Advanced Engineering Science
http://publish.mersin.edu.tr/index.php/ades
e-ISSN 2791-8580

Industrial internet of things (IIoT) in energy sector

Çetin Önder İncekara [1]

[1]BOTAŞ, Arazi Edinim Şube Müdürü, BOTAŞ Genel Müdürlüğü, Bilkent, Ankara, Türkiye, cetinincekara@gmail.com

Cite this study: İncekara, Ç. Ö. (2023). Industrial internet of things (IIoT) in energy sector. Advanced Engineering Science, 3, 21-30

Keywords
Industry 4.0
IoT
IIoT
Energy Sector
Fuzzy Logic
Machine Learning
Artificial Intelligence

Research Article
Received: 11.12.2022
Revised: 12.01.2023
Accepted: 15.01.2023
Published:17.01.2023

check for updates

Abstract

Internet of Things (IoT) represents a new production reality. Since 2000 the usage of IoT has been steadily increased in almost every sector, i.e., industry, business, entrepreneurs. The information derived from the data gathered from the new devices connected to the internet, i.e., IoT, can be used to develop new services, improve productivity and efficiency, improve decision making in real time, resolve critical problems and create innovative experiences. "Industry 4.0" concept has the flexibility to achieve interoperability between the different industrial engineering systems. Industrial Internet of Things (IIoT) is used to transfer the data from systems that monitor and control the industrial equipment to data processing systems that cloud computing has shown to be important tools for meeting processing requirements by using Wi-Fi, radio, satellite or cellular networks. In the study interviews with energy experts/managers are performed and fuzzy multi objective mathematical model is developed to calculate IIoT in energy sector. IoT technologies offer greater availability of information throughout the chain of value, allowing for amortization of better tools for decision making. Using sensor devices in energy sector offers automated execution of the processes and the usage of Machine Learning (ML) and Artificial Intelligence (AI) in energy industry allow systems to communicate with each other, making their own decisions. IIoT enables real-time quality monitoring, which helps identify the nonconformities within the processes and energy production sector easily.

1. Introduction

Over the previous decade, the Internet of Things (IoT) revolution has had a significant impact on manufacturing, energy, agriculture, transportation, and other industrial sectors. The Industrial IoT (IIoT) is an industry-specific variant of the IoT, which provides an impressive potential for businesses via connected machines, sensors, and applications. It is one of the most exciting technologies now reshaping industrial enterprises, prompting them to modernize their processes, system intelligence, and facilities in order to cope with emerging disruptive technologies. IIoT improves manufacturing efficiency, safety, scalability, production time, and profitability in the industrial sector.

The worth of the Internet of Things (IoT) market in the energy sector is expected to grow at the Compound Annual Growth Rate (CAGR) of 11.8% over the period of 2021-2025. This embarks a significant impact of using IoT-powered solutions to make the energy sector better and more advanced. The use of sensors has enabled real-time monitoring of productivity, simplified applications, and have remote control over the energy consumption patterns. Major factors that drive the growth of IoT in the energy sector include data management and the advantage of using IoT-based agile systems. The inclusion of IoT helps reduce the challenges and allow the management to evolve through all possible issues coming their way. IoT applications in the energy sector focus on improving asset and industrial efficiency create enhanced revenue generation, and effective resource utilization.

Over time, the entire production logic will change: in the future, intelligent machines, storage systems, operating resources, etc., will be organized independently in real-time-capable systems along the entire value-added chain. The ultimate goal is the Smart Factory. This is characterized by flexibility, resource efficiency and ergonomic design. The integration of customers' and business partners' value-added processes is also part of this.

The emerging "Industry 4.0" concept is an umbrella term for a new industrial paradigm which embraces a set of future industrial developments including cyber-physical systems (CPS), the Internet of things (IoT), the Internet of services (IoS), robotics, big data, cloud manufacturing and augmented reality. Industrial processes need most tasks to be conducted locally due to time delays and security constraints, and structured data needs to be communicated over the internet. Control technology plays a major role in the success of Industry 4.0. It will ultimately control the machines that produce the real products. Anticipated benefits include improved effectiveness, innovation leaps, increased information transparency and competitive advantages.

Transforming the energy sector with IoT technology is an innovative way to promote improved productivity and recognize/arrange the consumption patterns to cut-short the excessive energy usage. In the energy sector, IoT devices have been able to create intelligent networks, i.e., Smart Grids, through the collection, transmission and use of large quantities of data. In this way, it integrates in an intelligent manner all of the assets connected to the network, optimizing operation and increasing the flexibility of the systems.

2. Material and Method

In this study, an integrated Fuzzy AHP- Fuzzy TOPSIS- Fuzzy VIKOR approach is used to assess/evaluate Industrial Internet of Things (IIoT) in Energy Sector. In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers [1-23] by using MATLAB program.

