

Performance evaluation of SMEs towards Industry 4.0 using fuzzy group decision making methods



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Received: 19 November 2019 / Accepted: 21 January 2020 / Published online: 6 February 2020 © Springer Nature Switzerland AG 2020

Abstract

The concept of Industry 4.0 is becoming increasingly important. Many technologies are used with Industry 4.0 such as the Internet of Things, Cyber-Physical Systems, Big Data. These technologies have begun to be used by companies. In this article, the technologies used in smart factories are explained in detail. Literature searches were made for Industry 4.0, Fuzzy Analytic Hierarchical Process (Fuzzy AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS). Then, the comparison was made on the application and utilization rates of the technologies determined among the enterprises using the Industry 4.0 technologies. In this study, Fuzzy AHP and Fuzzy TOPSIS methods, which are used frequently in the literature and which determine the criteria and importance weights, are used in complex conflicting situations. The criteria were weighted by the Fuzzy AHP method and then the alternatives were ranked with the Fuzzy TOPSIS approach. It is expected that this study will shed light on companies in the transition to Industry 4.0 and the selected pilot companies for this application will benefit from this work in the context of seeing and developing their own deficiencies.

Keywords Industry 4.0 · Multi-criteria decision making · Smart factory · Fuzzy TOPSIS · Fuzzy AHP

1 Introduction

The concept of Industry 4.0, which was first used in Hannover in Germany in 2011 is becoming increasingly important [29]. At the same time, together with Industry 4.0, the notions of smart cities, smart houses, and smart factories have begun to take place in our lives. In this work, the concept of the smart factory, which has been focused on, contains many technologies. The use of these technologies varies by sector and people also describe Industry 4.0 technologies in different numbers and varieties. Oesterreich and Teuteberg have defined these technologies like the Internet of Things (IoT), Big Data, 3D Printing, Augmented Reality, Cloud Computing and Cyber-Physical Systems (CPS) or Embedded systems [20]. Among the technologies of Industry 4.0 that Bortolini et al. [5] have shown with the figure is an Internet of Things, Big Data, Real-Time Optimization, Cloud Computing, Cyber-Physical Systems, Additive Manu evaluations fracturing, Cobot, Augmented Reality and Machine Learning.

The smart factory, Fig. 1, has shown that the real and virtual world is integrated with the internet of objects as follows. The number of products produced by CPS is known at the same time. Simulation of the product is seen during the design phase. With Additive Manufacturing, it is possible to produce products at once without loss of material. The barcodes used in RFID make it easy to identify the products, flow of product and load the product.

While the first three industrial revolutions emerged as the result of electricity, Information Technology (IT) and mechanization, the Fourth Industrial Revolution has come into being through the creation of the IoT. Cyber-Physical

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SN Applied Sciences (2020) 2:355 | https://doi.org/10.1007/s42452-020-2085-9

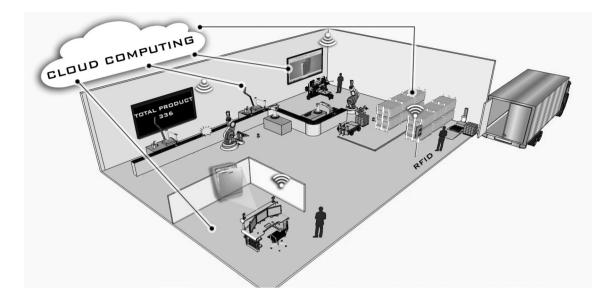


Fig. 1 Smart factory

Systems consists of an intelligent machine, storage systems, and production facilities that initiate and maintain events that can interact independently of each other. Specially defined smart products include past, future, and instant processes. It continues to progress in alternative ways that it has without any intervention [15]. Industry 4.0 has a flexible structure to meet a wide range of customer requirements. The system can be automatically reconfigured when a new product is desired to be produced. Because the machines are easily integrated into the system in the plug and play the production continues without interruption as the new machine enters the system in defects. Looking at the smart factory, it will be seen that products with small quantities are produced more efficiently by reducing set-up times. By using Big Data source, the amount to be produced and the raw material needs can be determined in the most suitable way. Advanced technology machines provide energy savings during break times and include speed control motors. The machines can run automatically without too much human intervention. As people and machines can communicate with each other through the cloud, remote maintenance and repair work are possible [36].

Against the background of natural catastrophes or political, economic crises, Industry 4.0 can help to get rid of this loss with minimal damage by running simulations of bad situations. In those cases, the manufacturer who has to change the supplier can choose the best supplier with simulations [15].

In horizontal integration, the software used by the enterprise and the software used by the suppliers works in an integrated manner. Vertical integration is the creation

SN Applied Sciences A Springer Nature journal and communication of the relation of all the data in the business. This event object embedded in software, RFID chips and used SCADA, MES, ERP system is realized through the interaction [11].

Decision-making is one of the indispensable processes of human life, and decision making becomes more difficult as systems become more complex. Initially, decisions were made for a single goal, but now it becomes too much for the purpose. As technology improves and environmental factors of businesses change, individuals or businesses want to make multi-objective decisions. While trying to optimize multiple goals, businesses trying to minimize time and cost are having trouble deciding on this process because of the complexity. Studies have been made for the solution of the multi-objective decision-making problem and methods have been developed. It has been observed that successful results are obtained when applied methods are applied [34].

Multi-Criteria Decision Making (MCDM) techniques were first developed in 1960 [25]. Different types of MCDM methods are applied in most researches. Also, in the case of many criteria, MCDM methods hybrid methods are used so that the decision-maker can better understand and conceive the event [26]. Multi-criteria decision-making methods help the decision-maker to make more informed decision-making is unclear, complex situations [24].

