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Assessing the environmental competitiveness of cities based on a novel MCDM approach

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Abstract

Many factors affect the competitiveness of cities. One of the most important of these factors is the environmental dimension, which can affect and be influenced by economic and socio-cultural aspects of urban competitiveness. The present study assesses the environmental competitiveness of cities with populations of more than 500,000 in Iran. Our research weighting approach consists of integrated ITARA-FUCOM methods to obtain nine criteria weights based on actual data evaluation and expert ideas. In addition, experts' statements are presented using gray logic and transformed into crisp numbers. Then, a modified MARCOS method that uses logarithmic normalization is introduced and implemented to assess fourteen target cities. Finally, The results of MARCOS-LN are compared to those of MARCOS itself, as well as three more MCDM methods (EDAS, CODAS, TOPSIS) and their versions, which utilize logarithmic normalization. The research findings showed that the city of Rasht is the most environmentally competitive, while the city of Kerman is the least competitive (rank 14) among the Iranian cities with populations greater than 500,000. The research results indicate that to improve the competitive position of Iranian cities, the internal capacities, relative advantages, and the competitive role each city can have on a transnational scale, their internal capacities should be paid attention to. This requires decentralized national and transnational planning and development competitiveness scenarios for medium and long-term periods.

Keywords: *Environmental competitiveness, Multiple criteria decision making (MCDM), logarithmic normalization, Indifference threshold-based attribute ratio analysis (ITARA), Full consistency method (FUCOM), MARCOS-LN method*

JEL Classification: C44, F64, F63

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1 INTRODUCTION

In 2018, 55% of the world's population lived in urban areas, a proportion expected to increase to 68% by 2050 (United Nations, 2018). Environmental studies are essential with increasing urbanization and the use of natural resources. Excessive exploitation of natural resources while degrading the environment has made it difficult to achieve development goals. According to the World Meteorological Organization (WMO) (2016), by 2025, 66% of the world's population, or two-thirds of the world's population, will face a water crisis.

Lack of water resources, air pollution, an increase in dust, climate change, the destruction of pastures, and water management issues have created major problems for citizens or will create them in the near future. Environmental issues that result from the wrong activities of humans (human factor) or the inherent characteristics of geographical environments have caused environmental competition in different places. Therefore, the environmental competitiveness of cities is one of the key factors determining current and future development. Sustainability is

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a key goal for environmental policy, which is considered an essential element and strategy of competitiveness in countries. Superior environmental performance is essential as an element of competitiveness in countries, especially if it becomes an environmental policy (Esty et al., 2013). Accordingly, several studies have long tried to measure and evaluate cities' competitiveness by setting criteria and formulating various variables (; Jiang & Shen, 2010; Saez & Perianez, 2015). However, these indicators have only received serious attention in the last three decades, and there is still little public agreement or global acceptance of their definition and consolidation. Based on a competitive perspective and using the comparative study method, this paper seeks to answer this question: What are the conditions of environmental competitiveness in Iranian cities with over 500,000 inhabitants)?

To answer this question, we use the latest multi-criteria decision-making methods. To the best of our knowledge:

- No previous study has integrated Indifference Threshold-based Attribute Ratio Analysis (ITARA) and Full Consistency Method (FUCOM) to create a combined weighting approach. In addition, FUCOM priorities have rarely been determined using gray theory.
- Once more, no previous study has modified the measurement alternatives and ranking according to compromise solution (MARCOS) by utilizing logarithmic normalization and assessing the results.
- Most previous studies examined the urban competitiveness of cities by paying attention to economic, industrial, and social aspects. Thus, comprehensive research that studies environmental competitiveness attributes is needed.

In this study, a novel integrated weighting-assessing MCDM method is implemented based on two newly introduced weighting methods which are ITARA and FUCOM, to obtain nine environmental competitiveness criteria weights along with the introduction and utilization of the MARCOS-LN method to assess 14 Iranian cities with over 500,000 residents. The results are compared to MARCOS ranking and three more popular MCDM methods (EDAS, CODAS, and TOPSIS) and their modified versions, which take advantage of logarithmic normalization.

The remaining parts of the paper are organized as follows: Section 2 describes our research problem, assessing the environmental competitiveness of Iranian cities with over 500,000 inhabitants. A literature review along with a criteria description are provided in Section 3. Section 4 presents the materials and data. The research methodology is explained in Section 5. Section 6 contains the results and their analysis. A research discussion is given in Section 7, and socio-economic suggestions are provided in Section 8. Finally, we conclude our paper in Section 9.

Since the mid-1990s, the concept of competitiveness, in addition companies, has also been applied at the level of cities, countries, and regions (Sgambati & Gargiulo, 2022). In general, urban competitiveness and relative competitive advantages also include economic, social, and environmental aspects (Komasi et al., 2022b; Tang et al., 2022; Ebrahimzadeh & Komasi, 2014), which have internal dependencies and can influence each other. For instance, improving environmental competitiveness can move the economic competitiveness of cities forward. Accordingly, the social competitiveness of cities should also improve.

Consider that according to the global competitiveness report in 2016-2017, compared to the previous report in 2015-2016 and with the participation of 140 countries, Iran's position fell two spots to 76th in the world (Table 1). Improving the environmental competitiveness of Iranian cities can increase the economic and social competitiveness of these cities and thus

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improve the competitiveness of Iran at the global level, especially in the tourism sector (Komasi et al., 2023; Torabi et al., 2023; Komasi et al., 2022a).

Tab. 1 – Iran's ranks in global competitiveness reports

Title	2010-1011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017
Number of countries	139	142	144	148	144	140	138
Iran's rank	69	62	66	82	83	74	76
Score (1-7)	4.14	4.26	4.22	4.1	4	4.1	4.12

Tehran Chamber of Commerce Industries Mines and Agriculture, 2017

The goal of this study is to first identify the environmental competitiveness indicators and then to compar4 Iran's cities with populations greater than 500,000 in terms of the competitiveness index. Evaluating the environmental competitiveness of cities while revealing the strengths and opportunities of competitiveness relative to each other will also determine the weaknesses and threats of their competitiveness. The output of this assessment will facilitate planning to improve the environmental competitiveness of cities**.**

2 THEORETICAL BACKGROUND

This section presents a comprehensive review of studies related to the competitiveness of cities with an environmental approach.

Regions can only become competitive if their cities have strong economies (Ni et al., 2014; Jeney, 2010). Economic growth and reducing environmental turbulences are tremendous challenges for cities (Zolfani et al., 2011; Zolfani et al., 2018; Yazdani et al., 2016). Urban competitiveness has been frequently debated among scholars (Činčikaitė and Meidute-Kavaliauskiene, 2021a&b). Jiang and Shen (2010) assessed the concept of competitiveness from the environmental point of view, but the competitiveness concept was first used at a company level by Krugman (1996). In the wake of the first steps, various factors of urban competitiveness were identified, and researchers have formed urban competitiveness models. Kresl (1995) believed that urban competitiveness factors include economic and strategic determinants. Webster and Muller (2000) declared that economies are a prerequisite to formulating competitiveness strategies and divided the determinants into an economic structure, regional endowment, human resources, and institutional environments. Gordon and Cheshire (1998) conveyed different definitions of urban competitiveness from the economic terms. But, soon, the scholars found economic terms incomplete in evaluating urban competitiveness, urban scientists paid more attention to research on other influential issues in the city, and researchers like Rogerson (1999) and Begg (1999) emphasized the quality of life as a determinant of the competitiveness of cities (Kahvand et al., 2015; Torkayesh, et al., 2021). Dou et al. (2000) constructed an index system for evaluating the competitiveness of Chinese cities based on four factors: capital, urban infrastructure, industrial performance, and structure. Based on the competitiveness model proposed by the World Economic Forum and the diamond model, Ning and Tang (2001) developed an evaluation index.

City competitiveness may be a multidimensional build that centers on a city's relevant environmental qualities that will be summarized around sustainable development and quality of life (Nasi et al., 2022). Zhu and Xu (2022), considering sustainable development, analyze the impact of China's clean air action on competitiveness. In a study of urban sustainability logic in Kalamazoo, Michigan, Roznowski (2022) proposes that environmental issues can be settled through technical equipment, particularly market-led innovative advancements, and initiate competition. Qiu et al. (2020) analyzed and observationally examined the relationship between the green fabricating advancement capacity of Chinese fabricating undertakings and competitive advantage, and it appears that there is a positive relationship between the two components.

