Autonomy Selection in Self-Driving Vehicles by an Integrated Spherical Fuzzy TODIM

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Abstract

Technological improvement for the safe and efficient use of self-driving vehicles continues at full speed. The development in this area in the coming years seems to affect human lives significantly. By the progress in Industry 4.0, products and hardware developed with software can exchange smart da-ta to ensure their management and optimization. It is possible to say that there will be much work about this technology shortly, even if they are not yet widely used. The investments of giant companies in this technology al-so support this development. However, the benefits and costs of autonomous vehicles are still mostly hypothetical. Self-driving cars layer their autonomy into six categories according to the capability of different levels of self-driving. Deciding on the autonomy of self-driving vehicles is a complicated procedure that requires various attributes to consider. Multi-Criteria Decision Making (MCDM) techniques are built to assist these kinds of decision-making problems. Fuzzy extensions aim to define judgments of decision-makers more explicitly and informatively by building on membership functions having three distinct dimensions. A new extension of ordinary fuzzy sets has been developed recently based on generalized three-dimensions called SFSs (Spherical Fuzzy Sets). In this study, the aim is to apply SF-TODIM (Spherical Fuzzy Tomada de Decisão Interativa Multicritério) MCDM method to evaluate autonomy selection in self-driving vehicles problem in a Group Decision Making environment. The autonomy selection in self-driving vehicles is assessed with five layers of autonomy using six criteria in order to demonstrate the applicability and validity of the developed SF-TODIM approach.

Keywords

Self-Driving Vehicles; Autonomy Selection; Group Decision Making; MCDM; TODIM; Spherical Fuzzy Sets.

1. Introduction

The transition to the self-driving vehicle in-vehicle technologies has accelerated in the past few years. Fully autonomous vehicles, through the automatic control systems they contain in, able to travel without any intervention from the driver by perceiving the environment, traffic flow, and the road without the need for a driver. Nevertheless, the automation layer defines the level of intervention from a human driver. Autonomous vehicles can detect surrounding objects by applying technologic enablers and systems such as radar, computer vision, odometry, GPS, lidar. Self-driving automobiles seem to cause a revolution in the automotive industry, leading to a revolution in the passenger car industry. By the progress in Industry 4.0, products and hardware developed with software can exchange smart data to confirm their optimization management of the production line. The swift progress of self-driving vehicle technologies will alter the rubrics of Henry Ford's game very soon. Although the costs of these services are currently a problem, they will be widely used in a few years with the novel Industry 4.0 solutions. The automotive industry, in particular, will be one of the units furthermost affected by this progress. It is believed that autonomous or driverless vehicles will also be in the lead for unique social, environmental, and economic alteration soon. The characteristics will lead to excellent social status equality based on citizens. Self-driving vehicles ensure that the physically disabled, the elderly, or young people have the liberty to travel personally. Including a small number of radical modifications in the technological arena, variations in consumer demand can also be triggered by the manufacture of stronger batteries, the endowment of more ecologically approachable energies, and the production of autonomous vehicles. These variations in the demands of the users also cause extreme modifications in the design made by the manufacturers.

In the 1960s, Multi-Criteria Decision Making (MCDM) methods were developed to assist decision-making. MCDM methods consist of approaches and methods that try to reach the best possible/appropriate solution that meets multiple conflicting criteria (Büyüközkan et al., 2018). Methods such as Maximin, Maximax, TOPSIS, ELECTRE, Analytic Hierarchy Process, DEMATEL, Analytical Network Process, PROMETHEE, and VIKOR are some examples of MCDM methods. The TODIM technique is also one of the MCDM methods which can assess the quantitative and qualitative criteria. The TODIM technique is a relatively new MCDM method, although that is not commonly included in the literature. Gomes and Lima (1992) carried out the initial effective case studies of the method in 1992. Besides, the fuzzy TODIM approach is also not extensively applied in the literature, and the first studies of the fuzzy cluster combined approach date back to the early 2000s (Nobre et al., 1999). The escalating number of research paper on the fuzzy TODIM approach in latest years enhances the applications of the method in the literature. The practical use of the classical TODIM method dates back to the early '90s. Later, these applications continued; Studies have been carried out in different fields such as energy, economy, education, and technology (Gomes and Lima, 1992; Nobre et al., 1999). Nobre and Trotta (1999) realized the first fuzzy application of TODIM.

