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Research Note

Fuzzy cognitive mapping approach to the assessment of Industry 4.0 tendency

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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.

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

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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-

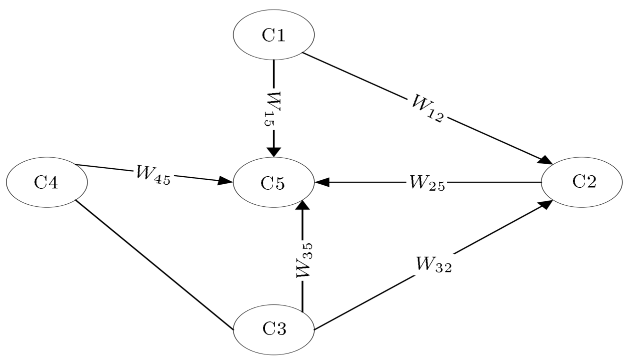

Figure 1. Structure of Fuzzy Cognitive Maps (FCMs).

Table 1. Industry 4.0 evaluation models in the literature.

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	Medical
[20]	Decision support systems	
[21]	Classification	
[22]	Decision support systems	
[23]	Decision support systems	
[24]	Modelling	Engineering
[25]	Modelling and decision support systems	
[26]	Decision support systems	Business
[27]	Information representation	
[28]	Classification and decision support systems	
[29]	Decision support systems	Environment and agriculture
[30]	Policy scenarios	
[31]	Classification	
[32]	Optimization, modelling	Information technologies
[30]	Modelling	
[33]	Policy scenarios	
[34]	Policy scenarios	Energy
[35]	Modelling, optimization, prediction	
[36]	Modelling, policy scenarios	

crease/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:

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

where $A_i^{(k+1)}$ is the value of concept C_i at step $(k+1)$, $A_j^{(k)}$ 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:

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

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

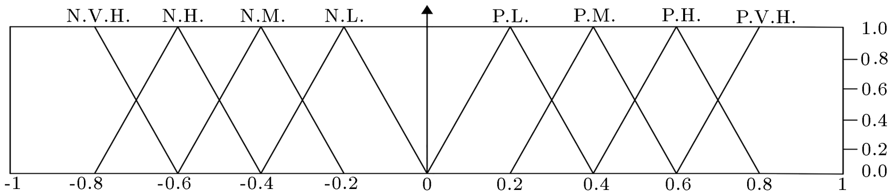

Figure 2. Numerical equivalents of linguistic variables.

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.

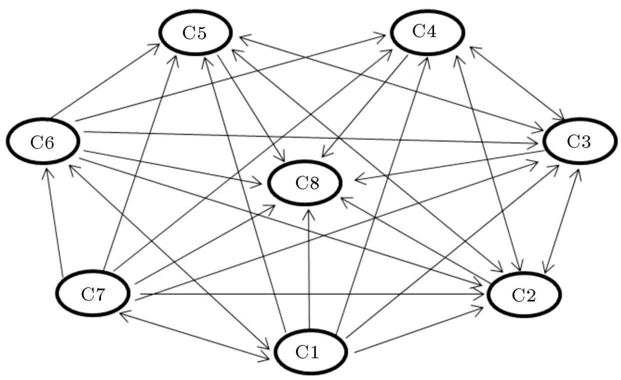

Figure 3. Industry 4.0 relationship map.

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.

$$D_i = \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij}, \tag{4}$$

$$R_j = \sum_{j=1}^{N} \sum_{i=1}^{N} W_{ji}, \tag{5}$$

where i indicates columns and j represents the number

$$W = \frac{\sum_{i=1}^{n} x_i \times u(x_i)}{\sum_{i=1}^{n} u(x_i)},$$

$$W_{C1\rightarrow C8} = \frac{((0.6\times 0) + (0.8\times 1) + (1\times 0) + (0.4\times 0) + (0.6\times 1) + ... + (0.6\times 0))}{(0+1+0+0+1+0+0+1+0)} = 0.733. \tag{3}$$

Box I

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	0.733	–0.800	0.733
C2	0	0	0.600	0.600	0.600	0	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

of rows. 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.

Table 5. Causality matrix.

