Information Sciences 301 (2015) 75–98

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Development of a novel multiple-attribute decision making model via fuzzy cognitive maps and hierarchical fuzzy TOPSIS

Adil Baykasoğlu [a,*], İlker Gölcük [a,b]

[a] Dokuz Eylül University, wFaculty of Engineering, Department of Industrial Engineering, Izmir, Turkey
[b] The Graduate School of Natural and Applied Sciences, Dokuz Eylül University, Izmir, Turkey

ARTICLE INFO

Article history:
Received 10 February 2014
Received in revised form 31 October 2014
Accepted 26 December 2014
Available online 5 January 2015

Keywords:
Hierarchical fuzzy TOPSIS
Fuzzy cognitive map
Interdependence
Problem structuring

ABSTRACT

In this paper, a new fuzzy Multiple-Attribute Decision Making (MADM) model is developed by integrating the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy Cognitive Maps (FCMs). The proposed model exhibits some desirable features that enable decision makers to model complex decision-making problems. Providing an effective methodology for problem structuring, the ability to model interdependencies among the problem attributes and the capability of handling uncertainties are some of the main characteristics of the proposed hierarchical MADM model. The proposed model is implemented in a Strengths, Weaknesses, Opportunities, and Threats (SWOT)-based strategy selection problem in order to demonstrate its applicability.

1. Introduction

The increasing complexity of the rapidly evolving business environment entails making right decisions when considering a diversity of factors. These decision factors may involve political, environmental, social, psychological, and economic considerations. Unfortunately, most of these factors are not well defined nor well understood. For this reason, multiple-attribute decision making (MADM) supports decision makers with a comprehensive collection of approaches to address complex, poorly defined problems with multiple and interrelated criteria.

In recent years, the awareness in regards to the long-term impact of high-quality decisions on overall organizational performance has attracted increased attention to MADM methods. Many state-of-the-art methods, such as Multi-Attribute Utility Theory (MAUT) [25,29,46], Analytic Hierarchy Process (AHP) [80], Analytic Network Process (ANP) [82], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [40], Elimination et Choice Translating Reality (ELECTRE) [79], VlseKriterijumska Optimizacija I Kompromisno Resenje technique (VIKOR) [66], Decision-Making Trial and Evaluation Laboratory (DEMATEL) [31], conjoint analysis [51,99], and Choquet integral [37,56,57], are proposed in the literature in order to help decision makers make better evaluations. Despite the availability of a wide variety of decision analysis tools, practitioners are usually not familiar with all of the methods in the literature and cannot estimate the benefits of a particular method for their specific problem. Each method has very distinct features, and to select the so-called "best" approach among too many available tools is indeed a very challenging task.

The most influential features of a MADM method are "aiding decision makers to understand and structure the decision criteria", "modeling capability of the possible interactions among the criteria", and "transforming linguistically expressed

* Corresponding author. Tel.: +90 232 3017600; fax: +90 232 3017608.
E-mail address: adil.baykasoglu@deu.edu.tr (A. Baykasoğlu).

http://dx.doi.org/10.1016/j.ins.2014.12.048
0020-0255/

judgments of decision makers into meaningful preference structures". In this line of thought, we have proposed a hybrid MADM approach by combining hierarchical fuzzy TOPSIS [42,44] and Fuzzy Cognitive Maps (FCMs) [48] for modeling and solving decision problems with multiple, conflicting, and interdependent attributes under complex, poorly defined and uncertain environments. The rationale underlying the proposed method is the need to find a comprehensive analysis by taking into account possible interdependencies among attributes and conducting analysis in a hierarchical problem setting. Such an approach reduces both cognitive and structural complexity. Analysis of the related literature reveals that most of the MADM methods do not provide all of the above-mentioned features simultaneously. Therefore, this paper proposes an integrated MADM method that handles fuzziness, criteria interactions and hierarchical decomposition in a combined way. The applicability of the proposed method is presented in a Strengths, Weaknesses, Opportunities, and Threats (SWOT) based strategy selection problem of an industrial engineering department. This paper contributes to the literature in the following ways:

- Characteristics of a sufficient MADM method are discussed and analysed in detail. The relationship between problem structure and criteria interaction is given. Complexity caused by the problem structure has spurred us to find a trade-off between the traditional hierarchy and network structure; hence, a new balanced complexity structure of top-down decomposition with horizontal interactions is provided. These topics are covered in Section 2.
- Hierarchical fuzzy TOPSIS and FCMs are combined for the first time in the literature. Hierarchy and fuzziness add considerable value to a MADM method. Although the traditional TOPSIS method does not take criteria interactions into account, causal dependencies are taken into consideration via FCMs to overcome the restrictive assumption of preference independence. The proposed method is explained in detail in Section 3.
- The importance of SWOT factors are quantified by making use of FCMs. A SWOT-based strategy selection problem of the industrial engineering department at Dokuz Eylül University is resolved by using the proposed model. Application details of the proposed method are presented in Section 4. Concluding remarks are given in Section 5.

In the next section, we discuss the important characteristics of a sufficient MADM method.

2. Characteristics of an adequate MADM method

2.1. What is lacking in the literature?

One of the most influential features of a MADM method is the modeling capability of possible interactions among the decision criteria. However, the majority of the MADM methods assume that the criteria are independent from each other, which is not a realistic assumption in most real-world problems. As several forms of interactions among criteria might occur in real-life problems, more sophisticated techniques are required to address the particular needs of the problem under consideration. In the related literature, two bodies of methods are predominant to model criteria interactions: ANP and the Choquet integral.

The Choquet integral, also known as the member of non-additive integrals or fuzzy integrals, makes use of fuzzy measures or capacities [92,93] to assign a degree of importance to the criteria. An important feature of the fuzzy measures is that they assign importance degrees not only to criteria but also to the coalition of criteria. Accordingly, the importance degree of a coalition is highly influenced by its members. For instance, a criterion may not be very important for a decision maker; however, when it is evaluated in the coalition, being assessed in the presence of other criteria might lead to higher degrees of importance or vice versa. Several real-world applications of the Choquet integral are reported in the literature. Tzeng et al. [97] proposed a hierarchical model with the Choquet integral for evaluating enterprise intranet web sites. Yang et al. [103] integrated the Interpretive Structural Modeling (ISM) [85], AHP and Choquet integral for a vendor selection problem. Büyüközkan et al. [15] evaluated fourth-party logistics operating models using a two-additive Choquet Integral. Feng et al. [28] developed a hybrid fuzzy integral decision-making model for selecting a manufacturing center. Magoč and Modave [53] used a two-additive Choquet integral to model the dependencies among assets during portfolio selection. The main shortcoming of the Choquet integral is that the identification of fuzzy measures is an arduous task for decision makers. Suppose that we have n criteria. The Choquet integral requires $(2^n - 2)$ coefficients to be defined. For instance, if we have 10 criteria, 1022 coefficients need to be defined. If two-additive capacities are used, the number of coefficients to be defined equals 55. Defining fuzzy measures is a very problematic issue while working with the Choquet integral, and it restricts the wide range of applicability of the method. More information about capacity identification methods can be found in [36].

The other important method to model criteria interactions is the generalization of AHP, where the standard AHP method can only model static and unidirectional interactions among the decision elements [87]. However, real-life problems can be very difficult to model via AHP structures because there are many interactions among the elements of different levels. Conversely, ANP offers much more flexibility for considering complex interactions among different elements [82]. There is no doubt that ANP is the most preferred MADM method for modeling dependence and feedback situations. More than one thousand ANP related papers have been recorded in the Scopus databases since 2005. ANP is applied to a wide variety of problems, such as project selection [52], quality improvement [45], manufacturing system selection [59], logistics service provider selection [41], supplier selection [32], and strategic vendor selection [89]. Despite the fact that it is by far more popular than the other MADM methods, ANP has several difficulties in practice. Yu and Tzeng [104] emphasized the main shortcomings of ANP as follows:

- ANP requires too many pairwise comparisons, which might be time consuming and difficult to obtain.
- For particular situations, pairwise comparison questions might be meaningless or difficult to interpret.

The pairwise comparison matrices are used to quantify the degree of influence an element has on the other elements in the decision network of the ANP. If the number of alternatives/criteria is represented by n, the number of required pairwise comparisons for each matrix is calculated by $(n^2 - n)/2$. A decision problem involving four independent criteria and five alternatives requires 46 pairwise comparisons. Suppose that a decision maker needs to compare 10 alternatives with respect to only two criteria. This problem requires 90 (45 comparisons for each criterion) pairwise comparison matrices. Consequently, the pairwise comparison matrices demand an enormous cognitive effort from the decision maker, which is both time consuming and discouraging. Apart from the number of required comparisons, pairwise comparison questions might be nonsensical or very difficult to answer, especially when the inner dependencies exist in the cluster.

Furthermore, the structure of the criteria/cluster is assumed to be known a priori in ANP. The pairwise comparisons are conducted based on the criteria structure, indicating which criterion has impact on the other criteria of the other/same cluster depicted in the network relations of the model. Conversely, the Choquet integral method suffers from the same problem. Although structuring criteria is conducted by means of coalitions, the Choquet integral does not provide any guidelines regarding how to form these coalitions. For this reason, Tzeng and Huang [96] suggested the use of ISM or DEMATEL like methods to check preference independence and preference separability conditions in order to capture the preference structure before applying the Choquet integral.

Determination of the attributes and their interrelationships can be seen as a subset of a much broader term problem structuring. Increasing attention was paid to the problem structuring of MADM models since the field became more established, especially after the 1980s [10]. Keeney [47] stated that the existing methodologies can only be applied once the problem is structured, and they are not helpful when the problem is ill-defined. Belton and Stewart [9] considered problem structuring as an integral part of the MADM process. In their study, problem structuring was involved with the determination of values, goals, constraints, external environment, stakeholders, alternatives, uncertainties and key issues. In parallel with these, many attentions with several different perspectives have been developed in order to develop new ideas that are applicable to problem structuring for MADM. Probably, value-focused thinking [47] and the causal/cognitive mapping [2,13,26] are the most widely recognized approaches. Rosenhead and Mingers [77] emphasized five main methods for problem structuring: strategic options development and analysis [27], soft systems methodology [17], strategic choice approach [30], robustness analysis [76] and drama theory [11]. Although several advancements have been made in the problem structuring issues [61], structuring criteria and clarifying interactions are not completely resolved issues. Belton and Stewart [10] stated that the problem structuring methods aim to have the following characteristics:

- Identification of alternatives or decision options.
- A set of criteria which is preferentially independent, complete, concise, well defined and operationally meaningful.
- Specification and incorporation of stakeholder perspectives.
- An appreciation of critical uncertainties and the way they will be explored.

Accordingly, the problem structuring process aims at separating decision criteria that will be independent of each other. This sounds reasonable because most of the MADM methods demand criteria to conform a preferential independence assumption. However, this assumption might lead to erroneous results in many decision-making problems.

There is a large gap in the literature for alternatives of the highly complicated methods of ANP or the Choquet integral in order to take criteria interactions into account. Furthermore, recent advances in the problem structuring methods do not adequately address interdependent criteria and how to organize them in a decision problem. Hence, the mentioned research gap motivated us to develop a simple and effective method. We selected the hierarchical fuzzy TOPSIS method because it is able to model problems within hierarchical structures and it has simple procedures for implementation. In recent years, the hierarchical fuzzy TOPSIS method has been applied to a wide variety of problems. In Table 1, we briefly summarized the applications of the hierarchical fuzzy TOPSIS method.

Unfortunately, hierarchical fuzzy TOPSIS also assumes preferential independence of criteria. To overcome the preferential independence assumption, we integrated FCMs into the decision hierarchy. A hierarchical construction of FCMs was applied in a few studies in the literature. Hierarchical top-down cognitive mapping within the cognitive-fuzzy model was presented by Gonzalez et al. for online design and self-fine-tuning of fuzzy logic controllers and their performance analysis in adaptive control applications in subsequent studies [34,35]. Xirogiannis et al. [102] developed a novel expert decision support for the area of urban design. Multi-branch map hierarchies were generated and updating equations for calculating concept values were proposed for different hierarchy levels. Glykas [33] generated FCM based financial strategy map scenarios. Hierarchically structured financial metrics and sub-metrics were constituted with FCM concepts. The FCM reasoning mechanism went from lower level to higher level metrics, and hierarchical calculations for updating concept values were provided.