The conventional fuzzy sets have been extended in several types (Zadeh, 1965), such as: Orthopair, Pythagorean, Hesitant, Neutrosophic, Type 2, and very recently SFS (Kutlu Gündoğdu and Kahraman, 2019a). Since then, numerous applications of SFS are utilized in various subjects. Gündoğdu and Kahraman (2020a) applied SFS to robot technology selection by applying the Quality Function Deployment method. Gündoğdu and Kahraman (2019b) also applied TOPSIS MCDM for the first time to SFS in an interval setting to evaluate the 3D printer selection problem. Mahmood et al. (2019) presented the concept of SFS toward decision making in medical diagnosis problems. Many other studies integrated the SFS to its methodology to evaluate problems, but no study uses the TODIM MCDM method in conjunction with the SFS environment. On the other side, it has been seen that TODIM methods are used in different areas and sectors for performance evaluation or determination of the best alternative according to specific criteria. This is the first study to offer a TODIM MCDM method under the SFS environment in the GDM setting. The properties of TODIM MCDM, combined with the properties of SFS theory, bring a suitable advantage to the developed method in this paper.

The study consists of four chapters. Firstly, the introductory part where the purpose of the study is explained. In the second part, information about the methods to be used is given. In the third part, the proposed approach is utilized with the results obtained by performing an application. The results are laid out in the last section to finalize and interpret the findings, and final evaluations are made.

2. Proposed Methodology

Spherical Fuzzy Sets (SFS) $\widetilde{\boldsymbol{A}}$ is defined by the following Equation (1). For each x, the degree of membership, non-membership, and hesitancy to $\widetilde{\boldsymbol{A}}$ is defined by the values $\boldsymbol{\mu}_{\widetilde{\boldsymbol{A}}}(\boldsymbol{x}), \boldsymbol{v}_{\widetilde{\boldsymbol{A}}}(\boldsymbol{x})$, and $\boldsymbol{\pi}_{\widetilde{\boldsymbol{A}}}(\boldsymbol{x})$, respectively. Let $\widetilde{\boldsymbol{A}}$ and $\widetilde{\boldsymbol{B}}$ be two distinct SFS values, and $\boldsymbol{\lambda} > \boldsymbol{0}$ a scalar, SFS operators (Kutlu Gündoğdu and Kahraman, 2019b) are used for the arithmetic operations. Spherical weighted arithmetic mean (SWAM) (Kutlu Gündoğdu and Kahraman, 2019b) is applied for aggregation. The proposed method flows, as illustrated in the detailed steps below.

Where $\boldsymbol{\mu_{\tilde{A}}}: \boldsymbol{X} \to [\boldsymbol{0}, \boldsymbol{1}]$, $\boldsymbol{v_{\tilde{A}}}: \boldsymbol{X} \to [\boldsymbol{0}, \boldsymbol{1}]$, $\boldsymbol{\pi_{\tilde{A}}}: \boldsymbol{X} \to [\boldsymbol{0}, \boldsymbol{1}]$, and

$$\tilde{A} = \{\langle x, (\mu_{\tilde{A}}(x), v_{\tilde{A}}(x), \pi_{\tilde{A}}(x))\rangle | x \in X\} \quad (1)$$

$$0 \le {\mu_{\tilde{A}}}^2 + {v_{\tilde{A}}}^2 + {\pi_{\tilde{A}}}^2 \le 1$$
(2)

The First step is defining the set of decision criteria and alternatives. The criteria set $\boldsymbol{C_j = \{C_1, C_2, \ldots, C_n\}, j = 1, 2, \ldots, n}$ is applied to evaluate the set of $\boldsymbol{A_i = \{A_1,\ A_2, \ldots,\ A_m\}}$, $\boldsymbol{i = 1, 2, \ldots, m}$ alternatives.