2.1. Fuzzy Multi Criteria Decision Making Methods (FMCDM)

In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers and Fuzzy AHP & Fuzzy TOPSIS are also used in many sectors, i.e. to select best renewable energy resource of Turkey, to select best project, performance evaluation of national R&D companies , to evaluate intelligent timetable, to evaluate the criteria for human resource for science and technology, for analyzing customer preferences, to evaluate risk analysis in green supply chain, and to select machine tools.

2.2. Fuzzy AHP Method

Since the standard AHP method does not include the possibility of situations with ambiguity in the estimation, it is possible to upgrade this method with fuzzy approach. This approach is called the Fuzzy AHP method. Instead of one defined value, in the Fuzzy AHP method full range of values that include unsafe attitudes of decision maker should be generated. For that process it is possible to use triangular fuzzy numbers, trapezoidal or Gaussian fuzzy numbers. The Fuzzy AHP method suggests their application directly in criteria pairs comparison matrix. Triangular fuzzy numbers are used in most cases/problems by many researchers in literature because of this reason in the study triangular fuzzy numbers method is used in Fuzzy AHP method. A triangular fuzzy number that is defined in R set can be described as $\tilde{N}= (l, n, u)$ where l is the minimum, n is the most possible and u is the maximum value of a fuzzy case. Its triangular membership function is characterized below which is presented in Figure 1 and in Equation (1).

$$\mu\tilde{N}(x) = \begin{cases} (x-l)/(n-l), & l \leq x \leq n \\ (x-u)/(n-u), & n \leq x \leq u \\ 0, & x < l \text{ or } x > u \end{cases} \tag{1}$$

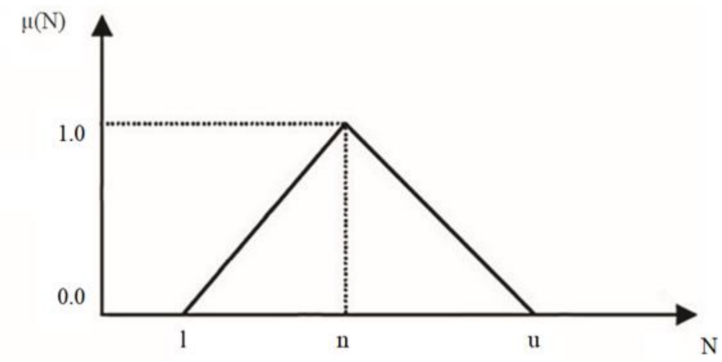

Figure 1. Triangular fuzzy number

Triangular fuzzy number Ñ (shown in Figure 1) can be described as an interval of real numbers where each of them has a degree of belonging to the interval between 0 and 1. Triangular fuzzy number is defined with three real numbers, expressed as l, n and u. In the study the performance of each scenario to each criterion is introduced as a fuzzy number. And in the study the ratings of qualitative criteria are considered as linguistic variables. These linguistic variables can be expressed in positive triangular fuzzy numbers as described in Table 1.

Table 1. Linguistic Variables for the Alternatives

Linguistic Terms-Abbreviation	Linguistic Variables	Triangular Fuzzy Numbers
SDA	Strongly Disagree	(0, 0, 0.15)
DA	Disagree	(0.15, 0.15, 0.15)
LDA	Little Disagree	(0.30, 0.15, 0.20)
NC	No Comment	(0.50, 0.20, 0.15)
LA	Little Agree	(0.65, 0.15, 0.15)
A	Agree	(0.80, 0.15, 0.20)
SA	Strongly Agree	(1, 0.20, 0)

After forming a matrix of fuzzy criteria comparison, it should be defined vector of criteria weights W. For that purpose, the following equations/steps were used in the study.

Let X = {x1, x2,..., xm } be an object set, and G={g1, g2,...,gn} be a goal set. N extent analysis values for each object can be obtained as $\mathrm{N}_{gi}^{1}, \mathrm{N}_{gi}^{2}, \ldots, \mathrm{N}_{gi}^{n}$ i= 1,2,…n

Step 1: The values of fuzzy extensions for the i-th object are given in Equation (2);

$$\mathrm{Si} = \sum_{j=1}^{n} \mathrm{N}_{gi}^{j} \otimes \left[\sum_{i=1}^{m} \sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right]^{-1} \tag{2}$$

