Fuzzy cognitive mapping approach to the assessment of Industry 4.0 tendency

A. Kiraz, Ö. Uygun, E.F. Erkan*, and O. Canpolat

Department of Industrial Engineering, Faculty of Engineering, Sakarya University, Sakarya, Turkey.

Received 11 June 2018; received in revised form 14 November 2018; accepted 12 October 2019

KEYWORDS
Fuzzy cognitive maps; Industry 4.0; Strategic management.

Abstract. Proper understanding of the conceptual and practical counterparts of Industry 4.0 is of great importance as global competition has made the technology-based production a necessity. The aim of the present study was to propose a model that would predict the existing and future Industry 4.0 levels for companies. The changes of the concepts were examined and interpreted for three different hypothetically developed scenarios. In the first scenario, an organization that was poorly managed in terms of the development of Industry 4.0 was considered. The Industry 4.0 tendency was calculated at 0.04, reaching a steady state after 12 time periods using the Fuzzy Cognitive Maps (FCMs) algorithm. Moderate and well managed organizations were considered in Scenarios 2 and 3, respectively. The Industry 4.0 tendency reached 0.12 after 15 time periods in Scenario 2 and 0.95 at the end of five iterations in the third scenario with the concept values indicating well managed situation in the latter case. In addition, strategy and organization, smart operation, and smart factory concepts were found to make the most significant contribution to the Industry 4.0 level in the static analysis.

© 2019 Sharif University of Technology. All rights reserved.

1. Introduction

Today’s world is dominated by web technologies, applications, business and information systems, smartphones, computers, 3D printers, etc., which make daily life greatly easier. Developing technology also leads to great competition in the industrial environment. However, most organizations are not fully prepared for Industry 4.0, an industrial revolution which makes technology more adaptable to production [1].

The main focus of Industry 4.0 is to be able to perceive hidden information within systems for synthesizing the acquired information with scientific methods and easily adapting to their behavior. Intelligent manufacturing systems and processes as well as appropriate engineering methods and tools will be the key factors for coordinating different and interconnected manufacturing facilities in future smart plants [2]. Today, there are many studies on Industry 4.0 in different areas, some samples of which are shown in Table 1.

Industry 4.0 transformation is a complex process that affects many departments in institutions. Fuzzy Cognitive Maps (FCMs) can play an important role in reducing this complexity and providing decision support. The studies in the literature have employed questionnaires in the analysis of the Industry 4.0 components. However, in this study, FCMs are used for the first time to analyze the importance of the concepts affecting Industry 4.0 as well as its future trend through hypothetically determined scenarios.

The aim of this study is to establish a model
by determining the basic concepts related to Industry 4.0. Thus, in order to achieve higher organizational levels, it is necessary to determine which concepts should be focused on. FCMs, founded on fuzzy logic and cognitive maps, are employed in this study, which constitute a suitable method for modeling and analysis of complex systems with uncertainty [10-13]. The proposed model can give insights about the possible future of Industry 4.0 levels.

The rest of the paper is organized as follows. In Section 2, the literature on the applications of FCMs is reviewed. Section 3 contains technical explanations about FCMs. In Section 4, the model developed for Industry 4.0 is examined through static and dynamic analyses. Finally, Section 5 presents the conclusion of the study.

2. Literature review

FCMs method was developed by Kosko [14] after the emergence of cognitive maps as a visually enriched decision support model for analyzing complex systems [15]. It examines the dynamic interactions and behavior of a system. FCMs are a simple way of illustrating the causal relationships between concepts and graphically explaining the behavior of a complex system by utilizing its accumulated knowledge [16].

FCMs are employed in the analysis of system states with structures and applied to the fields of politics, social sciences, medicine, engineering, business systems, environment and agriculture, information technologies, energy modeling, decision support systems, classification, estimation, research, and information system. The studies carried out in recent years on the applications of FCMs to the above-mentioned areas are briefly provided in Table 2.

The FCMs method is chosen to develop a prediction model and determine the Industry 4.0 trend. Industry 4.0 is a complex process and expert opinions are required in determining its levels. The FCMs method is suitable for the analysis of the predictions in this process.