The Second step is prioritizing the DMs' importance. The weight of DMs is defined by the term $\boldsymbol{\lambda_k}$, $\boldsymbol{\sum_{k=1}^{K} \lambda_k = 1}$ for $\boldsymbol{k = 1, 2, \ldots, K}$. The evaluation of each DM is gathered in the form of linguistic expressions. The judgments are transformed into SFS values, and Equation (3) is used to find the priorities.

Let $\boldsymbol{D_k = \{D_1,\ D_2, \ldots,\ D_K\}}$, with, denote the set of DMs having influence weights $\boldsymbol{\lambda_k}$ for each $\boldsymbol{D_k}$; $\boldsymbol{\sum_{k=1}^{K} \lambda_k = 1}$. The preferences of each DM are collected in the form of verbal variables. The verbal variables are adapted from the seven-point SFS scale of (Kutlu Gündoğdu and Kahraman, 2020a) with some modifications.

$$\lambda_k = \frac{\left[\mu_{\tilde{A}}(x) + \pi_{\tilde{A}}(x)\left[\frac{1-\pi_{\tilde{A}}(x)}{\mu_{\tilde{A}}(x)}\right]\right]}{\sum_{k=1}^{K}\left[\mu_{\tilde{A}}(x) + \pi_{\tilde{A}}(x)\left[\frac{1-\pi_{\tilde{A}}(x)}{\mu_{\tilde{A}}(x)}\right]\right]}, \sum_{k=1}^{K} \lambda_k = 1 \quad (3)$$

The Third Step is collecting the DMs' judgments on all factors. The assessment of each DM is obtained in linguistic terms. The preference matrix is established by the SFS scale in (Kutlu Gündoğdu and Kahraman, 2020b).

The Fourth step is the aggregation of the individual decision criteria values to compute the weighs of each criterion. The transformed DM assessment is combined in the SFS environment by the use of the SWAM aggregation operator so that a fused criteria matrix may be generated. Let $\boldsymbol{w_j = \{w_1, w_2, \ldots, w_n\}}$ be the vector set used for defining the criteria weights, where $\boldsymbol{w_j \ge 0}$, and $\boldsymbol{\sum_{j=1}^{n} w_j = 1}$.

$$W_j = \frac{\left(\mu_{\tilde{A}}(x) - \pi_{\tilde{A}}(x)\right)^2 - \left(v_{\tilde{A}}(x) - \pi_{\tilde{A}}(x)\right)^2}{\sum_{j=1}^{n}\left(\mu_{\tilde{A}}(x) - \pi_{\tilde{A}}(x)\right)^2 - \left(v_{\tilde{A}}(x) - \pi_{\tilde{A}}(x)\right)^2} \quad (4)$$

The Fifth Step is the aggregation of the individual alternative values to construct the SFS preference matrix. Let $\boldsymbol{\tilde{x}_{ij} = (\mu_{\tilde{A}}(x), v_{\tilde{A}}(x))}$ be the SFS values representing the aggregated performance value of $\boldsymbol{i}$th alternative for the $\boldsymbol{j}$th criterion. The Sixth Step is used to normalize the decision matrix. If all criteria are either benefit type or cost type, there is no need for normalization. In case that there are both benefit type and cost type criteria present, a normalization procedure is applied for the SFS decision matrix by the Equation (5) to establish a normalized matrix $\boldsymbol{\tilde{R} = [\tilde{r}_{ij}]_{mxn}}$ with $\boldsymbol{\tilde{r}_{ij}}$=$\boldsymbol{(\mu_{\tilde{A}}(x), v_{\tilde{A}}(x))}$, for benefit criteria and cost criteria, respectively;

$$\tilde{r}_{ij} = \tilde{x}_{ij} = (\mu_{\tilde{A}}(x), v_{\tilde{A}}(x)),\ \tilde{r}_{ij} = {\tilde{x}_{ij}}^C = (\mu_{\tilde{A}}(x) = v_{\tilde{A}}(x), v_{\tilde{A}}(x) = \mu_{\tilde{A}}(x))^C \quad (5)$$

