Prioritizing the Factors Affecting the Application of Industry 4.0 Technology in Electrical Appliance Manufacturing using a Fuzzy Analytical Network Process Approach

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Abstract—**The fourth industrial revolution is a technological advancement that is posing new challenges in manufacturing and services. Industries must adopt innovations to create value-added for their products and services to gain a competitive advantage and increase production efficiency. Therefore, this research aims to study the factors that influence the application of Industry 4.0 technology for managing electrical appliance production by focusing on five major factors: the internet of things, cloud manufacturing, big data analytics, additive manufacturing, and cyber-physical systems, which can be further subdivided into 23 sub-factors. The fuzzy analytic network process (FANP) technique is used to prioritize the factors to develop criteria for selecting appropriate applications of Industry 4.0 technology in manufacturing. Besides, a questionnaire based on the FANP approach is used to collect data from 82 electrical appliance manufacturers to calculate the weight of each factor. Consequently, the Internet of Things is ranked first, followed by big data analytics and additive manufacturing. While the results have indicated the importance of sub-factors as data-driven, data collection, tracking, monitoring, and automation, respectively. The benefit of this research is that manufacturers of electrical appliances can use this research as a criterion for implementing Industry 4.0 technology for long-term effectiveness.**

Keywords—Industry 4.0; big data analytics; internet of things; cloud manufacturing; additive manufacturing; cyber-physical systems; fuzzy analytic network process

I. Introduction

The manufacturing industry is currently undergoing a transformation in innovation and technology, which is pushing successful output. Connectivity and data analytics advancements are a part that can help the manufacturing industry create value-added and competitive advantages for its products and services. Therefore, integrated production processes are critical in the industrial revolution to enhance production levels and make them more efficient by incorporating Industry 4.0 concepts such as Internet technology, communication technology, and automated production. Besides, the manufacturing system is combined with precision machine tools and devices that may be connected to the internet for efficient production control and data analysis. Various industries have adapted to the Industry 4.0 transformation using new technologies, which will create new business needs and opportunities [1, 2], including machine-to-machine communication for automated control [3, 4]. Therefore, smart factories must have sensors connected to devices or machines to control their operations effectively, resulting in real-time data management and exchange [5, 6]. Additionally, these devices or machines in the manufacturing process can help to create effective preventive maintenance plans for machines and equipment in production [7, 8]. Technological advances enable the detection and processing of communication capabilities with devices and services, resulting in higher standards and a more efficient manufacturing operating environment [1, 7, 9]. Consequently, Industry 4.0 technology is a necessary technology for increasing production efficiency and creating sustainability.

This study presents the challenges of sustainable manufacturing in Industry 4.0, intending to study the impact of various factors in the application of Industry 4.0 in the manufacturing of electrical appliances, as well as the significance of these factors in forecasting decision-making's tendency in the future application of Industry 4.0 technology. The fuzzy analytical network process (FANP) approach in the multiple criteria decision-making principle (MCDM) is used in this research because FANP can simplify complex problems and allow dependence and feedback in the hierarchy. Thus, the FANP approach is applied for prioritizing factors to analyze and compare their relative importance, which impacts the decision-making for applying Industry 4.0 technology in the electrical appliance industry. Finally, the study's findings will assist stakeholders in making informed decisions in terms of the implementation of Industry 4.0 technology in their manufacturing processes to increase their businesses' competitiveness and performance in the long run.

In the first section, we review Industry 4.0 technology and its applications to determine the factors that affect the application of Industry 4.0 technology in manufacturing. In the following section, we describe the research methodology used in this study, as well as related theories such as the fuzzy set and fuzzy analytical network process, which are used for prioritizing factors influencing decision makers in electrical appliance manufacturers in terms of Industry 4.0 technology application. The study's results have shown the importance of factors and sub-factors including their ranking by FANP in

Section IV. Section V discusses the findings and management implications. Finally, Section VI concludes with a summary of the study's findings, limitations, and future research.