3. Fuzzy Cognitive Maps (FCMs)

FCMs are a combination of fuzzy logic and cognitive maps. They can express the structure of systems with related events and allow receiving feedback on the status of the system over time [37]. FCMs were first proposed by Kosko [14] in 1986 to fuzzify the relationships between concepts and since then, they have continuously been developed. A simple FCMs structure is shown in Figure 1. Arrows show causality between concept nodes and $W_{ij}$ indicates the causality weight of each concept [38]. Three conditions are possible with regard to the weights.

$W_{ij} > 0$ indicates positive relationship between the concept variables $C_i$ and $C_j$, that is, an increase/decrease in node $C_i$ causes an increase/decrease in node $C_j$. $W_{ij} < 0$ indicates a negative relationship between the conceptual variables $C_i$ and $C_j$, that is, an increase/decrease in node $C_i$ leads to a de-

![Figure 1. Structure of Fuzzy Cognitive Maps (FCMs).](image)

| Model | Ref. | Assessment approach |
|-------|------|---------------------|
| IMPULS (2015) | [3] | An evaluation structure consisting of six main criteria and 18 sub-criteria |
| An improved implementation strategy for Industry 4.0 (2016) | [4] | Considering Industry 4.0 as part of a process model and checking it quickly |
| Industry 4.0 digital operations self-evaluation (2016) | [5] | Online self-assessment system based on six criteria |
| Connected enterprise maturity model (2014) | [6] | A five-step technology-based assessment approach with four main criteria to achieving Industry 4.0 |
| Industry 4.0 maturity model (2015) | [7] | An evaluation structure consisting of three main criteria and 13 sub-criteria |
| Industry 4.0 maturity model for manufacturing organizations (2016) | [8] | An evaluation structure consisting of nine main criteria and 62 sub-criteria |
| Industry 4.0: establishing a digital enterprise (2016) | [9] | What organizations should do to reach Industry 4.0 digital? |
Table 2. Fuzzy Cognitive Maps (FCMs) applications.

| Ref. | Problem solving                                    | Area                        |
|------|----------------------------------------------------|-----------------------------|
| [17] | Prediction and learning                            | Political and social sciences|
| [18] | Modelling and policy scenarios                     |                             |
| [19] | Decision support systems                           |                             |
| [20] | Decision support systems                           |                             |
| [21] | Classification                                     | Medical                     |
| [22] | Decision support systems                           |                             |
| [23] | Decision support systems                           |                             |
| [24] | Modelling                                          | Engineering                 |
| [25] | Modelling and decision support systems              |                             |
| [26] | Decision support systems                           |                             |
| [27] | Information representation                         | Business                    |
| [28] | Classification and decision support systems         |                             |
| [29] | Decision support systems                           |                             |
| [30] | Policy scenarios                                   | Environment and agriculture |
| [31] | Classification                                     |                             |
| [32] | Optimization, modelling                            |                             |
| [30] | Modelling                                          | Information technologies    |
| [33] | Policy scenarios                                   |                             |
| [34] | Policy scenarios                                   |                             |
| [35] | Modelling, optimization, prediction                | Energy                      |
| [36] | Modelling, policy scenarios                        |                             |

c/crea/increase in node $C_j$. Finally, $W_{ij} = 0$ indicates that there is no relation between $C_i$ and $C_j$ concept variables.

The value of the concept variable $A_i$ is calculated for each $C_i$ concept:

$$A_i^{(k+1)} = f\left(2 \times A_i^{(k)} - 1 + \sum_{j-i,j \neq i} W_{ij} \times \left(2 \times A_j^{(k)} - 1\right)\right).$$ (1)

where $A_i^{(k+1)}$ is the value of concept $C_i$ at step $(k+1)$, $A_i^{(k)}$ is the value of concept $C_j$ at step $(k)$, and $W$ is the interaction matrix. $f$ is the threshold function for transformation within $[0, 1]$. Various functions have been used for transformation. In this study, the sigmoid function is employed to ensure that the value of each concept will be within $[0, 1]$ as follows:

$$f(x) = \frac{1}{1 + e^{-x}}. \quad (2)$$

In this study, linguistic variables of Negative Very High (NVH), Negative High (NH), Negative Medium (NM), Negative Low (NL), Positive Low (PL), Positive Medium (PM), Positive High (PH), Positive Very High (PVH) are adopted along with FCMs in order to evaluate the Industry 4.0 tendency. Expressions of linguistic variables are easy to intuitively reach with triangular membership functions [39].