In order to obtain the expression $\left[\sum_{i=1}^{m} \sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right]$ it is necessary to perform additional fuzzy operations with n values of the extent analysis, which is represented in Equation (3) and (4);

$$\sum_{j=1}^{n} \mathrm{N}_{gi}^{j} = \left(\sum_{j=1}^{n} \mathrm{lj}, \sum_{j=1}^{n} \mathrm{nj}, \sum_{j=1}^{n} \mathrm{uj}\right) \tag{3}$$

$$\left[\sum_{i=1}^{m} \sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right] = \left(\sum_{i=1}^{m} \mathrm{li}, \sum_{i=1}^{m} \mathrm{ni}, \sum_{i=1}^{m} \mathrm{ui}\right) \tag{4}$$

And it is required to calculate the inverse vector above by using Equation (5);

$$\left[\sum_{i=1}^{m} \sum_{j=1}^{n} \mathrm{N}_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{m} \mathrm{ui}}, \frac{1}{\sum_{i=1}^{m} \mathrm{ni}}, \frac{1}{\sum_{i=1}^{m} \mathrm{li}}\right) \tag{5}$$

Step 2: While N1 and N2 are triangular fuzzy numbers, the degree of possibility for N2≥N1 is defined as:

$$\mathrm{V}\ (\mathrm{N2} \geq \mathrm{N1}) = \mathrm{supy{\geq}x}\ \left(\min(\ \mu\mathrm{N}_1\ (x),\ \ \mu\mathrm{N}_2\ (y)\right)) \tag{6}$$

It can be represented in the following manner by Equation (7):

$$\mathrm{V}\ (\mathrm{N2} \geq \mathrm{N1}) = \mathrm{hgt}\ (\mathrm{N2} \cap \mathrm{N1})\ \mu\mathrm{N2(d)} \tag{7}$$

$$= \begin{cases} 1, & \text{if } n_2 \geq n_1 \\ 0, & \text{if } l_1 \geq l_2 \\ \dfrac{(l_1 - u_2)}{(n_2 - u_2)(m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{8}$$

Where d is the ordinate of the highest intersection point D between μN1 and μN2.
To compare μN1 and μN2, values of both, V (N2 ≥ N1) and V (N1 ≥ N2) are needed.

Step 3: The degree of possibility for a convex fuzzy number to be greater than k convex numbers Ni (i=1,2,...,k) can be defined by Equation (9);

$$V\ (N \geq N1, N2,..., Nk) = V[(N \geq N1), (N \geq N2), \dots, (N \geq Nk)] = \min V\ (N \geq Ni=1,2,3,\dots,k) \tag{9}$$

Assume that Equation (10) is;

$$d'\ (Ai) = \min V\ (Si \geq Sk) \tag{10}$$

for k=1,2,...,n; k ≠ i. So, the weight vector is obtained by Equation (11);

$$W' = (d'(A1), d'(A2),..., d'(Am))T \tag{11}$$

where, Ai (i =1,2,...,n) consists of n elements.

Step 4: Through normalization, the weight vectors are reduced to Equation (12);

$$W = (d(A1), d(A2),..., d(An))T \tag{12}$$

where W represents an absolute number.

2.3. Fuzzy TOPSIS Method

The fuzzy TOPSIS calculation most important step is given in Equation (13), i.e., Creating the Decision Matrix; aggregated ratings are calculated by using Equation (13):

$$\tilde{V}ij = \frac{1}{2}\ [\tilde{v}_{ij}^{1} \oplus \tilde{v}_{ij}^{2} \ \oplus \dots\ \tilde{v}_{ij}^{s}\ ] \tag{13}$$

where $\tilde{v}_{ij}^{s}$ is the performance rating value obtained from s-th decision maker.
The basic steps of proposed fuzzy TOPSIS method can be described as follows:

Step 1: In the first step, a panel of decision makers (DMs) who are knowledgeable about supplier selection process is established. In a group that has K decision-makers (i.e., D1, D2, ..., Dk) are responsible for ranking (yjk) of each criterion (i.e., C1, C2, ..., Cn) in increasing order. Then, the aggregated fuzzy importance weight for each criterion can be described as fuzzy triangular numbers $\tilde{v}j$ = (aj, bj, cj) for k = 1, 2, ..., K and j = 1, 2, ..., n. The aggregated fuzzy importance weight can be determined as follows:

$$dj = \frac{min}{k}\ \{yjk\},\ bj = \frac{1}{\boldsymbol{K}} \textstyle\sum_{k=1}^{K} yjk,\ cj = \frac{max}{k}\ \{yjk\} \tag{14}$$

Then, the aggregated fuzzy importance weight for each criterion is normalized as follows:

$$\tilde{v}j = (aj1, bj2, cj3)$$

$$\text{where } vj1 = \frac{\frac{1}{dj}}{\sum_{j=1}^{n}\frac{1}{dj}},\ vj2 = \frac{\frac{1}{bj}}{\sum_{j=1}^{n}\frac{1}{bj}},\ vj3 = \frac{\frac{1}{cj}}{\sum_{j=1}^{n}\frac{1}{cj}} \tag{15}$$