When the literature is examined, it is seen that many different MCDM approaches are used, such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Elimination and Choice Translating Reality English (ELECTRE), Analytic Hierarchical Process (AHP), The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Analytic Network Process (ANP), Simple Additive Weighting (SAW), Decision Making Trial and Evaluation Laboratory (DEMATEL) are used in the applications. In this study, Fuzzy TOPSIS and Fuzzy AHP will be used for the evaluation of the alternatives based on the defined criteria.

The rest of the paper organized as follow. Chapter 2 which is the literature review was conducted for Industry 4.0 and MCDM techniques. In chapter three, Fuzzy TOPSIS and Fuzzy AHP approach solution steps are explained. In Chapter four, a case study was conducted to draw attention to Industry 4.0 technologies as well as to apply fuzzy MCDM techniques. In the last section, an evaluation was made about Industry 4.0, and future perspective shared.

2 Literature review

As a result of an extensive literature review, it has not been found that the technologies used in smart factories are determined by MCDM. According to the researches that have been made in the smart factories, the characteristics that the smart factories should have been determined by various researchers. They are not based on scientific researches.

G. Reischauer mentioned that Industry 4.0 is a trend initiated by the German government as a national innovation policy in his study. In 2013, BITKOM (Information Technology, Telecommunication, and New Media Association), VDMA (Mechanical Engineering Industry Association) and ZVEI (Electrical and Electronic Manufacturers Association) cooperated to establish the 'Industry 4.0 platform'. By 2015, the platform was opened with the participation of various trade union and association members, academicians and politicians in a very large amount. The author compares the long-wave theory and innovation-discursive view, in terms of Industry 4.0. Within Industry 4.0, innovations should be made and implemented as coordination between businesses, academia, and politics. This coordination forms the basis of the Triple Helix model. A province in Germany has been shown as an example for Industry 4.0 to be implemented in an effective manner. In these cities, companies, academia and policy resources to form a cluster, easy reach is working in a coordinated [22].

Ahuett-Garza and Kurfess [1], described several Industry 4.0 technologies in their studies. These technologies are Big Data, Machine Learning, Robotics, Internet of Things, Cyber-Physical Systems and Additive Manufacturing. Among these technologies, the Internet of Things, additive manufacturing, machine learning, and Cyber-Physical Systems are explained. Easily assembled data from environments where Industry 4.0 is used, transformed into information or used with machine learning to make effective decisions [1]. Ancarini et al. analyzed competitive priorities that could lead backshoring companies to adopt new technologies. For this reason they used secondary data of 495 relocation initiatives in Europe to analyze the adaptation of new technologies [2].

Vaidya et al. have explained comprehensively which nine pillars of Industry 4.0 and challenges. Industry 4.0 consists of nine pillars: Big Data and Analytics, Autonomous Robots, Simulation, Horizontal and Vertical System Integration, Internet of Things, Cybersecurity and Cyber-Physical Systems, The Cloud, Additive Manufacturing, Augmented Reality. Vaidya talked about the problems and challenges related to Industry 4.0: In intelligent production systems, automation and self-managing systems must be found, unlike the lack of automation in today's systems. IWN protocols should be fast enough. it is difficult to record the data and ensure its completeness. The system should be designed so that the system can manage its own production system. Security measures must be taken against the cyber-attack. Industry 4.0 application requires high costs. Modular systems that provide continuity and flexibility in production are needed [35]. Frank et al. proposed a conceptual framework to analyze adoption patterns of Industry 4.0. For this purpose they performed a survey in 92 manufacturing companies to evaluate implementation of front-end and base technologies of Industry 4.0 [13].

With Industry 4.0, new risks arise in the design-changing industries. For that reason, a different approach to risk management should be developed. New types of risk have been identified against increasing threats such as piracy, cyber-attacks. The robot, machine, etc. the best way to protect these tools is Information and Communication Technologies (ICT). In addition to the accessibility of information, the correct handling of information is also a responsibility for information security. An integrated multi-directional management system with standards should be established. The implementation of the management system with reference to Deming's PDCA (Plan-Do-Check-Act) cycle has been comprehensively prepared. According to the authors' research, there is no work that has integrated Key Performance Indicators (KPI) and Key Risk Indicator (KRI). The risks identified are grouped into groups and colored according to their importance (operational or strategic). The identified risks are monitored by the KRIs that affect the KPIs associated with institutional performance. In addition, risks can be grouped individually [33].

Sung described the Industry 4.0, its scope, its difficulties, and its implications in his study. According to Sung Industry 4.0 has four design principles. These are connections, decentralized decisions, information transparency, and technical assistance. The Korean government recognized Industry 4.0 in favor of the. But it cannot fully implement the industry as a result of the inadequate implementation and operation. Suggestions have been made for the successful implementation of Industry 4.0 in Kore [29]. Tjahjono et al. point out that in the context of Industry 4.0 a supply chain. They have evaluated the opportunities and threats of Industry 4.0 technology in the supply chain, storage, and transportation [32]. Cinar has worked on the selection of bank branches. She used the Fuzzy TOPSIS method. Five criteria and alternatives have been identified. The most important criterion in opening a new branch is determined as population density [9]. Tekez and Bark have made a study for furniture factory supplier selection. There are 6 criteria and 6 alternatives in the studies they use the Fuzzy TOPSIS method [31].