4. Implementation

In this study, both the static and dynamic types of analysis are gone through. Through the former, the situation of the system is presented in a general framework. The reason for employing the static analysis approach is the assumption that the determined weights will not change over time after gathering the
expert opinions. These weights indicate the importance of relationships between concepts. On the other hand, by the latter, i.e., the dynamic analysis approach, the scenarios are analyzed with regard to time to provide insights about the future of organizations in terms of Industry 4.0.

4.1. Static analysis
In the static analysis, the relations of the concepts in the developed Industry 4.0 model are examined. For this purpose, first, the criteria to be used in evaluating the level of Industry 4.0 are determined based on the literature and IMPULS (Readiness Online Self-Check for Businesses) Industry 4.0 model criteria. In addition, as a negative concept, “Corporate Risks” have been added to the IMPULS criteria and a model is proposed. Table 3 shows the concepts and related explanations.

The relationship map of the created model is drawn by a consensus among three experts working in the field of Industry 4.0. It is given in Figure 3.

Three experts offered their linguistic variables, as represented in Figure 2, for each of the relationships shown in Figure 3. For example, the first, second, and third experts believed that the influence from C1 to C8 was PVH, PH, and PVH, respectively. Using the centre of gravity method in Eq. (3), as shown in Box I, the weight between concepts C1 and C8 was found. Each relationship is interpreted in the same way and linguistic expressions are digitized using the centre of gravity method as shown in Table 4.

Decision Making Trial and Evaluation Laboratory (DEMATEL) is an effective method for examining the structure and relationships between the system concepts. It determines the importance of the concepts according to their relationships with each other. An extensive analysis of concept relations has been carried out by using the DEMATEL method in part with the created weight matrix. This analysis should obtain meaningful results from expert opinions. The degree of prominence and cause and effect groups of concepts can be determined with the values of $D + R$ and $D - R$, respectively. Table 5 shows the total causality matrix. Absolute values are adopted to avoid the reducing role of negative effect weights in the calculation of total effect levels.

The sum of the rows ($D$) calculated using Eq. (4) gives the sum of the effects of a concept on all other concepts. The sum of the columns ($R$), calculated by Eq. (5), shows the effect that a concept has on all other concepts.

$$D_i = \sum_{j=1}^{N} W_{ij},$$

$$R_j = \sum_{i=1}^{N} W_{ji},$$

where $i$ indicates columns and $j$ represents the number

![Figure 2. Numerical equivalents of linguistic variables.](image)

![Figure 3. Industry 4.0 relationship map.](image)
Table 3. Industry 4.0 model concepts and explanations.

| Criterion                              | Explanation                                                                                                                                 |
|----------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Strategy and organization (C1)         | Companies need to develop Industry 4.0 strategy to make decisions about the technologies and innovations or the investment activities to be realized.  |
|                                        | The existing organizational structures of the companies should also correspond to this strategy.                                                |
| Smart factory (C2)                     | It consists of equipment infrastructure of the organizations, data collecting and using, digital modeling activities and information technology systems, and smart factory systems. |
| Smart operation (C3)                   | In comprises organizations’ information sharing, cloud using activities, security of information technologies, and self-deciding independent processes. |
| Smart products (C4)                    | They carry out self-reporting, integration, location determination, automatic identification and tracking, etc.                                |
| Data-driven services (C5)              | Unlike the traditional model, companies offer comprehensive after-sales services for the products.                                          |
| Employees (C6)                         | Employees need to acquire new skills and qualifications within the scope of the transformation that companies need to realize. On-site implementation and continuous training activities should be carried out for this purpose. |
| Corporate risks (C7)                   | All types and sizes of organizations face internal and external factors and influences that cause uncertainty about whether they can achieve their goals. Corporate risks are those uncertainties as to the goals of an organization. |
| Industry 4.0 tendency (C8)             | It is the output concept to be analyzed.                                                                                                  |

Table 4. Weight matrix.