Then the normalized aggregated fuzzy importance weight matrix is constructed as $\tilde{V}$ = ($\tilde{v}$1, $\tilde{v}$2, ..., $\tilde{v}$n)

Step 2: A decision matrix is formed.

$$X = \begin{bmatrix} x11 & x12 & \cdots & x1n \\ x21 & x22 & \vdots & x2n \\ \cdots & \cdots & & \cdots \\ xm1 & xm2 & \ldots & xmn \end{bmatrix} \tag{16}$$

Step 3: After forming the decision matrix, normalization is applied. The calculation is done using Equations 17 and 18.

$$rij = \frac{\frac{1}{xij}}{\sqrt{\sum_{i=1}^{m} \frac{1}{xij^2}}} \quad \text{for minimization objective, where i = 1, 2, ..., m and j = 1, 2, ..., n} \tag{17}$$

$$rij = \frac{xij}{\sqrt{\sum_{i=1}^{m} xij^2}} \quad \text{for maximization objective, where i = 1, 2, ..., m and j = 1, 2, ..., n} \tag{18}$$

Then, normalized decision matrix is obtained as:

$$R = \begin{bmatrix} r11 & r12 & \cdots & r1n \\ r21 & r22 & \vdots & r2n \\ \cdots & \cdots & & \cdots \\ rm1 & rm2 & \ldots & rmn \end{bmatrix} \tag{19}$$

Step 4: Considering the different weights of each criterion, the weighted normalized decision matrix is computed by multiplying the importance weight of evaluation criteria and the values in the normalized decision matrix. The weighted normalized decision matrix Ṽ for each criterion is defined as:

$$\tilde{V} = [\tilde{V}ij]mxn \quad \text{for i = 1, 2, ..., m and j = 1, 2, ..., n} \tag{20}$$

Where Ṽij = rij X õj
Here Ṽij denotes normalized positive triangular fuzzy numbers.

Step 5: Then fuzzy positive (Ã*) and fuzzy negative (Ã−) ideal solutions are determined as follows:

$$\begin{gathered} \tilde{A}^* = (\tilde{v}1^*, \tilde{v}2^*, \ldots, \tilde{v}n^*) \quad \text{where} \\ \tilde{V}j^* = \left\{\max_i(vij1),\ \max_i(vij2),\max_i(vij3)\right\} \quad \text{and} \\ \tilde{A}\text{-} = (\tilde{v}1\text{-}, \tilde{v}2\text{-}, \ldots, \tilde{v}n\text{-}) \quad \text{where} \\ \tilde{V}j\text{-} = \left\{\min_i(vij1),\ \min_i(vij2),\min_i(vij3)\right\} \\ \text{for i = 1, 2, ..., m and j = 1, 2, ..., n} \end{gathered} \tag{21}$$

Step 6: Then the fuzzy distance of each alternative from fuzzy positive and fuzzy negative ideal solutions are calculated as:

$$\tilde{a}i^* = \sqrt{\sum_{j=1}^{n}(\tilde{v}_j^* - \tilde{v}_{ij}^*)} \quad \text{and} \quad \tilde{a}i\text{-} = \sqrt{\sum_{j=1}^{n}(\tilde{v}_j^- - \tilde{v}_{ij}^-)} \qquad i = 1, 2, \ldots, m \tag{22}$$

Step 7: Then the fuzzy closeness coefficient Ñ is determined as:

$$\tilde{N}i = \frac{\tilde{a}_i^-}{\tilde{a}_i^* + \tilde{a}_i^-} \quad i = 1, 2, \ldots, m \tag{23}$$

The fuzzy closeness represents the distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution simultaneously.

Step 8: The fuzzy closeness coefficient defuzzied as follows:

$$Ni = \sqrt[3]{N_{i1} \cdot N_{i2} \cdot N_{i3}} \tag{24}$$

2.3. Selection of Industrial Internet of Things (IIoT) in Energy Sector: Dimensions and Evaluation Model

IIoT in Energy Sector, i.e., measuring scale, consists of 6 dimensions-main criteria and 29 evaluation factors-sub-criteria are evaluated by decision makers (DMs). A questionnaire was developed following the methodology proposed for the below methods, which was answered by 25 experts/DMs.

In the study 6 main criteria, i.e. Process Monitoring and Resource Optimization (C1), Advanced Analytics (C2), Intelligent Grid (C3), Intelligent Grid (C4), Cost-savings and Data Management (C5), Sustainability (C6) and 29 related subcriteria are evaluated/assessed by each expert/DM. For the case of prioritization of the criteria, after the aggregation process performed with the answers of the 25 experts, the comparison matrix was obtained. The pairwise comparison matrices for subcriteria and alternatives are calculated.