Sennaroglu and Celebi have determined the weight of the criteria by using the AHP method for the military airport selection problem. Afterward, the best location was determined using PROMETHEE and VIKOR methods. Both methods achieved the same result [24]. Wu et al. conducted a study on supplier selection for the nuclear power industry. The studies that they use the VIKOR method consist of two stages. In order to reduce the complexity in the first stage, qualified ones among the suppliers were selected. In stage 2, the extended VIKOR method under linguistic information is proposed [38].

Sisman and Dogan have conducted a study evaluating the financial performance of banks. The weights of the criteria were determined with the fuzzy AHP, and the problem was solved with the Fuzzy MOORA. Ten banks are evaluated under ten criteria [27].

Ertugrul and Karakasoglu have studied on computer selection. While using Fuzzy AHP in weighting criteria, they use the ELECTRE method to solve the problem [12]. In Manouselis and Costopoulou's articles have extensively researched, analyzed and classified the multi-criteria recommender system [18] (Table 1).

3 Methodologies

3.1 Fuzzy AHP

The AHP, a multi-criteria decision-making technique, was first developed by T. Saaty. Since AHP does not fully reflect human thoughts, the Fuzzy AHP method has emerged by combining it with fuzzy logic [23]. In Fuzzy AHP, people are taken into consideration subjective and not precise meaning. It is possible to get more realistic results because of the reason. In the study, only the criteria weights were taken as Fuzzy AHP. But in this chapter, all the steps of the Fuzzy AHP method developed by Buckley have been explained [4, 6].

Step 1 Experts form a matrix \tilde{A}^k by comparing the advantages of the criteria relative to each other. When this comparison is made, the linguistic variables in Table 5 are used. \tilde{d}^k_{ij} represents the linguistic triangular expression of the superiority of the l criterion to the j criterion according to the k decision-maker,

$$\tilde{A}^{k} = \begin{bmatrix} \tilde{d}_{11}^{k} & \tilde{d}_{12}^{k} & \cdots & \tilde{d}_{1n}^{k} \\ \tilde{d}_{21}^{k} & \cdots & \cdots & \tilde{d}_{2n}^{k} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{d}_{n1}^{k} & \cdots & \cdots & \tilde{d}_{nn}^{k} \end{bmatrix}$$
(1)

Step 2 The fuzzy linguistic variables expressed by each decision maker are summed and divided by the number of decision-makers. As a result of this operation, the average \tilde{d}_{ii} value is found,

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{\kappa} \tilde{d}_{ij}^k}{\kappa}$$
⁽²⁾

Step 3 Based on the averages found in step 2, *Ã* matrix a is created again,

$$\tilde{A} = \begin{bmatrix} \tilde{d}_{11} & \cdots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \cdots & \tilde{d}_{nn} \end{bmatrix}$$
(3)

Step 4 The geometric mean of each fuzzy comparison value is calculated,

$$\tilde{r}_i = \left(\prod_{j=1}^n \tilde{d}_{ij}\right)^{\frac{1}{n}}$$
 $i = 1, 2, 3 ..., n$ (4)

Step 5 Weights for each criterion are found in the form below,

The vector sum of each \tilde{r}_i is found. – 1 power of the vector sum is calculated.

To find the fuzzy weight of each criterion, the value of each \tilde{r}_i is multiplied by the vector,

$$\widetilde{w}_{i} = \widetilde{r}_{i} \otimes \left(\widetilde{r}_{1} \oplus \widetilde{r}_{2} \oplus \dots \oplus \widetilde{r}_{n}\right)^{-1} = \left(\mathsf{I}w_{i}, mw_{i}, uw_{i}\right)$$
(5)

Step 6 The fuzzy \tilde{w}_i value is done de-fuzzified,

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \tag{6}$$

Step 7 M_i value is normalized,

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| Table 1 Summary of the related researches | d rese | arches | | |
|---|--------|--|-----------------------|---|
| Author | Year | Article Name | Method | Subject |
| Sennaroglu and Celebi [24] | 2018 | 2018 A military airport location selection by AHP integrated PROMETHEE and VIKOR methods | AHP PROMETHEE VIKOR | A location selection problem for a military airport using multiple criteria decision-making methods |
| Reischauer [22] | 2018 | 2018 Technological Forecasting and Social Change Industry 4.0 as a policy-driven discourse to institutionalize innovation systems in manufacturing | Review | Industry 4.0 application in manufacturing |
| Vaidya et al. [35] | 2018 | 2018 Industry 4.0—A Glimpse | Review | Nine pillars of Industry 4.0 |
| Sung [29] | 2017 | 2017 Industry 4.0: A Korea perspective | Review | The relationship between Korea and Industry 4.0 |
| Tupa et al. [33] | 2017 | 2017 Aspects of risk management implementation for Industry 4.0 | Review | Industry 4.0 and Risk management |
| Tjahjono [32] | 2017 | 2017 What does Industry 4.0 mean to Supply Chain? | Review | Supply Chain and Industry 4.0 |
| Sisman and Dogan [27] | 2016 | 2016 Evaluation of Financial Performance of Turkish Banks with Fuzzy AHP and Fuzzy MOORA Methods | Fuzzy AHP Fuzzy MOORA | To evaluate the financial performance of 10 deposit banks traded in Borsa Istanbul (BIST) by integrating Fuzzy AHP and fuzzy MOORA approaches |
| Çinar [9] | 2010 | 2010 Fuzzy TOPSIS Method in Selection of Establishment and An Fuzzy TOPSIS Application in Banking Sector | Fuzzy TOPSIS | Choosing the most suitable place to open a bank branch with the MCDM approach |
| Ertugrul and Karakasoglu [12] | 2010 | Ertugrul and Karakasoglu [12] 2010 Computer Selection for a Company with ELECTRE and Fuzzy AHP Methods | Fuzzy AHP ELECTRE | To help the decision-making process in organizations by using ELECTRE and Fuzzy Analytic Hierarchy methods. |
| Kaptanoglu and Özok [16] | 2006 | 2006 A fuzzy model for academic performance evaluation | Fuzzy AHP | Proposed a Fuzzy AHP model to evaluate academicians performance |
| | | | | |

