\ value$

$\tilde{s}_{j}: relative\ importance$

$$\tilde{s}_{jl} = \sqrt[D]{\left(\tilde{s}_{jl1}\right)\left(\tilde{s}_{jl2}\right)\left(\tilde{s}_{jl3}\right) \dots \left(\tilde{s}_{jlD}\right)} \quad (3)$$

$$\tilde{s}_{jm} = \sqrt[D]{\left(\tilde{s}_{jm1}\right)\left(\tilde{s}_{jm2}\right)\left(\tilde{s}_{jm3}\right) \dots \left(\tilde{s}_{jmD}\right)} \quad (4)$$

$$\tilde{s}_{ju} = \sqrt[D]{\left(\tilde{s}_{ju1}\right)\left(\tilde{s}_{ju2}\right)\left(\tilde{s}_{ju3}\right) \dots \left(\tilde{s}_{juD}\right)} \quad (5)$$

The coefficient is calculated by using Equations 6, 7, and 8.

$\tilde{k}_{jl}: coefficient\ lower\ limit\ value\ of\ criterion\ j$

$\tilde{k}_{jm}: coefficient\ the\ most\ promising\ value\ of\ criterion\ j$

$\tilde{k}_{ju}: coefficient\ upper\ limit\ value\ of\ criterion\ j$

$\tilde{k}_{j}: coefficient\ of\ criterion\ j$

$$\tilde{k}_{jl} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{ju} \end{cases} \quad (6)$$

$$\tilde{k}_{jm} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{jm} \end{cases} \quad (7)$$

$$\tilde{k}_{ju} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{jl} \end{cases} \quad (8)$$

This coefficient can be seen in Equation 9.

$$\tilde{k}_j = \left(\tilde{k}_{jl}; \tilde{k}_{jm}; \tilde{k}_{ju}\right) \tag{9}$$

$\tilde{q}_{jl}$: *fuzzy weight lower limit value of criterion j*

$\tilde{q}_{jm}$: *fuzzy weight the most promising value of criterion j*

$\tilde{q}_{ju}$: *fuzzy weight upper limit value of criterion j*

$\tilde{q}_j$: *fuzzy weight of criterion j*

$$\tilde{q}_{jl} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)l}}{\tilde{k}_{ju}} \end{cases} \tag{10}$$

$$\tilde{q}_{jm} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)m}}{\tilde{k}_{jm}} \end{cases} \tag{11}$$

$$\tilde{q}_{ju} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)u}}{\tilde{k}_{jl}} \end{cases} \tag{12}$$

The fuzzy weights of the criteria can be seen in Equation 13.

$$\tilde{q}_j = \left(\tilde{q}_{jl}; \tilde{q}_{jm}; \tilde{q}_{ju}\right) \tag{13}$$

Relative weights of criteria are calculated by using Equations 14,15, and 16.

$\widetilde{w}_{jl}$: *relative weight lower limit value of criterion j*

$\widetilde{w}_{jm}$: *relative weight the most promising value of criterion j*

$\widetilde{w}_{ju}$: *relative weight upper limit value of criterion j*

$\widetilde{w}_j$: *relative weight of criterion j*

$$\widetilde{w}_{jl} = \frac{\tilde{q}_{jl}}{\sum_{j=1}^{n} \tilde{q}_{ju}} \tag{14}$$

$$\widetilde{w}_{jm} = \frac{\tilde{q}_{jm}}{\sum_{j=1}^{n} \tilde{q}_{jm}} \tag{15}$$

$$\widetilde{w}_{ju} = \frac{\tilde{q}_{ju}}{\sum_{j=1}^{n} \tilde{q}_{jl}} \tag{16}$$

Relative weights can be seen in Equation 17.

$$\widetilde{w}_j = \left(\widetilde{w}_{jl}; \widetilde{w}_{jm}; \widetilde{w}_{ju}\right) \tag{17}$$

These weight values show the fuzzy importance levels of criteria according to Fuzzy PIPRECIA.

3.2. Fuzzy COPRAS (Fuzzy COmplex PRoportional ASsessment)

F-COPRAS is one of the MCDM methods. The procedure of F-COPRAS is as follows (Yazdani et al., 2011, 31-33).

The DM evaluates the performance of the alternatives by using the fuzzy scale. The evaluations of the DM construct the initial fuzzy decision matrix. The initial fuzzy decision matrix for the first DM can be seen in Equation 18.

$i: alternative; i = 1,2,3, \dots, m$

$\tilde{x}_{ijd}: fuzzy\ performance\ value\ of\ alternative\ i\ with\ respect\ to\ criterion\ j$

$according\ to\ decision\ maker\ d$

$\tilde{x}_{ijld}: fuzzy\ performance\ lower\ limit\ value$

$\tilde{x}_{ijmd}: fuzzy\ performance\ the\ most\ promising\ value$

$\tilde{x}_{ijud}: fuzzy\ performance\ upper\ limit\ value$

$$\begin{bmatrix} \tilde{x}_{111} & \tilde{x}_{121} & \cdots & \tilde{x}_{1n1} \\ \tilde{x}_{211} & \tilde{x}_{221} & \cdots & \tilde{x}_{2n1} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m11} & \tilde{x}_{m21} & \cdots & \tilde{x}_{mn1} \end{bmatrix} \tag{18}$$

The opinions of the DMs construct the triangular fuzzy number in Equation 19.

$$\tilde{x}_{ijd} = \left(\tilde{x}_{ijld}; \tilde{x}_{ijmd}; \tilde{x}_{ijud}\right) \tag{19}$$

The opinions of the DMs are integrated by using Equations 20, 21, and 22.

$\tilde{x}_{ij}: integrated\ fuzzy\ performance\ value\ of\ alternative\ i\ with\ respect\ to\ criterion\ j$

$\tilde{x}_{ijl}: integrated\ fuzzy\ performance\ lower\ limit\ value$

$\tilde{x}_{ijm}: integrated\ fuzzy\ performance\ the\ most\ promising\ value$

$\tilde{x}_{iju}: integrated\ fuzzy\ performance\ upper\ limit\ value$

$$\tilde{x}_{ijl} = \sqrt[D]{\prod_{d=1}^{D} \tilde{x}_{ijld}} \tag{20}$$

$$\tilde{x}_{ijm} = \sqrt[D]{\prod_{d=1}^{D} \tilde{x}_{ijmd}} \tag{21}$$

$$\tilde{x}_{iju} = \sqrt[D]{\prod_{d=1}^{D} \tilde{x}_{ijud}} \tag{22}$$

An integrated fuzzy decision matrix can be seen in Equation 23.

$$\begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{23}$$

Integrated opinions construct the triangular fuzzy number in Equation 24.

$$\tilde{x}_{ij} = \left(\tilde{x}_{ijl}; \tilde{x}_{ijm}; \tilde{x}_{iju}\right) \tag{24}$$

Fuzzy performance values are normalized by using Equations 25, 26, and 27.

$\tilde{r}_{ij}: normalized\ fuzzy\ performance\ value\ for\ alternative\ i, criterion\ j$

$\tilde{r}_{ijl}: normalized\ fuzzy\ performance\ lower\ limit\ value$

$\tilde{r}_{ijm}: normalized\ fuzzy\ performance\ most\ promising\ value$

$\tilde{r}_{iju}: normalized\ fuzzy\ performance\ upper\ limit\ value$

$$\tilde{r}_{ijl} = \frac{\tilde{x}_{ijl}}{\sum_{i=1}^{m}[\tilde{x}_{ijl}+\tilde{x}_{ijm}+\tilde{x}_{iju}]} \quad (25)$$

$$\tilde{r}_{ijm} = \frac{\tilde{x}_{ijm}}{\sum_{i=1}^{m}[\tilde{x}_{ijl}+\tilde{x}_{ijm}+\tilde{x}_{iju}]} \quad (26)$$

$$\tilde{r}_{iju} = \frac{\tilde{x}_{iju}}{\sum_{i=1}^{m}[\tilde{x}_{ijl}+\tilde{x}_{ijm}+\tilde{x}_{iju}]} \quad (27)$$

These values construct the triangular fuzzy number in Equation 28.

$$\tilde{r}_{ij} = (\tilde{r}_{ijl}; \tilde{r}_{ijm}; \tilde{r}_{iju}) \quad (28)$$

Fuzzy weighted normalized performance values are calculated by using Equations 29, 30, and 31.