Zhang and Qu (2020) utilized the board information of 33 resource-based cities from 2008 to 2018 to experimentally analyze the effect of environmental regulation and advancement remuneration on scientific and technological competitiveness. Also, Fan et al. (2021) proposed that governments should adjust some sensible environmental regulations that encourage cities to innovate in pollution control technology so that enterprises can diminish energy consumption and pollutant emanations, as well as stimulate technological innovation to improve production technology and competitiveness.

Furthermore, many other researchers have attempted to figure out the principles of competitive cities based on economic, social, and environmental terms, improving the quality of life, smart city, and focusing on technology and assessing how cities might promote their competitiveness compared to other cities (Campagnolo et al., 2018; Parlikad and Heaton, 2019; Chai et al., 2020; Ranchod, 2020; Činčikaitė and Meidute-Kavaliauskiene, 2021b; Abusaada and Elshater~~.~~, 2021; Chung et al., 2021).

No consensus exists in the competitiveness literature on classifying urban competitiveness factors. Some researchers have categorized these factors based on the extent to which they affect development (Lengyel, 2003), and others have relied on the factors that control possibilities (Reiljan et al., 2000: 89).

For this study, which emphasizes environmental competitiveness, Table 2 presents various indicators affecting environmental competitiveness.

Tab. 2 – Indicators of Environmental Competitiveness

	Indicators	References
C_1	Number of days with clean air	Du et al., 2014; Jiang and Shen, 2010; Bruneckiene et al., 2010; Liu et al., 2016; Guo et al., 2018; Wang et al., 2021
C_2	Number of days with healthy air	Du et al., 2014; Jiang and Shen, 2010; Bruneckiene et al., 2010; Liu et al., 2016; Guo et al., 2018; Wang et al., 2021
C_3	Number of months Thermal comfort indexes a day	Liu et al., 2016; Guo et al., 2018; Wang et al., 2021
C_4	Number of months Thermal comfort indexes at night	Liu et al., 2016; Guo et al., 2018; Wang et al., 2021
C_5	Number of non-frost days per year	Liu et al., 2016; Wang et al., 2021
C_6	Annual rainfall (mm)	Liu et al., 2016; Wang et al., 2021
C_7	The number of days without dust	Bruneckiene et al., 2010; Jiang and Shen, 2010; Liu et al., 2016; Wang et al., 2021
C_8	Green space per capita (square meters)	Yalcintas, 2008; Liu et al., 2016; Wang et al., 2021
C_9	The total area of forests, pastures, and good desert phenomena (hectares)	Liu et al., 2016; Wang et al., 2021

3 RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The study area of the present research is 15 Iranian cities above 500,000 inhabitants. The population size and their spatial distribution pattern are shown in Table 3 and Figure 1. These areas have a total population of more than 23.7 million people, which is equivalent to 31.6% of the population of Iran and 44.2% of the population of urban areas of Iran. The size distribution of the population varies significantly between these cities, and except for the capital, Tehran, other cities in this group have a population of 1 to 3 million people, according to Table 4.

Tab. 3 – Cities above 500,000 Inhabitants in Iran (2011)

City	population (Person)	Share of the country's population	Regional population of these cities
Total population (persons)	23721884	100%	55576507
Hamedan	525794	2%	1758268
Arak	526182	2%	1413959
Kerman	534441	2%	2938988
Zahedan	560725	2%	2534327
Rasht	639951	3%	2480874
Urmia	667499	3%	3080576
Kermanshah	851405	4%	1945227
Qom	1074036	5%	1151672
Ahvaz	1112021	5%	4531720
Shiraz	1460665	6%	4596658
Tabriz	1494988	6%	3724620
Karaj	1614626	7%	2412513
Esfahan	1756126	7%	4879312
Mashhad	2749374	12%	5944402
Tehran	8154051	34%	12183391

Source:(Statistical Centre of Iran, 2016)

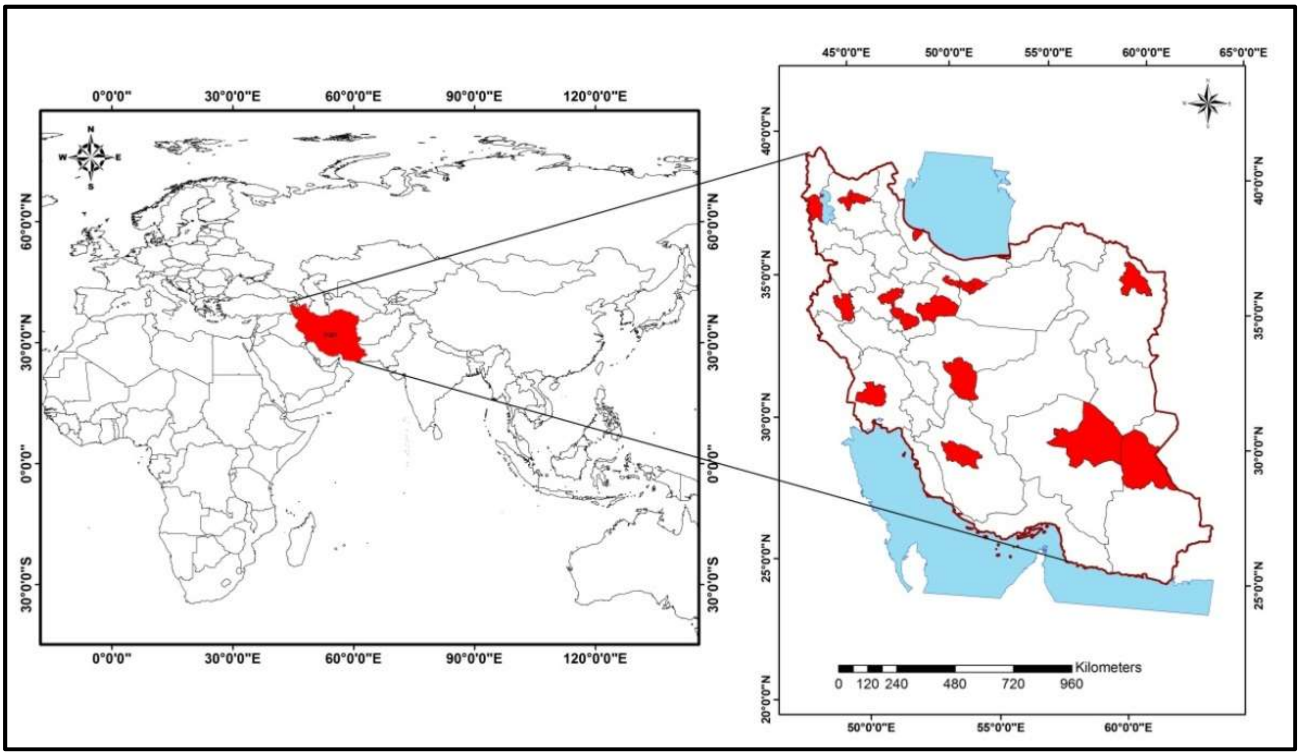

Fig. 1 – Location and pattern of the spatial distribution of cities above 500,000 inhabitants in Iran.
Source: Mapping Organization, 2016

Tab. 4 – Indicators and Cities (population over 500,000)

	C_1*	C_2*	C_3**	C_4**	C_5 ***	C_6	C_7***	C_8	C_9
Tehran	15	208	4	5	363	232	343	15	235002
Mashhad	49	169	5	3	356	251	333	13	305900
Esfahan	7	224	3	3	363	125	345	26	688035
Karaj	22	205	5	3	359	243	361	12	187209
Tabriz	89	163	4	1	342	283	347	9	593626
Shiraz	32	244	5	3	365	334	301	18	598106
Ahvaz	4	111	6	7	365	209	299	14	569393
Qom	23	196	5	3	365	148	354	16	2498
Kermanshah	51	14	3	1	360	439	336	11	164634
Urmia	32	217	6	1	345	339	360	10	550767
Rasht	168	50	5	4	365	1337	364	3	51000
Zahedan****	---	---	6	4	365	89	292	4	200000
Kerman	4	192	6	2	365	148	333	17	23306
Arak	35	154	6	2	349	337	345	21	443209
Hamedan	65	173	6	0	344	317	317	10	63000
Average	42.57	165.71	4.93	2.71	357.57	338.71	338.43	13.93	319691.79

Source: Statistics Center of Iran from 2011 to 2016, Meteorological Organization, Environmental Organization 2016

*March 20, 2016, to December 20, 2016, Includes data (Co ،O3 ،SO_2 ،NO_2 ،PM_{10} ،$PM_{2.5}$)

** Monthly average (40-year period) 1970-2010

***Annual average (1951-2005)

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**** The city of Zahedan has not been compared due to the lack of air quality control stations (healthy and clean).