|       | C1       | C2       | C3       | C4       | C5       | C6       | C7       | C8       |
|-------|----------|----------|----------|----------|----------|----------|----------|----------|
| C1    | 0        | 0.800    | 0.733    | 0.733    | 0.733    | -0.800   | 0.733    |          |
| C2    | 0        | 0        | 0.600    | 0.600    | 0.600    | 0        | 0.667    |          |
| C3    | 0        | 0.533    | 0        | 0.333    | 0.533    | 0        | 0        | 0.267    |
| C4    | 0        | 0.200    | 0.333    | 0        | 0        | 0        | 0        | 0.533    |
| C5    | 0        | 0.400    | 0.533    | 0        | 0        | 0        | 0        | 0.267    |
| C6    | 0.533    | 0.267    | 0.600    | 0.400    | 0.400    | 0        | 0        | 0.467    |
| C7    | -0.733   | -0.533   | -0.467   | -0.267   | -0.267   | -0.467   | 0        | -0.733   |
| C8    | 0        | 0        | 0        | 0        | 0        | 0        | 0        | 0        |

The values of $W$, which indicates the weights between the concepts, are taken from Table 4. The significance level of the relevant concept is indicated by $(D+R)$. Strategy and organization (C1) with the highest $(D+R)$ is the most important concept in the developed Industry 4.0 model. The $(D+R)$ values of smart factory (C2) and smart operation (C3) concepts show that they are also important for Industry 4.0. The $(D+R)$ values of the remaining concepts are provided in Table 5.
The values of \((D - R)\) illustrate the concepts in the cause and effect groups. C1, C6, and C7 concepts with positive \((D - R)\) values are in the cause group C2, C3, C4, C5, and C8 with negative \((D - R)\) values are effects. The concepts in the cause group are very important for the model and exert the strongest impacts on other concepts. The decision-makers should first focus on these concepts in order to achieve broader and faster development in Industry 4.0. The Industry 4.0 tendency (C8) with the lowest negative \((D - R)\) value due to the output concept is the most affected concept.

4.2. Dynamic analysis

FCMs are employed considering weight matrix and the effects of other concepts for the Industry 4.0 tendency and the status of the systems is analyzed using three different scenarios developed by the experts. In all scenarios, Industry 4.0 tendency (C8) criterion is set to zero so that the effects on it can be better analyzed.

The first, second, and third scenarios represent organizations that are poor, medium, and strong in terms of the concepts, respectively:

**Scenario 1:** In this scenario, it is assumed that all concepts are poorly managed. The high value of the corporate risks (C8) means a bad situation for Industry 4.0. The initial vector \(A\) of the first scenario is as follows:

\[
A^{\text{initial}}_{(1)} = [0.1 \ 0.2 \ 0.1 \ 0.2 \ 0.1 \ 0.9 \ 0],
\]

\[
A^{\text{final}}_{(1)} = [0.30 \ 0.08 \ 0.06 \ 0.10 \ 0.08 \ 0.30 \ 0.65 \ 0.04].
\]

Figure 4 shows the graph for all the concepts applying Eqs. (1) and (2). It is evident that the concepts do not lead the Industry 4.0 tendency to a good point in the future through this scenario.

**Scenario 2:** In this scenario, it is assumed that Industry 4.0 is well managed at a moderate level. The initial vector \(A\) of this scenario is as follows:

\[
A^{\text{initial}}_{(2)} = [0.5 \ 0.4 \ 0.5 \ 0.4 \ 0.5 \ 0.4 \ 0.5 \ 0],
\]

\[
A^{\text{final}}_{(2)} = [0.45 \ 0.18 \ 0.15 \ 0.21 \ 0.18 \ 0.45 \ 0.53 \ 0.12].
\]

The graph for all the concepts in this scenario is drawn in Figure 5 by calculating Eqs. (1) and (2). It is observed that the Industry 4.0 tendency experiences a developing trend for a while and then, the development is attenuated. The reason is the favorable effect of moderately good management of other concepts.
Scenario 3: In this scenario, it is assumed that all the concepts in the organization are well managed. This scenario is the best one among all. The organization manages all of its processes in accordance with Industry 4.0. The initial vector $A$ of this scenario is as follows:

$$A^{initial}_{[3]} = [0.9 0.8 0.9 0.9 0.8 0.1 0].$$

$$A^{final}_{[3]} = [0.70 0.91 0.94 0.89 0.91 0.69 0.34 0.95].$$

Figure 6 for all the concepts in this scenario following Eqs. (1) and (2) indicates that after four iterations, Industry 4.0 tendency reaches an equilibrium point and the already well-conducted concepts lead it to the desired level. In this situation, the organization can easily adapt to the current competitive conditions.