Although the modeling capabilities of FCMs provide compelling evidence that they can play a crucial role in real world decision making applications, few studies have incorporated FCMs into MADM problems. FCMs were mostly used for

Table 1
Review of hierarchical fuzzy TOPSIS applications.

Author(s) (pub. year)	Ref. no.	Domain of the problem
Roshandel et al. (2013)	[78]	Supplier evaluation and selection
Wang and Chan (2013)	[100]	Assessment of improvement areas in green supply chain initiatives
Baykasoğlu et al. (2013)	[6]	Truck selection in a land transportation company
Mehrjerdi (2013)	[60]	RFID-based systems evaluation
Bao et al. (2012)	[5]	Road safety performance evaluation
Uysal and Tosun (2012)	[98]	Computerized maintenance management system selection
Paksoy et al. (2012)	[68]	Organizational strategy model selection for distribution channel management
Tolga (2008)	[94]	R&D project selection
Perçin (2008)	[74]	Selecting the best business process outsourcing decision
Mahdavi et al. (2007)	[54]	Supplier selection in supply chain management
Kahraman et al. (2007)	[43]	New product initiatives evaluation
Kahraman et al. (2007)	[42]	Logistics information technology selection

constructing and analysing different scenarios rather than selecting the best alternative among a set of discrete options. Some of these studies were supported by AHP for selecting the key criteria, in which relationships between the key criteria were investigated. For instance, Shiau and Liu [88] developed an indicator system for evaluating transport sustainability strategies by using AHP and FCMs. AHP was used to select key indicators among transport sustainability indicators for local governments. Then, FCMs were used to construct the cause-effect relationships among the key indicators. Four scenarios were generated via FCMs. The most promising strategy was selected based on the final concept values and possible improvements of four strategies. Another use of AHP in conjunction with FCMs aims for capturing the intensity degrees of relationships among decision criteria by pairwise comparisons. Biloslavo and Grebenc [12] integrated Delphi analysis, AHP and FCMs to analyse different climate warning scenarios. In that study, the degree of causal relations among climate warning factors was found using a multiplicative AHP method. The time delay function was incorporated into the dynamic simulation of scenarios. Unlike integrated approaches, Rodriguez-Repiso et al. [75] compared three methodologies, namely, critical success chains, AHP and FCMs, for modeling IT project success. Advantages, disadvantages and limitations of each methodology for particular IT project characteristics were emphasized. In their study, FCM was considered to be a viable alternative to model IT project success due to its ease of use and dynamic analysis capabilities. Furthermore, Akgun et al. [1] proposed an integrated approach for a vulnerability assessment of critical facilities using fuzzy sets, Simple Multi-Attribute Rating Technique (SMART) and FCMs. Vulnerability criteria were weighted by the SMART method, and physical dependencies among system functions were captured by FCMs. FCM simulation was used to obtain ultimate vulnerability values of each criterion. Lastly, only one published work integrated the TOPSIS method with FCMs, in which FCMs were used to simulate scenarios rather than for modeling interactions among the criteria. In their study, Salmeron et al. [86] combined Delphi analysis, FCMs and TOPSIS methods for scenario-based decision-making problems. Delphi analysis was used to construct the concepts, relationships, and scenarios. FCMs were used to simulate different scenarios and to collect ultimate concept values. Finally, each scenario was evaluated by using the TOPSIS method and the best scenario is selected.

The originality and the main contribution of the proposed method is that the proposed method is the first study combining FCMs and hierarchical fuzzy TOPSIS for modeling and solving MADM problems. The proposed method is fundamentally distinguished from the previous studies with respect to the fact that the algorithm combining FCMs and hierarchical fuzzy TOPSIS is utilized for the ranking of discrete alternatives in a purely MADM setting. The underlying motivation inferred from the literature is that modeling interactions among hierarchically structured decision criteria within a relatively practical MADM method, i.e., TOPSIS, by taking into account decision makers' vague and imprecise evaluations can provide great benefits to practitioners who need simple and effective methodologies that are applicable to real world problems. Collecting the strong features of highly complicated methodologies proposed in diverse types of disciplines, the proposed method preserves a high degree of flexibility, such as by allowing scenario analysis or making use of different types of FCMs. These features distinguish the proposed method from the conventional MADM methods of the literature with highly rigid procedures, such as ANP.

In the next section, we analysed what features an effective MADM method should provide and how they relate to our proposed method.

2.2. Three pillars of an effective MADM method

Selection of the most appropriate MADM method among possible alternatives in the massive universe of literature is an extremely challenging task in which no simple answer exists. One of the courageous attempts to help decision makers to select the best method was provided by Guitouni and Martel [38]. Although the provided tentative guidelines are said to be helpful for selecting the most relevant decision analysis tools, the process, in general, is time consuming and seems improbable to be realized in today's highly agile production and service system decision practices. Conversely, it is not easy to find an expert who has knowledge of all of the decision analysis methods and to arrive at a best mix of methodologies after a detailed comparative study. Adversely, an excessive number of available methodologies causes firms to abandon scientific methods of decision making; rather, they analyse and solve problems by the ways they are accustomed to, which are mostly intuitionistic.

Decision makers very often confront a tradeoff situation by selecting a method with some desirable properties at the expense of abandoning others' strong features. As a result, the expected features of a MADM method that are crucial for generic decision-making situations should be determined. Perhaps tens of evaluation criteria can be counted regarding what features a sufficient MADM method should provide. In our regard, there are three main characteristics that a MADM method should have:

- Uncertainty.
- Hierarchical structure.
- Criteria interactions.

We elaborate on these concepts below.

2.2.1. Uncertainty

There are many methods to model uncertainty in decision problems. Probabilistic approaches [7], fuzzy logic [105], Dempster–Shafer theory [22], and possibility theory [24] are some examples of the options. For different uncertainty situations, decision makers are supported by the variety of uncertainty models. In our regard, fuzziness is one of the most appropriate uncertainty modeling tools for decision making problems with multiple attributes. There are different sources of imprecision in the decision making process, such as unquantifiable information, incomplete information, non-obtainable information, and partial ignorance [19]. In classical MADM methods, the importance degrees of criteria and the performance scores of alternatives are assumed to be known precisely. However, practical constraints of the real world hinder the use of crisp values. The problems faced in practice occur in such an environment that goals, constraints and consequences of alternatives are not precise [8]. Furthermore, the ambiguities, uncertainties and vagueness inherent in decision makers' evaluations necessitate the use of the fuzzy set theory. In our proposed framework, we argue that a sufficient MADM method should incorporate fuzziness; in other words, a fuzzy MADM method is essential to model today's complex decision making problems.

2.2.2. Hierarchical structure

A typical MADM problem solution procedure starts with problem structuring. Obviously, a problem is disaggregated into smaller parts because experts can more easily handle the smaller portions of the problem. It is indeed extremely difficult to manage the entire problem at once. Another benefit of problem structuring is that the decision makers can better understand the problem and improve their information processing capabilities with these smaller portions of the problem [3].

Most of the problem structures in the literature are geometric in nature. Geometric structures are not only triangles and circles, but they are also vertices and edges connecting them via paths and cycles [84]. In most of the studies, vertices stand for the attributes or system variables, and the lines or arcs represent the perceived influence associating them. Hence, geometric structures have attractive features, which escalate our abstract cognition of influences among elements and their interactions.

Among many geometric structures, hierarchical structure is the most widely used one. Hierarchical structure is very suitable for human thought processes, where our brains utilize hierarchies as a powerful tool to classify or order information in order to understand the complex world surrounding us [83]. In decision problems, influences among criteria can be very complex; in this case, a network of influences is taken into account. Nevertheless, network structures contain hierarchies; in other words, a collection of hierarchies constitute networks [84]. Hence, hierarchies are not as complex as networks; rather, they are stratified systems used to organize all sorts of information and even intangibles, such as one's beliefs and values [84].

Although there are "general purpose" approaches to help structuring problems, we adopted qualitative top-down hierarchical decomposition [81] in our proposed model. In the top-down hierarchical decomposition approach, the overall objective is determined and placed at the top of the hierarchy. The top element of the hierarchy is decomposed into sub levels at successive iterations. To decompose the system into sub-levels, questions such as "which sub-goals must be satisfied to fulfil this objective?" Guide the descending process from the top [55]. This type of decomposition approach is very useful and intuitive; as a result, because most of the practitioners are familiar with the AHP approach, they do not have difficulties interpreting and applying the methodology.

In the proposed model, the top-down hierarchical decomposition approach is reinforced with the horizontal causal influences to model criteria interactions. Because the criteria structure and the interaction phenomenon are highly interrelated, we explain further concepts in the next section.

2.2.3. Criteria interaction

The theoretical foundations of the decision analysis mostly rely on MAUT. There are critical distinctions of independence assumptions in MAUT, such as preferential independence, utility independence, weak-difference independence, difference independence and additive independence [47]. Although these distinctive independence concepts are only defined for the case of decision making under uncertainty, preferential independence assumption endures for the other MADM methods.

Preferential independence clearly states that preference orders of alternatives do not change when the levels of attributes are altered. Each attribute is assumed to be an independent entity and evaluated on its own, thus the presence of the other attributes does not change the final preference orders. However, in real life, the decision attributes are rarely independent and their interdependencies, especially in the long run, change the relative importance of attributes and the ultimate preference orders.

As the most practical and convenient method to grasp interdependencies among the evaluation of attributes, graphical structure representations, such as networks or hierarchies, are employed. In the most primitive form of dependency, as with the hierarchical structures, attributes are only dependent on the immediate upper level attributes. On the contrary, network structures allow all sorts of dependencies in the structure. We criticize the fact that decision makers, in many situations, are stuck between traditional hierarchical decomposition and the network structures. If interdependencies among attributes exist, regardless of the dimensions and intensities, the ANP seems to be the only choice. Although the ANP is a strong technique capable of modeling all sorts of dependencies, the cost of switching from AHP to ANP is immense. We argue that the network structure with ANP is not the only choice for modeling dependence and feedback situations. In many decision situations, interactions can be handled in a hierarchical problem setting with lower cost. We suggest a generic hierarchical structure, which is an extended version of the structure mentioned by Wedley et al. [101] by means of horizontal links. This structure has been recently used by Baykasoğlu et al. [6]. Suggested generic hierarchical structure has the following properties:

1. The lower level is dependent upon every item of the immediate upper level. For example, in Fig. 1, all sub-attributes (SA) in level 2 are dependent upon the main attribute (MA) in level 1.
2. The upper level does not depend upon one or more items of the lower level. For example, in Fig. 1, the main attribute in level 1 is independent of all of the sub-attributes of level 2.
3. Each attribute belongs to only one attribute of the level immediately above. In other words, an attribute belonging to ith level of the hierarchy is a sub-attribute of only one of the attributes of the $(i-1)$-th level. This type of structure is called a partitioned structure [21]. We also call the group of attributes influenced by the same attribute of the level immediately above as partition. For example, in Fig. 2, an example of a non-partitioned hierarchical structure is given.

The necessary condition to be a partitioned structure is violated because the sub-attribute SA_{21} belongs to both the MA_1 and MA_2 main attributes from the first level.

4. The same level of attributes whose immediate upper level attribute is also the same can be dependent on each other. In other words, interaction may exist among the attributes of each partition. Different partitions are assumed to be independent. In Fig. 3, interaction among the same level of attributes is shown.

Note that this representation allows for modeling the attributes, which can be either dependent or independent.

In Fig. 4, traditional hierarchy, top-down hierarchical decomposition with horizontal interactions, and network structure are shown. We argue that traditional hierarchy is a very simple form, suitable only for modeling uncomplicated problems. AHP is the most widely applied method by utilizing traditional hierarchical structure. However, real-life problems are rarely easily solved, many complicated problems are encountered and network structures are used, such as ANP.

Providing richer analysis with its sound mathematical formalism, ANP strives to elicit a high amount of data from the experts, which might be discouraging and extremely time consuming, even for domain experts. Additionally, the structural complexity is indeed uncommonly very high compared to other methods. Actually, there is a need to find a balance between simplistic and very complex decision settings. We place our proposed hierarchy between the traditional hierarchy and complex network structures. We argue that, analogously to the normal distribution of probability theory, traditional hierarchy and network structures represent the left and right tails of the probability distribution curve, and the majority of real world problems accumulate in the balancing complexity area, which are neither as cognitively demanding as networks nor as trivial as traditional hierarchy.