3.1 Methodology

In this module, a novel integrated multi-criteria decision-making model is introduced. In the first part, since the actual data is used in this research, the ITARA method is represented along with its solving algorithm, and criteria weights are obtained utilizing ITARA. Furthermore, to involve experts' opinions in the weighting process, the authors describe the FUCOM weighting method. Experts are asked to express their ideas in 7 linguistic terms about each criterion in this part. Then, linguistic terms are transformed into gray intervals and whitened to obtain comparative priorities and rankings. The third part integrates ITARA and FUCOM weights to obtain the final weights. Ultimately, to assess the 14 cities based on the nine criteria, the authors present MARCOS-LN, which benefits from logarithmic normalization.

3.2 ITARA Method

Indifference threshold-based attribute ratio analysis (ITARA) was introduced by Hatefi (2018) to resolve the ambiguity of information provided by experts about criteria. ITARA assigns smaller weights to a criterion if its attributed values are almost identical. ITARA has been widely used in solving different problems, such as the identification of critical failure modes in products and systems (Lo et al., 2021a), material selection (Alper Sofuoğlu, 2019), sustainable supplier evaluation (Lo et al., 2021b), and developing a cleaner building industry model (Hasheminasab~~.~~, 2022), etc.

Step 1. Create a primary decision matrix and identify the indifference threshold values (IT_j)*.*
A primary decision matrix based on the alternatives and criteria is assigned in the first step. The primary decision matrix is composed of *"t"* alternatives designated as rows, *"f"* criteria designated as columns, and elements (a_{ij}) that represent the performance of the alternatives as a function of those criteria. As part of the evaluation process, experts are asked to determine an indifference threshold for each criterion. $IT_j, j \in F = \{1, 2, \ldots, f\}$

$$A = [a_{ij}] = \begin{bmatrix} a_{11} & \cdots & a_{1f} \\ \vdots & \ddots & \vdots \\ a_{t1} & \cdots & a_{tf} \end{bmatrix}, i = 1, 2, \ldots, t; j = 1, 2, \ldots, f$$

Based on (Lo et al., 2021b), we assume that IT_j should be less than the standard deviation of the values attributed to each criterion (σ_f).

Step 2. Normalize the primary decision matrix.
Utilizing equations (1) and (2), normalized decision matrix along with normalized indifference threshold (NIT_j) values will be obtained to continue the steps on one scale.

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{t} a_{ij}} \quad (1)$$

$$NIT_j = \frac{IT_j}{\sum_{i=1}^{t} a_{ij}} \quad (2)$$

$$N = [n_{ij}] = \begin{bmatrix} n_{11} & \cdots & n_{1f} \\ \vdots & \ddots & \vdots \\ n_{t1} & \cdots & n_{tf} \end{bmatrix}, i = 1, 2, \ldots, t; j = 1, 2, \ldots, f$$

Step 3. Add an ascending order to the normalized values.
According to (Hatefi, 2019), in order to obtain matrix β, each column's elements from step 2 are sorted ascendingly (Equation 3).

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$$\beta_{ij} \leq \beta_{i+1,j} \tag{3}$$

$$\beta = [\beta_{ij}] = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1f} \\ \vdots & \ddots & \vdots \\ \beta_{t1} & \cdots & \beta_{tf} \end{bmatrix}, i = 1, 2, \dots, t; j = 1, 2, \dots, f$$

Step 4. Estimate the ordered distances between neighboring cities.
The following formula is used to calculate the ordered distances between sorted values:

$$\gamma_{ij} = \beta_{i+1,j} - \beta_{ij} \tag{4}$$

Step 5. Calculate the intervals between γ_{ij} and NIT_j.
As γ_{ij} and NIT_j are normalized, considerable differences can be evaluated using equation (5)

$$\delta_{ij} = \begin{cases} \gamma_{ij} - NIT_j \; for \; \gamma_{ij} > NIT_j & , \gamma_{ij} > NIT_j \\ 0 & , \gamma_{ij} \leq NIT_j \end{cases} \tag{5}$$

Step 6. Evaluate the criteria weights.

As (Hatefi, 2019) presented, $v_j = \left(\sum_i^{t-1} \delta_{ij}^p\right)^{\frac{1}{p}}$ to obtain the final weights. Here we use $p = 1$ (Manhatan metric) to obtain the distances. Final weights are calculated using equations 6 and 7:

$$v_j = \sum_{i=1}^{t-1} \delta_{ij} \qquad for \;\; j \in F \tag{6}$$

$$w_j = \frac{v_j}{\sum_{i=1}^{t-1} v_j} \qquad for \;\; j \in F \tag{7}$$

3.3 FUCOM Method

The full consistency method (FUCOM) was proposed by Pamućar et al. in 2018 to cover AHP and BWM extra pairwise comparisons while keeping consistency (Pamućar et al., 2018). This method starts with ranking the criteria based on experts' ideas and continues with obtaining comparative priorities to solve a mathematical model while trying to satisfy full consistency. FUCOM came to many researchers' attention in solving decision-making problems such as inventory management (Vukasović et al., 2021), sustainable traffic management (Blagojević et al., 2021), Fighter aircraft selection (Hoan & Ha, 2021), etc.

Step 1. Rank the criteria and obtain the comparative priorities.

In order to challenge the uncertain opinions, first, experts are asked to express their thoughts about nine criteria in this study using seven linguistic terms from Table 5. Each linguistic term is attributed to a specific gray interval scaled from 1 to 8. Then, linguistic terms are transformed into gray intervals based on the average values for lower and upper bounds. Finally, whitening degrees are calculated using Equation (8) (Badi & Pamućar, 2020). Based on the whitening degrees, rankings are done in descending order.

A gray number is defined as (Liu et al., 2016):

$$\otimes G \in [G^l, G^u], \; G^l \leq G^u$$

$$G_W = \frac{G^l + G^u}{2} \tag{8}$$

Tab. 5 – Linguistic terms and attributed gray numbers

Importance	Abbreviation	Scale of gray numbers
Very Low	VL	[1 , 2]
Low	L	[2 , 3]
Low Moderate	LM	[3 , 4]
Moderate	M	[4 , 5]
High Moderate	HM	[5 , 6]
High	H	[6 , 7]
Very High	VH	[7 , 8]

Then comparative priority vectors will be evaluated based on the rankings.

Step 2. Define the restriction conditions in the mathematical model.

Model constraints are based on two conditions. Condition 1: The ratio of the criteria weight coefficients is equal to the comparative values of the defined criteria (Equation (9)).

$$w_k / w_{k+1} = \varphi_{k/(k+1)} \tag{9}$$

Condition 2: The criteria weight coefficients should meet the mathematical transitivity condition (Equation (10)).

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \times \varphi_{(k+1)/(K+2)} \tag{10}$$

Step 3 : Define the mathematical model.

Considering the required full consistency satisfaction and the two conditions explained in step 2, the mathematical model below is proposed to obtain the optimal weights of the criteria.

$$\begin{aligned}
&\min \chi \\
&s.t. \\
&\left| \frac{w_k}{w_{k+1}} - \varphi_{k/(k+1)} \right| \leq \chi, \qquad \forall i \\
&\left| \frac{w_k}{w_{k+2}} - \varphi_{k/(k+1)} \times \varphi_{(k+1)/(K+2)} \right| \leq \chi, \qquad \forall i \\
&\sum_{i=1}^{n} w_i = 1, \qquad \forall i \\
&w_i \geq 0, \forall i \\
&i = 1,2, \dots, n
\end{aligned} \tag{11}$$

3.4 ITARA and FUCOM integration

In order to integrate the ITARA and FUCOM weights, Equation (12) is implemented (Zavadskas & Podvezko, 2016; Ulutas et al., 2020):

$$W_{i\,INT} = \frac{w_{i\,FUCOM} \times w_{i\,ITARA}}{\sum_{i=1}^{n} w_{i\,FUCOM} \times w_{i\,ITARA}} \tag{12}$$

3.5 MARCOS-LN Method

Measurement alternatives and ranking according to the compromise solution or MARCOS is a novel methodology based on evaluating ideal and anti-ideal solutions and assessing their relations to alternative values. This method uses utility degrees and utility functions to obtain the compromise ranking. The alternative with the highest utility function value or, in other words, the one closer to an ideal solution and further to an anti-ideal solution among the other alternatives is ranked one. (Stević et al., 2020). Since MARCOS calculates ideal and anti-ideal solutions from the beginning of the solving process, it has been widely used in different fields such as the evaluation of human resources in a transport company (Stević and Brković, 2020), performance assessment of battery electric vehicles (Ecer, 2021), stackers selection in a logistics system (Ulutas et al., 2020), etc.