	D	$D+R$	$D-R$
C1	5.265	6.531	3.999
C2	2.467	5.2	−0.266
C3	1.666	4.932	−1.6
C4	1.066	3.399	−1.267
C5	1.2	3.733	−1.333
C6	2.667	3.867	1.467
C7	3.467	4.267	2.667
C8	0	3.667	−3.667

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:

$$A_{(1)}^{initial} = [0.1\ 0.2\ 0.1\ 0.1\ 0.2\ 0.1\ 0.9\ 0],$$

$$A_{(1)}^{final} = [0.30\ 0.08\ 0.06\ 0.10\ 0.08\ 0.30\ 0.65\ 0.04].$$

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:

$$A_{(2)}^{initial} = [0.5\ 0.4\ 0.5\ 0.4\ 0.5\ 0.4\ 0.5\ 0],$$

$$A_{(2)}^{final} = [0.45\ 0.18\ 0.15\ 0.21\ 0.18\ 0.45\ 0.53\ 0.12].$$

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.

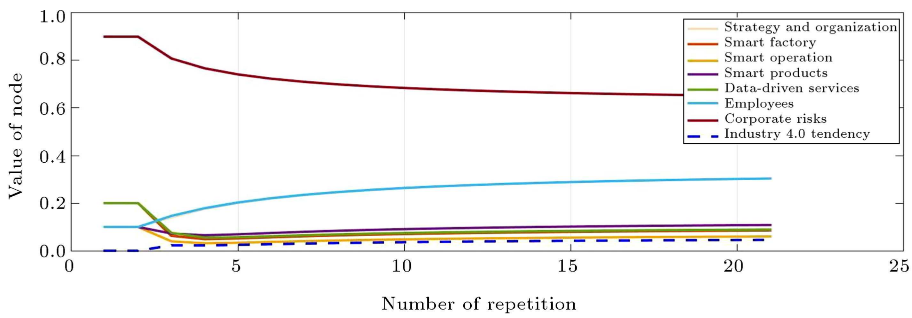

Figure 4. Graph of Scenario 1.

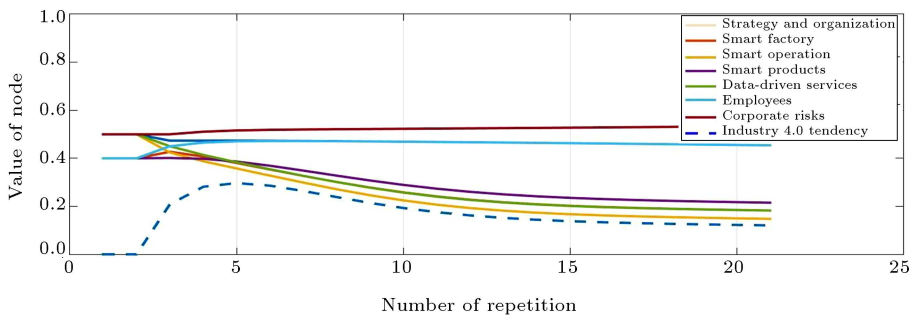

Figure 5. Graph of Scenario 2.

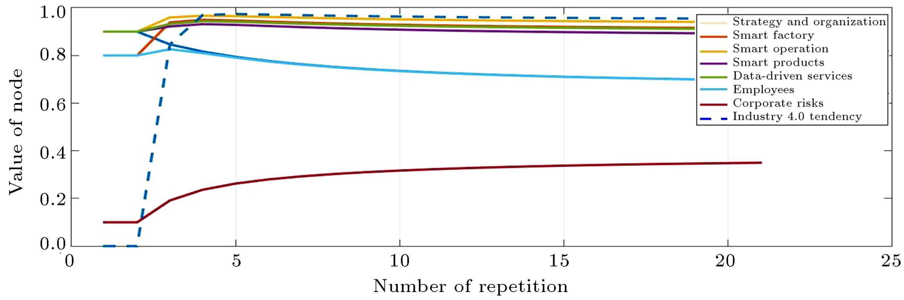

Figure 6. Graph of Scenario 3.

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:

$$A_{(3)}^{initial} = [0.9\ 0.8\ 0.9\ 0.9\ 0.9\ 0.8\ 0.1\ 0],$$

$$A_{(3)}^{final} = [0.70\ 0.91\ 0.94\ 0.89\ 0.91\ 0.69\ 0.34\ 0.95].$$

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.

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