II. Literature Review

Building a competitive advantage requires the development of systems [10], whereas the evolution of Industry 4.0 enables more transparent resource utilization through efficient practices in both production and innovation [11, 12]. Furthermore, the government has recognized the critical importance of Industry 4.0, information technology, and the environment in driving the economy, issuing a slew of regulations to support and safeguard them [13]. By incorporating intelligent mechanisms and automation in the industrial environment, Industry 4.0 enables businesses to improve production processes [5]. The challenges of Industry 4.0 encompass not only the technological dimension, but also the organizational, social, and national economic dimensions. Thus, organizations and governments must adapt to Industry 4.0 to achieve operational success [14]. The fourth industrial revolution is the result of rapid technological advancement [15], as evidenced by the interconnection of intelligent manufacturing systems used in Industry 4.0. The goal is to create human-machine interaction by automating and resilient production, parts and product tracking, and machine-to-machine communication. This will result in increased productivity and lower costs. To enable on-demand production and more efficient supply and demand, the intelligent manufacturing system will connect product design, analytics, manufacturing processes, stock and supply chain systems, product customization, delivery systems, and customers [16]. While, the Internet and technology are future-oriented, and they improve the human-machine interaction paradigm to provide added value to processes [14, 17, 18]. Information technology is a critical component of the economy's driving force [19], enabling the digitization of production processes, the relationships between physical and controllable objects, and the improvement of integration between the physical and digital worlds [20]. Manufacturing technologies are being developed to communicate and deliver big data, allowing businesses to improve forecasting and productivity [21, 22]. Additionally, the technology incorporates processing capabilities to improve manufacturing processes, organizational interactions, human resource utilization, waste reduction, environmental impact reduction, energy savings, as well as the industrial value chain, all of which contribute to sustainability [5] From the literature review of Industry 4.0, this study has identified five major factors affecting the application of Industry 4.0 technology as follows: Internet of Things (IoT), Cloud Manufacturing (CMg), Big Data Analytics (BDA), Additive Manufacturing (AM), and Cyber-Physical Systems (CPS), as shown in Table I.

TABLE I. PREVIOUS RESEARCH ON THE APPLICATION OF INDUSTRY 4.0 TECHNOLOGY

Factors	Sub-Factors	Reference
Internet of Things (IoT)	Monitoring	[30], [48], [49], [50], [51], [55]
	Tracking	[20], [32], [33]
	Information	[20], [54]
	Automation	[20], [37], [47], [54]
Cloud Manufacturing (CMg)	Security	[31], [38], [39], [45], [52]
	Resources as service	[34], [40], [41], [43], [46]
	Orchestration	[31], [38], [40]
	Resource management	[38], [41], [42], [43], [46], [57]
	Utilization	[40], [41], [44], [46]
Big Data Analytics (BDA)	Predictive	[14], [18], [20], [51], [52]
	Data Collection	[32], [33], [51], [55]
	Data-Driven	[20], [30], [32], [33], [51], [52], [53], [55]
	Accurate	[20], [32], [51], [52], [54]
	Predictive	[14], [18], [20], [51], [52]
Additive Manufacturing (AM)	Prototype	[7], [23], [33], [60],[61],[62],[63]
	Flexibility	[33], [62], [63]
	Optimization	[1], [19], [52], [56]
	Reduction	[20], [22], [23], [27],[28], [33]
Cyber-Physical System (CPS)	Collaborates	[7], [30], [33], [40], [51], [52], [64]
	Detects Production System	[20], [33], [36]
	Decision Making	[20], [33], [51], [54], [59]
	Visibility and Traceability	[30], [32], [52]
	Synchronization	[8], [9], [20], [52]
	Intelligent	[20], [36], [37], [47], [65], [66], [67]

A. Internet of Things

The Internet of Things (IoT) is a collection of intelligent devices and sensors that can communicate with one another via the Internet [7, 23]. It can identify specific physical and virtual connections for communication, configuration, management, and data collection [14, 17, 18]. Besides, IoT can accurately monitor and measure a wide range of processes, such as real-time tracking, predictive maintenance, production volume management, and sales data [21]. Consequently, the collected data is routed to a central processing system for analysis and decision-making, resulting in solutions in automated manufacturing processes, lower production costs, and higher technological standards [20, 22]. IoT also has access to product lifecycle data, allowing products to be traced from the factory to the customer [23]. Furthermore, it can improve product cycle visibility, reduce resource consumption, increase productivity [24, 25, 26] provide maintenance traceability, monitor labor activities, and improve work safety [27, 28], as well as manage resources for increasing competitiveness and long-term success.

1) Monitoring: The process of visualizing the recording data from real-time monitoring of the status change of production parameters to a specified standard was known as monitoring [29]. It was possible to continuously monitor or audit production data by recording, analyzing, or evaluating traceability data in real-time [30]. When non-standard problems such as critical overloads or insecurity were detected, the collected data could be assessed, and timely corrective action could be ordered [31]. Thus, organizations must regularly monitor and control operations under countermeasures to ensure process reliability, flexibility, and long-term productivity.

2) Tracking: A system that enabled the periodic monitoring of operational procedures and displays the data could be useful for analyzing current and future situations. Controlling and processing operations could also check the status of each step of the process, allowing for real-time tracking of goods flow [20]. Thus, Internet of Things applications that connect all relevant departments to collaborate via the Internet could improve efficiency in operational control decentralization [32, 33]. It provided a real-time tracking system for the manufacturing process, making the operation more convenient and increasing customer confidence.