The modified MARCOS method, which is introduced in this research, uses logarithmic normalization proposed by Zavadskas and Turskis (2008) and implemented by some researchers in different MCDM methods. A reanalysis of VIKOR and TOPSIS methods using logarithmic normalization was done by Zolfani et al. (2020). Biswas and Pamućar (2021) used logarithmic normalization for the CODAS method to select the best smartphone between 25 alternatives. Ali et al. (2022) integrated logarithmic normalization, four more normalization methods for CoCoSo, and three weighting methods (FO-BWM, IDOCRIW, and aggregated FO-BWM-IDOCRIW) in order to assess five energy systems (Mini-Grid, SHS, Coal, Solar Park, Wind) for future planning and development.

Step 1. Build the primary decision matrix and identify the ideal (AI) and anti-ideal solutions (AAI).

Primary decision matrix *X* is designed based on *"m"* alternatives and *"n"* criteria shown by indices *"i"* and *"j"*. x_{ij} Refers to an attributed value of alternative *"i" to* the criterion *"j"*.

Ideal (*AI*) and anti-ideal solutions (*AAI*) are calculated based on the type of each criterion (costs or benefits) using equations (13) and (14):

$$AI = max\ x_{ij}\ if\ j\ is\ a\ Benefit\ crierion\ and\ min\ x_{ij}\ if\ j\ is\ a\ Cost\ crierion. \tag{13}$$

$$AAI = min\ x_{ij}\ if\ j\ is\ a\ Benefit\ crierion\ and\ max\ x_{ij}\ if\ j\ is\ a\ Cost\ crierion. \tag{14}$$

Step 2. Normalize the primary decision matrix.

Logarithmic normalization (Equations (15) & (16)) is used in this research instead of the original normalization method used in the MARCOS normalization step. n_{ij} Shows the normalized logarithmic value in the normalized matrix *N*.

$$n_{ij} = \frac{\ln(x_{ij})}{\ln(\prod_{m}^{i} x_{ij})}\quad if\ j\ is\ a\ Benefit\ criterion \tag{15}$$

$$n_{ij} = 1 - \frac{\frac{\ln(x_{ij})}{\ln(\prod_{m}^{i} x_{ij})}}{m-1}\quad if\ j\ is\ a\ Cost\ criterion \tag{16}$$

Step 3. Obtain the weighted normalized decision matrix Z= $[z_{ij}]_{m\times n}$ *using Equation (17).*

$$z_{ij} = n_{ij} \times w_j \tag{17}$$

Step 4. Calculate the utility degree of each alternative by implementing Equations (18) and (19).

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{18}$$

$$K_i^- = \frac{S_i}{S_{aai}} \tag{19}$$

Where S_i is the sum of the values of alternative i (row i) from matrix Z. Also, S_{ai} and S_{aai} are respectively sum of the ideal and anti-ideal solutions from matrix Z.

Step 5. Compute the utility function of each alternative by utilizing Equation (20) and rank the alternatives using utility function values.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{20}$$

Where $f(K_i^+)$ and $f(K_i^-)$ respectively show the utility function of each alternative in relation to the ideal (*AI*) and anti-ideal (*AAI*) solutions using equations (21) and (22).

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{21}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{22}$$

Finally, the alternatives are ranked based on the utility function values.

4 Results

This section presents the results of our novel integrated MCDM method. First, the criteria weights are calculated, and then research alternatives are prioritized using MARCOS-LN.

4.1 ITARA outcomes

The primary decision matrix includes average, standard deviation, indifference threshold values based on experts' opinions, and a summation of the values for each column (criterion) represented in Table 6.

Tab. 6 – Primary decision matrix established using ITARA step 1.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Tehran	15	208	4	5	363	232	343	15	235002
Mashhad	49	169	5	3	356	251	333	13	305900
Esfahan	7	224	3	3	363	125	345	26	688035
Karaj	22	205	5	3	359	243	361	12	187209
Tabriz	89	163	4	1	342	283	347	9	593626
Shiraz	32	244	5	3	365	334	301	18	598106
Ahvaz	4	111	6	7	365	209	299	14	569393
Qom	23	196	5	3	365	148	354	16	2498
Kermanshah	51	14	3	1	360	439	336	11	164634

Urmia	32	217	6	1	345	339	360	10	550767
Rasht	168	50	5	4	365	1337	364	3	51000
Kerman	4	192	6	2	365	148	333	17	23306
Arak	35	154	6	2	349	337	345	21	443209
Hamedan	65	173	6	1	344	317	317	10	63000
Average Value	42,5714286	165,7143	4,928571	2,714286	357,5714	338,7143	338,4286	13,92857	319691,8
Standard deviation	43,493084	66,04477	1,071612	1,815683	8,785603	300,4764	20,62752	5,649525	247251,6
IT_j	2	10	0.3	0.3	5	25	1	0.5	50000
Sum	596	2320	69	38	5006	4742	4738	195	4475685

Source: own research

- In order to not confront LN(0) in the MARCOS-LN normalization step and to keep the integrity of weightings along with assessing the alternatives, Hamedan's initial value concerning criterion 4 has altered from 0 to 1 from the beginning of the evaluation process.

According to ITARA step 2, normalization has been done using Equations (1) and (2) for primary decision matrix elements and indifference threshold values. Table 7 shows the normalized decision matrix.

Tab. 7 – Normalized decision matrix N (n_{ij})

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Tehran	0.0252	0.0897	0.058	0.1282	0.0725	0.0489	0.0724	0.0769	0.0525
Mashhad	0.0822	0.0728	0.0725	0.0769	0.0711	0.0529	0.0703	0.0667	0.0683
Esfahan	0.0117	0.0966	0.0435	0.0769	0.0725	0.0264	0.0728	0.1333	0.1537
Karaj	0.0369	0.0884	0.0725	0.0769	0.0717	0.0512	0.0762	0.0615	0.0418
Tabriz	0.1493	0.0703	0.058	0.0256	0.0683	0.0597	0.0732	0.0462	0.1326
Shiraz	0.0537	0.1052	0.0725	0.0769	0.0729	0.0704	0.0635	0.0923	0.1336
Ahvaz	0.0067	0.0478	0.087	0.1795	0.0729	0.0441	0.0631	0.0718	0.1272
Qom	0.0386	0.0845	0.0725	0.0769	0.0729	0.0312	0.0747	0.0821	0.0006
Kermanshah	0.0856	0.006	0.0435	0.0256	0.0719	0.0926	0.0709	0.0564	0.0368
Urmia	0.0537	0.0935	0.087	0.0256	0.0689	0.0715	0.076	0.0513	0.1231
Rasht	0.2819	0.0216	0.0725	0.1026	0.0729	0.2819	0.0768	0.0154	0.0114
Kerman	0.0067	0.0828	0.087	0.0513	0.0729	0.0312	0.0703	0.0872	0.0052
Arak	0.0587	0.0664	0.087	0.0513	0.0697	0.0711	0.0728	0.1077	0.099
Hamedan	0.1091	0.0746	0.087	0.0256	0.0687	0.0668	0.0669	0.0513	0.0141
NIT_j	0.0034	0.0043	0.0043	0.0077	0.001	0.0053	0.0002	0.0026	0.0112

Source: own research

Then, normalized values are sorted in ascending order (Equation (3)), which are illustrated in Table 8.

Tab. 8 – Sorted normalized matrix β (β_{ij})

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Sort 1	0.0067	0.006	0.0435	0.0256	0.0683	0.0264	0.0631	0.0154	0.0006
Sort 2	0.0067	0.0216	0.0435	0.0256	0.0687	0.0312	0.0635	0.0462	0.0052

Sort 3	0.0117	0.0478	0.058	0.0256	0.0689	0.0312	0.0669	0.0513	0.0114
Sort 4	0.0252	0.0664	0.058	0.0256	0.0697	0.0441	0.0703	0.0513	0.0141
Sort 5	0.0369	0.0703	0.0725	0.0513	0.0711	0.0489	0.0703	0.0564	0.0368
Sort 6	0.0386	0.0728	0.0725	0.0513	0.0717	0.0512	0.0709	0.0615	0.0418
Sort 7	0.0537	0.0746	0.0725	0.0769	0.0719	0.0529	0.0724	0.0667	0.0525
Sort 8	0.0537	0.0828	0.0725	0.0769	0.0725	0.0597	0.0728	0.0718	0.0683
Sort 9	0.0587	0.0845	0.0725	0.0769	0.0725	0.0668	0.0728	0.0769	0.099
Sort 10	0.0822	0.0884	0.087	0.0769	0.0729	0.0704	0.0732	0.0821	0.1231
Sort 11	0.0856	0.0897	0.087	0.0769	0.0729	0.0711	0.0747	0.0872	0.1272
Sort 12	0.1091	0.0935	0.087	0.1026	0.0729	0.0715	0.076	0.0923	0.1326
Sort 13	0.1493	0.0966	0.087	0.1282	0.0729	0.0926	0.0762	0.1077	0.1336
Sort 14	0.2819	0.1052	0.087	0.1795	0.0729	0.2819	0.0768	0.1333	0.1537

Source: own research

In order to obtain the ordered distances between neighboring cities, Equation (4) is implemented, and the results are shown in Table 9.