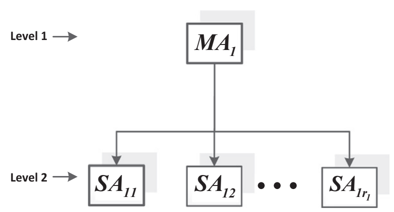

Fig. 1. Dependencies between upper and lower level criteria.

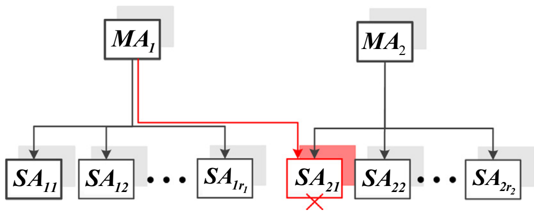

Fig. 2. Example of a non-partitioned hierarchical structure.

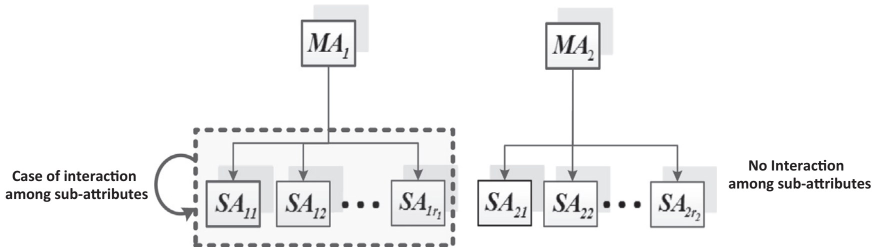

Fig. 3. Example hierarchies with/without interactions.

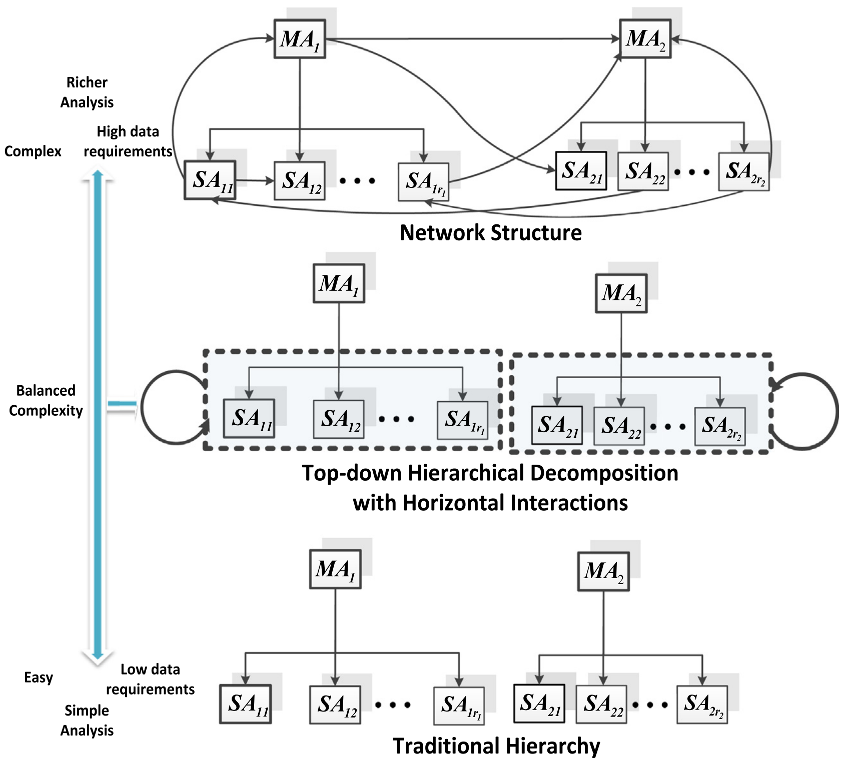

Fig. 4. Balancing complexity of the problem structure.

3. The proposed method

We proposed a hybrid MADM technique combining fuzzy hierarchical TOPSIS and FCMs in order to evaluate hierarchically structured decision problems, which incorporates fuzziness and criteria interactions into the analysis. The methodology is well suited for hierarchical structures. We explain all steps of the proposed model based on Fig. 5. We use the same notations of Kahraman et al. [42] throughout the paper in order to help readers to compare the traditional hierarchical fuzzy TOPSIS with our proposed model. We seek for a balance between practicality and richness of the model. Such a balanced

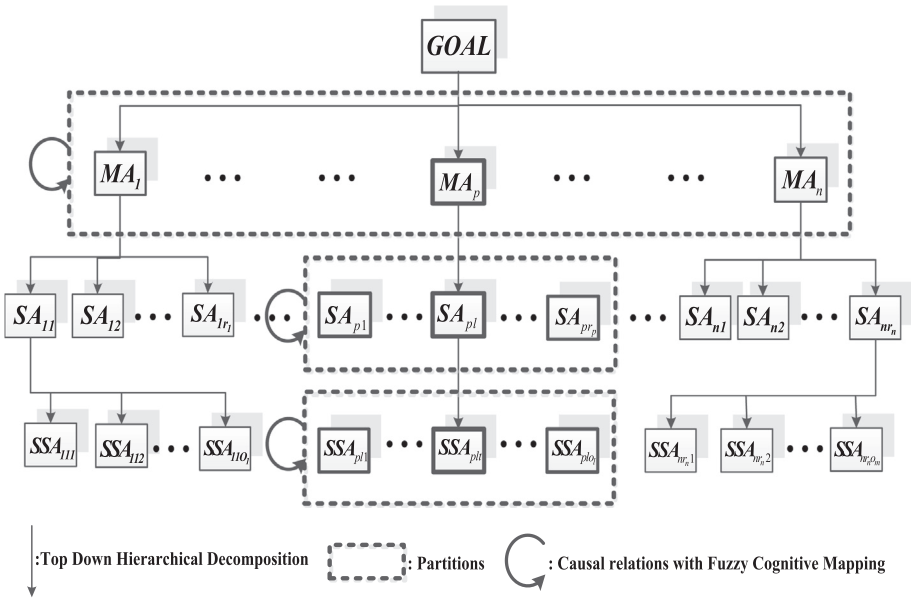

Fig. 5. The complete evaluation scheme with top-down hierarchical decomposition approach and interacting attributes.

structure can be achieved by combining top-down hierarchical decomposition of the conventional hierarchical fuzzy TOPSIS with FCMs for modeling causal relationships. Hence, the proposed hybrid hierarchical fuzzy decision-making technique conforms to the characteristics of a sufficient MADM method, as mentioned earlier.

The hierarchical fuzzy TOPSIS method is the extension of the classical TOPSIS method [42,44]. The hierarchical fuzzy TOPSIS method is composed of two significant parts: acquiring the criteria weights from the hierarchical structures and fuzzy TOPSIS algorithm implementation to rank the alternatives. The major drawback of the hierarchical fuzzy TOPSIS is the assumption of preferential independence. We overcome the independence assumption by utilizing FCMs within the hierarchical decision-making framework. A brief overview of the FCMs is given in Appendix A.

We believe that FCMs have much to offer in the field of MADM. We selected FCMs for the following reasons:

- In FCMs, the criteria are represented by concepts and causal influences are represented by links connecting them, which provide an intuitively easy interpretation of all modeling components. Additionally, causal relationship is very close to human thinking, and it is quite easy to elicit information from the decision makers.
- FCMs make use of the concept values and influence degrees among concepts using fuzzy logic. Linguistic values are much easier to obtain than crisp values.
- FCMs have the ability to model positive and negative causal influences simultaneously.
- FCMs have the flexibility to exploit different threshold functions, which help to capture the system behavior in the long term [14,95]. In addition, dynamic nonlinearity can be visualized by time.
- FCMs also allow static analysis without conducting simulation experiments [67].
- Semi-automated or automated construction of FCMs [90] with different granulation levels is possible [73]. In this case, minimum or no expert intervention is required to form FCMs [72].
- Utilizing different learning algorithms, the degree of influence among concepts can be learned [69,91].
- There are many variants of FCMs, such as rule-based FCMs [16], fuzzy cognitive networks [50], and evolutionary FCMs [58]. An opportunity to select the most appropriate FCM extension is possible.
- The updating equation of the FCM model can be modified according to the nature of the problem under consideration. Different updating equations are possible, i.e., different aspects can be incorporated into the model, such as time delay weights, conditional weights and non-linear membership functions [39].

We provide the basic steps of the hierarchical fuzzy TOPSIS and FCMs combination in two parts. The first part consists of obtaining the overall attribute weights, and the second part is dedicated to implementing the fuzzy TOPSIS algorithm in order to rank the alternatives.

Let us assume that we have the criteria hierarchy as shown in Fig. 5. We have n attributes, m sub-attributes, o sub-sub attributes, k alternatives and s decision makers. It is assumed that there are r_i sub-attributes belonging to each main attribute. There are m sub-attributes, which are expressed by $\sum_{i=1}^{n} r_i$. Similarly, the total number of sub-sub attributes belonging to sub-attributes is given by $\sum_{i=1}^{m} o_i$. We begin with explaining how to derive attribute weights within the proposed model.

3.1. Obtaining attribute weights

3.1.1. Obtaining weights of the main attributes

In the hierarchical fuzzy TOPSIS evaluation, matrices for main attributes, sub-attributes, sub-sub attributes and performance matrices are required. Following the top-down decomposition approach, the first matrix represents the weights of the main attributes, which is denoted by I_{MA}. Three generic steps, preparing the initial relative importance weights, establishing FCM structure, and simulation of FCMs, are required in order to calculate the main attribute weights as follows:

3.1.1.1. Preparing the initial relative importance weights.

3.1.1.1.1. Eliciting the fuzzy weights of the main attributes. The weights of the main attributes with respect to the goal are elicited from the decision makers. The fuzzy weight score of the ith decision maker for the pth main attribute with respect to the goal is denoted by $\tilde{w}_{pi}$.

3.1.1.1.2. Aggregating fuzzy weights of the main attributes. The arithmetic mean of the fuzzy weights elicited from a group of decision makers is calculated as:

$$\tilde{w}_p = \frac{\sum_i^s \tilde{w}_{pi}}{s}, \quad p = 1, 2, \ldots, n \tag{1}$$

The $\tilde{w}_p$ values represent the aggregated fuzzy weights.

3.1.1.1.3. Defuzzifying the aggregated fuzzy weights. The centroid method is used to defuzzify the fuzzy weights of the main attributes. The centroid method is one of the defuzzification methods that is gaining widespread acceptance and applications due to its simplicity. It utilizes the concept of centre of gravity (CoG). In the literature, the crisp equivalent, i.e., the so called Best Non-fuzzy Performance (BNP) of a triangular fuzzy number $\widetilde{N} = (l, m, r)$, is given by the CoG method [65] as:

$$\mathrm{BNP} = l + [(m - l) + (r - l)]/3 \tag{2}$$

The aggregated fuzzy weights $\tilde{w}_p$ are defuzzified by using Eq. (2).

3.1.1.1.4. Normalizing the crisp weight vector. Once the aggregated fuzzy weights of the pth main attribute are defuzzified, the normalized crisp weight vector, denoted by nw_p, is calculated using Eq. (3):

$$nw_p = \frac{w_p}{\sum_{i=1}^n w_i}, \tag{3}$$

3.1.1.2. Establishing FCM structure.

3.1.1.2.1. Setting up the initial concept values. The normalized weight vector is considered as the initial concept values, as in Eq. (4):

$$\begin{bmatrix} C_{MA_1}^{t=0} \\ C_{MA_2}^{t=0} \\ \vdots \\ C_{MA_p}^{t=0} \\ \vdots \\ C_{MA_n}^{t=0} \end{bmatrix} = \begin{bmatrix} nw_1 \\ nw_2 \\ \vdots \\ nw_p \\ \vdots \\ nw_n \end{bmatrix} \tag{4}$$

where $C_{MA_i}^{t=0}$ is the concept value of the ith main attribute when $t = 0$.

3.1.1.2.2. Eliciting the fuzzy influence matrices. The degree of causal dependency between each attribute is obtained from decision makers by filling out fuzzy influence matrices. Each influence matrix is denoted by $\tilde{e}_{jiu}^{MA}$, which represents the influence matrix of the main attributes elicited from the uth decision maker.

3.1.1.2.3. Aggregating the fuzzy influence matrices. Fuzzy influence matrices, which are elicited from a group of decision makers, are aggregated by using Eq. (5):

$$\tilde{e}_{ji}^{MA} = \frac{\sum_{u=1}^s \tilde{e}_{jiu}^{MA}}{s} \tag{5}$$

where $\tilde{e}_{ji}^{MA}$ denotes the aggregated fuzzy influence matrix of the main attributes.