The Seventh Step is established to weight the normalized decision matrix. By using the calculated criteria weights in the fourth step, the normalized decision matrix is weighted by Equation (6). The Eighth Step is the calculation of the relative weights (Qin et al., 2017), and the Ninth Step is the establishment of the dominance for each alternative. Subsequently, the spherical distance is used according to Gündoğdu and Kahraman (2020c);

$$\dot{\tilde{R}} = \tilde{r}_{ij} \otimes W_j \tag{6}$$

$$w_{jr} = \frac{w_j}{w_r}, \text{ where, } w_r = max\,\{w_j | j = 1, 2, \dots, n\} \tag{7}$$

$$\Phi_j(A_i, A_l) = \begin{cases} \sqrt{\frac{w_{jr}}{\sum_{j=1}^{n} w_{jr}}}\, d(\tilde{r}_{ij}, \tilde{r}_{lj}) & if\ (\tilde{r}_{ij} > \tilde{r}_{lj}) \\ 0 & if\ (\tilde{r}_{ij} = \tilde{r}_{lj}) \\ -\frac{1}{\theta}\sqrt{\frac{\sum_{j=1}^{n} w_{jr}}{w_{jr}}}\, d(\tilde{r}_{ij}, \tilde{r}_{lj}) & if\ (\tilde{r}_{ij} < \tilde{r}_{lj}) \end{cases} \tag{8}$$

The Tenth Step is the setting up the dominance matrix. Where $\Phi_{ii}^{j} = 0, i = 1, 2, \dots, m, l = 1, 2, \dots, m; j = 1, 2, \dots n$ and the Eleventh Step is obtaining the global dominance degree and normalizing the dominance measurements

$$\Phi_j = \left[\Phi_{il}^{j}\right]_{mxm} = \begin{array}{c c} & \begin{array}{ccc} A_1 & \dots & A_m \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{pmatrix} \Phi_{11}^{j} & \cdots & \Phi_{1m}^{j} \\ \vdots & \ddots & \vdots \\ \Phi_{m1}^{j} & \cdots & \Phi_{mm}^{j} \end{pmatrix} \end{array} \tag{9}$$

$$\zeta(A_i, A_l) = \sum_{j=1}^{n} \Phi_j(A_i, A_l) \tag{10}$$

$$\delta_i = \sum_{l=1}^{m} \zeta(A_i, A_l) - \min_{i \in M} \sum_{l=1}^{m} \zeta(A_i, A_l) \,/\, \max_{i \in M} \sum_{l=1}^{m} \zeta(A_i, A_l) - \min_{i \in M} \sum_{l=1}^{m} \zeta(A_i, A_l) \tag{11}$$

The Last Step is the ranking. The best candidate is a selection of alternative according to the rank of δ_i. The lover the value of δ_i, the worse the alternative, A_l.

3. Case Study

The self-driving level differs according to the capability of cars, and researchers described six levels of autonomy for cars. In the first level, humans are in control of all major systems (A_1). The intervention of humans in the second level is restricted to specific systems, and the control for the some of the underlying systems can be left to cars, such as automatic braking or cruise control (A_2). Humans are required for the safe operation of the system in the third level, but at least two simultaneous functions, like steering and acceleration, are automated (A_3). Level four is the intervention of humans if alerted; otherwise, all safety-critical functions can be automated (A_4). Full automation is considered under some driving scenarios in level five, while not all of them (A_5). In the last level, self-driving is applied in every situation with full automation (A_6). The criteria set is defined as five criteria. The Safety (C_1) is a predominant concern. Traffic accidents kill thousands of people every year. Equity (C_2) criterion is another critical attribute. Autonomous vehicle technology could support the mobilization of individuals who are incapable of driving themselves. Environmental impact (C_3) criterion is a significant attribute having uncertainty. Self-driving offers convenient, affordable, and accessible driving to enable more shared rides to drop the emissions even further. Transportation cost (C_4) is another essential factor to consider in autonomous vehicles. Convenience (C_5) criterion is another factor to take into consideration. The driver can spend time doing pleasurable things in a self-driving vehicle. Every year, a primary automaker-powered website in Turkey is launching a design competition asking designers to create concept cars for the real world. A focus group is established to work on the design ideas for the concept car. The case study in this paper is a small part of the bigger picture. Thus, the automation levels as distinct alternatives are evaluated using the given criteria by three DMs to determine the conception of a new car for the next five years.