$\tilde{t}_{ij}: fuzzy\ weighted\ normalized\ performance\ value for\ alternative\ i, criterion\ j$

$\tilde{t}_{ijl}: fuzzy\ weighted\ normalized\ performance\ lower\ limit\ value$

$\tilde{t}_{ijm}: fuzzy\ weighted\ normalized\ performance\ most\ promising\ value$

$\tilde{t}_{iju}: fuzzy\ weighted\ normalized\ performance\ upper\ limit\ value$

$$\tilde{t}_{ijl} = \widetilde{w}_{jl}\tilde{r}_{ijl}\ for\ \forall i,j \quad (29)$$

$$\tilde{t}_{ijm} = \widetilde{w}_{jm}\tilde{r}_{ijm}\ for\ \forall i,j \quad (30)$$

$$\tilde{t}_{iju} = \widetilde{w}_{ju}\tilde{r}_{iju}\ for\ \forall i,j \quad (31)$$

The sums of the fuzzy weighted normalized performance values for cost criteria are found using Equations 35, 36, and 37.

$$j: cost\ criterion; j = k+1, k+2, k+3, \ldots, n$$

$\tilde{R}_i: sum\ of\ fuzzy\ weighted\ normalized\ performance\ value\ for\ cost\ criteria$

$\tilde{R}_{il}: sum\ of\ fuzzy\ weighted\ normalized\ performance\ lower\ limit\ value$

$\tilde{R}_{im}: sum\ of\ fuzzy\ weighted\ normalized\ performance\ most\ promising\ value$

$\tilde{R}_{iu}: sum\ of\ fuzzy\ weighted\ normalized\ performance\ upper\ limit\ value$

$$\tilde{R}_{il} = \sum_{j=k+1}^{n} \tilde{t}_{ijl}\ for\ \forall i \quad (35)$$

$$\tilde{R}_{im} = \sum_{j=k+1}^{n} \tilde{t}_{ijm}\ for\ \forall i \quad (36)$$

$$\tilde{R}_{iu} = \sum_{j=k+1}^{n} \tilde{t}_{iju}\ for\ \forall i \quad (37)$$

The sums of the fuzzy weighted normalized performance values of benefit criteria are defuzzified using Equation 38 according to the best non-fuzzy performance (BNP) method.

$P_i: defuzzified\ weighted\ normalized\ performance\ value\ of\ benefit\ criteria$

$$P_i = \frac{(\tilde{P}_{iu}-\tilde{P}_{il})+(\tilde{P}_{im}-\tilde{P}_{il})}{3} + \tilde{P}_{il}\ for\ \forall i \quad (38)$$

The sums of the fuzzy weighted normalized performance values of cost criteria are defuzzified using Equation 39 according to the best non-fuzzy performance (BNP) method.

R_i: *defuzzified weighted normalized performance value of cost criteria*

$$R_i = \frac{(\tilde{R}_{iu}-\tilde{R}_{il})+(\tilde{R}_{im}-\tilde{R}_{il})}{3} + \tilde{R}_{il} \ for \ \forall i \quad (39)$$

The relative utility values of the alternatives are calculated by using Equation 40.

Q_i: *relative utility value of alternative*

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{1}{R_i}} \ for \ \forall i \quad (40)$$

The utility degrees of the alternatives are calculated by using Equation 41.

N_i: *utility degree of alternative i*

$$N_i = \frac{Q_i}{\max_i Q_i} \quad (41)$$

The highest utility degree shows the best alternative in the MCDM problem according to the F-COPRAS method.

4. Case Study

In this study, an evaluation of truck tractor alternatives in Turkey was conducted. In the first phase of the study, the most important criteria when considering a truck tractor selection were determined. The criteria discussed in the study have been put forward in the light of the literature and in line with the opinions of three experts collected by interviews. However, the criteria were also confirmed by a separate expert opinion. It should be noted that one of our contributing authors has been certified as a heavy vehicle instructor. Therefore, it is thought that the criteria included in the study represent the perspectives both in terms of practical and theoretical.

In this case, three experts contributed to our study with their opinions. The experts are the owner of one of the transportation companies operated in Turkey since 1975 and the two drivers working there. Interviews were held with these experts in order to reveal the criteria for the truck tractor selection problem. According to the interviews, the selection criteria were obtained, as shown in Table 5.

Code	Criterion name	Explanation
K1	Common Spare Parts	It is critical for the company or individual who operates a truck tractor to supply the necessary maintenance parts in a breakdown immediately.
K2	Sufficient Number of Service Specialists	In the event of a malfunction, it is critical to have personnel who can accurately locate the source of the malfunction and perform the proper repair.
K3	Engine Life	It is directly related to the vehicle's life; long engine life is essential to avoid high engine renewed costs and fixed costs.
K4	Fuel Consumption	Fuel is a significant expense for businesses. The less we consume, the better. The importance of this criterion increases exponentially in countries like Turkey, where high fuel taxes crush users.
K5	Financial Support	With the long-term loans available, this criterion makes it easier for the vehicle to join and buy the fleet.
K6	Fast Delivery	It refers to the participation of the purchased vehicle in the working cycle as soon as possible. The faster delivery is made, the better the company is.
K7	Comfort	This criterion is essential for increasing the efficiency of the working driver, and some drivers choose whether or not to work based on the comfort elements of the vehicle.
K8	Brand Reputation	This criterion is directly related to the vehicle's used value and is related to the fact that it can be converted into cash faster than other brands and has a lower value loss.

Table 5. Criteria and their explanations

In order to strengthen the selected criteria, it is possible to make a comparative discussion with the criteria used in the relevant literature. However, it would be better to emphasize that the studies in the related literature focused on different vehicle groups. For this reason, it is clear that the criteria may vary in terms of the vehicles that are the subject of the study. Revealing the common criteria and differentiating criteria with literature studies will strengthen the study.

The selection criteria handled in this study are confirmed with the help of literature as well. Common spare parts, fuel performance, comfort, and service personnel are also handled in truck selection problem (Baykasoglu et al., 2013). Fuel consumption and comfort are the common criteria, with the study focused on selecting sedan cars (Singh et al., 2019; Mumani and Maghableh, 2021). In addition, Sarkar et al. (2020) handled engine criterion in the family car selection problem. Ömürbek et al. (2014) considered fuel, brand, and service criteria to evaluate the commercial vehicles. Fuel consumption again draws attention to the second-hand automobile selection problem (Aytekin and Durucasu, 2021). Common spare parts, comfort, fuel consumption, financial support criteria get involved in the problem of high commercial vehicle selection (Doğan et al., 2017). The brand image was also included in the car selection problem as a determinant factor (Apak et al., 2012; Chand and Avikal, 2016).

In addition to the common criteria with the studies in the literature, a detailed explanation is required to clarify why we could not include the prominent criteria in our study. It can be said that this situation arises from the differentiation of the truck tractor vehicles from other vehicles. Cost/price, market share, second-hand price, maximum speed, engine power, torque, durability, fuel tank capacity, service, maintenance criteria are explained in detail.

The decision-makers focus on the cost or price criterion in any selection problem. In the related literature, some studies considered cost or price in their decision problem (Oztaysi et al., 2021; Mumani and Maghableh, 2021; Roy et al., 2018; Patil et al., 2017; de Sousa Junior et al., 2014). However, when a problem is evaluated within its own framework, the important criteria in other studies may lose their meaning. In this study, alternatives were chosen, especially within the same segment and within the framework of power outputs. Although there is a definite price difference between these alternatives, experts emphasized some points resulting from the interviews. During the meeting, the experts shared a common opinion that companies prefer to make multiple purchases by getting financial support. Furthermore, experts refrained from selecting price criterion as determinant since the price of the cheap vehicle may exceed the price of the expensive vehicle with the addition of interest and credit costs in case of no financial support. Accordingly, the price criterion was not included in our study.

In the related studies (i.e., Doğan et al., 2017 and Ömürbek et al., 2014) , market share and second-hand prices were handled as criteria in selecting commercial vehicles. This situation is acceptable, but it is also possible to include these criteria in the study with a single criterion. For this reason, we consider the market share and second-hand prices as a whole in the brand reputation criterion.

The maximum speed criterion was also considered for light commercial vehicles (Ömürbek et al., 2014) and eco-friendly car selection (Mumani and Maghableh, 2021).

It should be noted that all of these vehicles are limited to 90 km/h from the factory. Therefore, authorized services cannot change the maximum speed limit. However, it is known that speed limits are interfered with illegally in small industrial workshops. For this reason, the speed limit is not included in the criteria.

Moreover, engine power and torque were also handled in the literature (i.e., Aytekin and Durucasu, 2021; Mumani and Maghableh (2021); Singh et al. (2019); Doğan et al., 2017). However, there is no significant difference in engine power and torque between the Truck tractor alternatives discussed in this study. Therefore, engine power and torque cannot be considered as criteria in the truck tractor selection problems.