$$N_i = \frac{M_i}{\sum_{i=1}^n M_i} \tag{7}$$

3.2 Fuzzy TOPSIS

Human judgments are inconsistent, subjective and numerically difficult to express. In this sense, fuzzy logic has emerged first. It is better to use linguistic value instead of a numeric value. The Fuzzy TOPSIS method is a method that helps group decision making in a fuzzy environment with a flexible structure that deals with the criterion values of both qualitative and quantitative decision criteria. In the fuzzy TOPSIS method, the best solution is reached at the closest distance to the positive ideal solution and the distance where the negative ideal solution is farthest [7, 10, 28]. The Fuzzy TOPSIS method, which is one of the MCDM methods to be used in this study, is based on the TOPSIS method developed and applied by Hwang and Yoon [14].

The steps for the Fuzzy TOPSIS Method are explained below [10].

 Step 1 The group with K decision-makers is created. Criteria and alternatives are determined. X^K_{ij} express that *i*th alternative of *j*th criteria value. The criterion values formulas of alternatives are given below,

$$\check{x}_{ij} = \frac{1}{K} \Big[\check{x}_{ij}^1 + \check{x}_{ij}^2 + \dots \, \check{x}_{ij}^K \Big]$$
 (8)

 Step 2 There are K decision makers, w^K_j express that importance weight of *j*th decision criterion. The importance weight of decision criterion *a* is given below,

$$\check{w}_j = \frac{1}{K} \left[\check{w}_j^1 + \check{w}_j^2 + \dots \, \check{w}_j^K \right]$$
(9)

Step 3 x_{ij} and w_j are linguistic variants for ∀ i, j. These linguistic variables are described by triangular fuzzy numbers with x_{ij} = (a_{ij}, b_{ij}, c_{ij}) and w_j = (w_{j1}, w_{j2}, w_{j3}). Ď fuzzy decision matrix and w the matrix of fuzzy weights is shown below.

$$\check{D} = \begin{bmatrix} \check{x}_{11} & \check{x}_{12} & \dots & \check{x}_{1n} \\ \check{x}_{21} & \check{x}_{22} & \dots & \check{x}_{2n} \\ \dots & \dots & \dots \\ \check{x}_{m1} & \check{x}_{m2} & \dots & \check{x}_{mn} \end{bmatrix}$$
(10)

$$\check{W} = \left[\check{W}_1, \check{W}_2, \dots, \check{W}_n\right] \tag{11}$$

• *Step 4* The normalized fuzzy decision matrix obtained from the fuzzy decision matrix is shown below.

$$\check{R} = \left[\check{r}_{ij}\right]_{m*n} \tag{12}$$

B is the set of benefit criteria, and C is the cost set. Normalization preserves the fact that normalized triangular fuzzy numbers are in the range [0, 1].

$$\check{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \quad j \in B$$
(13)

$$\check{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \quad j \in C$$
(14)

$$c_j^* = \max_i c_{ij} \quad j \in B$$
$$a_j^- = \min_i a_{ij} \quad j \in C$$

• *Step 5* A weighted normalized fuzzy decision matrix is constructed by using different weights of each criterion.

$$\check{V} = [\check{v}_{ij}]_{m*n}$$
 $i = 1, 2, ..., m$ $j = 1, 2, ..., n$ (15)

$$\check{\mathsf{V}}_{ij} = \check{\mathsf{f}}_{ij} \ast \check{\mathsf{W}}_j \tag{16}$$

• Step 6 According to the weighted normalized fuzzy decision matrix, \check{v}_{ij} elements for $\forall i, j$ normalized triangular fuzzy numbers and the weights of those elements are [0, 1] closed weight. The fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution (A^-) are shown below,

$$A^{+} = (\check{v}_{1}^{+}, \check{v}_{2}^{+}, \dots, v_{n}^{+}),$$
(17)

$$A^{-} = (\check{v}_{1}^{-}, \check{v}_{2}^{-}, \dots, v_{n}^{-}),$$
(18)

$$\check{v}_{j}^{+} = (1, 1, 1); \quad \check{v}_{j}^{-} = (0, 0, 0); \quad j = (1, 2, ..., n)$$

 Step 7 Calculation of the distance of each alternative of A⁺ and A⁻ is done by the following formulas,

$$d_i^+ = \sum_{j=1}^n d(\check{\mathbf{v}}_{ij}, \mathbf{v}_j^+), \quad \mathbf{i} = 1, 2, \dots, \mathbf{m}$$
 (19)

$$d_i^- = \sum_{j=1}^n d(\check{\mathbf{v}}_{ij}, \mathbf{v}_j^-), \quad i = 1, 2, ..., m$$
 (20)

The distance measurement between two fuzzy numbers is shown as d (.,.) and this is calculated by the Vertex Method.

• Step 8 The closeness coefficient value is calculated from the following formula,

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$$CC_{i} = \frac{d_{i}^{-}}{d_{i}^{-} + d_{i}^{+}}$$
(21)

The closeness coefficients take a value between 0 and 1, and the closeness coefficient is used to rank the alternatives. The large coefficient of closeness is defined as an indication of the choice of the alternative by decision-makers.