Subsequently, the normalized pairwise comparison matrix of criteria was obtained. The priority vector and the CR for the criteria were obtained. To obtain the other priorities, the same procedure presented for the criteria was applied. In order to facilitate the calculations; which enters the individual judgments of the experts and generates the local and global preferences of all levels of the hierarchical tree (criteria and subcriteria).

It uses sensor devices and gateway connectivity to derive actionable insights and use them to develop new and advanced services for enhanced productivity. It further improves real-time decision-making, complex operability, and overall experiences.

Hereunder, IIoT in energy sector's main criteria and related sub-criteria are described.

2.3.1. Process monitoring and resource optimization

Using sensor devices in a power plant offers automated execution of the processes and render better services that are mostly error-free. IoT technology is a smart concept that also protects excessive resource utilization and helps maintain consistency. IoT allows smart process monitoring that gives every detail of the plant-process in the form of data.

2.3.2. Advanced analytics

Sensor-based functioning of the power industry is bringing a revolutionary change. It uses advanced techniques to fulfill the business requirements and generate quality production. The industrialists are making the most out of using advanced analytics with their business. It uses sensor-enabled data to extract information from the assets and make better decisions than before. Data analytics helps the power sector to optimize generation and planning.

2.3.3. New opportunities

IoT brings new business opportunities along with newer and advanced concepts. It involves sensor devices, gateway connectivity, and communication protocols that combine and form IoT architecture for multipurpose businesses. One can use IoT technology to avail business benefits and enable smart techniques for better productivity and growth. IoT is a futuristic technology, which empowers businesses through its real-time monitoring features, smart data management, and analytics.

2.3.4. Intelligent grid

IoT provides a smart grid system to get control over the power flow or curb the energy consumption at significant levels. It further curtails the energy load to match the real-time generation or near real-time. IoT is an automated concept that offers a cost-effective approach to interconnect the users for effective power usage.

2.3.5. Cost-savings and data management

IoT in the energy sector is an advanced process that includes planning and energy management of the consumption patterns in multiple domains. It allows the managers to take complete control of energy data from scratch and optimize the process significantly. Using an IoT-powered solution in the energy sector utilizes sensor-based methods to establish the automated functioning of the industry.

2.3.6. Sustainability

All assets/machines/equipment have been made to talk to each other through IoT. The energy sector is the major driver of accountability that seeks smart ways to reduce environmental issues. IoT facilitates automated maintenance and reporting, optimization of smart grids, renewable energy generation, and measure carbon consumption in real-time. The technology is enabling sustainability around the industrial world through its smart techniques and is allowing the managers to make informed decisions for better business growth.

2.4. Determining the evaluation criteria weights with Fuzzy AHP Approach

Firstly, each DM practiced pair-wise comparisons of IIoT's dimensions and evaluation factors by using fuzzy AHP. Using the survey data acquired from these experts, integrated pair-wise comparison matrices are formed by combining all expert opinions. Thus, the pair-wise comparison values are converted to triangular fuzzy numbers and fuzzy pair-wise comparison matrices are created, presented in Table 2.

$$\text{lij} = \text{mink}\{\text{aijk}\} \qquad \text{nij} = \frac{1}{\text{K}}\sum_{\text{j}=1}^{K} \text{b}_{ijk} \qquad \text{uij} = \text{maxk}\{\text{cijk}\} \tag{25}$$

Table 2. Fuzzy mutual criteria comparison

	C1	C2	C3	C4	C5	C6
C1	(1, 1, 1)	(1/9, 1/7, 1/5)	(1/5, 1/3, 1)	(5, 7, 9)	(7, 9, 11)	(1/7, 1/5, 1/3)
C2	(5, 7, 9)	(1, 1, 1)	(1/7, 1/5, 1/3)	(1, 3, 5)	(7, 9, 11)	(1/7, 1/5, 1/3)
C3	(1, 3, 5)	(3, 5, 7)	(1, 1, 1)	(5, 7, 9)	(5, 7, 9)	(1/7, 1/5, 1/3)
C4	(1/9, 1/7, 1/5)	(1/5, 1/3, 1)	(1/9, 1/7, 1/5)	(1, 1, 1)	(1/9, 1/7, 1/5)	(5, 7, 9)
C5	(1/11, 1/9, 1/7)	(1/11, 1/9, 1/7)	(1/9, 1/7, 1/5)	(5, 7, 9)	(1, 1, 1)	(1/7, 1/5, 1/3)
C6	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1/9, 1/7, 1/5)	(3, 5, 7)	(1, 1, 1)

After acquiring the fuzzy comparison matrices, importance weights of IIoT in Energy Sector's dimensions; evaluation criteria is calculated by the FAHP method. According to the calculated criteria weights for IIoT in Energy Sector's weights; the most important evaluation dimension/main-criteria is "Cost-savings and Data Management" with 0.316 importance weight, the second important evaluation dimension is "Process Monitoring and Resource Optimization" with 0.219 importance weight and the third important evaluation dimension is "Advanced Analytics" with 0.197 importance weight.