3.1 Application

The five criteria, $C_5 = \{C_1, C_2, \dots, C_5\}$, is utilized to evaluate the six alternatives, $A_6 = \{A_1, A_2, \dots, A_6\}$. The evaluations of each DM are gathered in the form of linguistic expressions and the calculated DMs weights. The three

DMs' importance is determined. The aggregated decision criteria values by the use of SWAM aggregation operator are used to calculate criteria weights. Due to space requirements, only final global dominance and ranking table are disclosed. The alternatives are ranked in ascending order. As a result, $\boldsymbol{A_5}$ is revealed as the best alternative. Moreover, the ranking order of alternatives is displayed in Table 1.

Table 1. Global Dominance and Ranking of Alternatives,

	$\boldsymbol{A_1}$	$\boldsymbol{A_2}$	$\boldsymbol{A_3}$	$\boldsymbol{A_4}$	$\boldsymbol{A_5}$	$\boldsymbol{A_6}$	$\boldsymbol{\delta_i}$	**Rank**
$\boldsymbol{A_1}$	0.000	1.171	0.801	0.313	0.931	0.523	0.583	2
$\boldsymbol{A_2}$	1.531	0.000	0.575	1.129	1.359	0.936	0.369	3
$\boldsymbol{A_3}$	1.449	1.062	0.000	0.911	2.505	1.125	0.136	5
$\boldsymbol{A_4}$	1.833	1.129	1.583	0.000	2.041	1.342	0.000	6
$\boldsymbol{A_5}$	0.898	1.042	0.720	0.566	0.000	1.055	1.000	1
$\boldsymbol{A_6}$	0.542	0.911	0.612	0.777	1.248	0.000	0.293	4

3.2 Sensitivity Analysis

In this section, a sensitivity analysis is conducted to examine the impact of the weight changes on the results. The final ranking of the decision-making process, which is the final stage of the prioritization of alternatives, depends heavily on the weight of the criteria. Therefore, how possible changes in relative weights will affect the final ranking should be investigated. Since these weights often depend on the subjective assessment of experts, alternative ranking is of paramount importance when there are different criteria weights. For this purpose, scenarios containing relative importance of the criteria and reflecting their status in terms of different views should be examined. In this case, prioritizing the changes in the results by giving increasing or decreasing weight for each criterion and listing the alternatives should be observed. As a result, the sensitivity analysis is made for this purpose helps to provide information in order to fix the alternative ranking. Accordingly, the final rankings of the alternatives evaluated for five different situations (scenarios) are examined. Based on the data in this table, the performances of the candidates have been recalculated for five different cases. When the results are examined, it is observed that the mentioned changes in the criteria slightly changed the ranking of some alternatives. However, the results for the first four alternatives have remained the same. A summary of these candidate performance values (rankings) for different situations is shown in Figure 1.