Tab. 9 – Ordered distances γ_{ij}

C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
0	0.0155	0	0	0.0004	0.0049	0.0004	0.0308	0.0046
0.005	0.0263	0.0145	0	0.0002	0	0.0034	0.0051	0.0062
0.0134	0.0185	0	0	0.0008	0.0129	0.0034	0	0.0027
0.0117	0.0039	0.0145	0.0256	0.0014	0.0049	0	0.0051	0.0227
0.0017	0.0026	0	0	0.0006	0.0023	0.0006	0.0051	0.005
0.0151	0.0017	0	0.0256	0.0002	0.0017	0.0015	0.0051	0.0107
0	0.0082	0	0	0.0006	0.0067	0.0004	0.0051	0.0158
0.005	0.0017	0	0	0	0.0072	0	0.0051	0.0307
0.0235	0.0039	0.0145	0	0.0004	0.0036	0.0004	0.0051	0.024
0.0034	0.0013	0	0	0	0.0006	0.0015	0.0051	0.0042
0.0235	0.0039	0	0.0256	0	0.0004	0.0013	0.0051	0.0054
0.0403	0.003	0	0.0256	0	0.0211	0.0002	0.0154	0.001
0.1326	0.0086	0	0.0513	0	0.1894	0.0006	0.0256	0.0201

Source: own research

In the next step, considerable intervals need to be estimated. So, Equation (5) is utilized, and Table 10 contains the significant gaps between sorted values.

Tab. 10 – Significant gaps δ_{ij}

C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
0	0.0112	0	0	0	0	0.0002	0.0282	0
0.0017	0.022	0.0101	0	0	0	0.0032	0.0026	0
0.0101	0.0142	0	0	0	0.0076	0.0032	0	0
0.0084	0	0.0101	0.0179	0.0004	0	0	0.0026	0.0115
0	0	0	0	0	0	0.0004	0.0026	0
0.0117	0	0	0.0179	0	0	0.0013	0.0026	0
0	0.0039	0	0	0	0.0015	0.0002	0.0026	0.0047
0.0017	0	0	0	0	0.0019	0	0.0026	0.0195
0.0201	0	0.0101	0	0	0	0.0002	0.0026	0.0129
0	0	0	0	0	0	0.0013	0.0026	0
0.0201	0	0	0.0179	0	0	0.0011	0.0026	0
0.0369	0	0	0.0179	0	0.0158	0	0.0128	0
0.1292	0.0043	0	0.0436	0	0.1841	0.0004	0.0231	0.0089

Source: own research

Finally, by utilizing Equations (6) and (7), criteria weights and ranks are introduced in Table 11.

Tab. 11 – Criteria weights using ITARA

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
v_j	0.2399	0.0556	0.0304	0.1154	0.0004	0.2109	0.0114	0.0872	0.0575
w_j	0.2967	0.0688	0.0376	0.1427	0.0005	0.2608	0.0141	0.1078	0.0711
Rank	1	6	7	3	9	2	8	4	5

Source: own research

4.2 FUCOM outcomes

Based on the nine defined criteria from Table 2, four experts are asked to indicate their ideas about the criteria using seven linguistic terms from Table 10. Then linguistic terms are transformed to gray intervals using average values for lower and upper bounds, and according to Equation (8), whitening degrees are calculated to utilize for obtaining comparative priorities. Experts' scores and results are shown in Table 12.

Tab. 12 – Experts' scores, along with gray number characteristics and ranks

	EXPERT 1	EXPERT 2	EXPERT 3	EXPERT 4	LOWER BOUND	UPPER BOUND	Whitening degree	Rank
C_1	VH	VH	VH	VH	7	8	7.5	1
C_2	VH	H	VH	HM	6.25	7.25	6.75	3
C_3	M	HM	H	H	5.25	6.25	5.75	7
C_4	L	H	M	LM	3.5	4.5	4	8
C_5	VL	M	M	M	3.25	4.25	3.75	9
C_6	VH	H	H	H	6.25	7.25	6.75	3
C_7	H	VH	VH	H	6.5	7.5	7	2
C_8	H	VH	VH	HM	6.25	7.25	6.75	3
C_9	HM	H	HM	H	5.5	6.5	6	6

Source: own research

Criteria ranks are evaluated as follows: $C_1 > C_7 > C_2 = C_6 = C_8 > C_9 > C_3 > C_4 > C_5$.

Based on the obtained priorities from Table 12, which are shown by whitening degrees, to satisfy condition 1:

$\varphi_{C_1/C_7} = w_{C_1}/w_{C_7} = {}^{7.5}/_{7} = 1.071,\ \varphi_{C_7/C_2} = w_{C_7}/w_{C_2} = {}^{7}/_{6.75} = 1.037,\ \varphi_{C_2/C_6} = w_{C_2}/w_{C_6} = {}^{6.75}/_{6.75} = 1,\ \varphi_{C_6/C_8} = w_{C_6}/w_{C_8} = {}^{6.75}/_{6.75} = 1,\ \varphi_{C_8/C_9} = w_{C_8}/w_{C_9} = {}^{6.75}/_{6} = 1.125,\ \varphi_{C_9/C_3} = w_{C_9}/w_{C_3} = {}^{6}/_{5.75} = 1.043,\ \varphi_{C_3/C_4} = w_{C_3}/w_{C_4} = {}^{5.75}/_{4} = 1.437,$

$\varphi_{C_4/C_5} = w_{C_4}/w_{C_5} = {}^{4}/_{3.75} = 1.067$

In order to fulfill mathematical transitivity (condition 2):

$w_{C_1}/w_{C_2} = 1.071 \times 1.037 = 1.111,\quad w_{C_7}/w_{C_6} = 1.037 \times 1 = 1.037,\quad w_{C_2}/w_{C_8} = 1 \times 1 = 1,\ w_{C_6}/w_{C_9} = 1 \times 1.125 = 1.125,\ w_{C_8}/w_{C_3} = 1.125 \times 1.043 = 1.174,\ w_{C_9}/w_{C_4} = 1.043 \times 1.4375 = 1.5,\ w_{C_3}/w_{C_5} = 1.4375 \times 1.067 = 1.533$

Then, the stated model in step 3 is used to obtain optimal weights using the described mathematical model:

$\min \chi$

$s.t.$

$\left|\frac{w_{c1}}{w_{c7}} - 1.071\right| \le \chi,\ \left|\frac{w_{c7}}{w_{c2}} - 1.037\right| \le \chi,\ \left|\frac{w_{c2}}{w_{c6}} - 1\right| \le \chi,\ \left|\frac{w_{c6}}{w_{c8}} - 1\right| \le \chi,\ \left|\frac{w_{c8}}{w_{c9}} - 1.125\right| \le \chi,$

$\left|\frac{w_{c9}}{w_{c3}} - 1.043\right| \le \chi,\ \left|\frac{w_{c3}}{w_{c4}} - 1.437\right| \le \chi,\ \left|\frac{w_{c4}}{w_{c5}} - 1.067\right| \le \chi,\ \left|\frac{w_{c1}}{w_{c2}} - 1.111\right| \le \chi,\ \left|\frac{w_{c7}}{w_{c6}} - 1.037\right| \le \chi,$

$\left|\frac{w_{c2}}{w_{c8}} - 1\right| \le \chi,\ \left|\frac{w_{c6}}{w_{c9}} - 1.125\right| \le \chi,\ \left|\frac{w_{c8}}{w_{c3}} - 1.174\right| \le \chi,\ \left|\frac{w_{c9}}{w_{c4}} - 1.5\right| \le \chi,\ \left|\frac{w_{c3}}{w_{c5}} - 1.533\right| \le \chi$

$\sum_{i=1}^{9} w_i = 1,\ \forall i\,,\ w_i \ge 0, \forall i$

By solving the mentioned model, the final criteria weights are obtained with DFC = 0.00003, shown in Table 13.