3.1.1.2.4. Defuzzifying the aggregated fuzzy weights. In this step, Eq. (2) is employed to defuzzify the aggregated fuzzy influence matrix. Consequently, the aggregated crisp influence matrix e_{ji}^{MA} is reached.

3.1.1.3. Simulating FCMs and obtaining the final weights.
3.1.1.3.1. Determining the parameters of the activation function. Different activation (threshold) functions can be used in FCMs. Trivalent $(f(x) = -1, 0, 1)$, bivalent $(f(x) = 0, 1)$, hyperbolic tangent function $(\tanh(x))$ or unipolar sigmoid functions $(f(x) = 1/(1 + e^{-\lambda x})$ are examples of the commonly used activation functions in FCMs. In this step, parameters of the activation functions, such as λ, which determines the slope of the function to obtain proper shape, are defined.
3.1.1.3.2. Running of FCMs. To capture the long term influences among the main attributes, FCMs are simulated with an appropriate threshold function to capture the long term influences. FCM simulation is conducted to observe dynamic behavior based upon the equation:

$$C_{MA_i}^{t+1} = f\left(C_{MA_i}^{t} + \sum_{\substack{j=1\\ j\neq i}}^{n} e_{ji}^{MA} \times C_{MA_j}^{t}\right) \tag{6}$$

where $C_{MA_i}^{t}$ is the concept value of the ith main attribute at time t.
3.1.1.3.3. Normalizing the steady state weights. The steady-state concept values are normalized; hence, the final steady state weights of the main attributes are obtained:

$$w_i = \frac{C_{MA_i}}{\sum_{i=1}^{n} C_{MA_i}} \tag{7}$$

The final crisp weights are shown by:

$$\mathrm{I}_{MA} = \begin{array}{c} \\ MA_1 \\ MA_2 \\ \vdots \\ MA_P \\ \vdots \\ MA_n \end{array} \begin{array}{c} Goal \\ \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_p \\ \vdots \\ w_n \end{bmatrix} \end{array}, \quad \text{where } \sum_{i=1}^{n} w_i = 1 \tag{8}$$

3.1.2. Obtaining the weights of sub-attributes

Because we have given very detailed steps to obtain the main attribute weights in Section 3.1.1, we very briefly give the formulas of sub-attribute weights to avoid repetition. We note that calculations are made for all partitions in the hierarchy and calculation procedures are the same for each partition.

In this step, the weights of sub-attributes with respect to the main attributes are calculated and a I_{SA} matrix is formed. The arithmetic mean of the sub-attribute weights are represented by $\tilde{w}_{pl}$ and calculated by Eq. (9):

$$\tilde{w}_{pl} = \frac{\sum_{i}^{s} \tilde{w}_{pli}}{s} \tag{9}$$

where $\tilde{w}_{pli}$ is the ith decision maker's fuzzy weight score for the lth sub-attribute with respect to the pth main attribute.

Similarly, fuzzy weights for sub-attributes are defuzzified by using Eq. (2). Then, the normalization is calculated using Eq. (10):

$$nw_{pl} = \frac{w_{pl}}{\sum_{i=1}^{r_p} w_{pi}} \tag{10}$$

where nw_{pl} is the normalized weight of the lth sub-attribute with respect to the pth main attribute. Next, the normalized crisp weight vectors are regarded as the initial concept values of FCMs, as in the Eq. (11):

$$\begin{bmatrix} C_{SAp_1}^{t=0} \\ C_{SAp_2}^{t=0} \\ \vdots \\ C_{SAp_l}^{t=0} \\ \vdots \\ C_{SAp_{r_p}}^{t=0} \end{bmatrix} = \begin{bmatrix} nw_{p1} \\ nw_{p2} \\ \vdots \\ nw_{pl} \\ \vdots \\ nw_{pr_p} \end{bmatrix} \tag{11}$$

where $C_{SAp_l}^{t=0}$ is the concept value of the lth sub-attribute with respect to the pth main attribute when $t = 0$. The number of the sub-attributes under the pth main attribute is denoted by r_p. Influence matrix $e_{ji}^{SA_p}$, which denotes the crisp influence degrees among sub-attributes under the pth main attribute, is formed. The influence matrix is used in FCM calculation as given in Eq. (12):

$$C_{SAp_i}^{t+1} = f\left(C_{SAp_i}^{t} + \sum_{\substack{j=1 \\ j\neq i}}^{r_p} e_{ji}^{SA_p} \times C_{SAp_j}^{t} \right) \tag{12}$$

where $C_{SAp_i}^{t}$ is the concept value of the ith sub-attribute under the pth main attribute at time t. The steady-state concept values are normalized, as in Eq. (7); hence, the final steady state weights of the sub-attributes are obtained. The final crisp sub-attribute weights are given in Eq. (13):

$$I_{SA} = \begin{array}{cc} & \begin{array}{cccccc} w_1 & w_2 & \cdots & w_p & \cdots & w_n \\ MA_1 & MA_2 & \cdots & MA_p & \cdots & MA_n \end{array} \\ \begin{array}{c} SA_{11} \\ SA_{12} \\ \vdots \\ SA_{1r_1} \\ SA_{21} \\ SA_{22} \\ \vdots \\ SA_{2r_2} \\ \vdots \\ SA_{pl} \\ \vdots \\ SA_{n1} \\ SA_{n2} \\ \vdots \\ SA_{nr_n} \end{array} & \left[\begin{array}{cccccc} w_{11} & 0 & \cdots & 0 & \cdots & 0 \\ w_{12} & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots & & \vdots \\ w_{1r_1} & 0 & \cdots & 0 & \cdots & 0 \\ 0 & w_{21} & \cdots & 0 & \cdots & 0 \\ 0 & w_{22} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots & & \vdots \\ 0 & w_{2r_2} & \cdots & 0 & \cdots & 0 \\ \vdots & 0 & & \vdots & & \vdots \\ 0 & 0 & \cdots & w_{pl} & \cdots & 0 \\ \vdots & \vdots & & & & 0 \\ 0 & 0 & \cdots & 0 & \cdots & w_{n1} \\ 0 & 0 & \cdots & 0 & \cdots & w_{n2} \\ \vdots & \vdots & & \vdots & & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & w_{nr_n} \end{array} \right] \end{array} \tag{13}$$

It is simply the same calculations for the case of sub-sub attributes.

3.1.3. Obtaining the overall attribute weights

Finally, the overall attribute weights are calculated. For the sub-attribute w_{pl}, the overall weight W_{pl} is calculated as:

$$W_{pl} = \sum_{j=1}^{n} w_p w_{pj} \tag{14}$$

It is known that $w_{pj} = 0$ in the case of $j \neq l$, so the overall weight W_{pl} is calculated as:

$$W_{pl} = w_p w_{pl} \tag{15}$$

In a similar manner, the overall sub-sub attribute weight W_{plt} is calculated as:

$$W_{plt} = \sum_{j=1}^{m} w_p w_{pl} w_{plj} \tag{16}$$

Because $w_{plj} = 0$ for $j \neq t$, final weights are obtained as:

$$W_{plt} = w_p w_{pl} w_{plt} = W_{pl} w_{plt} \tag{17}$$

Eqs. (14)–(17) simply state that the final attribute weights are calculated as in the traditional hierarchical fuzzy TOPSIS or AHP methods. It is also important to note that interactions among the attributes of the first level are used to determine the weights of the main attributes. In the second level, interaction among the attributes of each partition was calculated to obtain the weights of the sub-attributes. This process is continued for sub-sub attribute levels. Actually, going through the lower levels of the hierarchy, the interaction phenomenon is considered only among attributes that belong to the same partition. In other words, interactions among the attributes in the upper level are implicitly reflected onto the attributes of lower levels by means of multiplication, which in turn reduces the required data. This process is depicted in Fig. 6.

3.2. Fuzzy TOPSIS calculations

When the attribute weights are determined, traditional fuzzy TOPSIS calculations are made in order to reach the final ranking of the alternatives. Despite many different fuzzy TOPSIS implementations in the literature, we applied a highly accepted method of Chen [18] due to its practicality. The fuzzy TOPSIS calculation steps are given as follows [18].

3.2.1. Constructing the decision matrix

As we already obtained the final attribute weights by using Eqs. (15) and (17), only a fuzzy decision matrix is constructed in this phase. A group of experts provided the fuzzy rating values of each alternative. First, aggregated ratings are calculated using Eq. (18):

$$\tilde{x}_{ij} = \frac{1}{s}[\tilde{x}_{ij}^1 \oplus \tilde{x}_{ij}^2 \oplus \cdots \oplus \tilde{x}_{ij}^s] \tag{18}$$

where $\tilde{x}_{ij}^s$ is the performance rating value elicited from the sth decision maker. The fuzzy evaluation matrix is obtained using Eq. (19):

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} X_1 & \cdots & X_j & \cdots & X_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & x_{in} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{19}$$

where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$.

3.2.2. Normalizing the evaluation matrix

The normalized fuzzy decision matrix is denoted by $\widetilde{R} = [\tilde{r}_{ij}]_{m\times n}$, where benefit criteria are represented by B and cost criteria are given by C. The normalization formulas are given in Eqs. (20)–(23):

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B \tag{20}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in C \tag{21}$$

$$c_j^* = \max_i c_{ij}, \quad if\ j \in B \tag{22}$$

$$a_j^- = \min_i a_{ij}, \quad if\ j \in C \tag{23}$$

After normalization with the above formulas, the fuzzy elements in the fuzzy evaluation matrix take the values between $[0, 1]$.

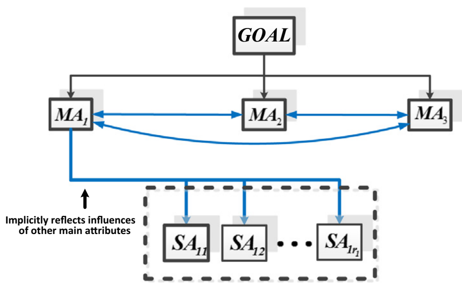

Fig. 6. Implicit flow of influence in the hierarchy.

3.2.3. Calculating the weighted normalized decision matrix

The weighted normalized fuzzy decision matrix, denoted by $\widetilde{V} = [\tilde{v}_{ij}]_{m \times n}$, is given by Eq. (24):

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes w_j, \quad i = 1, 2, \ldots, m, \text{ and } j = 1, 2, \ldots, n \tag{24}$$

3.2.4. Calculating the positive and negative ideals

Because the elements of the evaluation matrix are mapped into $[0, 1]$, Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) can be given practically as:

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*), \tag{25}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-), \tag{26}$$

where $\tilde{v}_j^* = (1, 1, 1)$, $\tilde{v}_j^- = (0, 0, 0)$ and $j = 1, 2, \ldots, n$.

3.2.5. Calculating the distances from FPIS and FNIS

The distances from FPIS and FNIS are calculated by making use of Eqs. (27) and (28):

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad i = 1, 2, \ldots, m \tag{27}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, 2, \ldots, m \tag{28}$$

The distance between two triangular fuzzy numbers $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ is calculated using Eq. (29):

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \tag{29}$$

3.2.6. Computing the closeness coefficients

Closeness coefficients of each alternative are calculated by making use of Eq. (30):

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}, \quad i = 1, 2, \ldots, m \tag{30}$$

If the CC_i value of the ith alternative is closer to 1, then the alternative is said to be closer to the FPIS and farther from the FNIS.

4. Application

4.1. Problem description

Higher education systems undergo profound transformations due to globalization. As a great contributor to the nation's competitiveness, governments are forced to adapt their higher education systems to the needs of the present. Especially in the era of knowledge societies, universities have an active role in the development of the economy [20]. Ongoing turmoil in different regions of the world, particularly in the Middle East, sluggish economic growth with increased unemployment, and competitive pressures have all triggered the array of revisions to the current higher education systems of the nations. For instance, in Europe, a need to form some assessment tools for higher education is realized at the European Union and at nation-wide levels [63]. In Spain and Portugal, studies regarding faculty or academic staff evaluation are presently in progress [4].

Turkey has recently recognized that the only way to be competitive is to generate new policies for the higher education system that foster innovation, high-tech talent and sustainable development. According to Mizikaci [62], Turkey has the state-centre model in higher education according to the classification of Olsen [64]. The Council of Higher Education (YÖK), which holds administrative control, coordinates most of the aspects of the higher education system. In a state-centred model, universities are considered as instruments in order to reach pre-determined national targets [23]. The Turkish higher education system is still anchored in state-centred regularities; however, the general paradigm has also been changing.