The durability criterion was discussed in the study conducted by Ömürbek et al. (2017). The most important indicator of durability is engine life for heavy commercial vehicles. Therefore, in our research, we refer to both durability and cost with the engine life criterion. An engine that expires prematurely incurs a heavy expense.

The fuel tank capacity was also another criterion considered in high commercial vehicle selection (Doğan et al. (2017); Sarkar et al. (2020); Mumani and Maghableh (2021)). It is an essential criterion in international transportation. However, due to the rules in the European Union and our country, this criterion does not have the same importance. On the contrary, since the total weight will increase as the fuel tank gets larger, the load it will carry in domestic transportation decreases, increasing consumption.

Another vital criterion is service which was also considered in the studies (i.e., Doğan et al. (2017); Ömürbek et al. (2014); Baykasoğlu et al. (2013)). However, the efficiency of the service means nothing without spare parts. More precisely, the evaluation of the service is related to reaching the spare parts. For this reason, we used spare parts as a criterion in our study.

Furthermore, the low maintenance cost was also considered by Aytekin and Durucasu (2021), Singh et al. (2019), and Baykasoğlu et al. (2013). However, cheap maintenance is possible using sub-industry parts and consumables. This situation never meets the standards of the original part. Therefore, this criterion was not included in our study.

After determining the criteria, the procedure of the application section is ready to be implemented. The process of the integrated F-PIPRECIA and F-COPRAS is given in Figure 1.

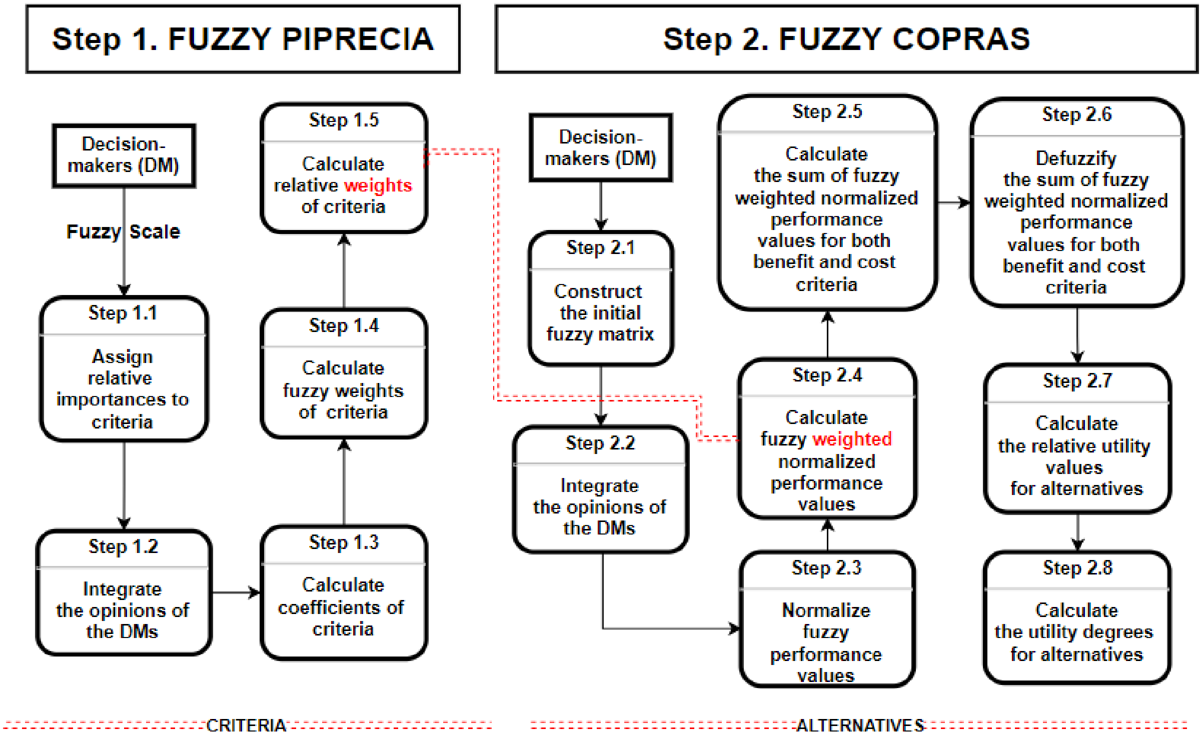

Figure 1. The process of the integrated F-PIPRECIA and F-COPRAS

In the first part, a questionnaire was formed for DMs to determine the criteria' weights in the MCDM problem. According to Figure 1, the opinions of the DMs constructed the relative importance of criteria in Step 1.1. The relative importance assigned by DM1 is demonstrated in Table 6 as an example.

	$\tilde{s}_{jl1}$	$\tilde{s}_{jm1}$	$\tilde{s}_{ju1}$
K1			
K2	0.5000	0.6670	1.0000
K3	0.4000	0.5000	0.6670
K4	0.3330	0.4000	0.5000
K5	0.4000	0.5000	0.6670
K6	0.3330	0.4000	0.5000
K7	0.2860	0.3330	0.4000
K8	0.2500	0.2860	0.3330

Table 6. Relative Importance for DM1

In Step 1.2. the opinions of the DMs were integrated by using Equations 3, 4, and 5; while the coefficients were calculated by using Equations 6, 7, and 8 in Step 1.3. The results can be seen in Table 7.

	Integrated Relative Importance			**Coefficients**		
	$\tilde{s}_{jl}$	$\tilde{s}_{jm}$	$\tilde{s}_{ju}$	$\tilde{k}_{jl}$	$\tilde{k}_{jm}$	$\tilde{k}_{ju}$
K1				1.0000	1.0000	1.0000
K2	0.4642	0.6059	0.8737	1.1263	1.3941	1.5358
K3	0.3763	0.4642	0.6059	1.3941	1.5358	1.6237
K4	0.3009	0.3540	0.4309	1.5691	1.6460	1.6991
K5	0.3217	0.3853	0.4807	1.5193	1.6147	1.6783
K6	0.6056	0.7368	0.8067	1.1933	1.2632	1.3944
K7	0.7191	0.7845	0.8573	1.1427	1.2155	1.2809
K8	0.7275	0.8073	0.8704	1.1296	1.1927	1.2725

Table 7. Integrated Relative Importance and Coefficients

In Step 1.4, fuzzy weights of criteria were calculated using Equations 10, 11, and 12, relative weights of criteria were calculated using Equations 14, 15, and 16 in Step 1.5. The results can be seen in Table 8.

	Fuzzy Weights			Relative Weights		
	$\widetilde{q}_{jl}$	$\widetilde{q}_{jm}$	$\widetilde{q}_{ju}$	$\widetilde{w}_{jl}$	$\widetilde{w}_{jm}$	$\widetilde{w}_{ju}$
K1	1.0000	1.0000	1.0000	0.2638	0.3341	0.3745
K2	0.6511	0.7173	0.8879	0.1717	0.2396	0.3325
K3	0.4010	0.4670	0.6369	0.1058	0.1560	0.2385
K4	0.2360	0.2837	0.4059	0.0623	0.0948	0.1520
K5	0.1406	0.1757	0.2672	0.0371	0.0587	0.1000
K6	0.1008	0.1391	0.2239	0.0266	0.0465	0.0838
K7	0.0787	0.1145	0.1959	0.0208	0.0382	0.0734
K8	0.0619	0.0960	0.1734	0.0163	0.0321	0.0650

Table 8. Fuzzy Weights and Relative Weights

After determining the weights of criteria, alternatives were evaluated according to the F-COPRAS method, as shown in Step 2. The truck tractor alternatives handled in this study can be seen in Table 9.

Alternative code	Alternative name
A1	MERCEDES ACTROSS 510
A2	IVECO S WAY 510
A3	SCANIA R500
A4	FORD F-MAX 500
A5	MAN TGX 510
A6	RENAULT TRUCKS T-High 520
A7	VOLVO FH SERIES 500
A8	BMC TUĞRA 460

Table 9. Alternatives

While determining the alternatives, special care was taken to include models in the same segment with similar engine power outputs in the research. Each alternative was carefully chosen from among the brands in the Turkish market, with the most recent models included in the list of alternatives.

In the first step of the F-COPRAS method, the DMs evaluated the performance of the alternatives by using the fuzzy scale. In Step 2.1, the fuzzy initial decision matrix was constructed by each DM. A part of the initial fuzzy decision matrix (Criterion 1) can be seen in Table 10 as an example.