3) Information: Information was created by processing and analyzing data from the Internet and presenting it in the form of knowledge that was applied to the workplace. Quality information must be accurate and up to date, as well as consistently stored. It is also supported by paperwork reduction, production management access, and inventory management [30]. Complex work systems and real-time decision-making necessitated the use of information as well. Thus, managing the flow of goods in processes enabled supply chain participants to track the flow of goods in real time and make precise decisions based on the information obtained [29]. Consequently, precise data acquisition and management were accomplished, allowing for more efficient operations.

4) Automation: IoT automation connected the entire network and shared data with linked systems based on requirements [31, 34], allowing for cost-effective, convenient, and safe operations. Using automated systems, humans can perform high-accuracy and risky tasks. Furthermore, controlling or receiving commands in real-time [35], between devices or machines based on connectivity requirements resulted in increased production and management capabilities.

B. Cloud Manufacturing

Cloud manufacturing is a data collection and processing system that collects and processes data with servers on computer networks. It also included services and applications that could use a network connection to access and process data or resources on the Internet [7, 25]. In addition, cloud manufacturing was a technology that involved the delivery of computing resources via the Internet, resulting in lower operating costs and increased response time efficiency. It also enabled data access from any location at any time, responsive data sharing, and supply chain support continuity [36, 37]. Therefore, cloud computing technology could make storing and processing large amounts of data more efficient. It could also develop new services, such as quality monitoring and control functions that improve operations and production efficiency [23].

1) Security: Database management security was a critical aspect of security. Particularly concerning was the provision of information to third-party cloud systems [38] because corporate data includes customer data, business data, employee data, intellectual property, and so on [39]. As a result of the various levels of information security requirements that underpin cloud services as well as search and access capabilities, the issue of information security was a huge challenge in services. Data security risks might negatively impact the organization; therefore, trust in cloud service recipients is required [31].

2) Resources as service: The service-oriented manufacturing model was designed to manage resources by providing cloud-based manufacturing solutions, on-demand network technology services, cloud service capabilities, and service platforms [34, 40]. It was a model that combines various technologies to facilitate collaboration, including sharing and managing production resources [41], where cloud manufacturing entailed the transformation of production resources (hardware and software), cloud service capabilities, and the ability to control services, as well as the management of production resources, processes, operations, and Internet transactions [40].

3) Orchestration: Capabilities for customer-focused collaboration and the creation of a new production line from a dedicated manufacturing service [40], were additional cloud manufacturing services for creating capabilities such as intelligent routing, preparation, data integrity checking, and security [41, 42], as well as business process service management that could be modeled and structured to support a smooth business.

4) Resource management: Cloud productivity capabilities enabled organizational planning and resource allocation to achieve goals. In resource management, resource simulation must consider the importance of resource diversity, user demand requirements, and performance requirements [31, 38] by connecting objects and production resource management for supporting manufacturing [43, 44]. Besides, it was a tool for organizing and managing information about production resources, including physical and virtual resources to maximize resource management capabilities [42].

5) Utilization: Using cloud computing technology facilitates and shares data to maximize productivity utilization [45], and the availability of dynamic cloud management would meet real-time needs [34]. By allocating production resources appropriately, cloud manufacturing could reduce costs and increase resource utilization. This allows for a smooth transition from service-oriented manufacturing to remediation [46], resulting in improved utilization or capacity of production resources.

C. Big Data Analytic

Big data analytics is a challenge for corporate performance in driving manufacturing because it can be used for real-time communication, monitoring, and transactions via multi-directional data networks and supported digital supply chain strategies [16]. On the other hand, data collection, analysis, and dissemination from machines and equipment enable efficient data storage, monitoring, and decision-making evaluation. [20, 47]. Meanwhile, predictive analytics, agility, and business insights [21], enable machines and devices to analyze data trends with artificial intelligence, including rapid communication of customer data, which can improve product quality and the business's supply chain [23]. Consequently, big data analytics improves the ability to collect data in real-time to meet objectives on time [48, 49, 50]. Furthermore, it can also learn from data for more accurate predictive production.

1) Predictive: Predictive analytics provided insights into potential trends [51] by utilizing mathematical techniques, simulations, multi-criteria decision-making, planning automation, risk management, and demand forecasting, among other things [52]. Predictive analytics also employed planning and control to accurately forecast production to meet demand and make real-time decisions.

2) Data collection: Data collection enabled real-time decision-making by analyzing data from various sources such as production data, customer feedback, or product ordering systems [33]. The data would be saved and collected in the storage system for further analysis [31]. To derive value from various types of data stored on demand, organizations must collect a large amount of data and require adequate data storage to support big data from resources.