5. Conclusion

Organizations desire to continuously develop by adapting to the changing conditions and they strive to get ahead of other organizations. In this regard, it is necessary for them to determine and apply their strategies correctly. Organizations need to know about their current situation and be aware of how certain concepts can directly affect them in adopting short- or long-term strategies.

This paper was aimed at determining which concepts would change the Industry 4.0 tendency and to what extent by employing FCMs as a good method for modeling complex systems. The IMPULS model criteria were considered for the FCMs method. The main contributions of the present research were determining the Industry 4.0 level for a considered organization and providing useful insights about the future Industry 4.0 tendency using the FCMs method.

The concepts affecting Industry 4.0 were interpreted using three different scenarios. Scenario 1 dealt with an organization in which all the concepts in the developed Industry 4.0 model were poorly managed. Scenario 2 considered a better management level than that in Scenario 1. Finally, Scenario 3 accounted for an organization in which all concepts were well managed in the current situation. In all the three scenarios, the output concept was set to zero as an initial value in order to better address the tendency. The steady state of Industry 4.0 tendency (C8) for the first, second, and third scenarios was 0.04, 0.12, and 0.95, respectively. The number of steps until reaching a steady state was also important in the study.

Strategy and organization (C1), smart operation (C2), and smart factory (C3) concepts were found to make the most significant contribution to the Industry 4.0 level in the static analysis. When these concepts are managed well, the Industry 4.0 level will be in a better status in the future and the number of steps to reach a steady state will decrease as well.

In today’s world, the need for fulfilling the Industry 4.0 requirements is becoming more and more popular among organizations. Accordingly, the Industry 4.0 tendency of organizations was analyzed with the help of the developed model and FCMs to provide them with insights about their status of development.

The presented research study faced two limitations. First, the developed model was implemented based on opinions of three expert. Although the number of experts may be sufficient to demonstrate accuracy and applicability of the model, by increasing the number of experts, better results can be obtained. Second, modelling of the systems is complex and unstable; moreover, the changes that may affect the system are not fully known. In processes such as Industry 4.0, organizations sometimes encounter unexpected external and internal problems, which are very difficult to foresee.

The FCMs approach, which is a decision support method, is suitable for complex models in the literature. Integration of different methods into FCMs seems promising for the future.

References

1. Lisi, H., Fettke, P., Kemper, H.-G., Feld, T., et al. “Industry 4.0”, Bus. Inf. Syst. Eng., 6(3), pp. 239–242 (2014).
2. Shrouf, F., Ordieres, J., and Miragliotta, G. “Smart factories in Industry 4.0: A review of the concept
and of energy management approached in production based on the Internet of Things paradigm”, *IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 697–701 (2014).

3. Lichtblau, G., Stich, V., Berentnath, R., Blum, M., et al., *IMPULS – Industrie 4.0 – Readiness*, Impuls-Stift. VDMA (2015).

4. Lanza, G., Nylais, P., Majid, A.S., Kuprat, T., et al. “Empowerment and implementation strategies for Industry 4.0”, *Technische Informationsbibliothek, 111*(1–2), pp. 76–79 (2016).

5. Pricewaterhouse Coopers, “The Industry 4.0: Digital operations self assessment” (2016).

6. Rockwell Automation “The connected enterprise maturity model” (2014).

7. Oberstereich “Intelligent production for institution” (2015).

8. Schmieder, A., Erol, S., and Sih, W. “A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises”, *Procedia CIRP, 52*, pp. 161–166 (2016).

9. Rice water house cooper’s. “Industry 4.0: Building the digital enterprise” (2016).

10. Rowhaninamash, A. and Akbarzadeh-T, M.R. “Perception-based heuristic granular search: Exploring uncertainty for analysis of certain functions”, *Sci. Iran., 18*(3), pp. 617–626 (2011).

11. Booker, J.M. and Ross, T.J. “An evolution of uncertainty assessment and quantification”, *Sci. Iran., 18*(3), pp. 669–676 (2011).