Currently, the total number of universities has reached 175 in 81 different cities in Turkey. Additionally, the shift toward much more innovative and entrepreneurial universities is observed. Unlike the historical peculiarities of the higher education system, new universities are more global and have greater autonomy in terms of crucial aspects of governance. Despite the promising developments in the higher education system, debate on the categorization of universities is still unsolved. Some argue that universities should be divided into two categories: research-intensive universities and teaching-intensive universities. This sort of categorization brings about different resource allocation policies based upon the university category. Although there are some developments in this direction, they are still in their infancy. In parallel to progress in the top management of higher education, universities, individually, should arrive at a comprehensive portrayal of policy developments. Furthermore, departments are expected to come up with multifaceted policies that span from research directions to relationships with society.

The industrial engineering department of Dokuz Eylül University, with its 42 years of academic background, is among the top departments in Turkey. As a reactive organization due to its strong academic ties, the industrial engineering department focused on the domestic exigencies by taking external pressures into account and decided to reshape its current statute with the changing paradigms. The department is currently making several reforms, such as making changes in the curriculum, establishing new laboratories to strengthen physical infrastructure, and reinforcing the academic staff to better adapt itself for the highly competitive real world. Additionally, it has long been realized that success heavily relies on the department's ability to create its own strategies and act according to these strategies in a participatory manner. In parallel with these thoughts, a real case of the strategy selection problem by means of preparatory efforts to develop a renewed strategic plan for the industrial engineering department of Dokuz Eylul University is solved by using the proposed approach.

The problem hierarchy is given in Fig. 7.

4.2. Solution

A group decision-making setting involving three evaluators is established to solve our problem. First, the linguistic scales are determined. For the relative importance of the attribute weights, a linguistic scale, as shown in Table 2, is constructed. A

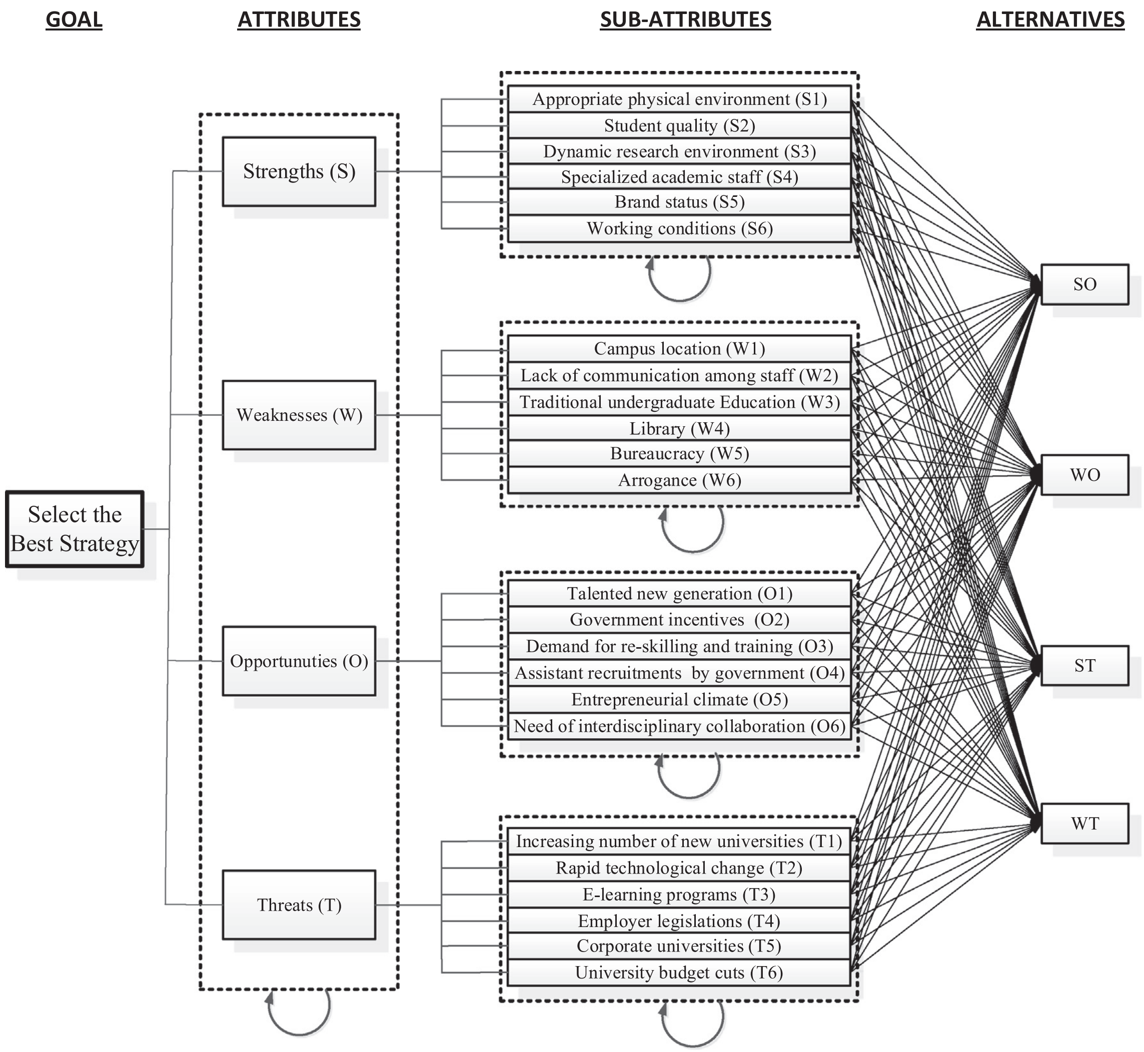

Fig. 7. Hierarchical evaluation framework.

Table 2
Linguistic variables for relative importance weights of attributes.

Linguistic variable	Triangular fuzzy number
Very low (VL)	$(0, 0, 0.1)$
Low (L)	$(0, 0.1, 0.3)$
Medium low (ML)	$(0.1, 0.3, 0.5)$
Medium (M)	$(0.3, 0.5, 0.7)$
Medium high (MH)	$(0.5, 0.7, 0.9)$
High (H)	$(0.7, 0.9, 1)$
Very High (VH)	$(0.9, 1, 1)$

Table 3
Linguistic variables for causal relationships among attributes.

Linguistic variable	Triangular fuzzy number
Very very low (VVL)	$(0, 0.1, 0.2)$
Very low (VL)	$(0.1, 0.2, 0.35)$
Low (L)	$(0.2, 0.35, 0.5)$
Medium (M)	$(0.35, 0.5, 0.65)$
High (H)	$(0.5, 0.65, 0.8)$
Very high (VH)	$(0.65, 0.8, 0.9)$
Very very high (VVH)	$(0.8, 0.9, 1)$

linguistic scale for causal relationships is formed, as shown in Table 3. The other linguistic scale is used to the rate the alternatives with respect to attributes, as seen in Table 4.

To solve the problem using the hybrid hierarchical fuzzy TOPSIS and FCMs, we first determine the overall attribute weights and then calculate the best strategy using the fuzzy TOPSIS algorithm. Initially, we calculate the attribute weights for the main attributes. We show the calculation steps for deriving the weights of the main attributes in detail. First, the relative importance weights of each of the main attributes S, W, O, and T are obtained from three decision makers, as shown in Table 5. For the sake of clarity, each decision maker is denoted by DM_1, DM_2, and DM_3, respectively.

Then, the degrees of dependency among each of the main attributes are obtained (Tables 6–8).

When the linguistic assessments are obtained from the three decision makers, aggregated fuzzy evaluations for relative importance of attributes are calculated based on Eq. (1). Then, the defuzzified and normalized relative importance of attributes is calculated based on Eq. (2) and Eq. (3), respectively. Aggregated relative importance weights of the main attributes are given in Table 9.

Aggregated fuzzy influence matrices are acquired by using Eq. (5). The resulting aggregated dependency degrees among the main attributes are given in Table 10.

Employing Eq. (2), aggregated dependency degrees among the main attributes are defuzzified to be used in the FCM model, as shown in Table 11. The resulting topology of the map is depicted in Fig. 8.

Table 4
Linguistic variables for rating of alternatives.

Linguistic variable	Triangular fuzzy number
Very poor (VP)	$(0, 0, 1)$
Poor (P)	$(0, 1, 3)$
Medium poor (MP)	$(1, 3, 5)$
Fair (F)	$(3, 5, 7)$
Medium good (MG)	$(5, 7, 9)$
Good (G)	$(7, 9, 10)$
Very good (VG)	$(9, 10, 10)$

Table 5
The relative importance weights of the main attributes.

	DM_1	DM_2	DM_3
S	H	H	H
W	ML	L	M
O	H	VH	MH
T	H	VH	ML

Table 6
Dependency degrees among main attributes obtained from DM_1.

DM_1	S	W	O	T
S	–	VVL	L	
W	L	–		H
O			–	VL
T		H	M	–

Table 7
Dependency degrees among main attributes obtained from DM_2.

DM_2	S	W	O	T
S	–	VL	H	
W	VL	–		M
O			–	VL
T		VH	VH	–

Table 8
Dependency degrees among main attributes obtained from DM_3.

DM_3	S	W	O	T
S	–	M	L	
W	VVL	–		H
O			–	M
T		VH	H	–

Table 9
Aggregated relative importance weights of main attributes.

	Aggregate weights	Defuzzified weights	Normalized weights
S	(0.70, 0.90, 1)	0.87	0.32
W	(0.13, 0.30, 0.50)	0.31	0.11
O	(0.70, 0.87, 0.97)	0.84	0.31
T	(0.57, 0.73, 0.83)	0.71	0.26

Table 10
Aggregated dependency degrees among main attributes.

	S	W	O	T
S	(0, 0, 0)	(0.15, 0.27, 0.40)	(0.30, 0.45, 0.60)	(0, 0, 0)
W	(0.10, 0.22, 0.35)	(0, 0, 0)	(0, 0, 0)	(0.45, 0.60, 0.75)
O	(0, 0, 0)	(0, 0, 0)	(0, 0, 0)	(0.18, 0.30, 0.45)
T	(0, 0, 0)	(0.60, 0.75, 0.87)	(0.50, 0.65, 0.78)	(0, 0, 0)

The underlying assumption of normalized weights, which were given earlier in Table 9, is that the main attributes are independent of each other. However, this assumption is not valid in our situation, where attributes influence each other in the long term. To be able to capture the long term influences, the normalized weights are considered as the initial values of the concepts in the FCMs, as expressed in Eq. (31).

$$\begin{bmatrix} C^{t=0}_{MA_{strenghts}} \\ C^{t=0}_{MA_{weaknesses}} \\ C^{t=0}_{MA_{opportunities}} \\ C^{t=0}_{MA_{threats}} \end{bmatrix} = \begin{bmatrix} 0.32 \\ 0.11 \\ 0.31 \\ 0.26 \end{bmatrix} \tag{31}$$

Aggregated and defuzzified dependency degrees among the main attributes are considered as the influence matrix of FCMs, as given by Eq. (32):

Table 11
Aggregated defuzzified dependency degrees among main attributes.

	S	*W*	*O*	*T*
S	0	0.27	0.45	0
W	0.22	0	0	0.60
O	0	0	0	0.31
T	0	0.74	0.64	0

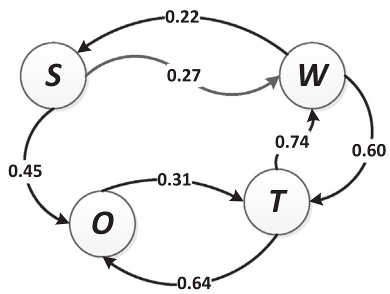

Fig. 8. Topology of the SWOT map.

$$[e_{ji}^{MA}] = \begin{bmatrix} 0 & 0.27 & 0.45 & 0 \\ 0.22 & 0 & 0 & 0.60 \\ 0 & 0 & 0 & 0.31 \\ 0 & 0.74 & 0.64 & 0 \end{bmatrix} \tag{32}$$

We selected a hyperbolic tangent function as an activation function and employed Eq. (6) in order to capture the dynamic behavior of the main attributes via FCMs simulation. Table 12 shows the concept values during the simulation.

The dynamic behavior of the main attributes is depicted in Fig. 9. It is observed that after twelve iterations, steady state concept values are reached.