2.5. Ranking the alternatives by Fuzzy TOPSIS methods

For the evaluation of IIoT factors in Energy Sector, Fuzzy TOPSIS approach is conducted with the collected data of DM's surveys/interviews. Primarily, the linguistic variables of the alternatives are created. By the help of criteria weights, Fuzzy-TOPSIS method's steps are performed/completed and IIoT in Energy Sector that affect factors are ranked from the best to the worse. Primarily, the linguistic variables of the alternatives are created.

2.6. Machine-to-machine (M2M) communication

Industry 4.0's underlying need is effective and efficient communication between a plethora of production units, services, diagnoses, handheld devices, and enterprise systems in the push to design, manufacture, and service the good in question. This is obvious to most forward-looking engineers, but the exploding number of often ad hoc connected sensors, controllers, and actuators is creating swarms of devices that are difficult to interconnect and organize in an industrial network.

For Industry 4.0 to prevail, communication technologies will need to connect machinery over varying distances in a flexible manner with high security, robustness, and availability at a low cost. One option is self-organizing logistics, but logistics becomes difficult once the number of product variants increases and production volumes fluctuate. The risk of supplier shortages or errors in the supply chain intensifies with complexity. Machine-to-machine (M2M) communication provides a solution by registering and tracking material, pallets, trucks, and so on.

Machine-to-machine (or M2M) is a broad term that describes any technology that allows networked devices, without human assistance, to exchange information and take action. Machine Learning (ML) and Artificial Intelligence (AI) allow systems to communicate with each other, making their own decisions. M2M technology was initially adopted in industrial and manufacturing settings. Initially, technologies like Supervisory Control and Data Acquisition (SCADA) or remote monitoring are used to control and manage data from the equipment remotely, especially in energy sector. However, M2M technology has been used in many other industries, including healthcare, insurance, and other businesses. M2M is also the foundation of the Internet of Things (IoT), allowing effective communication among equipment/machines. IoT provides b/m advantages; improved operational efficiency, better product quality and services, detail-oriented decision-making, cost-efficiency and increased Return on Investment (ROI), unlimited scalability, remote machine monitoring, accurate asset tracking, reduced power consumption, packet-switch services, real-time monitoring, time tolerance and control, geo-fencing, continuous data transfer, predictive maintenance.

M2M, central to the shop-floor, impacts Industry 4.0 and refers to technologies allowing for the automated exchange of information between the CPS, which constitute the industry 4.0 production environment. M2M can be considered as the integral technology of the 'Internet of Things' (IoT). Through advanced embedded sensor and actuator applications technology, the entire production floor can relay meaningful information, forming the interface between the physical and the virtual worlds. This provides a level of transparency that enables huge improvements in manufacturing, from performance management to entire new business models. While the most evident usage forms of M2M will be in intra-company linking of production assets, M2M is also the key enabler when it comes to cross-company operations.

Considering manufacturing advancements supported by communication and networking technologies, manufacturing industries are ready to improve the production processes with big data analytics to take the advantage of higher compute performance with open standards and achieve the availability of industry know-how in advance. As a result of the penetration of manufacturing intelligence, manufacturers can be able to enhance quality and increase manufacturing output.

3. Results

Industry 4.0 has been defined as "a name for the current trend of automation and data exchange in manufacturing technologies, including cyber-physical systems, the Internet of things, cloud computing and cognitive computing and creating the smart factory". Industry 4.0 is used interchangeably with the fourth industrial revolution and represents a new stage in the organization and control of the industrial value chain.

Sensor technology, big data and analytics are used to optimize operations, such as efficiently balancing supply and demand as customers connect to a smart grid. The usage of IoT in energy production helps to satisfy the energy demands in smart cities in an efficient way. However, a robust digital infrastructure is crucial for the roll-out of an architecture of connectivity and data.

Industry 4.0 is the new heavy trend of the industry. Also called the 4th Industrial Revolution, it defines the concept of Smart Factory. Behind this concept lies a mix of technologies serving the factory of the future. Connect the machines to the Internet, through the Internet of Things (IIOT), collect the data in the Cloud, and treat them through Artificial Intelligence algorithms, to optimize the operations, reduce costs through preventive / predictive maintenance. In a general way, to allow an optimized and centralized management of its installations, its equipment, its machines. Offer better operational and business tools.