Tab. 13 – FUCOM results

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
w_j	0.2967	0.0688	0.0376	0.1427	0.0005	0.2608	0.0141	0.1078	0.0711

Source: own research

The FUCOM optimization model is solved using the Pyomo library in Python.

4.3 Weights integration outcomes

Table 14 presents the integrated criteria weights based on ITARA-FUCOM using Equation (12):

Tab. 14 – Integrated ITARA-FUCOM results

	C1	C2	C3	C4	C5	C6	C7	C8	C9
w_j	**0.345**	0.0714	0.0328	0.0877	0.0003	0.2707	0.0152	0.1119	0.065

Source: own research

4.4 MARCOS-LN results

Table 15 shows the primary decision matrix along with the ideal (*AI*) and anti-ideal (*AAI*) solutions for each criterion based on Equations (13) and (14).

Tab. 15 – Primary decision matrix along with the ideal (*AI*) and anti-ideal (*AAI*) solutions

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Tehran	15	208	4	5	363	232	343	15	235002
Mashhad	49	169	5	3	356	251	333	13	305900
Esfahan	7	224	3	3	363	125	345	26	688035
Karaj	22	205	5	3	359	243	361	12	187209
Tabriz	89	163	4	1	342	283	347	9	593626
Shiraz	32	244	5	3	365	334	301	18	598106
Ahvaz	4	111	6	7	365	209	299	14	569393
Qom	23	196	5	3	365	148	354	16	2498
Kermanshah	51	14	3	1	360	439	336	11	164634
Urmia	32	217	6	1	345	339	360	10	550767
Rasht	168	50	5	4	365	1337	364	3	51000
Kerman	4	192	6	2	365	148	333	17	23306
Arak	35	154	6	2	349	337	345	21	443209
Hamedan	65	173	6	1	344	317	317	10	63000
AI	168	244	6	7	365	1337	364	26	688035
AAI	4	14	3	1	342	125	299	3	2498

Source: own research

Then, logarithmic normalization is performed using Equations (15) and (16), and the results are presented in Table 16.

Tab. 16 – Normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Tehran	0.0592	0.0772	0.0631	0.1362	0.0716	0.0691	0.0716	0.0763	0.0734
Mashhad	0.0851	0.0742	0.0732	0.0929	0.0714	0.0701	0.0713	0.0723	0.075
Esfahan	0.0425	0.0782	0.05	0.0929	0.0716	0.0613	0.0717	0.0918	0.0798
Karaj	0.0676	0.077	0.0732	0.0929	0.0715	0.0697	0.0722	0.07	0.0721
Tabriz	0.0981	0.0737	0.0631	0	0.0709	0.0717	0.0718	0.0619	0.0789
Shiraz	0.0758	0.0795	0.0732	0.0929	0.0717	0.0738	0.07	0.0814	0.079
Ahvaz	0.0303	0.0681	0.0815	0.1646	0.0717	0.0678	0.0699	0.0744	0.0787
Qom	0.0685	0.0763	0.0732	0.0929	0.0717	0.0634	0.072	0.0781	0.0464
Kermanshah	0.0859	0.0382	0.05	0	0.0715	0.0772	0.0714	0.0676	0.0713
Urmia	0.0758	0.0778	0.0815	0	0.071	0.074	0.0722	0.0649	0.0785
Rasht	0.112	0.0566	0.0732	0.1173	0.0717	0.0914	0.0723	0.031	0.0644
Kerman	0.0303	0.076	0.0815	0.0586	0.0717	0.0634	0.0713	0.0798	0.0597
Arak	0.0777	0.0728	0.0815	0.0586	0.0711	0.0739	0.0717	0.0858	0.0772
Hamedan	0.0912	0.0745	0.0815	0	0.071	0.0731	0.0706	0.0649	0.0656
AI	0.112	0.0795	0.0815	0.1646	0.0717	0.0914	0.0723	0.0918	0.0798

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AAI	0.0303	0.0382	0.05	0	0.0709	0.0613	0.0699	0.031	0.0464

Source: own research

In the next step, the weighted normalized matrix elements were computed by implementing Equation (17). The weighted normalized values are presented in Table 17.

Tab. 17 – Weighted normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	Sum
Tehran	0.0204	0.0055	0.0021	0.0119	0.00002	0.0187	0.0011	0.0085	0.0048	0.07302
Mashhad	0.0293	0.0053	0.0024	0.0082	0.00002	0.019	0.0011	0.0081	0.0049	0.07832
Esfahan	0.0147	0.0056	0.0016	0.0082	0.00002	0.0166	0.0011	0.0103	0.0052	0.06332
Karaj	0.0233	0.0055	0.0024	0.0082	0.00002	0.0189	0.0011	0.0078	0.0047	0.07192
Tabriz	0.0338	0.0053	0.0021	0	0.00002	0.0194	0.0011	0.0069	0.0051	0.07372
Shiraz	0.0261	0.0057	0.0024	0.0082	0.00002	0.02	0.0011	0.0091	0.0051	0.07772
Ahvaz	0.0105	0.0049	0.0027	0.0144	0.00002	0.0184	0.0011	0.0083	0.0051	0.06542
Qom	0.0236	0.0054	0.0024	0.0082	0.00002	0.0172	0.0011	0.0087	0.003	0.06962
Kermanshah	0.0296	0.0027	0.0016	0	0.00002	0.0209	0.0011	0.0076	0.0046	0.06812
Urmia	0.0261	0.0056	0.0027	0	0.00002	0.02	0.0011	0.0073	0.0051	0.06792
Rasht	0.0386	0.004	0.0024	0.0103	0.00002	0.0247	0.0011	0.0035	0.0042	0.08882
Kerman	0.0105	0.0054	0.0027	0.0051	0.00002	0.0172	0.0011	0.0089	0.0039	0.05482
Arak	0.0268	0.0052	0.0027	0.0051	0.00002	0.02	0.0011	0.0096	0.005	0.07552
Hamedan	0.0315	0.0053	0.0027	0	0.00002	0.0198	0.0011	0.0073	0.0043	0.07202
AI	0.0386	0.0057	0.0027	0.0144	0.00002	0.0247	0.0011	0.0103	0.0052	0.10272
AAI	0.0105	0.0027	0.0016	0	0.00002	0.0166	0.0011	0.0035	0.003	0.03902

Source: own research

Finally, Equations (18) to (2) are utilized to complete the remaining steps of evaluating the utility functions for each alternative. Table 18 shows these values and also the MARCOS-LN final ranking.

Tab. 18 – Utility functions and final ranks of alternatives

	K_i^+	K_i^-	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$	Rank
Tehran	0.7109	1.8713	0.7247	0.2753	0.6436	6
Mashhad	0.7625	2.0072	0.7247	0.2753	0.6903	2
Esfahan	0.6164	1.6228	0.7247	0.2753	0.5581	13
Karaj	0.7002	1.8432	0.7247	0.2753	0.6339	8
Tabriz	0.7177	1.8893	0.7247	0.2753	0.6498	5
Shiraz	0.7566	1.9918	0.7247	0.2753	0.685	3
Ahvaz	0.6369	1.6766	0.7247	0.2753	0.5766	12
Qom	0.6778	1.7842	0.7247	0.2753	0.6136	9
Kermanshah	0.6632	1.7458	0.7247	0.2753	0.6004	10

Urmia	0.6612	1.7406	0.7247	0.2753	0.5986	11
Rasht	0.8647	2.2763	0.7247	0.2753	0.7828	1
Kerman	0.5337	1.4049	0.7247	0.2753	0.4832	14
Arak	0.7352	1.9354	0.7247	0.2753	0.6656	4
Hamedan	0.7011	1.8457	0.7247	0.2753	0.6348	7

Source: own research

5 Sensitivity analysis

In order to assess the results, the MARCOS-LN ranking is compared to the rankings obtained by MARCOS, EDAS, CODAS-LN, CODAS, TOPSIS-LN, and TOPSIS, which are shown in Table 19 and Figures 2 to 5.