Steady state concept values are normalized by using Eq. (7) to reach the final weights of the main attributes. Final weights of the main attributes are given in Table 13.

The normalized weights are regarded as the final attribute weights by considering interdependencies. Final attribute weights are given in Eq. (33):

$$I_{MA} = \begin{array}{c} \\ MA_1 \\ MA_2 \\ MA_3 \\ MA_4 \end{array} \begin{array}{c} Goal \\ \begin{bmatrix} 0.21 \\ 0.26 \\ 0.27 \\ 0.26 \end{bmatrix} \end{array} \tag{33}$$

Comparative attribute weights for the main attributes are depicted in Fig. 10.

Table 12
Concept values of main attributes for each iteration.

Iteration	Main Attributes			
	S	*W*	*O*	*T*
0	0.320	0.110	0.310	0.260
1	0.331	0.370	0.551	0.399
2	0.391	0.638	0.742	0.659
3	0.486	0.843	0.872	0.854
4	0.586	0.923	0.927	0.926
5	0.658	0.943	0.945	0.943
6	0.699	0.949	0.951	0.947
7	0.720	0.951	0.954	0.948
8	0.730	0.951	0.955	0.948
9	0.735	0.952	0.955	0.948
10	0.737	0.952	0.956	0.948
11	0.738	0.952	0.956	0.948
12	0.739	0.952	0.956	0.948

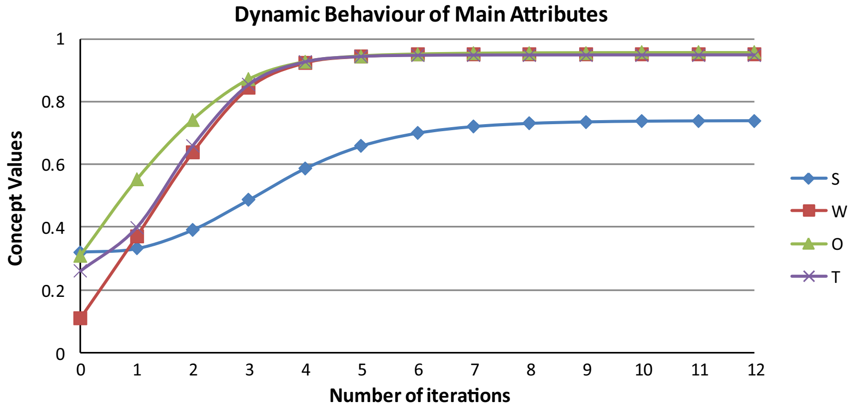

Fig. 9. Dynamic behavior of main attributes.

Similar to calculations for the main attributes, sub-attribute weights for each partition are updated by using an FCM simulation. For the sake of clarity and understandability, we only give the simulation results of strengths and treat the sub-attributes with their interpretations. For the strength sub-attributes, steady state concept values are reached in eight iterations, as shown in Fig. 11.

Fig. 12 depicts comparative attribute weights for the strengths sub-attributes.

An interesting behavior of the appropriate physical environment attribute is captured by FCMs. Upon analysing the dynamic behavior and the resulting attribute weights, the relative importance of the appropriate physical environment has been decreased from 0.09 to 0.02. The main reason is that although the appropriate physical environment influences student quality, dynamic research environment, specialized academic staff, brand status and working conditions attributes, it is not influenced by any of the attributes in the partition. Discussions with the decision makers have revealed their belief that improving the physical environment principally entails infrastructure investments. Other attributes in the partition do not contribute to the development of physical environment components, such as labs, classes, teaching materials and buildings. Hence, the concept value stands still in the graphical representation in a dynamic simulation analysis. It is inferred that the appropriate physical environment will not be as important as it is today in the long run. However, student quality, dynamic research environment and working conditions will become more important as a consequence of nonlinear interactions.

Another interesting finding has been observed in the dynamic behavior of the threats sub-attributes, which is given in Fig. 13.

Table 13
Final weights of main attributes.

	Steady state concepts	Normalized weights
S	0.739	0.21
W	0.952	0.26
O	0.956	0.27
T	0.948	0.26

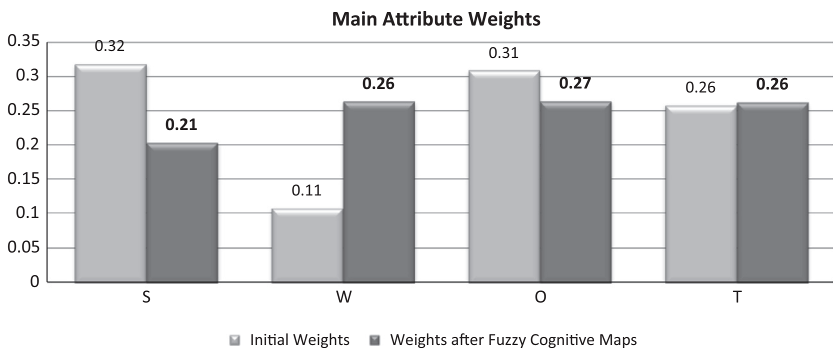

Fig. 10. Weights of the main attributes before/after simulation.

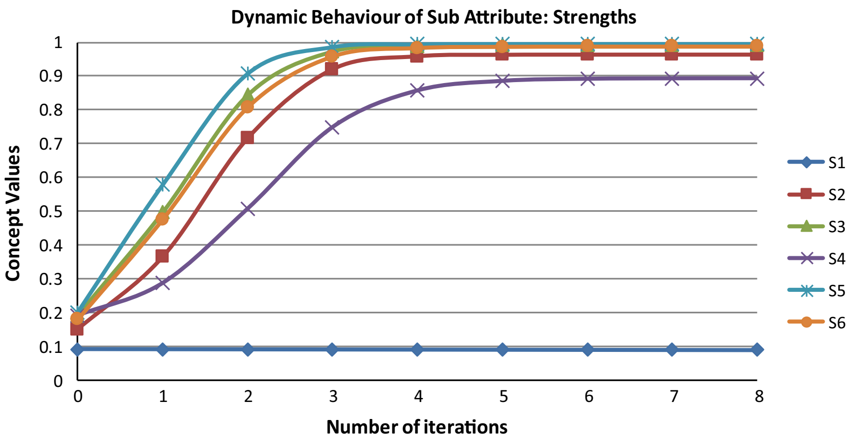

Fig. 11. Dynamic behavior of strengths sub-attributes.

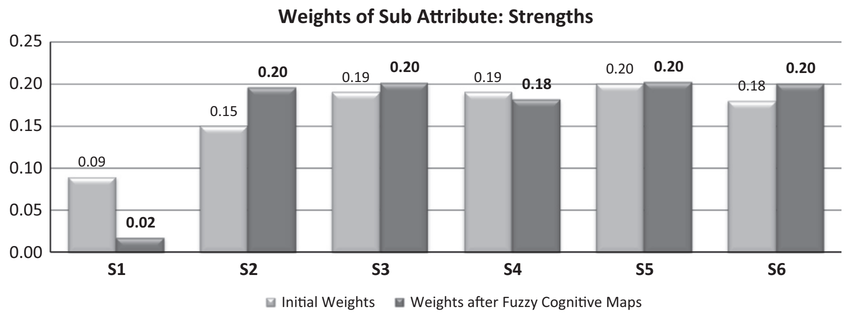

Fig. 12. Weights of strengths sub-attributes before/after simulation.

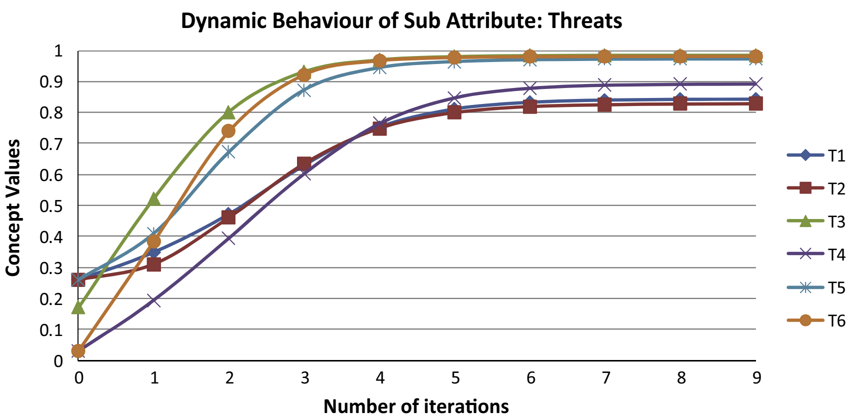

Fig. 13. Dynamic behavior of threats sub-attributes.

The steady state concept values are reached within nine iterations for the threats sub-attributes. Weights of the threats sub-attributes before/after FCM simulation is depicted in Fig. 14.

Assuming that the decision attributes are preferentially independent of each other, the decision makers assign relatively low weights to T_4 and T_6; this refers to the fact that the sub-attributes employer legislations and university budget cuts are not notable threat attributes. However, FCM simulation revealed that significant attention should be paid to T_4 and T_6. For instance, after FCM simulation, the relative importance of the university budget cuts sub-attribute dramatically increased

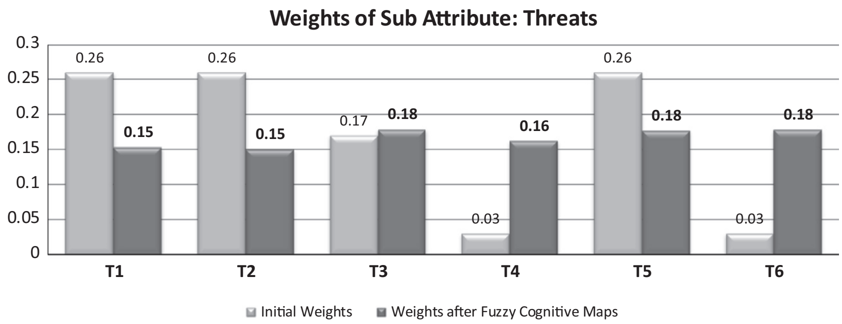

Fig. 14. Weights of the threats sub-attributes before/after simulation.

Table 14
Overall priorities of SWOT attributes.

SWOT attributes	SWOT weights	SWOT sub-attributes	Sub-attribute weights	Overall weights
Strengths	0.210	Appropriate physical environment (S1)	0.020	0.004
		Student quality (S2)	0.200	0.042
		Dynamic research environment (S3)	0.200	0.042
		Specialized academic staff (S4)	0.180	0.038
		Brand status (S5)	0.200	0.042
		Working conditions (S6)	0.200	0.042
Weaknesses	0.260	Campus location (W1)	0.030	0.008
		Lack of communication among staff (W2)	0.220	0.057
		Traditional undergraduate education (W3)	0.190	0.049
		Library (W4)	0.130	0.034
		Bureaucracy (W5)	0.210	0.055
		Arrogance (W6)	0.210	0.055
Opportunities	0.270	Talented new generation (O1)	0.160	0.043
		Government incentives (O2)	0.170	0.046
		Demand for re-skilling and training (O3)	0.150	0.041
		Assistant recruitments by government (O4)	0.170	0.046
		Entrepreneurial climate (O5)	0.170	0.046
		Need of interdisciplinary collaboration (O6)	0.170	0.046
Threats	0.260	Increasing number of new universities (T1)	0.150	0.039
		Rapid technological change (T2)	0.150	0.039
		E-learning programs (T3)	0.180	0.047
		Employer legislations (T4)	0.160	0.042
		Corporate universities (T5)	0.180	0.047
		University budget cuts (T6)	0.180	0.047

from 0.03 to 0.18. This is because the presence and development of corporate universities, increasingly spreading e-learning programs, rapid technological change and its implications to the transformation of higher education systems, and established new universities all have considerable impacts on possible future budget cuts. For this reason, the value of the concept representing university budget cuts has increased profoundly. Similarly, the increasing number of universities is found to have a huge impact on employer legislations of the state, hence the employer legislations attribute become much more important.

Dynamic simulation analysis provides invaluable insights for decision makers regarding how the attributes will influence each other and how the system will behave in the long run. In this regard, helping decision makers with the future implications of the interactions among attributes is unique and is not offered by the other methods within the MADM setting, except for FCMs.

After calculating all attribute and sub-attribute weights, the overall priorities are calculated based on Eqs. (14)–(17). The overall priorities are given in Table 14.

Once the overall attribute weights are calculated, the next step is to prioritize alternative strategies. Accordingly, the fuzzy rating values of alternatives are elicited from decision makers and a fuzzy decision table is constructed as given in Table 15.