3.3 Criteria definitions

Internet of Things Internet of Things notion was introduced by English entrepreneur Kevin Asthon. This idea was used in 1999 to describe the system with which the real-world and computers communicate with sensors. By 2009, the number of network-connected devices exceeds the world population. The IoT does not only refer to objects but also includes processes, animals and atmospheric phenomena [37]. With the internet of objects, the reliability of equipment will be constantly under control. Providing reliable, accurate and fast information sharing, with good coordination, it will provide advantages in supply chain and it reduces the problems that may arise between supply and demand [21].

Cyber-Physical Systems Integrated into the production process, CPS creates self-governing intelligent factories. It provides information flow between the real world and the virtual world [30]. CPS involved in defense systems, process control, high-confidence medical devices and systems, advanced automotive systems, traffic control and safety, critical infrastructure control [17]. The sensors from the sub-elements of Cyber-Physical Systems can easily identify the failure occurring at any stage of the production and this non-decentralized system continues to function properly [19].

Radio Frequency Identification (RFID) Radio Frequency Identification devices, makes the determination by detecting radio waves. It does not require direct visual sight to read any data [3]. In RFID chips, which are basically composed of a label and reader, each object has its own identification number. These nets contain information about the object. RFID is also used in shopping centres, air-cargo companies, production processes, warehouse management, and inventory control. With RFID tags, detailed information on the machines can be reached, and maintenance times and remaining lifetimes can be easily determined. Processes with accurate information that can be accessed by RFID will continue to be managed effectively without interruption. **Big Data** As life continues, mobility continues and the information is generated at every stage. These innumerable pieces of information are stored somewhere. But most of them do nothing other than stop there. Nowadays populations are getting bigger data, meaningful relationships are formed between these data and the data becomes effective. According to Forrester, there are four components of big data. These are volume, variety, velocity and value [37].

Augmented Reality Augmented reality is one of Industry 4.0's software technology. Augmented reality works at the same time in the human–environment and allows people to interact with both real and virtual objects [5]. Augmented reality is a live, direct or indirect physical appearance of the real-world environment and its contents, enriched generated by computer sound, image, graphics, and GPS data.

Additive Manufacturing It is the process of establishing a rigid form of any 3D object created in virtual environments. This technology reduces raw material waste and creates complex shapes without the need for other tools. In addition, Specific orders based on this technology are produced easily [5].

Cyber Security With the industry's 4.0, internet connections and stored data have increased, which has led to an increase in cyber threats. In addition to this safe and continuous communication, advanced access methods are also needed [35].

Cloud Computing The new computing model called cloud computing is used to store and analyze enormous data sets specific to Industry 4.0 applications. With Industry 4.0, a lot of data is being created and stored. There is a need to share more information both inside and outside the company [35].

4 Case study

This study aimed to make a comparison between businesses using Industry 4.0 technologies. It was made for a limited number of facilities, as there are not many facilities implementing Industry 4.0. The study is carried out for three chemical, automotive and iron-steel production facilities determined in Ankara. This study carried out in the SINCAN Organize Industry and Technology Development Area which is located in Sincan/Ankara. A factory working in the chemical field Company A has 125, a factory working in the automotive field Company B has 320, and a factory working in the steel-iron field Company C has 260 employees. All of these companies are exporting abroad. Company A was established in 2000 and works on paint products, construction products, textile and leather products, pressure-sensitive adhesives, and industrial adhesives. They also carry out new product development and marketing activities in this field. Company B serves as a system supplier to almost all original equipment manufacturers in Turkey. It mainly produces plastic injectionbased products, interior, and exterior lighting products, trim parts and other injection parts. The Company designs its products in-house and also attaches importance to the fact that all its products are registered trademarks. Which produces for the automotive sector. Company C is producing customized products according to production conditions in the iron-steel sector (Tables 2, 3).

Following the determination of the firms, 3 evaluators were selected in order to evaluate the determined criteria and detailed information about the problem was

 Table 2
 Linguistic expressions used for evaluation of alternatives
 [8]
 [8]
 Image: Second Seco

| Linguistic term | Representative | Fuzzy numbers |
|-----------------|----------------|---------------|
| Very-low | VL | (0, 0, 1) |
| Low | L | (0, 1, 3) |
| Medium-low | ML | (1, 3, 5) |
| Medium | М | (3, 5, 7) |
| Medium-high | MH | (5, 7, 9) |
| High | Н | (7, 9, 10) |
| Very-high | VH | (9, 10, 10) |

 Table 3
 Representation of criteria and alternatives

| Criteria name | Representative | Enterprise | Representative |
|-----------------------------------|----------------|------------|----------------|
| Internet of Things | CR1 | Mnf1 | A |
| Cyber-Physical Systems | CR2 | Mnf2 | В |
| Radio Frequency Identification | CR3 | Mnf3 | С |
| Big Data | CR4 | | |
| Augmented Reality | CR5 | | |
| Additive Manufacture | CR6 | | |
| Cyber Security | CR7 | | |
| Cloud Computing | CR8 | | |

 Table 4
 Features of decision-makers

| Experts | Occupation | Organization | Experience |
|---------|---------------------|-----------------------|------------|
| K1 | Industrial Engineer | Professor at academy | 25 |
| K2 | Industrial Engineer | Asst. Prof at academy | 10 |
| K3 | Computer Engineer | Private sector | 15 |

given to them. Criteria such as experience, knowledge, field expertise and impartiality have been paid special attention in the selection of evaluators. The first of the selected decision-maker is a Chemical Engineer with 15 years of experience working in many international companies. The second decision-maker is an engineer with 20 years of field experience and academic research. The third decision-maker is a senior executive who is actively involved in the iron and steel industry. General information about decision-makers is given in Table 4. Criteria were determined as a result of an extensive literature review. Eight criteria were defined which is consist of the most discussed technologies within the scope of Industry 4.0. With Fuzzy AHP, the weights of the criteria were determined. Then these fuzzy solutions were used with fuzzy TOPSIS. The hierarchical structure of criteria and alternatives for enterprise selection is shown in Fig. 2 below.