Tab. 19 – Ranking comparison

	MARCOS-LN	MARCOS	EDAS	CODAS -LN	CODAS	TOPSIS-LN	TOPSIS
Tehran	6	10	10	9	11	10	11
Mashhad	2	5	4	4	7	2	5
Esfahan	13	8	13	13	6	13	9
Karaj	8	11	9	11	12	8	12
Tabriz	5	2	2	2	2	3	2
Shiraz	3	3	3	6	3	4	7
Ahvaz	12	9	12	12	10	12	10
Qom	9	13	11	10	13	9	13
Kermanshah	10	12	7	5	9	7	4
Urmia	11	7	8	8	8	11	8
Rasht	1	1	1	1	1	1	1
Kerman	14	14	14	14	14	14	14
Arak	4	4	5	7	5	6	6
Hamedan	7	6	6	3	4	5	3

Source: own research

In the case of EDAS and EDAS-LN, logarithmic normalization was implemented in the normalization step, but the results were far from other methods' rankings in this case study. This issue shows that logarithmic normalization has limitations in adjusting to some techniques and special cases and may show considerable variants in the results. Since EDAS-LN results differed from other utilized MCDM methods in this research, its ranking was omitted. Table 20 illustrates EDAS-LN outcomes.

Tab. 20 – EDAS-LN ranking

Cities	Ranks
Tehran	10
Mashhad	1
Esfahan	13
Karaj	3
Tabriz	11
Shiraz	4
Ahvaz	12

Qom	6
Kermanshah	7
Urmia	5
Rasht	14
Kerman	9
Arak	2
Hamedan	8

Source: own research

As shown in Table 20, Rasht City is ranked 14 among all alternatives, which is odd in reality. The reason is that when NSP_i is calculated based on logarithmic normalization, -0.0211 will be obtained by $\frac{\ln(1.85)}{\ln(0.097\times0.061\times0.204\times0.025\times0.432\times0.130\times0.191\times0.038\times0.148\times0.077\times1.85\times0.043\times0.089\times0.192)}$ and NSN_i cannot compensate for this value in the AS_i calculation. This leads to unreal ranks for the cities of Kerman and Arak compared to other target cities. According to the authors' observations from the primary decision matrix and final rankings obtained by MCDM methods, results can be different in cases where alternatives are close to one another, mainly while logarithmic normalization is implemented. The results show that Rasht City is the best alternative, and Kerman comes at the end of the ranking. Based on average rankings, Rasht, Tabriz, Shiraz, Mashhad, and Hamedan are the top five cities in this study. Moreover, experts verified the mentioned result.

Figure 2 illustrates the comparative results of MARCOS-LN, CODASL-LN, and TOPSIS-LN. The findings show that the highest rank discrepancy is for Kermanshah city, which is five.

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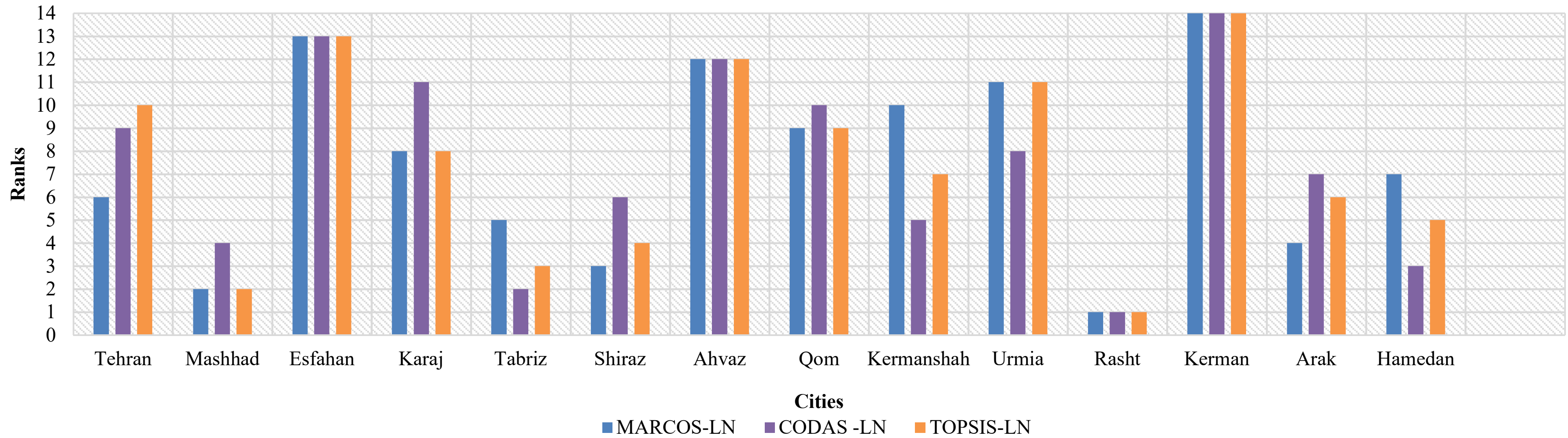

Fig. 2 – Cities rankings based on MARCOS-LN, CODAS-LN, and TOPSIS-LN methods. Source: own research

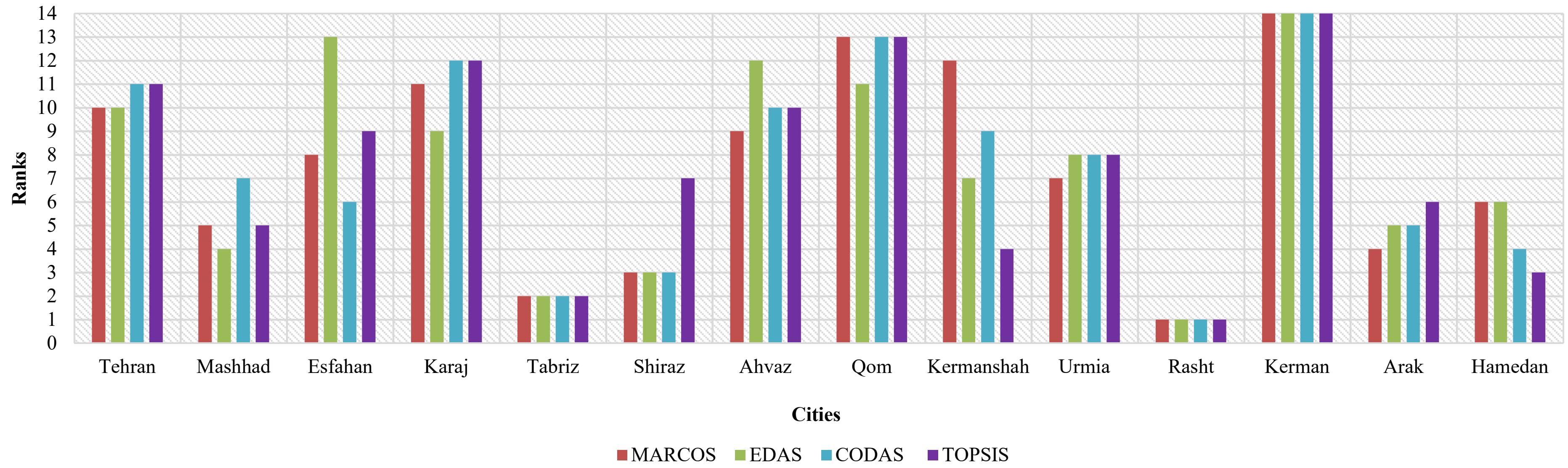

Fig. 3 – Cities rankings based on MARCOS, EDAS, CODAS, and TOPSIS methods. Source: own research

Results of the original EDAS, MARCOS, CODAS, and TOPSIS are depicted in Figure 3. By comparing the results, we conclude that original methods have more differences in ranks (Isfahan city) than the modified versions, which benefit from logarithmic normalization. This issue shows the reliability of implemented logarithmic-based methods.

Figure 4 represents the comparative results of seven implemented MCDM methods in this research. The highest overall difference in rank is for Kermanshah City. Furthermore, experts confirmed that the ranking of cities by utilizing logarithmic normalization is more accurate. This statement is also verified by Zolfani et al. (2020) by implementing logarithmic normalization in TOPSIS and VIKOR, and Biswas and Pamućar (2021) by taking advantage of this normalization in CODAS. Moreover, The MARCOS-LN has four same ranks as the original MARCOS, one more than CODAS and CODAS-LN, as well as TOPSIS and TOPSIS-LN.