	$\widetilde{x}_{i1ld}$	$\widetilde{x}_{i1md}$	$\widetilde{x}_{i1ud}$
A1	5	6	7
A2	3	4	5
A3	4	5	6
A4	5	6	7
A5	4	5	6
A6	3	4	5
A7	3	4	5
A8	4	5	6

Table 10. The initial fuzzy decision matrix (Criterion 1; DM1)

In step 2.2. the opinions of the DMs were integrated by using Equations 20, 21, and 22. The integrated fuzzy decision matrix includes "Criterion 1", which can be seen in Table 11.

	$\widetilde{x}_{i1l}$	$\widetilde{x}_{i1m}$	$\widetilde{x}_{i1u}$
A1	5.6462	6.6494	7.0000
A2	3.3019	4.3089	5.3133
A3	4.3089	5.3133	6.3164

A4	5.3133	6.3164	7.0000
A5	4.3089	5.3133	6.3164
A6	3.3019	4.3089	5.3133
A7	3.3019	4.3089	5.3133
A8	3.6342	4.6416	5.6462

Table 11. The integrated fuzzy decision matrix (Criterion 1)

In Step 2.3. fuzzy performance values were normalized. The normalized fuzzy decision matrix (Criterion 1) can be seen in Table 12.

	$\tilde{r}_{i1l}$	$\tilde{r}_{i1m}$	$\tilde{r}_{i1u}$
A1	0.0461	0.0543	0.0571
A2	0.0270	0.0352	0.0434
A3	0.0352	0.0434	0.0516
A4	0.0434	0.0516	0.0571
A5	0.0352	0.0434	0.0516
A6	0.0270	0.0352	0.0434
A7	0.0270	0.0352	0.0434
A8	0.0297	0.0379	0.0461

Table 12. The normalized fuzzy decision matrix (Criterion 1)

The weights obtained by F-PIPRECIA were used in Step 2.4 of the F-COPRAS method. Fuzzy weighted normalized performance values were calculated by using Equations 29, 30, and 31. The fuzzy weighted normalized performance values for Criterion 1 can be seen in Table 13.

	$\tilde{t}_{ijl}$	$\tilde{t}_{ijm}$	$\tilde{t}_{iju}$
A1	0.0122	0.0181	0.0214
A2	0.0071	0.0118	0.0162
A3	0.0093	0.0145	0.0193
A4	0.0114	0.0172	0.0214
A5	0.0093	0.0145	0.0193
A6	0.0071	0.0118	0.0162
A7	0.0071	0.0118	0.0162
A8	0.0078	0.0127	0.0173

Table 13. The weighted normalized fuzzy decision matrix (Criterion 1)

The sum of the fuzzy weighted normalized performance values for benefit criteria was found using Equations 32, 33, and 34. In addition, the sums of the fuzzy weighted normalized performance values for cost criteria were found by using Equations 35, 36, and 37. This procedure is represented in Step 2.5. The calculated values can be seen in Table 14.

	$\tilde{P}_i$ **Values**			$\tilde{R}_i$ **Values**		
	$\tilde{P}_{il}$	$\tilde{P}_{im}$	$\tilde{P}_{iu}$	$\tilde{R}_{il}$	$\tilde{R}_{im}$	$\tilde{R}_{iu}$
A1	0.0269	0.0441	0.0636	0.0024	0.0055	0.0128
A2	0.0184	0.0327	0.0541	0.0019	0.0050	0.0123
A3	0.0222	0.0380	0.0599	0.0030	0.0071	0.0157
A4	0.0253	0.0417	0.0626	0.0030	0.0062	0.0139
A5	0.0215	0.0368	0.0597	0.0023	0.0060	0.0140
A6	0.0177	0.0317	0.0527	0.0020	0.0041	0.0109
A7	0.0184	0.0329	0.0543	0.0020	0.0050	0.0124
A8	0.0184	0.0317	0.0515	0.0034	0.0067	0.0148

Table 14. $\tilde{P}_i$ Values and $\tilde{R}_i$ Values

In Step 2.6, the sum of the fuzzy weighted normalized performance values of benefit and cost criteria was defuzzified using Equation 38, 39 according to the best non-fuzzy performance (BNP) method. After that, in Step 2.7, the relative utility values of the alternatives were calculated using Equation 40. Finally, the utility degrees of the alternatives were calculated by using Equation 41 in Step 2.8. The highest utility degree shows the best alternative in the selection problem according to the F-COPRAS method. These values and rankings can be seen in Table 15.

	P_i	R_i	Q_i	N_i	Rank
A1	0.0449	0.0069	0.0522	1.0000	1
A2	0.0351	0.0064	0.0430	0.8233	6
A3	0.0400	0.0086	0.0459	0.8798	4
A4	0.0432	0.0077	0.0498	0.9535	2
A5	0.0393	0.0074	0.0461	0.8836	3
A6	0.0340	0.0057	0.0430	0.8226	7
A7	0.0352	0.0065	0.0430	0.8235	5
A8	0.0339	0.0083	0.0400	0.7656	8

Table 15. P_i, R_i, Q_i, N_i Values and Rankings

As a result of the experts' opinions, it is seen that the first two alternatives are local production. The main reason for this can be seen as benefiting from credit incentives when purchasing domestic production and receiving domestic financing support at a lower cost. This result is not surprising, as there is faster delivery and comprehensive service/spare parts services in domestic production. The difference between alternatives 1 and 2 can be explained as the superior performance of the Mercedes-Benz Actros 510 in terms of brand reputation and comfort. The third alternative was obtained as Man TGX 510. This finding shows that Man TGX 510 performs well in terms of technical quality and comfort but falls short in spare parts, service network, financial support, and delivery speed. Scania R500 has a strong brand reputation throughout the country. However, it was ranked in fourth place since it falls short of domestic-origin companies in terms of service, spare parts, financial support, and fast delivery. While the Volvo FH Series 500 stands out in terms of comfort and brand reputation, just like its same-origin competitor Scania, it ranked fifth due to weaknesses in the service/spare parts network, financial support, and slow delivery. The Iveco S Way 510 was obtained in sixth place. The main reason for this can be explained as the extremely limited service and spare parts network. The Renault Trucks T-High 520 model was found out in the seventh place. Although like Iveco, this vehicle has the lowest fuel consumption among its competitors, the weakness of its service and spare parts network and its weaknesses in other criteria can be concluded as the main factors for its performance. A surprising situation is seen in the last alternative. Although domestic production, fast delivery, and financial support are high, BMC Tugra was in the last place among the alternatives due to its failure in criteria such as customer perception and comfort, engine power, and brand reputation in the previous periods. As a result, it is seen that performance above the average in all factors is required in order to survive and strengthen the position of the alternatives in the market.

4.1. Sensitivity Analysis

The results reported above were obtained when criterion weights were calculated with F-PIPRECIA. Sensitivity analysis was handled in four different ways. In this case, 12 different scenarios were generated to conduct the analysis. First of all, the effect of the change in criteria weights was observed. Then, the reverse rank was examined. Lastly, the exclusion of alternatives from the evaluation was discussed. The calculations were repeated by subtracting both the last-ranked alternative and the first-ranked alternative for each scenario, respectively.

4.1.1. The effect of changing criteria weights

In the case of having hypothetically different criteria weights, how the alternative rankings will change can be examined. For this reason, a sensitivity analysis is conducted in order to see the effects of criteria weight changes on alternatives. Twelve scenarios created with different weight sets were handled. While the first scenario (F-PIPRECIA) shows the weights found by the current method, the second (Equal) shows the situations where all weights are equal; the other 10 are sets of randomly generated weights that add up to 1. The weights to be used in these scenarios are given in Table 16.

Scenarios	K1	K2	K3	K4	K5	K6	K7	K8
F-PIPRECIA	0.3224	0.2389	0.1581	0.0969	0.0607	0.0484	0.0403	0.0342
Equal	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Scenario 1	0.0226	0.1370	0.2261	0.2535	0.0918	0.0137	0.2177	0.0375
Scenario 2	0.0368	0.0831	0.1650	0.1599	0.2697	0.0302	0.0386	0.2167
Scenario 3	0.0305	0.2438	0.1201	0.0389	0.1968	0.0909	0.0951	0.1838
Scenario 4	0.1471	0.0133	0.1924	0.0188	0.2364	0.1671	0.0406	0.1842
Scenario 5	0.1583	0.0469	0.0330	0.1925	0.1738	0.1303	0.1447	0.1204
Scenario 6	0.0376	0.0088	0.3520	0.1817	0.0449	0.2726	0.0414	0.0611
Scenario 7	0.0142	0.1243	0.0019	0.3476	0.1688	0.0200	0.1358	0.1874
Scenario 8	0.1348	0.0429	0.1804	0.1864	0.0916	0.0619	0.1701	0.1320
Scenario 9	0.1062	0.1470	0.1541	0.0932	0.1127	0.1764	0.0639	0.1465
Scenario 10	0.2053	0.0125	0.0266	0.0025	0.2767	0.2505	0.1509	0.0750

Table 16. Various scenarios with different weight sets

After the weights of the criteria were clarified, the final values of the alternatives were calculated with F-COPRAS and are as given in Table 17.