The decision-makers evaluated the criteria using the linguistic expressions in Table 5. Table 6 was formed after the evaluation.

 W_i values are determined with Eq. (5) and showed in Table 7. The weights are derived from Fuzzy AHP and used in the evaluation of the alternatives in Fuzzy TOP-SIS. The linguistic expressions in the assessment are converted to a fuzzy trapezoid number by using Table 2 and obtain in Table 8.

The fuzzy decision matrix in Table 9 is obtained using the Eq. (8).

The normalized fuzzy decision matrix in Table 10 is obtained using the Eqs. (12), (13) and (14).

The weighted normalized fuzzy decision matrix is obtained from the normalized fuzzy decision matrix and the fuzzy weights matrix with the Eqs. (15) and (16) as in Table 11.

d+ and d- values are obtained from weighted normalized fuzzy decision matrix with Eqs. (19) and (20).

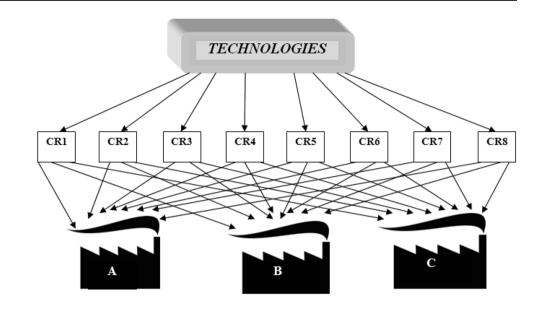


Table 5 The fuzzy scale used for evaluation of criterion [16]

Fig. 2 The hierarchical structure of production facility

selection

| Linguistic term | Fuzzy scale | Response scale |
|-------------------------|-------------|-----------------|
| Equally important | (1, 1, 1) | (1/1, 1/1, 1/1) |
| A little more important | (1, 3, 5) | (1/5, 1/3, 1/1) |
| Essentially important | (3, 5, 7) | (1/7, 1/5, 1/3) |
| Very strong important | (5, 7, 9) | (1/9, 1/7, 1/5) |
| Extreme important | (7, 9, 9) | (1/9, 1/9, 1/7) |

Closeness coefficients of the candidates are calculated with Eq. (21), then candidates are ranked as in Table 12 according to the order of Closeness Coefficients.

 CC_i values were calculated and showed in Fig. 3. It is seen that the best alternative is B when the closeness coefficients are sorted from large to small. B is followed by C and A respectively.

| Table 7 | Weights | of criteria |
|---------|---------|-------------|
|---------|---------|-------------|

| | W _i | | |
|-----|----------------|-------|-------|
| CR1 | 0.174 | 0.390 | 0.798 |
| CR2 | 0.081 | 0.220 | 0.557 |
| CR3 | 0.043 | 0.111 | 0.280 |
| CR4 | 0.011 | 0.022 | 0.067 |
| CR5 | 0.015 | 0.029 | 0.075 |
| CR6 | 0.033 | 0.061 | 0.196 |
| CR7 | 0.035 | 0.066 | 0.188 |
| CR8 | 0.028 | 0.101 | 0.220 |

According to Fig. 3, it is seen that the most important criterion is IoT according to expert opinions. GPS is followed by IoT in order of importance. Considering the importance of the criteria, IoT and CPS are among the

| Table 6 | Fuzzy | pairwise | comparision | matrix of | selection criterion | |
|---------|-------|----------|-------------|-----------|---------------------|--|
| | | | | | | |

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|----|-----------|-----------|-----------|-----------|-----------------|-----------------|-----------------|---------------|
| C1 | (1, 1, 1) | (1, 3, 5) | (3, 5, 7) | (7, 9, 9) | (7, 9, 9) | (3, 5, 7) | (3, 5, 7) | (5, 7, 9) |
| C2 | | (1, 1, 1) | (1, 3, 5) | (5, 7, 9) | (5, 7, 9) | (1, 3, 5) | (1, 3, 5) | (3, 5, 7) |
| C3 | | | (1, 1, 1) | (1, 3, 5) | (3, 5, 7) | (1, 3, 5) | (1, 1, 1) | (1, 3, 5) |
| C4 | | | | (1, 1, 1) | (1/7, 1/5, 1/3) | (1/7, 1/5, 1/3) | (1/5, 1/3, 1) | (1/5, 1/3, 1) |
| C5 | | | | | (1, 1, 1) | (1/7, 1/5, 1/3) | (1/7, 1/5, 1/3) | (1/5, 1/3, 1) |
| C6 | | | | | | (1, 1, 1) | (1, 1, 1) | (1/5, 1/3, 1) |
| C7 | | | | | | | (1, 1, 1) | (1/5, 1/7, 1) |
| C8 | | | | | | | | (1, 1, 1) |

| Table 8 | The opinion of decision-makers (DM) about alternatives in line with the determined criteria | |
|---------|---|--|
|---------|---|--|