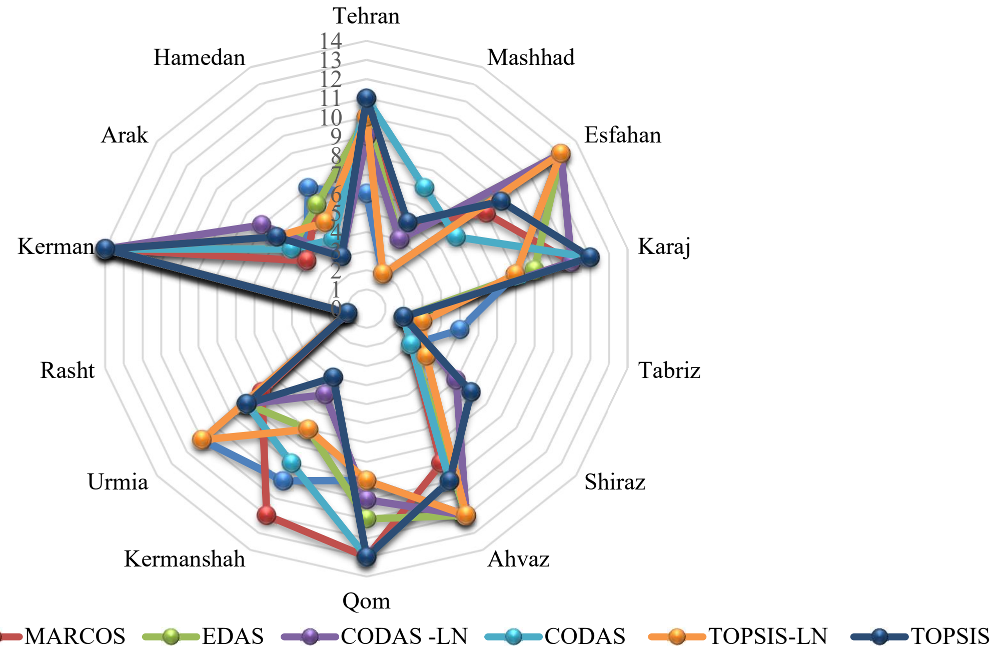

Fig. 4 – Comparative rankings based on 7 MCDM methods. Source: own research

6 DISCUSSION

In this study, we developed a novel MCDM approach based on ITARA and FUCOM methods that incorporate real data evaluation and experts' opinions to obtain criteria weights to increase the accuracy of criteria weights determination. Furthermore, the implementation of logarithmic normalization aid the methodology in obtaining robust outcomes for future policy-making.

Table 3 shows the quantitative values of various indicators of the environmental competitiveness index of Iranian cities with more than 500,000 people in a comparison. The data in this table shows the clear contrasts in environmental competitiveness among these 15 cities. For example, the average number of days with clean air within the first nine months of 2015 (X1) for all cities is 42.5 days, while this sum is 168 days for Rasht, having the most days of clean air, and only four days for the cities of Ahvaz and Kerman, having the least days of clean air.

The major differences in environmental competitiveness between cities with more than 500,000 inhabitants in Iran can be observed in the index of annual precipitation in millimeters (X6). In this graph, the average annual rainfall of these cities is 338.71 mm, which is the least in Zahedan, with 89 mm per year, and the highest in Rasht, with 1337 mm per year. Moreover, the average annual precipitation of the entire country is 240-250 mm per year, and in this sense, Iran's big cities, with 338.71 mm of annual precipitation, have much more reasonable conditions than the whole country.

According to the findings (Table 18) in this ranking, the city of Rasht has the first rank of environmental competitiveness among Iranian cities of more than 500,000 individuals. This city is higher than the average of the studied cities in the indicators of the number of days with clean air, the number of months with comfortable temperatures during the day, the number of months with comfortable temperatures at night, the number of non-freezing days, the amount of annual precipitation, and the number of dust-free days. In only three indicators, the number of days with healthy air, green space per capita, and the total area (forests, pastures, and good desert phenomena) is Rasht lower than the average of metropolitan cities, and the reason for the low number of days with healthy air compared to the national average is because of the high the number of days with clean air. The remarkable thing about Rasht City is its low green space per capita compared to other Iranian metropolises; it ranked last.

The results demonstrate that the city of Kerman is in the last place (rank 14) in environmental competitiveness among Iranian cities with a population of more than 500,000. In 55.55% of the indicators of the environmental competitiveness index, Kerman is lower than the national average, which incorporates:

The number of days with clean air in 9 months, months with a comfortable temperature at night, annual precipitation (mm), dry days of dust, and the whole area of forests, pastures, and good desert phenomena (hectares). In other indicators, it is higher than the national average.

Although the environmental competitiveness of cities is significant in their development in the coming years, this same competitive advantage can be used as a lever to generate income for target cities. In particular, we can mention the cities that satisfy the 9th criterion (the total area of forests, pastures, and good desert phenomena). Cities with suitable environmental attractions can bring in domestic and especially foreign tourists. The desert regions of Iran (Kerman City in this research) can provide pleasant moments for foreign tourists and attract more revenue for economic development.

Due to the environmental attractions of cities with good weather, such as Rasht and Shiraz, these cities can be the destination of many domestic and foreign tourists who come from dry and hot regions, and tourism investment in these cities can provide meaningful feedback. Moreover,

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considering the ancient monuments' attractiveness factor alongside the environmental attractiveness of a city like Shiraz improves such cities' strength in tourism attraction. Therefore, attracting tourists from the environmental competitiveness perspective can bring significant income to the economic cycle of target cities and Iran in general.

Due to the complexity of the subject, there are limitations on the indicators and data that can be used in competitiveness research. In the current study, access to experts was also limited, in addition to data access. The high cost of these studies is an additional limitation for research on the subject of competitiveness because it takes effort to prepare data and distribute questionnaires. It is preferable to look at other measures of competitiveness, including economic and social ones. In addition to being costly, completing all of these indicators takes a lot of time and usually needs funding from an official or private sponsor.

7 CONCLUSION

Since the 1960s, and with the quantitative levels of spatial explanation and analysis, geographers have concentrated on modern approaches to analyzing regional and urban inequalities. In this regard, the explanation of the competitiveness model of the cities that are discussed in this study can be considered as one of the evaluation methods to improve the differences in the competitiveness of Iranian cities with a population greater than 500,000.

In this study, we evaluated the environmental competitiveness of fourteen Iranian cities by developing a novel integrated ITARA-FUCOM-modified MARCOS MCDM model. This novelty aims to obtain the criteria weights using real data and experts' ideas, along with the precision of logarithmic normalization to assess the alternatives.

To progress, the competitive position of Iranian cities should pay attention to the internal capacities, relative advantages, and competitive role each city can have on a transnational scale. It requires decentralized national and transnational planning and development of competitiveness scenarios for medium and long-term periods. Also, due to the nature of urban competitiveness, which is multidimensional, it is essential to avoid a one-sided approach in urban competitiveness planning and to consider the economic, social, cultural, environmental, and security measurements of urban competitiveness in an integrated way. In addition, since local features form national and global prospects, in the transnational dimension, for competitiveness, the place and part of each Iranian city should be determined based on its relative capacity. This is because improving the level of competitiveness of each city will ultimately lead to the improvement of Iran's regional competitiveness (which is one of the goals of the vision document) as well as global competitiveness.

Discussions and decisions on the environmental competitiveness of places, in addition to influencing environmental factors, also affect other aspects of competitiveness, especially economic competitiveness. The findings of this study confirm that the continuation of inequalities and neglect of environmental issues in cities with low competitiveness, along with the destruction of environmental opportunities, causes national environmental crises and indirect economic, socio-cultural, and security crises in other places, especially Tehran. Natural crises will increase migration, especially in Tehran, as well as the northern cities of Iran, including the city of Rasht, which will cause these immigrant-friendly cities to face serious challenges.

The most critical variable influencing the natural competitiveness of some cities such as Kermanshah, in addition to natural factors such as the amount of precipitation, forests, pastures, and good desert phenomena, the number of non-freezing days, and human variables such as lack of management, is dealing with fine dust. The solution to getting out of the crisis of the micro dust phenomenon requires measures at the transnational level.

The powerless performance of urban administration within the development of public transportation is one of the essential variables influencing the natural competitiveness of cities. This variable has caused more traffic of private cars, resulting in an increase in the number of unhealthy weather days. The low green space capitation in some cities, such as Tabriz, Urmia, Hamedan, and Kermanshah, despite having the capacities of climate and soil, among other components, has impacted the competitiveness of these cities. In this case, despite the low green space capitation, the city of Rasht has been ranked first in Iran's natural competitiveness due to the favorable condition of other indicators influencing environmental competitiveness.

The following topics are suggested for future research:

1) Study on competitiveness in the environmental sector.
2) The identification of critical factors influencing competitiveness.
3) Comparative analysis of social, economic, and environmental viability.

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