Fuzzy TOPSIS calculations are made by employing Eqs. (18)–(30) (see Tables 16 and 17).

According to the closeness coefficients, alternative strategies are ranked as: $WO \succ SO \succ ST \succ WT$.

Table 15
Fuzzy rating values of alternatives.

	SO			*WO*			*ST*			*WT*		
	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3
S_1	G	VG	MG	G	G	VG	VG	G	G	P	MP	F
S_2	VG	G	MG	G	VG	G	G	MG	VG	F	MG	G
S_3	MG	P	F	P	F	MP	MP	F	F	F	G	MG
S_4	F	MG	G	P	MG	F	P	MP	F	P	P	F
S_5	G	F	MP	P	F	MG	MP	F	P	G	VG	F
S_6	P	VP	G	G	VG	G	G	VG	MG	G	F	F
W_1	P	MP	P	VG	G	MG	G	MG	F	P	F	VG
W_2	G	VG	MG	G	G	MG	VG	G	F	P	G	F
W_3	VG	VG	G	VG	G	F	G	F	MG	P	MP	G
W_4	F	MP	G	MG	F	G	P	MP	F	P	MP	F
W_5	F	MP	P	G	VG	F	G	F	VG	P	F	MP
W_6	G	MG	MG	F	MP	F	MP	P	P	MP	F	MG
O_1	VG	G	VG	G	P	VP	F	MG	MG	G	MG	F
O_2	G	MG	F	VG	G	MG	F	MP	F	G	F	MG
O_3	G	MG	MG	F	F	G	G	G	F	VG	G	F
O_4	P	MP	F	F	G	MG	MP	MP	P	F	MP	P
O_5	G	VP	P	P	G	MG	G	G	MG	F	MG	MG
O_6	VG	G	MG	VG	G	F	G	VG	MG	MG	G	G
T_1	MG	G	MP	G	VG	G	MP	F	P	F	G	F
T_2	G	MG	VG	G	VG	G	F	MP	MG	G	F	VP
T_3	P	MP	F	P	MP	F	VG	G	VG	P	G	G
T_4	F	MG	F	VG	G	MG	G	F	MG	P	F	VG
T_5	F	MG	G	G	VG	G	MG	VG	G	VG	G	G
T_6	P	MP	F	P	VP	MP	MP	VG	G	G	F	MG

Table 16
Distances of each alternative from FPIS and FNIS.

	d_i^*	d_i^-
SO	23.362	0.657
WO	23.318	0.699
ST	23.365	0.657
WT	23.391	0.629

Table 17
Closeness coefficients of each alternative.

Strategies	CC_i
SO	0.0274
WO	0.0291
ST	0.0273
WT	0.0262

5. Concluding remarks

In this study, a new hybrid MADM method, which combines hierarchical fuzzy TOPSIS and FCMs, is proposed. The proposed model is able to model interdependencies among the decision attributes under a fuzzy environment. The proposed method also makes use of the hierarchical decomposition approach to manage the complexity of the decision structure. Unlike the network structures, in which eliciting interaction degrees among the sub-attributes requires excessive cognitive effort and decision makers avoid allocating time to fill obscure survey questionnaires, our method elicits interaction degrees at the higher levels among non-homogeneous attributes. Influences only among the same partition of attributes are considered at the lower levels in order to reduce elaborate data requirements. The implicit influences among the attributes at different hierarchical levels are determined via the multiplication procedure of the hierarchical TOPSIS algorithm.

We believe that FCMs have much to offer in the field of decision analysis. Future studies should integrate different variants of FCMs for specific purposes. Additionally, influence matrices can be derived automatically from the available data by making use of intelligent learning algorithms. Furthermore, the proposed method can be applied to a wide variety of problems, especially for situations in which long term impacts, interdependencies among decision elements and uncertainties play a pivotal role on the final outcome.

Appendix A. FCMs

FCMs are fuzzy graph structures for representing causal reasoning [48]. In mathematical terms, an FCM is 4-tuple $(N, \boldsymbol{E}, \boldsymbol{C}, f)$ [48], where:

1. $N = \{N_1, N_2, \ldots, N_n\}$ is the set of n concepts, which are the nodes in the graph.
2. $\boldsymbol{E} : (N_i, N_j) \rightarrow e_{ij}$ is a function which associates e_{ij} to a pair of concepts (N_i, N_j), where the e_{ij} stands for the weight of the arc from N_i to N_j (N_i, N_j). If $i = j$, e_{ij} is equal to zero. Hence, $\boldsymbol{E}(N \times N) = (e_{ij}) \in \boldsymbol{K}^{n \times n}$.
3. $\boldsymbol{C} : N_i \rightarrow \boldsymbol{C}_i$ is a function that associates each concept N_i with the sequence of its activation degrees, such as for $t \in \boldsymbol{N}$, $C_i(t) \in L$, given its activation degree at the moment t. $C(0) \in L^n$ indicates the initial vector and specifies the initial values of all concept nodes, and $\boldsymbol{C}(t) \in L^n$ is a state vector at a certain iteration t.
4. $f : \boldsymbol{R} \rightarrow L$ is a transformation function, which includes a recurring relationship on $t \geqslant 0$ between $\boldsymbol{C}(t+1)$ and $\boldsymbol{C}(t)$. The state updating equation is presented in Eq. (A.1) [102]:

$$\forall i \in \{1, \ldots, n\}, \quad C_i^{(t+1)} = f\left(C_i^{(t)} + \sum_{\substack{j=1 \\ j \neq i}}^{n} e_{ji} C_j^{(t)}\right) \tag{A.1}$$

Each concept value in the state vector is calculated for successive iterations based on the formula above. The state vector provides the current value of each node/variable in a particular iteration. Conversely, the transformation function is used to bind the weighted sum in the desired range.

When one of the transformation functions is applied to interacting concepts, an FCM is expected to converge one the following states [49]:

- A fixed point, which means that the state vector stabilizes and remains unchanged for sequential iterations.
- A limit cycle, which means that the state vector keeps repeating indefinitely.
- A chaotic behavior, which means that the state vector keeps changing with iterations and no repeating states are observed.

For more information related to FCM applications, we refer to review papers [69–71].

References

[1] I. Akgun, A. Kandakoglu, A.F. Ozok, Fuzzy integrated vulnerability assessment model for critical facilities in combating the terrorism, Expert Syst. Appl. 37 (2010) 3561–3573.
[2] D.J. Armstrong, Causal mapping: a discussion and demonstration, in: Causal Mapping for Research in Information Technology, IGI Global, 2005, pp. 20–45.
[3] K.M. Aschenbrenner, D. Jaus, C. Villani, Hierarchical goal structuring and pupils' job choices: Testing a decision aid in the field, Acta Psychol. 45 (1980) 35–49.
[4] C.A. Bana e Costa, M.D. Oliveira, A multicriteria decision analysis model for faculty evaluation, Omega 40 (2012) 424–436.
[5] Q. Bao, D. Ruan, Y. Shen, E. Hermans, D. Janssens, Improved hierarchical fuzzy TOPSIS for road safety performance evaluation, Knowl.-Based Syst. 32 (2012) 84–90.
[6] A. Baykasoğlu, V. Kaplanoğlu, Z.D.U. Durmuşoğlu, C. Şahin, Integrating fuzzy DEMATEL and fuzzy hierarchical TOPSIS methods for truck selection, Expert Syst. Appl. 40 (2013) 899–907.
[7] D.E. Bell, H. Raiffa, A. Tversky, Decision Making: Descriptive, Normative, and Prescriptive Interactions, Cambridge University Press, 1988.
[8] R.E. Bellman, L.A. Zadeh, Decision-Making in a fuzzy environment, Manage. Sci. 17 (1970) 141–164.
[9] V. Belton, T. Stewart, Multiple Criteria Decision Analysis An Integrated Approach, Kluwer Academic Publishers, 2002.
[10] V. Belton, T. Stewart, Problem structuring and multiple criteria decision analysis, in: M. Ehrgott, J.R. Figueira, S. Greco (Eds.), Trends in Multiple Criteria Decision Analysis, Springer, US, 2010, pp. 209–239.
[11] P. Bennett, J. Bryant, N. Howard, Drama theory and confrontation analysis, in: J. Rosenhead, J. Mingers (Eds.), Rational Analysis for a Problematic World Revisited, John Wiley & Sons, Chichester, 2001.
[12] R. Biloslavo, A. Grebenc, Integrating group Delphi, analytic hierarchy process and dynamic fuzzy cognitive maps for a climate warning scenario, Kybernetes 41 (2012) 414–428.
[13] J.M. Bryson, F. Ackermann, C. Eden, C.B. Finn, Visible Thinking: Unlocking Causal Mapping for Practical Business Results, John Wiley & Sons, Chichester, 2004.
[14] S. Bueno, J.L. Salmeron, Benchmarking main activation functions in fuzzy cognitive maps, Expert Syst. Appl. 36 (2009) 5221–5229.
[15] G. Büyüközkan, O. Feyzioğlu, M.Ş. Ersoy, Evaluation of 4PL operating models: a decision making approach based on 2-additive Choquet integral, Int. J. Prod. Econ. 121 (2009) 112–120.
[16] J.P. Carvalho, J.A.B. Tome, Rule based fuzzy cognitive maps – expressing time in qualitative system dynamics, in: The 10th IEEE International Conference on Fuzzy Systems, 2001, 2001, pp. 280–283.
[17] P. Checkland, J. Scholes, Soft Systems Methodology in Action, Wiley Chichester, 1999.
[18] C.-T. Chen, Extensions of the TOPSIS for group decision-making under fuzzy environment, Fuzzy Sets Syst. 114 (2000) 1–9.
[19] S.J. Chen, C.L. Hwang, Fuzzy Multiple Attribute Decision Making: Methods and Applications, Springer-Verlag, Berlin, 1992.
[20] M. Coccia, Measuring scientific performance of public research units for strategic change, J. Informetrics 2 (2008) 183–194.
[21] S. Corrente, S. Greco, R. Słowiński, Multiple criteria hierarchy process with ELECTRE and PROMETHEE, Omega 41 (2013) 820–846.
[22] A.P. Dempster, Upper and lower probabilities induced by a multivalued mapping, Ann. Math. Stat. 38 (1967) 325–339.
[23] M. Dobbins, C. Knill, E. Vögtle, An analytical framework for the cross-country comparison of higher education governance, High Educ. 62 (2011) 665–683.
[24] D. Dubois, H. Prade, R. Sabbadin, Decision-theoretic foundations of qualitative possibility theory, Eur. J. Oper. Res. 128 (2001) 459–478.