| Criteria | Manufacturing | DM 1 | | | DM 2 | | | DM 3 | | | |
|----------|---------------|------|----|----|------|----|----|------|----|----|--|
| CR1 | Mnf1 | 5 | 7 | 9 | 7 | 9 | 10 | 7 | 9 | 10 | |
| | Mnf2 | 9 | 10 | 10 | 7 | 9 | 10 | 7 | 9 | 10 | |
| | Mnf3 | 7 | 9 | 10 | 7 | 9 | 10 | 5 | 7 | 9 | |
| CR2 | Mnf1 | 7 | 9 | 10 | 7 | 9 | 10 | 5 | 7 | 9 | |
| | Mnf2 | 7 | 9 | 10 | 9 | 10 | 10 | 7 | 9 | 10 | |
| | Mnf3 | 5 | 7 | 9 | 5 | 7 | 9 | 7 | 9 | 10 | |
| CR3 | Mnf1 | 3 | 5 | 7 | 3 | 5 | 7 | 5 | 7 | 9 | |
| | Mnf2 | 9 | 10 | 10 | 7 | 9 | 10 | 7 | 9 | 10 | |
| | Mnf3 | 5 | 7 | 9 | 5 | 7 | 9 | 5 | 7 | 9 | |
| CR4 | Mnf1 | 0 | 1 | 3 | 0 | 1 | 3 | 1 | 3 | 5 | |
| | Mnf2 | 5 | 7 | 9 | 5 | 7 | 9 | 9 | 10 | 10 | |
| | Mnf3 | 1 | 3 | 5 | 0 | 1 | 3 | 1 | 3 | 5 | |
| CR5 | Mnf1 | 3 | 5 | 7 | 3 | 5 | 7 | 1 | 3 | 5 | |
| | Mnf2 | 5 | 7 | 9 | 7 | 9 | 10 | 9 | 10 | 10 | |
| | Mnf3 | 3 | 5 | 7 | 5 | 7 | 9 | 5 | 7 | 9 | |
| CR6 | Mnf1 | 5 | 7 | 9 | 5 | 7 | 9 | 3 | 5 | 7 | |
| | Mnf2 | 9 | 10 | 10 | 7 | 9 | 10 | 7 | 9 | 10 | |
| | Mnf3 | 7 | 9 | 10 | 7 | 9 | 10 | 7 | 9 | 10 | |
| CR7 | Mnf1 | 9 | 10 | 10 | 7 | 9 | 10 | 9 | 10 | 10 | |
| | Mnf2 | 3 | 5 | 7 | 3 | 5 | 7 | 3 | 5 | 7 | |
| | Mnf3 | 7 | 9 | 10 | 7 | 9 | 10 | 5 | 7 | 9 | |
| CR8 | Mnf1 | 3 | 5 | 7 | 5 | 7 | 9 | 3 | 5 | 7 | |
| | Mnf2 | 5 | 7 | 9 | 5 | 7 | 9 | 7 | 9 | 10 | |
| | Mnf3 | 3 | 5 | 7 | 1 | 3 | 5 | 1 | 3 | 5 | |

Table 9 Fuzzy decision matrix

| | CR1 | | | CR2 | | | CR3 | | | CR4 | | |
|------|------|------|-------|------|------|-------|------|------|-------|------|------|------|
| Mnf1 | 6.33 | 8.33 | 9.67 | 6.33 | 8.33 | 9.67 | 3.67 | 5.67 | 7.67 | 0.33 | 1.67 | 3.67 |
| Mnf2 | 7.67 | 9.33 | 10.00 | 7.67 | 9.33 | 10.00 | 7.67 | 9.33 | 10.00 | 6.33 | 8.00 | 9.33 |
| Mnf3 | 6.33 | 8.33 | 9.67 | 5.67 | 7.67 | 9.33 | 5.00 | 7.00 | 9.00 | 0.67 | 2.33 | 4.33 |
| | CR5 | | | CR6 | | | CR7 | | | CR8 | | |
| Mnf1 | 2.33 | 4.33 | 6.33 | 4.33 | 6.33 | 8.33 | 8.33 | 9.67 | 10.00 | 3.67 | 5.67 | 7.67 |
| Mnf2 | 7.00 | 8.67 | 9.67 | 7.67 | 9.33 | 10.00 | 3.00 | 5.00 | 7.00 | 5.67 | 7.67 | 9.33 |
| Mnf3 | 4.33 | 6.33 | 8.33 | 7.00 | 9.00 | 10.00 | 6.33 | 8.33 | 9.67 | 1.67 | 3.67 | 5.67 |

Table 10 Normalized fuzzy-decision matrix

| | CR1 | | | CR2 | | | CR3 | | | CR4 | | |
|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Mnf1 | 0.63 | 0.83 | 0.96 | 0.63 | 0.83 | 0.96 | 0.36 | 0.56 | 0.76 | 0.04 | 0.17 | 0.39 |
| Mnf2 | 0.76 | 0.93 | 1.00 | 0.76 | 0.93 | 1.00 | 0.76 | 0.93 | 1.00 | 0.68 | 0.86 | 1.00 |
| Mnf3 | 0.63 | 0.83 | 0.96 | 0.56 | 0.76 | 0.93 | 0.50 | 0.70 | 0.90 | 0.06 | 0.25 | 0.46 |
| | CR5 | | | CR6 | | | CR7 | | | CR8 | | |
| Mnf1 | 0.24 | 0.45 | 0.66 | 0.43 | 0.63 | 0.83 | 0.83 | 0.97 | 1.00 | 0.39 | 0.61 | 0.82 |
| Mnf2 | 0.72 | 0.90 | 1.00 | 0.77 | 0.93 | 1.00 | 0.30 | 0.50 | 0.70 | 0.61 | 0.82 | 1.00 |
| Mnf3 | 0.45 | 0.66 | 0.86 | 0.70 | 0.90 | 1.00 | 0.63 | 0.83 | 0.97 | 0.18 | 0.39 | 0.61 |