12. Itadov, N. “Determination of the risk factors impact on the construction projects implementation using fuzzy sets theory”, *Acta Phys. Pol. A., 130*(1), pp. 107–111 (2016).

13. Aqar, N.G., Egriogut, A., and Koran, R. “Real time visual servoing of a 6-dof robotic arm using fuzzy-pid controller”, *Acta Phys. Pol. A., 128*(2B), pp. 348–352 (2015).

14. Kosko, B. “Fuzzy cognitive maps”, *International Journal of Man-Machine Studies, 24*, pp. 65–75 (1986).

15. Axelrod, R., *Structure of Decision: The Cognitive Maps of Political Elites*, Princeton University Press (1976).

16. Groumpos, P.P., *Fuzzy Cognitive Maps: Basic Theories and Their Application to Complex Systems*, Springer, pp. 1–22 (2010).

17. May, A.D., Lotfi, A., Langensiepen, A., Lee, K., et al. “Human emotional understanding for empathetic companion robots”, *Advances in Computational Intelligence Systems, 513*, pp. 277–285 (2017).

18. Nielas, A. and Doulas, H. “Developing robust climate policies: A fuzzy cognitive map approach”, *Robustness Analysis in Decision Aiding, Optimization, and Analytics*, pp. 230–263 (2016).

19. Amirkhani, A., Papageorgiou, E.I., Mosavi, M.R., and Mohammadi, K. “A novel medical decision support system based on fuzzy cognitive maps enhanced by intuitive and learning capabilities for modeling uncertainty”, *Appl. Math. Comput., 337*, pp. 562–582 (2018).

20. Romero-Córdoba, R., Olivas, J.A., Romero, F.P., Alonso-Gonzalez, F., et al. “An application of fuzzy prototypes to the diagnosis and treatment of fuzzy diseases”, *Int. J. Intell. Syst., 32*(2), pp. 191–210 (2017).

21. Sarlak, D.T. and Arthi, K. “Efficient breast cancer classification using improved fuzzy cognitive maps with csom”, *Int. J. Appl. Eng. Res., 11*(4), pp. 2478–2485 (2016).

22. Bevilacqua, M., Cianpica, F.E., and Mazzuto, G. “Fuzzy cognitive maps for adverse drug event risk management”, *Saf. Sci., 102*, pp. 194–210 (2018).

23. Han, Y., Lu, Z., Du, Z., Luo, Q., et al. “A YinYang bipolar fuzzy cognitive TOPSIS method to bipolar disorder diagnosis”, *Comput. Methods Programs Biomed., 158*, pp. 1–10 (2018).

24. Chen, C.T. and Chiu, Y.T. “A study of fuzzy cognitive map model with dynamic adjustment method for the interaction weights”, *International Conference on Advanced Materials for Science and Engineering (ICAMSE)*, pp. 699–702 (2016).

25. Case, D.M. and Stylios, C.D. “Fuzzy cognitive map to model project management problems”, *Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS)*, pp. 1–6 (2016).

26. Ribeiro, M.I.F., Ferreira, F.A.F., Jalali, M.S., and Meiduté-Kavaliuskiené, I. “A fuzzy knowledge-based framework for risk assessment of residential real estate investments”, *Technol. Econ. Dev. Econ., 23*(1), pp. 140–156 (2017).

27. Ferreira, F.A.F., Ferreira, J.M.I., Fernandes, C.I.M.A.S., and Meiduté-Kavaliuskiené, I. “Enhancing knowledge and strategic planning of bank customer loyalty using fuzzy cognitive maps”, *Technol. Econ. Dev. Econ., 23*(6), pp. 860–876 (2017).

28. Papageorgiou, E.I., Hatwagner, M.F., Buruzas, A., and Kóczy, L.T. “A concept reduction approach for fuzzy cognitive map models in decision making and management”, *Neurocomputing, 232*, pp. 16–33 (2017).

29. Pacilcy, F.C.A., Groot, J.C.J., Hofstede, G.J., Schaap, B.F., et al. “Analysing potato late blight control as a social-ecological system using fuzzy cognitive mapping”, *Agron. Sustain. Dev., 36*(2), p. 35 (2016).