3) Data-driven: Data-driven played an important role in supporting organizations' management, strategic planning, and goal setting, which necessitated large data storages to support big data in multiple formats while maintaining data quality and accuracy. Thus, the ability to process and control operations with big data has been applied to learning, analysis, and event-based decision-making. Consequently, data-driven systems capable of optimizing both production and predictive production are created [33, 52]. Besides, the visual ability of data flow throughout the supply chain, such as service quality, forecast accuracy, production efficiency, and inventory planning, would result in improved supply chain collaboration and effective network response [53].

4) Accuracy: Big data analytics could deliver real-time data quickly and accurately, as well as exchange data in planning, controlling, and forecasting for accurate decision-making [52]. In addition, big data analytics was critical in enabling multidimensional data to be considered and presented with accuracy, resulting in resource utilization that was consistent with demand, reducing losses and costs, controlling quality, and increasing productivity [21, 33] Moreover, big data analytics enabled real-time decision-making based on accurate data analysis results. It could be analyzed using big data platforms, which could generate sophisticated analytical models tailored to the situation and ensure more accurate production.

D. Additive Manufacturing

Additive manufacturing, also known as 3D printing, is a technique for creating parts from computer-aided designs, and it is most used to create prototypes [51, 33]. It is a manufacturing challenge that could replace traditional production, making it more convenient and supporting low-volume production [54, 35, 55]. Additive manufacturing aids product design in meeting needs and complexity, bringing products to market faster, and lowering transportation and storage costs. It also reduces material waste, improves, and develops products, and facilitates prototyping [23, 21, 22]. Thus, additive manufacturing technology has the potential to reduce production time and machine and raw material modification costs, improve reverse engineering ease, rapidly create new products and reproducibility, conduct testing and validation, increase customer satisfaction, and boost competitive advantage.

1) Prototype: Rapid prototyping played an important role in enabling diversified and enhanced production through technology for part design and creation, on-demand prototyping, minimizing design errors, prototyping testing and validation, pre-production customization, and product life cycle in new product development, which could be quickly adapted to change and meet market demands [21]. Furthermore, rapid prototyping increased the versatility of the fabrication process by enabling customization, ease of on-site production, and cost savings in production time and machine tool replacement, including raw materials [33]. Besides, prototyping was cost-effective and could lead to customer satisfaction.

2) Flexibility: The flexibility of additive manufacturing had accelerated the development and production of new products while also enabling convenient improvements or modifications to existing products [33]. Moreover, sophisticated and iterative products could be designed more quickly, saving money and time compared to traditional manufacturing methods while maintaining quality, durability, and functionality. In smart manufacturing, testing and validation were essential components of additive manufacturing [20], allowing manufacturing processes to be managed more efficiently.

3) Optimization: Additive manufacturing was a crucial method for structural design and manufacturing, as well as scalability, product design, and production integration. Furthermore, additive manufacturing could be used to create homogeneous structures with multiple sizes or layers [56]. This was an evolutionary structure optimization in which the optimal structure was determined by appropriate material distribution, resulting in the automatic optimization of specific input data.

4) Reduction: Because of the low scrap rate and easy disassembly of the structure for design and production, using additive manufacturing techniques could help manufacturers save money and support costs while also reducing waste [33]. Additive manufacturing techniques might also reduce the amount of labor, machinery, and equipment used in the manufacturing and prototyping of parts, which is especially labor-intensive and expensive in metal prototyping. Additionally, using additive manufacturing techniques could reduce costs associated with manufacturing, assembly, and inventory, resulting in more efficient prototype production.

E. Cyber-Physical System

A cyber-physical system (CPS) is an integrated engineering system that connects the physical and cyber worlds [42, 44, [57]. The physical world consists of devices, machines, humans, systems, etc. Whereas, the cyber world, also known as the digital world, processes and controls the physical world by connecting it with the Internet of Things (IoT), which oversees the physical world's connectivity, communication, and data transfer to the cyber world. While the cyber world computes, analyzes, or decides to send feedback control data to the physical world automatically. It also encourages the monitoring and control of environmental changes to facilitate manufacturing operations [20, 22] as a technology for management systems that wisely connect physical resources [38, 31, 43] As a result of this, machine performance, quality inspection, and control functions, as well as operation and production, have all improved [56, 40].

1) Collaboration: By directly processing data on the Internet, cyber-physical systems could collaborate indefinitely [33]. Computer collaboration in physical process operations such as machine and equipment control, warehouse management, and production process management could be planned and controlled by analyzing and processing data contained in the system [20, 58] to support collaboration, collaboration and resources, data sharing between service providers, and these capabilities were complementary to integration and collaboration [52].