Scenarios	A1	A2	A3	A4	A5	A6	A7	A8
F-PIPRECIA	1	0.8086	0.8726	0.9485	0.8727	0.8032	0.809	0.7523
Equal	1	0.866	0.9035	0.9125	0.888	0.8239	0.893	0.7162
Scenario 1	0.929	0.8841	0.9019	0.8309	0.9264	1	0.9894	0.6383
Scenario 2	0.9558	0.9185	0.9629	0.8874	0.9407	0.9378	1	0.7108
Scenario 3	1	0.8467	0.9229	0.931	0.882	0.7768	0.8758	0.7371
Scenario 4	1	0.8638	0.9021	0.9744	0.8548	0.7777	0.864	0.8002
Scenario 5	1	0.9088	0.9082	0.9108	0.9123	0.8801	0.9369	0.7252
Scenario 6	1	0.9211	0.8482	0.9352	0.8413	0.865	0.8813	0.7838
Scenario 7	0.8715	0.8425	0.8682	0.755	0.8996	0.9937	1	0.5834
Scenario 8	1	0.8963	0.9624	0.8793	0.9553	0.9327	0.9982	0.6544
Scenario 9	1	0.8421	0.8745	0.9276	0.8487	0.7777	0.8475	0.7447
Scenario 10	0.9776	0.8244	0.7961	1	0.7755	0.6974	0.7567	0.8607

Table 17. N_i values for various scenarios

According to the final values of the alternatives calculated with F-COPRAS, the rankings of the alternatives for each scenario were obtained as in Table 18.

Scenarios	A1	A2	A3	A4	A5	A6	A7	A8
F-PIPRECIA	1	6	4	2	3	7	5	8
Equal	1	6	3	2	5	7	4	8
Scenario 1	3	6	5	7	4	1	2	8
Scenario 2	3	6	2	7	4	5	1	8
Scenario 3	1	6	3	2	4	7	5	8
Scenario 4	1	5	3	2	6	8	4	7
Scenario 5	1	5	6	4	3	7	2	8
Scenario 6	1	3	6	2	7	5	4	8
Scenario 7	4	6	5	7	3	2	1	8
Scenario 8	1	6	3	7	4	5	2	8
Scenario 9	1	6	3	2	4	7	5	8

Scenario 10	2	4	5	1	6	8	7	3

Table 18. Rankings of alternatives for each scenario

In Figure 2, the rankings are demonstrated visually. Roughly speaking, it is seen that the best alternative in most scenarios is A1 whereas the worst alternative is A8. However, it is not possible to make a clear inference between the scenarios in the ranking of the other alternatives.

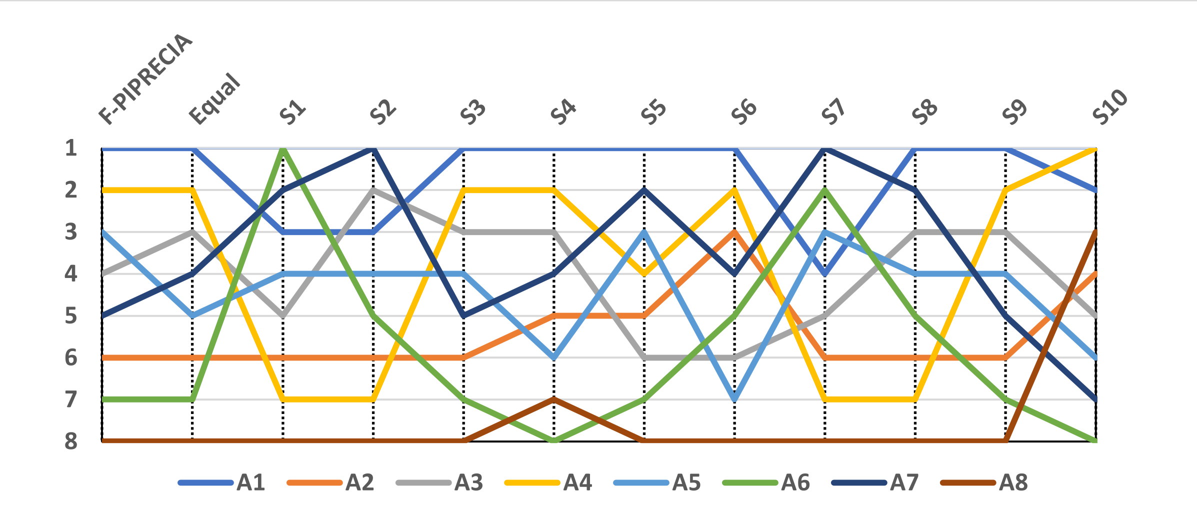

Figure 2. Ranking results based on various scenarios

4.1.2. The effect of reverse matrix

Secondly, the effect of reverse rank for each scenario was examined. The criteria weights were calculated reverse in each scenario. The ranking in the first version has been rearranged so that the most crucial criterion is the least important criterion. After that, the weights were subtracted from 1, and the calculations were performed to obtain the weights that add up to 1. The calculated weights of each scenario are given in Table 19.

Scenarios	K1	K2	K3	K4	K5	K6	K7	K8
F-PIPRECIA	0.0968	0.1087	0.1203	0.129	0.1342	0.1359	0.1371	0.138
Equal	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
S1	0.1396	0.1233	0.1106	0.1066	0.1297	0.1409	0.1118	0.1375
S2	0.1376	0.131	0.1193	0.12	0.1043	0.1385	0.1373	0.1119
S3	0.1385	0.108	0.1257	0.1373	0.1147	0.1299	0.1293	0.1166
S4	0.1218	0.141	0.1154	0.1402	0.1091	0.119	0.1371	0.1165
S5	0.1202	0.1362	0.1381	0.1154	0.118	0.1242	0.1222	0.1257
S6	0.1375	0.1416	0.0926	0.1169	0.1364	0.1039	0.1369	0.1341
S7	0.1408	0.1251	0.1426	0.0932	0.1187	0.14	0.1235	0.1161
S8	0.1236	0.1367	0.1171	0.1162	0.1298	0.134	0.1186	0.124
S9	0.1277	0.1219	0.1208	0.1295	0.1268	0.1177	0.1337	0.1219
S10	0.1135	0.1411	0.1391	0.1425	0.1033	0.1071	Af	0.1321

Table 19. Reverse rank weights

Afterward, F-COPRAS procedure was applied with the new weights given in Table 19 to calculate the final values (N_i) which are reported in Table 20.

Scenarios	A1	A2	A3	A4	A5	A6	A7	A8
F-PIPRECIA	1	0.8742	0.9079	0.9075	0.8902	0.8273	0.9053	0.7112
Equal	1	0.866	0.9035	0.9125	0.888	0.8239	0.893	0.7162
S1	1	0.8518	0.8929	0.9173	0.8726	0.7973	0.872	0.7229
S2	1	0.8526	0.8894	0.9115	0.8751	0.8058	0.8737	0.7139
S3	1	0.8686	0.9006	0.9102	0.8888	0.831	0.8955	0.7137

S4	1	0.865	0.9032	0.906	0.8927	0.8325	0.8979	0.7072
S5	1	0.8599	0.9028	0.9129	0.8846	0.8164	0.8869	0.7152
S6	1	0.858	0.9112	0.9096	0.8945	0.8185	0.8947	0.7071
S7	1	0.8488	0.8891	0.922	0.8681	0.7926	0.8627	0.7264
S8	1	0.861	0.895	0.9178	0.8785	0.8105	0.8789	0.7256
S9	1	0.8692	0.9076	0.9107	0.8937	0.8312	0.8998	0.7126
S10	1	0.8666	0.9157	0.9016	0.902	0.8446	0.9125	0.699

Table 20. N_i values for various scenarios with reverse rank

According to Table 20, the new rankings were demonstrated in Table 21 as shown below. At first glance, the rankings in the scenarios are similar.