After acquiring the fuzzy comparison matrices, importance weights of IIoT's dimensions; evaluation criteria is calculated by using Fuzzy method. According to the calculated criteria weights for IIoT's weights; the most important evaluation dimension/main-criteria is "Cost-savings and Data Management", the second important evaluation dimension is "Process Monitoring and Resource Optimization" and the third important evaluation dimension is "Advanced Analytics".

4. Conclusion

Industry is taking advantage of ever more complex and sophisticated systems. Systems not designed to communicate across production lines often require integration with pre-existing devices. The challenge of interoperability is thus one of the main concerns in designing intelligent human-to-machine and machine-to-machine cooperation.

"Industry 4.0" concept has the flexibility to achieve interoperability between the different industrial engineering systems. To connect the different industrial equipment and systems, the same standards and safety levels are required. The "Industry 4.0" concept was born to apply the ideas of cyber-physical systems (CPSs) and IoT to industrial automation and to create smart products, smart production, and smart services. It involves cyber-physical systems, IoT, cognitive computing and cloud computing and supports what has been termed "smart factory". IoT technologies offer greater availability of information throughout the chain of value, allowing for amortization of better tools for decision-making.

Industry 4.0 refers to a new phase in the Industrial Revolution that focuses heavily on interconnectivity, automation, machine learning, and real-time data. Industry 4.0, which encompasses IIoT and smart manufacturing, marries physical production and operations with smart digital technology, machine learning, and big data to create a more holistic and better-connected ecosystem for companies that focus on manufacturing and supply chain management. While every company and organization operating today is different, they all face a common challenge-the need for connectedness and access to real-time insights across processes, partners, products, and people.

Industry 4.0 is revolutionizing the way companies manufacture, improve and distribute their products. Manufacturers are integrating new technologies, including Internet of Things (IoT), cloud computing and analytics, and AI and machine learning into their production facilities and throughout their operations. These smart factories are equipped with advanced sensors, embedded software and robotics that collect and analyze data and allow for better decision making. Even higher value is created when data from production operations is combined with operational data from ERP, supply chain, customer service and other enterprise systems to create whole new levels of visibility and insight from previously siloed information. These digital technologies lead to increased automation, predictive maintenance, self-optimization of process improvements and, above all, a new level of efficiencies and responsiveness to customers not previously possible. Developing smart factories provides an incredible opportunity for the manufacturing industry to enter the fourth industrial revolution. Analyzing the large amounts of big data collected from sensors on the factory floor ensures real-time visibility of manufacturing assets and can provide tools for performing predictive maintenance in order to minimize equipment downtime.

Using high-tech IoT devices in smart factories leads to higher productivity and improved quality. Replacing manual inspection business models with AI-powered visual insights reduces manufacturing errors and saves money and time. With minimal investment, quality control personnel can set up a smartphone connected to the cloud to monitor manufacturing processes from virtually anywhere. By applying machine-learning algorithms, manufacturers can detect errors immediately, rather than at later stages when repair work is more expensive.

IIoT is used to transfer the data from systems that monitor and control the industrial equipment to data processing systems that cloud computing has shown to be important tools for meeting processing requirements by using Wi-Fi, radio, satellite or cellular networks.

In the study by using Fuzzy method; the calculated criteria weights for IIoT's weights are as follows: the most important evaluation dimension/main-criteria is "Cost-savings and Data Management", the second important evaluation dimension is "Process Monitoring and Resource Optimization" and the third important evaluation dimension is "Advanced Analytics".

IIoT provides the necessary connectivity, security, and manageability, while some of the existing devices cannot share data with the cloud. They should be modified to share their data. IIoT enables real-time quality monitoring, which helps identify the nonconformities within the processes and energy production sector easily. Many applications have already been implemented in the construction and the infrastructure fields. The net market value of deploying UAVs in support of construction and infrastructure inspection applications accounts for about 45% of the overall UAV market. UAVs are also used for the real-time inspection of power lines. Drones are used to detect trees and buildings close to power lines. They can also be deployed to monitor oil, natural gas and water pipe lines. UAV and IoT technologies are used for building inspections, oil and natural gas pipelines inspections in North America using the powerful machine learning to process the data collected. They provide asset inspection and data acquisition, advanced data processing with 2D and 3D images and detailed reports on the property inspected.

Acknowledgement

This study was partly presented at the 5th Advanced Engineering Days [24].