2) Detects production system: Sensing production systems connected with computers to exchange data (interface), such as the interaction between computer users, machines, and equipment [33]. Whereas cyber-physical systems could monitor, measure, perceive, and control system conditions to meet goals or prevent errors in the manufacturing process, including fault detection (Downtime due to faults, workflow restrictions, and error notification). Besides, identifying the source of the defective process improved systems to prevent faults from recurring.

3) Decision-making: Data obtained from the manufacturing process was used to drive decision-making processes, allowing cyber-physical systems to perform better [59]. Numerous real-time data exchanges occurred between systems to ensure the continuity of decision-making and situation management, resulting in a reduction in data planning errors and complex decision-making processes [20]. Additionally, this enabled analysis and decision-making to control systems and achieve goals. Furthermore, Intelligent decision-making and control, machine control, and troubleshooting all contributed to faster and more accurate decision-making, which increased productivity.

4) Visibility and traceability: Visibility and traceability were components of the cyber-physical system that assisted employees in making simple proactive decisions, inspecting parts, controlling quality, and planning and controlling production. Manufacturing traceability and intelligent forecasting in supply chains are supported to eliminate employee concerns [52] by automatically computing, analyzing data, and transmitting feedback control.

5) Synchronization: the cyber-physical system would be able to synchronize various production activities such as planning and controlling in real-time [52] based on orders, production processes, and responses. By synchronizing the production process with other related processes, it created production process continuity [45].

6) Intelligent: Cyber-physical systems, powered by intelligent data, digitized data that could be used for automated audits, data processing, and monitoring. as well as modeling. Automated learning relied on constantly changing data to make accurate predictions and intelligent decisions. Sensor systems were used in the production and maintenance of machines and equipment [20], to make them more reliable and efficient, and they were a smart manufacturing innovation.

III. MATERIALS AND METHODS

In this study, the survey method was used for data collection, which was followed by quantitative research. The research tool was a questionnaire based on five main factors and a fuzzy analytical network process approach: Internet of Things, cloud manufacturing, big data analytics, additive manufacturing, and cyber-physical system, as shown in Fig. 1.

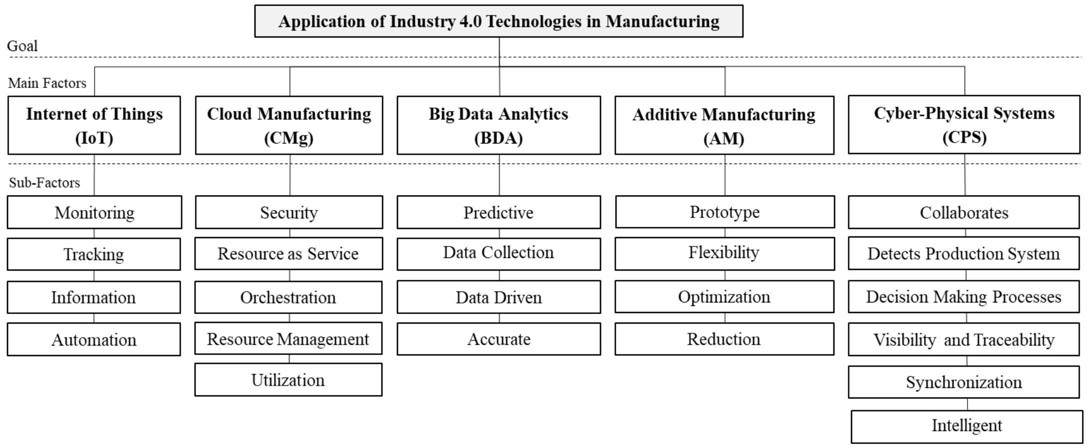

Fig. 1. Conceptual framework of the application of Industry 4.0 technologies in manufacturing.