Scenarios	A1	A2	A3	A4	A5	A6	A7	A8
F-PIPRECIA	1	6	2	3	5	7	4	8
Equal	1	6	3	2	5	7	4	8
S1	1	6	3	2	4	7	5	8
S2	1	6	3	2	4	7	5	8
S3	1	6	3	2	5	7	4	8
S4	1	6	3	2	5	7	4	8
S5	1	6	3	2	5	7	4	8
S6	1	6	2	3	5	7	4	8
S7	1	6	3	2	4	7	5	8
S8	1	6	3	2	5	7	4	8
S9	1	6	3	2	5	7	4	8
S10	1	6	2	5	4	7	3	8

Table 21. Rankings of alternatives for each scenario with the reverse rank

The results given in Table 21 were visualized in Figure 3. According to Figure 3, compared to first ranking results, more consensus was formed among scenarios. Especially for A1, A2, A6, and A8 placed in the same rank for each scenario. Moreover, the best and the worst alternatives remained the same compared to the first ranking results. This shows the robustness of the method.

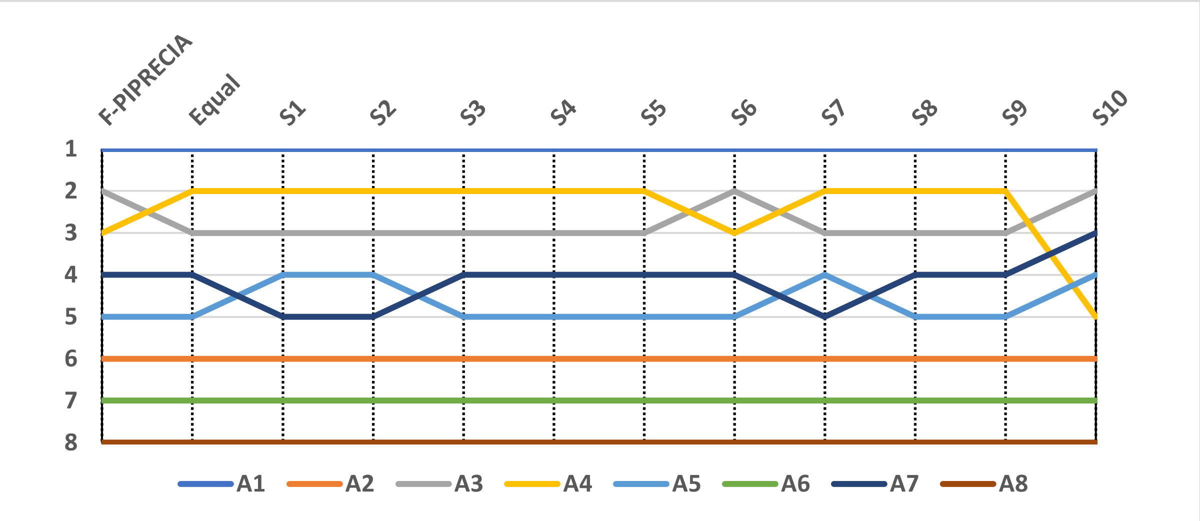

Figure 3. Ranking results based on various scenarios with the reverse rank

Moreover, the rankings' differences were examined by checking the results given in Table 18 and Table 21. To compare the rankings, studies published in the literature (i.e., Vesković et al., 2020; Blagojević et al., 2021) calculated Spearman's correlation coefficients. In order to reveal the ranking differences, Spearman's correlation coefficients were calculated and demonstrated in Figure 4. 6 scenarios out of 12 reached higher than 0.70 correlation. It can be concluded that the analysis with an utterly inverted weight set is satisfactory.

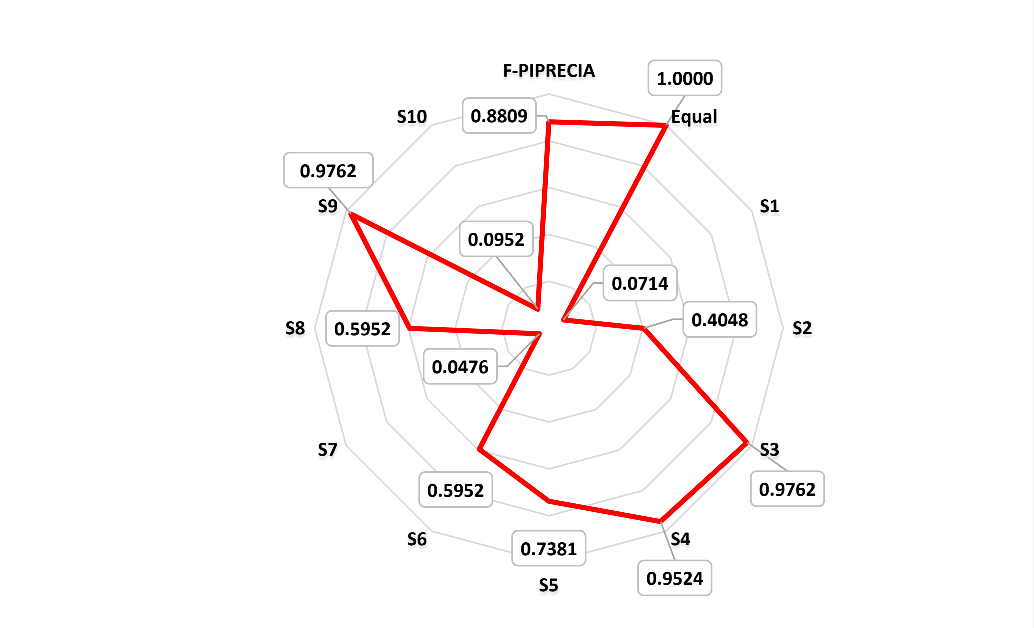

Figure 4. Spearman's correlation coefficients for each scenario

4.1.3. The effect of eliminating the best and the worst alternative

Lastly, the effects of removing the best and the worst alternatives from the solution were examined. In each scenario, firstly, the last-ranked alternative and then the first-ranked alternative was eliminated, and the calculation was conducted again with the (n-1) sized matrix. It would be better to clarify that this procedure was performed with the values given in Table 17. In each scenario, new rankings were obtained with the final values after removing the worst alternative. In the initial situation, the worst alternative was 8, except for scenarios 4 and 10. In scenarios 4 and 10, the worst alternative was 6. (n-1) alternative calculations were made accordingly.

When the worst alternative was excluded from the evaluation, minor changes were observed in 6 (S2, S5, S6, S7, S8, S9) of the 12 scenarios. However, when examined in detail, it is seen that these changes occur only in the rankings of the two alternatives. For example, in Scenario 2, A6 took 5th place in the first ranking, while it moved to 4th place after the change. Because of this, A5 regressed from 4th place to 5th place. However, Spearman's correlation coefficient was calculated as 0.9643 for six scenarios to make a general comment. Therefore, it can be said that there is no significant difference between the rankings. The general representation of the change in rankings after eliminating the worst alternative is shown in Figure 5 as well.

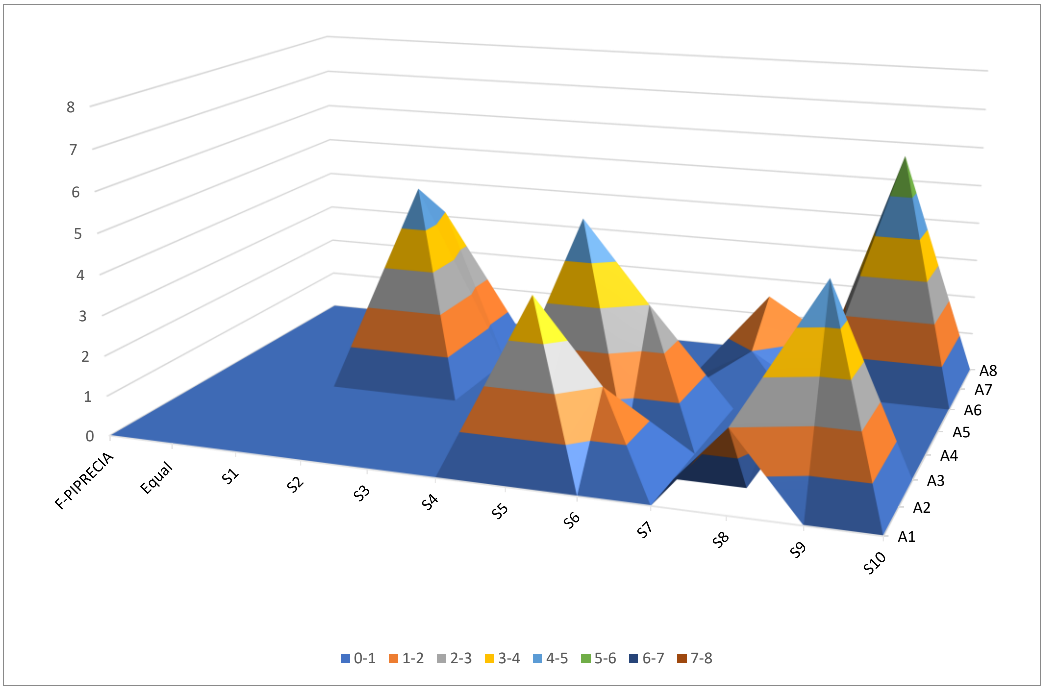

Figure 5. The change of rankings in case of the worst alternative is eliminated

In Figure 5, axis y shows the place of the ranking. The changed rankings are demonstrated in terms of each scenario for each alternative. In this case, the last-ranked alternative is eliminated in each scenario. For this reason, it is expected that the ranking difference should be "0". According to Figure 5, it is evident that F-PIPRECIA, Equal, S1, S3, S4, S10 remained the same. The values other than "0" show the rank number for related alternatives. In order to express the effect of the analysis more clearly, graphs for affected scenarios are given in the Appendix (A- 1-6).