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| | 5 | | | | | | | | | | | |
|------|------|------|------|------|------|------|------|------|------|------|------|------|
| | CR1 | | | CR2 | | | CR3 | | | CR4 | | |
| Mnf1 | 0.11 | 0.32 | 0.77 | 0.05 | 0.18 | 0.54 | 0.02 | 0.06 | 0.21 | 0.00 | 0.00 | 0.03 |
| Mnf2 | 0.13 | 0.36 | 0.80 | 0.06 | 0.21 | 0.56 | 0.03 | 0.10 | 0.28 | 0.01 | 0.02 | 0.07 |
| Mnf3 | 0.11 | 0.32 | 0.77 | 0.05 | 0.17 | 0.52 | 0.02 | 0.08 | 0.25 | 0.00 | 0.01 | 0.03 |
| | CR5 | | | CR6 | | | CR7 | | | CR8 | | |
| Mnf1 | 0.00 | 0.01 | 0.05 | 0.01 | 0.04 | 0.16 | 0.03 | 0.06 | 0.19 | 0.01 | 0.06 | 0.18 |
| Mnf2 | 0.01 | 0.03 | 0.07 | 0.03 | 0.06 | 0.20 | 0.01 | 0.03 | 0.13 | 0.02 | 0.08 | 0.22 |
| Mnf3 | 0.01 | 0.02 | 0.06 | 0.02 | 0.06 | 0.20 | 0.02 | 0.05 | 0.18 | 0.01 | 0.04 | 0.13 |
| | | | | | | | | | | | | |

Table 11 Weighted normalized fuzzy-decision matrix

 Table 12
 Positive, negative distances and closeness coefficient value

| | d+ | d– | CC _i |
|---|--------|--------|-----------------|
| A | 0.1847 | 0.0844 | 0.3136 |
| В | 0.0385 | 0.2288 | 0.8558 |
| С | 0.1804 | 0.0900 | 0.3329 |

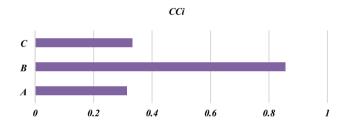


Fig. 3 CC_i values of three SMEs

essential technologies for companies that want to implement the Industry 4.0.

5 Conclusions

Intercompany competition has become indispensable with variable customer demand. As a result of increasing competition, productivity, sustainability, high technology, speed, quality and cost issues in production are gaining importance. In this race, Industry 4.0 technologies provide a great advantage for companies that connect the virtual world and the real world, create meaningful information from big data and prevent time-wasting. In this study, a comparison was made between enterprises using Industry 4.0 technologies. Multi-Criteria Decision-Making techniques were used when making this comparison. MCDM techniques use Fuzzy AHP and Fuzzy TOPSIS instead of classical AHP and classical TOPSIS. The linguistic expressions of decision-makers have been transformed into triangular fuzzy numbers. Because, while making these evaluations, people use uncertain and subjective expressions. Fuzzy helps to achieve more realistic results.

At the same time, it is requested to draw attention to Industry 4.0 technologies. It is desirable to provide general information about Industry 4.0 and Industry 4.0 technologies. With the use of Industry 4.0 technologies, the physical world and the real world will be communicating at the same time. The data will go quickly and efficiently. Significant information will be generated from the data collected without being lost. In these enterprises which have a flexible structure, the resources will be used in the most efficient way.

The study was applied in three chemical manufacturing factory in Ankara as a pilot application. Since the concept of Industry 4.0 is newly emerging in our country, there is a limited number of implementing facilities. With the help of decision-makers, and with the specified criteria, the company that best adapted to Industry 4.0 was identified. Criteria weights are taken from Fuzzy AHP. This comparison was made using the weights of the Fuzzy TOPSIS method. Attention is also drawn to the priorities of Industry 4.0 technologies, which are weighted by experts.

More enterprises will be done with increasing production facilities that will implement the Industry 4.0 approach in the future. Thanks to such applications, enterprises will be able to see their missing points and improve their development. Enterprises wishing to implement Industry 4.0 will have the opportunity to easily implement the Industry 4.0 approach through this application.

In future studies, the rapidly increasing Industry 4.0 literature can be further explored and consulted by experts to improve the number of criteria, thus enabling more accurate assessments. As an evaluation method, the Intuitionistic Fuzzy Analytic Hierarchy Method (IF-AHP) can be used in which decision makers are evaluated among themselves and the decision-makers' opinions are more accurately reflected in the model. Decision making methods can be used. For evaluations, the results can be compared by using Fuzzy ELECTRE, Fuzzy DEMATEL, Fuzzy PROMETHEE techniques. On the other hand, since the effective use of Industry 4.0 technology by firms will increase the quantitative data, the DEA method can be used which allows comparison with the use of numerical data. In addition, hybrid DEA—Fuzzy MCDM approaches that allow the qualitative and quantitative data to be evaluated together can be applied in a way that allows comprehensive evaluation.

Acknowledgements We would like to show our gratitude to the "anonymous" companies for sharing their information and wisdom with us during the course of this research, and we thank our decision-makers for their so-called insights and valuable comments.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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