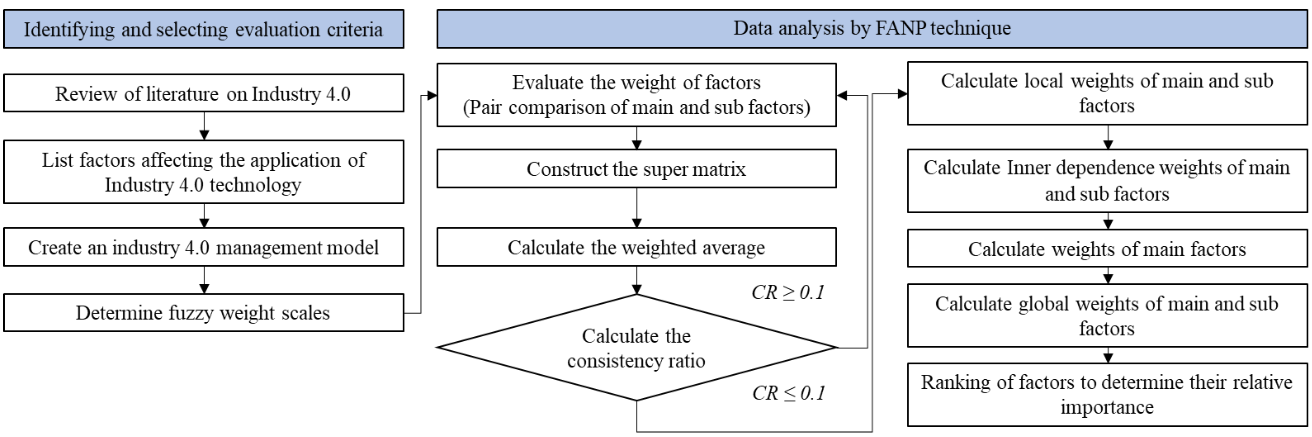

Fig. 2. The research framework of the application of Industry 4.0 technology.

According to the Institute of Electrical and Electronics, the population in this study consisted of 440 electrical appliance manufacturers in Thailand, with the Yamane's formula [68] indicating that the sample size for the study was 82 samples. Following the completion of the questionnaire, the researcher distributed it to 82 respondents sampled using the snowball method who were decision-makers in the implementation of industry 4.0 in electrical appliance manufacturers. At the start of this survey, experts from electrical appliance manufacturers were identified and called in to ask their permission to answer the questionnaire about the factors affecting the application of industry 4.0 technology in electrical appliance manufacturing. Following that, the data from the questionnaire were analyzed and carried out following the steps in the research framework depicted in Fig. 2.

A. *Fuzzy Set*

Zadeh (1965) developed a fuzzy set theory to deal with situations involving uncertainty, imprecision, and vagueness. Currently, fuzzy set theory is frequently used in multiple criteria decision-making techniques for practical applications in uncertain settings, and it is also effectively applied for modeling human decisions and judgments. [69, 70, 71]. The theory also allows for the application of mathematical operations and programming to the fuzzy domain. In general, a membership function defines the fuzzy set, which represents the grade of any element *x* of *X* that has partial membership to *M*. The degree to which an element belongs to a set is determined by a value between zero and one. Thus, the element x belongs to M, $\mu_M(x) = 1$ and $\mu_M(x) = 0$ [69, 72].

The triangular fuzzy number is made up of three parameters: (l, m, u) where $l \leq m \leq u$. The membership function $\mu_M(x)$ of TFN is derived by Eq. (1).

$$\mu_M(x) = \begin{cases} (x-l)/(m-l) & l \leq x \leq m \\ (u-x)/(u-m) & m \leq x \leq u \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Let $X = \{x_1, x_2, \ldots, x_n\}$ represent an object set and $U = \{u_1, u_2, \ldots, u_n\}$ represent a goal set. Chang (1992) extent analysis method takes each object and performs extent analysis for each goal g_i. For each object, m extent analysis values with the following signs can be obtained:

$$M_{g_i}^1, M_{g_i}^2, \cdots, M_{g_i}^m, \text{ i=1,2,}\cdots\text{,n} \quad (2)$$

Where M_{g1}^{j}, $(j = 1, 2, \ldots, m)$ represents in triangular fuzzy numbers.

B. *The Fuzzy Analytical Network Process*

The fuzzy analytic network process (Fuzzy ANP) is a multiple criteria decision-making (MCDM) technique that employs both criterion interdependence and criterion inner dependence with the pairwise comparison matrix. In this study, we present Chang's (1992, 1996) extent analysis method because the steps are simpler than those of the other fuzzy ANP techniques. The following are the steps of Chang's (1992, 1996) extent analysis approach:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1} \quad (3)$$

To obtain $\sum_{j=1}^{m} M_{gi}^{j}$, perform the fuzzy addition operation on m extent analysis values for a specific matrix so that:

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \quad (4)$$

And to obtain $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j}\right]^{-1}$, perform the fuzzy addition operation of extent analysis values for a specific matrix so that:

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \quad (5)$$

Then compute the inverse of the vector in the preceding equation so that

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \quad (6)$$

The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as:

$$V(M_2 \geq M_1) = \sup[\min(\mu_{M_1}(x), \mu_{M_2}(y)] \quad (7)$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = \begin{cases} 1 & \text{if } m_2 \geq m_1, \\ 0 & \text{if } l_1 \geq u_2, \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases} \quad (8)$$

$$V(M \geq M_1, M_2, \dots, M_k) = \min V(M \geq M_i), \quad i = 1, 2, \dots, k \quad (9)$$