A similar procedure was applied for the best alternative as well. In each scenario, the best alternative was eliminated, and then the calculations were performed again. As the first-ranked alternative is removed, the new ranking is expected to shift by one. The effect of eliminating the best alternative is visualized in Figure 6. In that figure, the y axis denotes the changes in the ranking. "1" defines that the alternative rankings changed as expected. "0" shows the eliminated alternatives placed in the first-ranked in the beginning. A value that is higher than one means that the ranking has not changed as expected. According to the results, only two scenarios (S1, S5) resulted in different rankings. For instance, in S1, only two alternatives (A1 and A5) did not meet the expectation. After the modification, the A1 alternative remained in the same order, while A5 increased by two units. However, Spearman's correlation coefficient for the full ranking was calculated as 0.9643, meaning there is no significant difference between rankings. In S5, A2, A3, A4, alternatives were placed differently. Nevertheless, the correlation between rankings was found to be 0.8929. The ranking graphs for these scenarios were also given in Appendix (A-7-8).

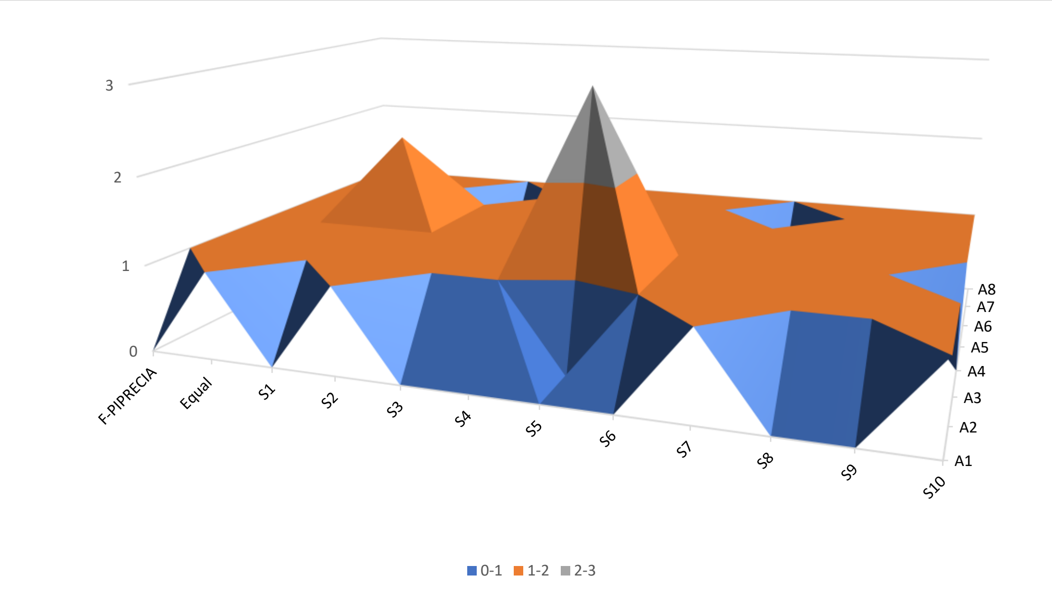

Figure 6. The change of rankings in case of the best alternative is eliminated

Sensitivity analysis was carried out in 4 different ways. First, the effect of the change in criterion weights was observed. Then, the reverse matrix was applied, and the changes were examined. After that, both the last alternative and the first alternative were subtracted for each scenario, respectively, and the calculations were repeated. As a result of the sensitivity analysis, it can be interpreted that the method is not sensitive to such changes; on the contrary, it is robust.

5. Discussion and Conclusion

This study used the F-PIPRECIA method, a new MCDM method integrated with F-COPRAS, to select the best truck tractor. A comprehensive investigation was conducted to reveal the most important criteria in the selection of truck tractor problems. The criteria were evaluated by both the transportation company owner and the drivers to reflect the sector's reality. In addition, the rankings of the alternatives were examined over various scenarios containing different weight sets for the criteria. With this sensitivity analysis, it was concluded that the first and the last alternatives were not affected by the weights. As a further investigation, the calculation was performed again after reversing rankings and excluding the last-ranked and the first-ranked alternatives from the study respectively to check whether there is a difference in ranking or not. With this comprehensive sensitivity analysis, it was concluded that the method used to solve the problem in our study is robust.

Truck tractors are an important component for logistics companies engaged in freight transportation in the road transportation sector to compete effectively with their competitors. The literature has some severe flaws in the studies focused on the same topic. Especially, comprehensive research of the criteria that are important in the decision phase of the truck tractor selection problem and a transparent examination of the alternatives is a gap in the literature. Alternative names are given in our study to ensure transparency and understand the underlying reason for the decision. Another point to mention is that in other studies, engine life is not considered in the cost-oriented approach. In today's Turkish market, the engine replacement cost of a tractor varies between 75,000 and 100,000 TL. For this reason, one of the most critical factors affecting the cost is the engine life. Another critical issue is the offered financial assistance, which only aids in the purchasing process. Since a company wants to incorporate every vehicle it purchases into its operational cycle as soon as possible, prompt delivery is also critical. It is clear that a firm will suffer economically if it takes 3-5 months for delivery. The way our study deals with the subject at these points is the most notable difference from other studies in the literature. Again, with a known fact in this study, the goal is to find the best alternative for the company with the most utilitarian approach in line with the multi-criteria evaluation based on country conditions.

The findings revealed that domestic production companies outperform in the majority of criteria. While the models of companies that have proven themselves in the international market, such as Volvo and Scania, are the best in terms of technical standpoint; the quality of service offered in the country in areas such as sales, service, and spare parts have entirely changed the ranking in terms of the enterprise perspective.

The limitations of the study should also be mentioned. Only vehicle brands operating in Turkey were taken into consideration. In addition, in order not to create unfair competition, only vehicles with a certain engine power were included in the evaluation. Furthermore, group decision-making was provided by 3 experts in the field. It should also be noted that the evaluations made are limited to the knowledge of the experts who contributed to the study.

For further studies, the same integrated MCDM model can be implemented to other decision-making problems in any field of application. Since our study focused on the brands available in the Turkish market, vehicles sold in different geographies can also be included for another study in the future. Also, similar problems with appropriate datasets can be handled with various MCDM methods, using different fuzzy extensions.

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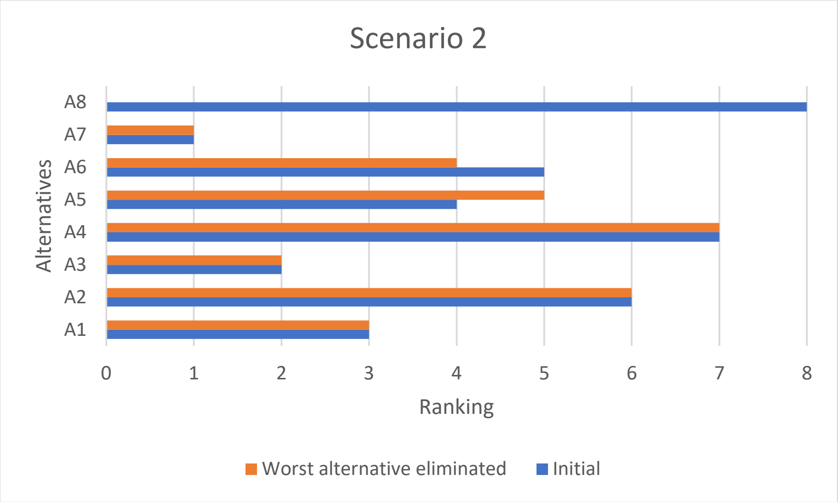
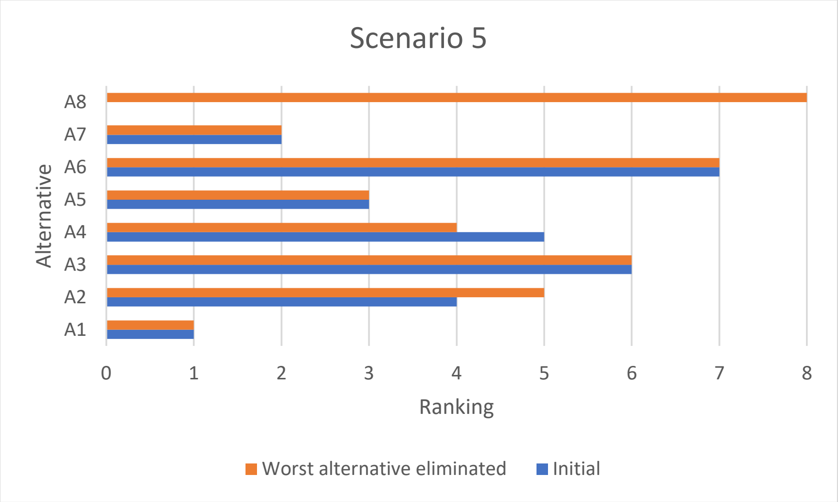
Appendix