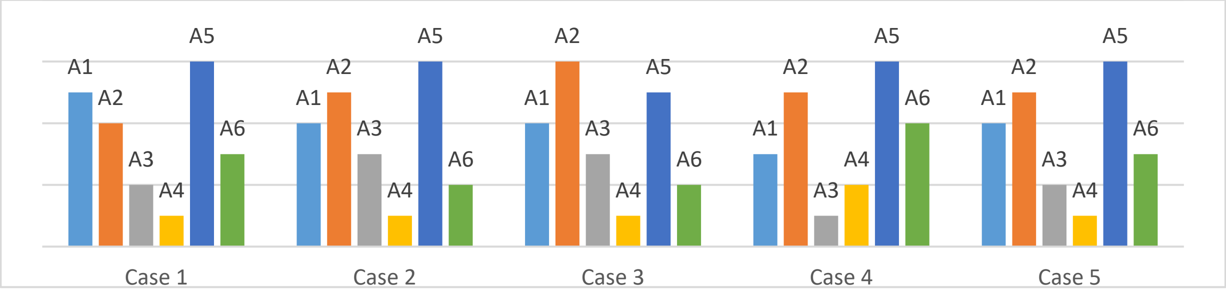

Figure 1. Performance of Alternatives concerning criteria

4. Conclusion

The main objective of this study is to evaluate autonomy selection in self-driving vehicles problem in a Group Decision Making setting by considering a set of evaluation criteria. The evaluation of automation requires an examination of diverse qualitative and quantitative factors. MCDM techniques are scientific methods that can evaluate qualitative and quantitative factors together. That is why, TODIM, which is one of the distance-based MCDM methods, has been used to evaluate the alternatives of self-driving automation layers. In order to select the best suitable level of automation, identification of decision criteria needs to be taken into account. An extant review of the literature and three DMs are used to do it suitable. The SFS TODIM MCDM method is applied to evaluate all candidate levels by the light of the given attributes. The SFS environment is chosen as an objective world to assess and rank the automation level for the given problem. The SFS has shown explicit advantages in handling uncertainty over crisp or fuzzy sets to depict DMs' evaluations, allowing for a more representative decision-making. Besides, it is chosen to derive the significance of the selection. A practical case is also demonstrated to validate the developed method. In the future, this research is aimed to focus on studies involving the application of this method to different sectors. Furthermore, in future studies, the results of these alternatives can be compared with other fuzzy logic-based MCDM approaches.

References

Büyüközkan, G., Göçer, F. and Feyzioğlu, O., "Cloud Computing Technology Selection Based on Interval Valued Intuitionistic Fuzzy COPRAS", in Kacprzyk, J., Szmidt, E., Zadrożny, S., Atanassov, K.T. and Krawczak, M. (Eds.), *Advances in Intelligent Systems and Computing (Proceedings of: EUSFLAT- 2017)*, Vol. 641, Springer International Publishing, pp. 318–329.2018.

Gomes, L. and Lima, M., "TODIM: Basics and application to multicriteria ranking of projects with environmental impacts", *Foundations of Computing and Decision Sciences*.1992.

Kutlu Gündoğdu, F. and Kahraman, C., "Spherical fuzzy sets and spherical fuzzy TOPSIS method", *Journal of Intelligent & Fuzzy Systems*, Vol. 36 No. 1, pp. 337–352.2019a.

Kutlu Gündoğdu, F. and Kahraman, C., "A novel fuzzy TOPSIS method using emerging interval-valued spherical fuzzy sets", *Engineering Applications of Artificial Intelligence*, Vol. 85, pp. 307–323.2019b.

Kutlu Gündoğdu, F. and Kahraman, C., "A novel spherical fuzzy QFD method and its application to the linear delta robot technology development", *Engineering Applications of Artificial Intelligence*, Vol. 87, p. 103348.2020a.

Kutlu Gündoğdu, F. and Kahraman, C., "Spherical Fuzzy Sets and Decision Making Applications", pp. 979–987.2020b.

Kutlu Gündoğdu, F. and Kahraman, C., "Spherical Fuzzy Sets and Decision Making Applications", pp. 979–987.2020c.

Mahmood, T., Ullah, K., Khan, Q. and Jan, N., "An approach toward decision-making and medical diagnosis problems using the concept of spherical fuzzy sets", *Neural Computing and Applications*, Vol. 31 No. 11, pp. 7041–7053, 2019.

Nobre, F.F., Trotta, L.T.F. and Gomes, L.F.A.M., "Multi-criteria decision making - an approach to setting priorities in health care", *Statistics in Medicine*, Vol. 18 No. 23, pp. 3345–3354.1999.

Qin, Q., Liang, F., Li, L., Chen, Y.-W. and Yu, G.-F., "A TODIM-based multi-criteria group decision making with triangular intuitionistic fuzzy numbers", *Applied Soft Computing*, Vol. 55, pp. 93–107, 2017.

Zadeh, L.A., "Fuzzy sets", *Information and Control*, Vol. 8 No. 3, pp. 338–353.1965.

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