Assume that:

$$d(S_i) = \min V(S_i \geq S_k), \quad k = 1, 2, \dots, n; k \neq i \quad (10)$$

Then the weights vector is computed by:

$$W' = (d(S_1), d(S_2), \dots, d(S_n))^T \quad (11)$$

And then, weight vectors are normalized as follows:

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T \quad (12)$$

IV. Results

For this study, the application of Industry 4.0 technology can be divided into five groups: Internet of Things (IoT), Cloud Manufacturing (CMg), Big Data Analytics (BDA), Additive Manufacturing (AM), and Cyber-Physical System (CPS). As illustrated in Fig. 2, each group includes several applications of Industry 4.0 technologies in manufacturing. Consequently, the goal of this research is to propose an industry 4.0 application for electrical appliance manufacturers' management to select appropriate technologies to integrate into their manufacturing processes to increase productivity and gain a competitive advantage. In this section, the research process can be divided into six steps to evaluate the factors affecting the application of 4.0 technology and prioritize those factors for appropriate decision-making by electrical appliance manufacturers in the application of industrial 4.0 technology. The first stage identifies the application of industry 4.0 technology for the framework of factors and sub-factors, as determined by a questionnaire survey using the fuzzy A technique to compute the weights of the factors and sub-factors. The application is built on the steps from the previous section and is explained step by step along with the results.

Step 1: The fuzzy scale is used to determine the important weighting of main factors and sub-factors from a decision-maker in charge of an organization's Industry 4.0 application management. Select appropriate linguistic variables to represent the relative weight of the factors. Using the linguistic scale in Table II, a pair-wise comparison is prepared for each factor based on expert opinion.

Step 2: A questionnaire survey is used to collect data from 82 electrical appliance manufacturers to investigate the application of Industry 4.0 technology for management in practices.

Step 3: Compute the consistency ratio (CR) by Eq. (13).

$$CR = \frac{CI}{RI} \quad (13)$$

When $CI = \frac{(\lambda_{max} - n)}{(n-1)}$ and $\lambda_{max} = \sum_{i=1}^{n}\left[\sum_{j=1}^{n} a_{ij} W_j\right]$

The CR value should be less than 0.1, indicating that the weights determined by decision-makers are consistent. If the CR value is greater than 0.1, it indicates that the determined weights are inconsistent. Thus, the research should begin with a review of the main factors and sub-factors.

Step 4: Compute the average fuzzy evaluation matrix based on the questionnaire survey, as well as the local weights of the main factors and sub-factors, as shown in Table II-VII.

Step 5: As illustrated in Table IX, compute the inner dependence weights and dependencies among the factors considered to be the main factors.

Step 6: To compute the global weights of sub-factors, multiply the local weights of the sub-factors by the interdependent weights of the main factors, as shown in Table X.

When weights of main factors were calculated, it was discovered that the Internet of Things was the most important, accounting for 34.3 percent of the total, the Big Data Analytics accounted for 31.0 percent, Cloud Manufacturing factor 12.5 percent, and Cyber-Physical System 9.4 percent respectively, as shown in Table III.

In terms of Internal of Things, tracking was identified as the most significant sub-factor in this area, accounting for 30.7 percent. Monitoring is the second most significant sub-factor, accounting for 27.2 percent, while Automation and Information had declined in importance, accounting for 25.7 percent and 16.5 percent, respectively, as shown in Table IV.

TABLE II. LINGUISTIC SCALE FOR RELATIVE WEIGHTS OF FACTORS

Risk Level	Triangular Fuzzy Scale	Triangular Fuzzy Reciprocal Scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally important	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important	(2, 5/2, 3)	(1/3, 2/5, 1/2)
More important	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

TABLE III. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF “MAIN FACTORS”

Main Factors	Internet of Things	Cloud Manufacturing	Big Data Analytics	Additive Manufacturing	Cyber-Physical System	Weights
Internet of Things	1.000, 1.000, 1.000	1.282, 1.738, 2.201	1.088, 1.516, 1.967	1.451, 1.951, 2.451	1.555, 2.055, 2.555	0.343
Cloud Manufacturing	0.540, 0.697, 0.933	1.000, 1.000, 1.000	0.459, 0.598, 0.797	0.688, 0.947, 1.301	0.909, 1.354, 1.870	0.125
Big Data Analytics	0.607, 0.813, 1.114	1.402, 1.870, 2.354	1.000, 1.000, 1.000	1.354, 1.854, 2.354	1.305, 1.805, 2.305	0.310
Additive Manufacturing	0.413, 0.523, 0.715	0.929, 1.317, 1.748	0.429, 0.549, 0.764	1.000, 1.000, 1.000	0.769, 1.126, 1.663	0.129
Cyber-Physical System	0.393, 0.489, 0.648	0.604, 0.846, 1.260	0.439, 0.565, 0.797	0.701, 1.039, 1.457	1.000, 1.000, 1.000	0.094