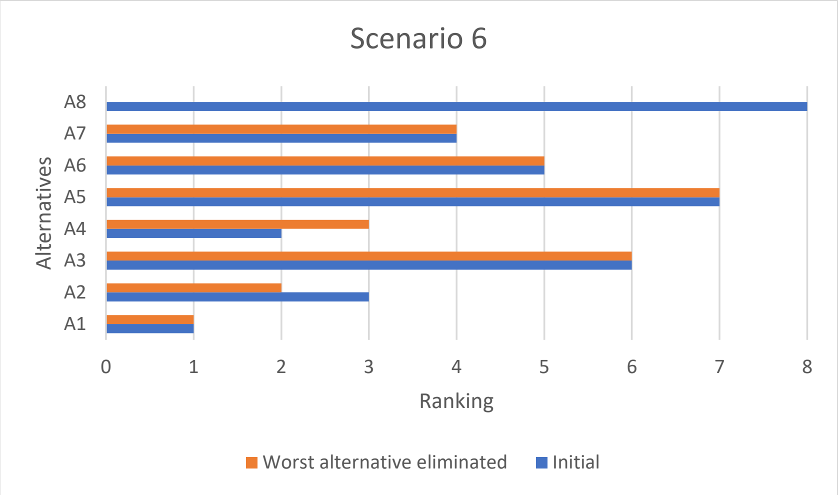
A-1: Ranking difference in case of worst alternative is eliminated in Scenario 2



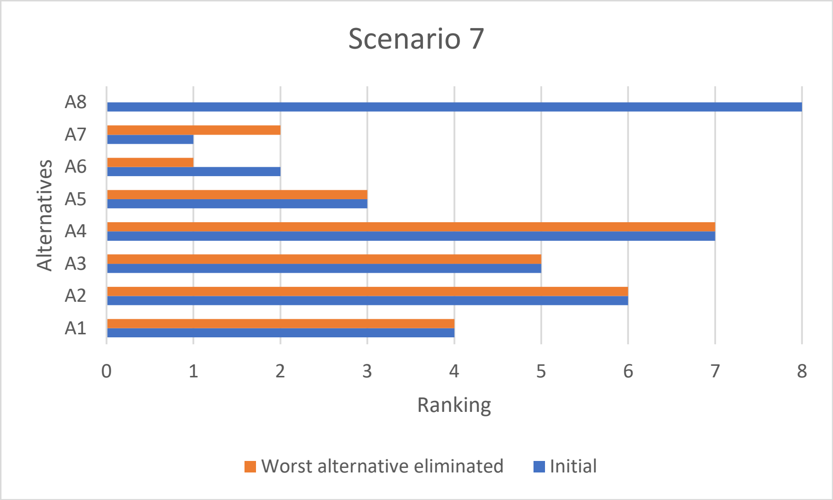
A-2: Ranking difference in case of worst alternative is eliminated in Scenario 5



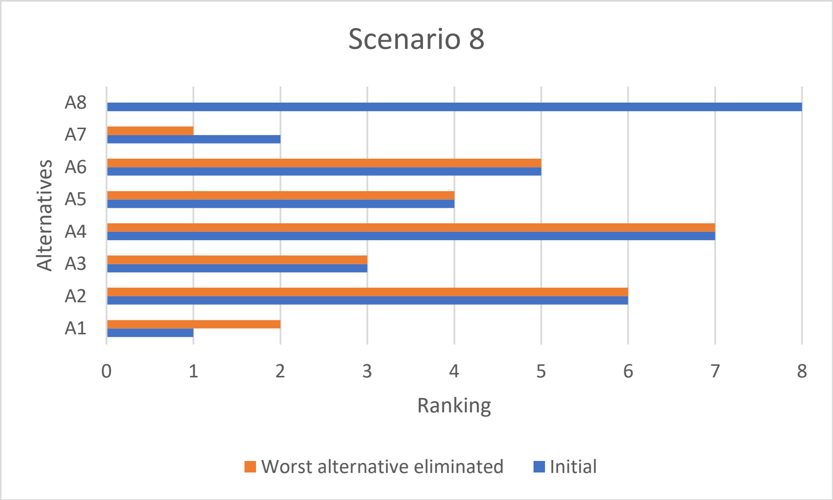
A-3: Ranking difference in case of worst alternative is eliminated in Scenario 6



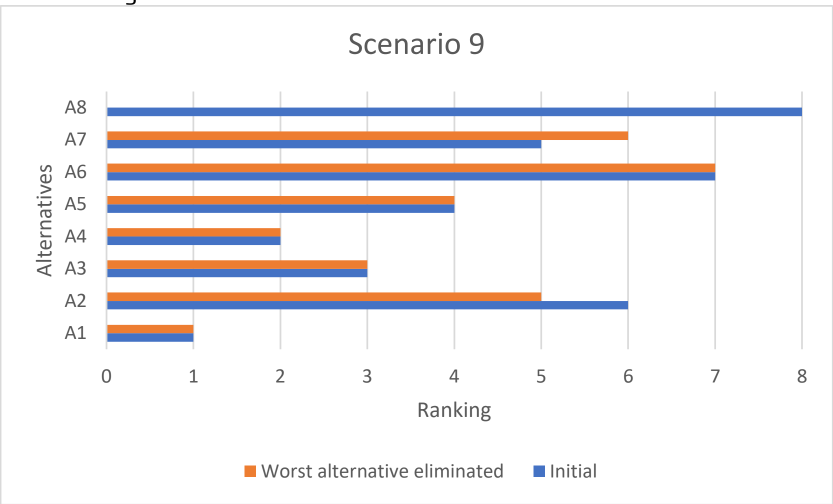
A-4: Ranking difference in case of worst alternative is eliminated in Scenario 7



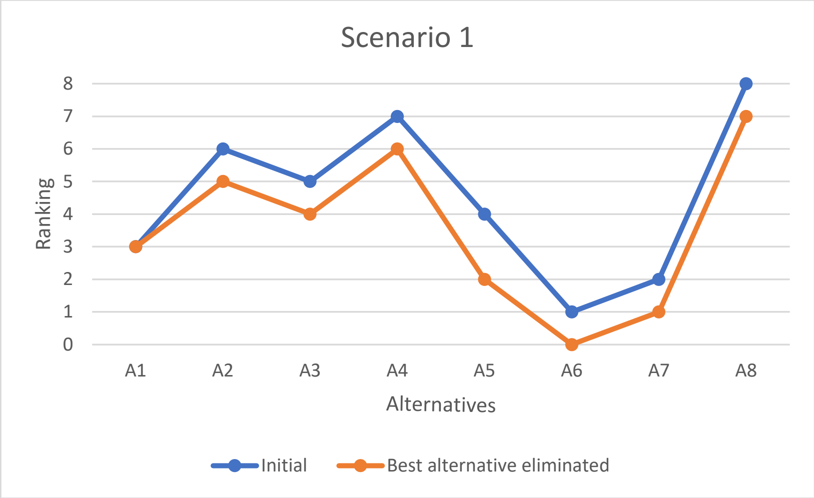
A-5: Ranking difference in case of worst alternative is eliminated in Scenario 8



A-6: Ranking difference in case of worst alternative is eliminated in Scenario 9



A-7: Ranking difference in case of the best alternative is eliminated in Scenario 1



A-8: Ranking difference in case of worst alternative is eliminated in Scenario 5