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Chan, F. T., & Kumar, N. (2007). Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega*, *35*(4), 417-431.
2. Wang, C. (2015). *A study of membership functions on mamdani-type fuzzy inference system for industrial decision-making*. Lehigh University.
3. Sahu, A. K., Datta, S., & Mahapatra, S. S. (2016). Evaluation and selection of resilient suppliers in fuzzy environment: Exploration of fuzzy-VIKOR. *Benchmarking: An International Journal*, 23(3), 651-673
4. Satrovic, E. (2018). The human development relies on renewable energy: Evidence from Turkey. 3rd International Energy & Engineering Congress, 19-27
5. İncekara, Ç. Ö., & Oğulata, S. N. (2011). Enerji darboğazında ülkemizin alternatif enerji kaynakları. *Sosyal ve Beşeri Bilimler Dergisi*, *3*(1).

6. İncekara, C. O., & Oğulata, S. N. (2012). EU and Turkey's Energy Strategies. *International Journal of Economics and Finance Studies*, *4*(2), 35-43.
7. Incekara, C. O., & Ogulata, S. N. (2017). Turkey's energy planning considering global environmental concerns. *Ecological Engineering*, *102*, 589-595.
8. İncekara, Ç. Ö. (2018). Ülkemizdeki Enerji Santral Yatırımlarının AHP Yöntemi ile Değerlendirilmesi. *Çukurova Üniversitesi Mühendislik-Mimarlık Fakültesi Dergisi*, *33*(4), 185-196.
9. Incekara, C. O. (2019). Use of an optimization model for optimization of Turkey's energy management by inclusion of renewable energy sources. *International Journal of Environmental Science and Technology*, *16*(11), 6617-6628.
10. Incekara, Ç. Ö. (2019). Türkiye ve AB'nin enerji hedefleri. *Journal of Turkish Operations Management*, *3*(2), 298-313.
11. Incekara, C.O. (2019c). Turkey's Energy Management Plan by Using Fuzzy Modeling Approach. Scholars' Press, ISBN-10: 6138829697, Book, 38-52.
12. İncekara, Ç. Ö. (2020). Türkiye'nin elektrik üretiminde doğalgaz talep tahminleri. *Journal of Turkish Operations Management*, *4*(2), 494-508.
13. İncekara, Ç. Ö. (2020). Evaluation of Turkey's International Energy Projects by Using Fuzzy Multi-Criteria Decision Making Methods. *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences*, *7*(9), 206-217. https://doi.org/10.38065/euroasiaorg.143
14. İncekara, Ç. Ö. (2020). Turkey's natural gas demand projections. *Ejons International Journal*, *4*(15), 489-505.
15. İncekara, Ç. Ö. (2020). Bulanık mantık ile sanayii sektöründe ISO 50001 enerji yönetim sistemi uygulaması. *Afyon Kocatepe Üniversitesi Fen Ve Mühendislik Bilimleri Dergisi*, *20*(6), 991-1013.
16. İncekara, Ç. Ö. (2020). Enerji Sektöründe Faaliyet Gösteren Bir İşletmede İş Sağlığı ve Güvenliği Yönetim Sistemi. *Mehmet Akif Ersoy Üniversitesi Uygulamalı Bilimler Dergisi*, *4*(1), 152-177.
17. İncekara, Ç. Ö. (2021). Bulanik TOPSIS ve bulanik vikor yöntemleriyle bir enerji şirketinde kurumsal hafizanin oluşturulması. *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences*, *8*(17), 1-20. https://doi.org/10.38065/euroasiaorg.589
18. Incekara, C. O. (2021). Post-COVID-19 ergonomic school furniture design under fuzzy logic. *Work*, *69*(4), 1197-1208.
19. İncekara, Ç. Ö. (2021). Dünya'nin ve Türkiye'nin doğal gaz talep senaryosu. *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences*, *8*(17), 44-57.
20. İncekara, Ç. Ö. (2021). Global Natural Gas Demand Projections under Fuzzy Logic. *Ejons International Journal*, *5*(18), 367-385. https://doi.org/10.38063/ejons.430
21. Incekara, C. O. (2022). Designing ergonomic post-Covid-19 school furniture. *South African Journal of Industrial Engineering*, *33*(2), 37-48.
22. İncekara, Ç. Ö. (2022). Sigorta eksperlerinin dask sigortasi değerlendirmelerinin bulanik mantik altinda incelenmesi. *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences*, *9*(21), 14-41. https://doi.org/10.38065/euroasiaorg.952
23. İncekara, Ç. Ö., & Lala. S. (2023). Enerji projelerinde arazi edinim faaliyetleri ve arazi değerlemesi. *Geomatik*, *8*(1), 61-71.
24. İncekara, Ç. Ö. (2022). Industrial internet of things (IIoT) in energy sector. *Advanced Engineering Days (AED)*, *5*, 181-184.