30. Vassileiou, J.M. and Jensen, O.P. “Fuzzy cognitive mapping in support of integrated ecosystem assessments: Developing a shared conceptual model among stakeholders”, *J. Environ. Manage., 166*, pp. 348–356 (2016).

31. Natara jan, R., Subramanian, J., and Papageorgiou, E.I. “Hybrid learning of fuzzy cognitive maps for sugarcane yield classification”, *Comput. Electron. Agric., 127*, pp. 147–157 (2016).
32. Mustapla, I., Ali, B.M., Sali, A., Rasid, M.F.A., et al. “An energy efficient reinforcement learning based cooperative channel sensing for cognitive radio sensor networks”, *Pervasive Mob. Comput.*, 35, pp. 165-184 (2017).

33. Kim, J., Han, M., Lee, Y., and Park, Y. “Futuristic data-driven scenario building: Incorporating text mining and fuzzy association rule mining into fuzzy cognitive map”, *Expert Syst. Appl.*, 57, pp. 311-323 (2016).

34. Amer, M., Daim, T.U., and Jetter, A. “Technology roadmap through fuzzy cognitive map-based scenarios: the case of wind energy sector of a developing country”, *Technol. Anal. Strateg. Manag.*, 28(2), pp. 131-155 (2016).

35. Kyriakarakos, G., Dounis, A.I., Arvanitis, K.G., and Papadakis, G. “Design of a fuzzy cognitive maps variable-load energy management system for autonomous PV-reverse osmosis desalination systems: A simulation survey”, *Appl. Energy*, 187, pp. 575-584 (2017).

36. Çolan, V. and Onar, S.C. “Modelling solar energy usage with fuzzy cognitive maps”, *Intelligence Systems in Environmental Management: Theory and Applications*, pp. 159-187 (2017).

37. Didson, J.A. and Kosko, B. “Virtual worlds as fuzzy cognitive maps”, *Proceedings of IEEE Virtual Reality Annual International Symposium*, pp. 471-477 (1993).

38. Bagdatli, M.E.C. “Kanayolu projelerinin fayda-maliyet analizleri için risk eldendiği yeni bir bilanç bilisel harita modeli”, Sakarya University (2016).

39. Sánchez, J.A. and Gómez, A.T. “Applications of fuzzy regression in actuarial analysis”, *J. Risk Insur.*, 70(4), pp. 665-699 (2003).

**Biographies**

**Alper Kiraz** received his PhD from Sakarya University. He is an Assistant Professor in the Department of Industrial Engineering at Sakarya University, where he has been a faculty member since 2007. He has been an Assessor of the EFQM (European Foundation for Quality Management) excellence model since 2015. His research interests are fuzzy logic, artificial neural networks, multi-criteria decision making methods, quality management, optimization, and virtual laboratories. He joined several conferences in his research area and has published about 30 conference papers, six articles in indexed journals, three book chapters, three national research projects, etc. He has served the Journal of Computer Engineering & Information Technology and Sakarya University Journal of Science as a referee.

Özer Uygun was born in Sakarya, Turkey, in 1976. In 1994, he entered the Department of Industrial Engineering at Sakarya University and received his BSc in Industrial Engineering in 1999. He also obtained his MSc in 2002 and PhD in 2008 in Industrial Engineering from the same university. He took an academic position at Marmara University and worked as a lecturer between 2000 and 2003. Afterwards, he was a Research Assistant at Sakarya University between 2003 and 2008. Now, he is an associate professor at this university. He was a researcher in EU FP6 Network of Excellence (IPROMS: 2004-2009) and FP6 STREP Project (IWARD: 2007-2009). He successfully completed the EFQM assessor training in Brussels in 2015.

**Enes Furkan Erkan** was graduated from Sakarya University in 2015. He has been working at the same university as a research assistant since 2015. He is associated with topics including fuzzy logic, fuzzy multi-criteria decision making methods, institutionalization, and management systems. He received his MD from Sakarya University in 2017.

**Onur Canpolat** is currently a Research Assistant in the Department of Industrial Engineering at Sakarya University, Turkey. He received BSc and MSc degrees in Industrial Engineering from the same university in 2012 and 2016, respectively, where he is currently a PhD candidate. His areas of interest include multi-criteria decision making, operations research, fuzzy logic, process planning, scheduling, and optimization.