[25] J.S. Dyer, Maut — multiattribute utility theory, in: Multiple Criteria Decision Analysis: State of the Art Surveys, Springer, New York, 2005, pp. 265–292.
[26] C. Eden, Using cognitive mapping for strategic options development and analysis (SODA), in: J. Rosenhead (Ed.), Rational Analysis for a Problematic World, Wiley, 1999, pp. 21–42.
[27] C. Eden, F. Ackermann, SODA – the principles, in: J. Rosenhead, J. Mingers (Eds.), Rational Analysis for a Problematic World Revisited, John Wiley & Sons Chichester, 2001, pp. 21–41.
[28] C.-M. Feng, P.-J. Wu, K.-C. Chia, A hybrid fuzzy integral decision-making model for locating manufacturing centers in China: a case study, Eur. J. Oper. Res. 200 (2010) 63–73.
[29] P.C. Fishburn, Utility Theory for Decision Making, Wiley, New York, 1970.
[30] J. Friend, The strategic choice approach, in: J. Rosenhead, J. Mingers (Eds.), Rational Analysis for a Problematic World Revisited, John Wiley & Sons, Chichester, 2001.
[31] A. Gabus, E. Fontela, The DEMATEL Observer, Battelle Geneva Research Center, Geneva, Switzerland, 1976.
[32] C. Gencer, D. Gürpinar, Analytic network process in supplier selection: a case study in an electronic firm, Appl. Math. Model. 31 (2007) 2475–2486.
[33] M. Glykas, Performance measurement scenarios with fuzzy cognitive strategic maps, Int. J. Inf. Manage. 32 (2012) 182–195.
[34] J.L. Gonzalez, L.T. Aguilar, O. Castillo, A cognitive map and fuzzy inference engine model for online design and self fine-tuning of fuzzy logic controllers, Int. J. Intell. Syst. 24 (2009) 1134–1173.
[35] J.L. Gonzalez, O. Castillo, L.T. Aguilar, Performance analysis of Cognitive Map-Fuzzy Logic Controller model for adaptive control application, in: IEEE International Conference on Fuzzy Systems, 2008, FUZZ-IEEE 2008, (IEEE World Congress on Computational Intelligence), 2008, pp. 2375–2381.
[36] M. Grabisch, I. Kojadinovic, P. Meyer, A review of methods for capacity identification in Choquet integral based multi-attribute utility theory: applications of the Kappalab R package, Eur. J. Oper. Res. 186 (2008) 766–785.
[37] M. Grabisch, C. Labreuche, A decade of application of the Choquet and Sugeno integrals in multi-criteria decision aid, Ann. Oper. Res. 175 (2010) 247–286.
[38] A. Guitouni, J.-M. Martel, Tentative guidelines to help choosing an appropriate MCDA method, Eur. J. Oper. Res. 109 (1998) 501–521.
[39] M. Hagiwara, Extended fuzzy cognitive maps, in: IEEE International Conference on Fuzzy Systems, 1992, 1992, pp. 795–801.
[40] C.L. Hwang, K. Yoon, Multiple Attribute Decision Making, Methods and Applications, Springer-Verlag, Now York, 1981.
[41] S. Jharkharia, R. Shankar, Selection of logistics service provider: an analytic network process (ANP) approach, Omega 35 (2007) 274–289.
[42] C. Kahraman, N.Y. Ateş, S. Çevik, M. Gülbay, S.A. Erdoan, Hierarchical fuzzy TOPSIS model for selection among logistics information technologies, J. Enterprise Inform. Manage. 20 (2007) 143–168.
[43] C. Kahraman, G. Büyüközkan, N.Y. Ateş, A two phase multi-attribute decision-making approach for new product introduction, Inf. Sci. 177 (2007) 1567–1582.
[44] C. Kahraman, S. Çevik, N.Y. Ates, M. Gülbay, Fuzzy multi-criteria evaluation of industrial robotic systems, Comput. Ind. Eng. 52 (2007) 414–433.
[45] C. Kahraman, T. Ertay, G. Büyüközkan, A fuzzy optimization model for QFD planning process using analytic network approach, Eur. J. Oper. Res. 171 (2006) 390–411.
[46] R.L. Keeney, Building models of values, Eur. J. Oper. Res. 37 (1988) 149–157.
[47] R.L. Keeney, Value-Focused Thinking: A Path to Creative Decision Making, Harvard University Press, Cambridge, Massachusetts, 1992.
[48] B. Kosko, Fuzzy cognitive maps, Int. J. Man Mach. Stud. 24 (1986) 65–75.
[49] B. Kosko, Fuzzy Engineering, Prentice Hall, Upper Saddle River, New Jersey, 1997.
[50] T.L. Kottas, Y.S. Boutalis, M.A. Christodoulou, Fuzzy cognitive network: a general framework, Intell. Decis. Technol. 1 (2007) 183–196.
[51] D. Krantz, Conjoint measurement: the Luce–Tukey axiomatization and some extensions, J. Math. Psychol. 1 (1964) 248–277.
[52] J.W. Lee, S.H. Kim, Using analytic network process and goal programming for interdependent information system project selection, Comput. Oper. Res. 27 (2000) 367–382.
[53] T. Magoč, F. Modave, The optimality of non-additive approaches for portfolio selection, Expert Syst. Appl. 38 (2011) 12967–12973.
[54] I. Mahdavi, N. Asadian, M. Khavarpour, A two phase multi-attribute decision-making approach for supplier selection in supply chain management, in: 37th International Conference on Computers and Industrial Engineering, 2007, pp. 519–529.
[55] K. Maier, V. Stix, A semi-automated approach for structuring multi criteria decision problems, Eur. J. Oper. Res. 225 (2013) 487–496.
[56] J.L. Marichal, An axiomatic approach of the discrete Choquet integral as a tool to aggregate interacting criteria, IEEE Trans. Fuzzy Syst. 8 (2000) 800–807.
[57] J.L. Marichal, Tolerant or intolerant character of interacting criteria in aggregation by the Choquet integral, Eur. J. Oper. Res. 155 (2004) 771–791.
[58] N.H. Mateou, A.S. Andreou, A framework for developing intelligent decision support systems using evolutionary fuzzy cognitive maps, J. Intell. Fuzzy Syst. 19 (2008) 151–170.
[59] L.M. Meade, J. Sarkis, Analyzing organizational project alternatives for agile manufacturing processes: an analytical network approach, Int. J. Prod. Res. 37 (1999) 241–261.
[60] Y.Z. Mehrjerdi, Hierarchical multi-criteria risk-benefit analysis in fuzzy environment, Appl. Soft Comput. 13 (2013) 590–599.
[61] J. Mingers, Soft OR comes of age—but not everywhere!, Omega 39 (2011) 729–741
[62] F. Mizikaci, Higher education in Turkey, UNESCO, Bucharest, CEPES, 2006.
[63] P. Murias, J.C. Miguel, D. Rodríguez, A composite indicator for university quality assesment: the case of spanish higher education system, Soc Indic Res 89 (2008) 129–146.
[64] J.P. Olsen, The institutional dynamics of the european university, in: P. Maassen, J.P. Olsen (Eds.), University Dynamics and European Integration, Springer, Netherlands, 2007, pp. 25–54.
[65] S. Opricovic, G.-H. Tzeng, Defuzzification within a multicriteria decision model, Int. J. Uncertain. Fuzz. Knowl.-Based Syst. 11 (2003) 635–652.
[66] S. Opricovic, G.-H. Tzeng, Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS, Eur. J. Oper. Res. 156 (2004) 445–455.
[67] U. Özesmi, S.L. Özesmi, Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach, Ecol. Model. 176 (2004) 43–64.
[68] T. Paksoy, N.Y. Pehlivan, C. Kahraman, Organizational strategy development in distribution channel management using fuzzy AHP and hierarchical fuzzy TOPSIS, Expert Syst. Appl. 39 (2012) 2822–2841.
[69] E.I. Papageorgiou, Learning algorithms for fuzzy cognitive maps—a review study, IEEE Trans. Syst. Man Cybern. Part C: Appl. Rev. 42 (2012) 150–163.
[70] E.I. Papageorgiou, Review study on fuzzy cognitive maps and their applications during the last decade, in: M. Glykas (Ed.), Business Process Management, Springer, Berlin Heidelberg, 2013, pp. 281–298.
[71] E.I. Papageorgiou, J.L. Salmeron, A review of fuzzy cognitive maps research during the last decade, IEEE Trans. Fuzzy Syst. 21 (2013) 66–79.
[72] W. Pedrycz, The design of cognitive maps: a study in synergy of granular computing and evolutionary optimization, Expert Syst. Appl. 37 (2010) 7288–7294.
[73] W. Pedrycz, W. Homenda, From fuzzy cognitive maps to granular cognitive maps, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2012, pp. 185–193.
[74] S. Perçin, Fuzzy multi-criteria risk-benefit analysis of business process outsourcing (BPO), Inf. Manage. Comput. Secur. 16 (2008) 213–234.
[75] L. Rodriguez-Repiso, R. Setchi, J.L. Salmeron, Modelling IT projects success: emerging methodologies reviewed, Technovation 27 (2007) 582–594.
[76] J. Rosenhead, Robustness analysis: keeping your options open, in: Rational Analysis for a Problematic World Revisited, Wiley, Chichester, 2001, pp. 181–207.
[77] J. Rosenhead, J. Mingers, Rational Analysis for a Problematic World Revisited, 2nd ed., John Wiley & Sons, Chichester, 2001.

[78] J. Roshandel, S.S. Miri-Nargesi, L. Hatami-Shirkouhi, Evaluating and selecting the supplier in detergent production industry using hierarchical fuzzy TOPSIS, Appl. Math. Model. 37 (2013) 10170–10181.
[79] B. Roy, The outranking approach and the foundations of ELECTRE methods, in: C. Bana e Costa (Ed.), Readings in Multiple Criteria Decision Aid, Springer, Berlin Heidelberg, 1990, pp. 155–183.
[80] T.L. Saaty, The Analytic Hierarchy Process, McGraw-Hill, New York, 1980.
[81] T.L. Saaty, How to make a decision: the analytic hierarchy process, Eur. J. Oper. Res. 48 (1990) 9–26.
[82] T.L. Saaty, Decision Making with Dependence and Feedback: The Analytic Network Process, RWS Publications, Pittsburgh, 1996.
[83] T.L. Saaty, N. Begicevic, The scope of human values and human activities in decision making, Appl. Soft Comput. 10 (2010) 963–974.
[84] T.L. Saaty, H.-S. Shih, Structures in decision making: on the subjective geometry of hierarchies and networks, Eur. J. Oper. Res. 199 (2009) 867–872.
[85] A.P. Sage, Interpretive Structural Modeling: Methodology for Large-scale Systems, McGraw-Hill, New York, NY, 1977.
[86] J.L. Salmeron, R. Vidal, A. Mena, Ranking fuzzy cognitive map based scenarios with TOPSIS, Expert Syst. Appl. 39 (2012) 2443–2450.
[87] J. Sarkis, Evaluating environmentally conscious business practices, Eur. J. Oper. Res. 107 (1998) 159–174.
[88] T.-A. Shiau, J.-S. Liu, Developing an indicator system for local governments to evaluate transport sustainability strategies, Ecol. Ind. 34 (2013) 361–371.
[89] H.J. Shyur, H.S. Shih, A hybrid MCDM model for strategic vendor selection, Math. Comput. Modell. 44 (2006) 749–761.
[90] W. Stach, L. Kurgan, W. Pedrycz, Expert-based and computational methods for developing fuzzy cognitive maps, in: M. Glykas (Ed.), Fuzzy Cognitive Maps, Springer, Berlin Heidelberg, 2010, pp. 23–41.
[91] W. Stach, L. Kurgan, W. Pedrycz, M. Reformat, Genetic learning of fuzzy cognitive maps, Fuzzy Sets Syst. 153 (2005) 371–401.
[92] M. Sugeno, Theory of fuzzy integrals and its applications, in, Tokyo Institute of Technology, 1974.
[93] M. Sugeno, Fuzzy measures and fuzzy integrals-a survey, in: S. Gupta, Gaines (Eds.), Fuzzy Automata and Decision Processes, North-Holland, Amsterdam, 1977, pp. 89–102.
[94] A.Ç. Tolga, Fuzzy multicriteria R&D project selection with a real options valuation model, J. Intell. Fuzzy Syst. 19 (2008) 359–371.
[95] A.K. Tsadiras, Comparing the inference capabilities of binary, trivalent and sigmoid fuzzy cognitive maps, Inf. Sci. 178 (2008) 3880–3894.
[96] G.-H. Tzeng, J.-J. Huang, Fuzzy integral technique, in: Multiple Attribute Decision Making: Methods and Applications, CRC Press, 2011, pp. 109–121.
[97] G.-H. Tzeng, Y. Ouyang, C. Lin, C. Chen, Hierarchical MADM with fuzzy integral for evaluating enterprise intranet web sites, Inf. Sci. 169 (2005) 409–426.
[98] F. Uysal, O. Tosun, Fuzzy TOPSIS-based computerized maintenance management system selection, J. Manuf. Technol. Manage. 23 (2012) 212–228.
[99] R. Verma, M.E. Pullman, An analysis of the supplier selection process, Omega 26 (1998) 739–750.
[100] X. Wang, H.K. Chan, A hierarchical fuzzy TOPSIS approach to assess improvement areas when implementing green supply chain initiatives, Int. J. Prod. Res. 51 (2013) 3117–3130.
[101] W.C. Wedley, B. Schoner, E.U. Choo, Clustering, dependence and ratio scales in AHP: rank reversals and incorrect priorities with a single criterion, J. Multi-Criteria Decis. Anal. 2 (1993) 145–158.
[102] G. Xirogiannis, J. Stefanou, M. Glykas, A fuzzy cognitive map approach to support urban design, Expert Syst. Appl. 26 (2004) 257–268.
[103] J.L. Yang, H.N. Chiu, G.-H. Tzeng, R.H. Yeh, Vendor selection by integrated fuzzy MCDM techniques with independent and interdependent relationships, Inf. Sci. 178 (2008) 4166–4183.
[104] R. Yu, G.-H. Tzeng, A soft computing method for multi-criteria decision making with dependence and feedback, Appl. Math. Comput. 180 (2006) 63–75.
[105] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (1965) 338–353.