TABLE IV. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF “INTERNET OF THINGS”

Sub-factors	Monitoring	Tracking	Information	Automation	Weights
Monitoring	1.000, 1.000, 1.000	0.798, 1.098, 1.431	1.240, 1.701, 2.169	0.766, 1.077, 1.431	0.272
Tracking	0.980, 1.301, 1.685	1.000, 1.000, 1.000	1.201, 1.669, 2.152	0.996, 1.360, 1.778	0.307
Information	0.538, 0.697, 0.947	0.499, 0.665, 0.931	1.000, 1.000, 1.000	0.649, 0.878, 1.230	0.165
Automation	0.929, 1.252, 1.650	0.704, 0.974, 1.305	0.983, 1.407, 1.854	1.000, 1.000, 1.000	0.257

The weight of cloud manufacturing, Resource Management was the most important in this category, accounting for 27.4 percent, The second most important sub-factor was Resource as Service for 22.6 percent, followed by Orchestration for 21.4 percent, Utilization 18.8 percent, and Security 9.7 percent, respectively, as shown in Table V.

The weight of sub-factors in Big Data Analytics revealed that Data-Driven for 36 percent was the most significant sub-factor in this domain. Meanwhile, the second most important sub-factor was Data Collection for 33.4 percent, followed by Accuracy fot 18.2 percent, and Predictive for 12.4 percent, respectively, as shown in Table VI.

The weight of Additive Manufacturing was considered, the findings indicated that the Flexibility was the most important in this area for 26.3 percent, Prototype accounting for 26.0 percent, Optimization for 25.3 percent, and Reduction for 22.4 percent, respectively, as shown in Table VII.

When considering the weight of sub-factors in the Cyber-Physical Production Systems domain, Decision-Making Processes was the most important at 21.4 percent, followed by Visibility and Traceability, which accounted for 20.9 percent. The Detects Production System was the second important sub-factor that accounted for 17.4 percent, followed by Collaboration for 14.7 percent, Synchronization for 14.2 percent, and Intelligent for 11.5 percent, respectively, as shown in Table VIII.

TABLE V. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF “CLOUD MANUFACTURING”

Main Factors	Security	Resource as Service	Orchestration	Resource management	Utilization	Weights
Security	1.000, 1.000, 1.000	0.505, 0.681, 0.996	0.488, 0.646, 0.894	1.000, 1.000, 1.000	0.479, 0.632, 0.931	0.097
Resource as Service	1.201, 1.669, 2.152	1.000, 1.000, 1.000	0.808, 1.116, 1.551	0.733, 1.051, 1.421	1.006, 1.441, 1.909	0.226
Orchestration	1.256, 1.724, 2.207	0.821, 1.169, 1.565	1.000, 1.000, 1.000	0.609, 0.850, 1.175	0.887, 1.278, 1.711	0.214
Resource Management	1.354, 1.854, 2.354	0.896, 1.234, 1.695	1.055, 1.457, 1.909	1,000, 1.000, 1.000	1.152, 1.652, 2.152	0.274
Utilization	1.104, 1.604, 2.104	0.577, 0.795, 1.126	0.698, 0.970, 1.386	0.476, 0.632, 0.963	1.000, 1.000, 1.000	0.188

TABLE VI. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF “BIG DATA ANALYTICS”

Sub-factors	Predictive	Data Collection	Data Driven	Accuracy	Weights
Predictive	1.000, 1.000, 1.000	0.530, 0.680, 0.900	0.410, 0.516, 0.699	0.776, 1.057, 1.409	0.124
Data Collection	1.330, 1.787, 2.250	1.000, 1.000, 1.000	0.794, 1.120, 1.486	1.110, 1.577, 2.061	0.334
Data Driven	1.451, 1.951, 2.451	0.794, 1.120, 1.518	1.000, 1.000, 1.000	1.087, 1.543, 2.006	0.360
Accuracy	0.924, 1.276, 1.675	0.517, 0.695, 0.992	0.579, 0.762, 1.063	1.000, 1.000, 1.000	0.182

TABLE VII. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF “ADDITIVE MANUFACTURING”

Sub-factors	Prototype	Flexibility	Optimization	Reduction	Weights
Prototype	1.000, 1.000, 1.000	0.867, 1.244, 1.640	0.812, 1.189, 1.585	1.000, 1.000, 1.000	0.260
Flexibility	0.776, 1.030, 1.390	1.000, 1.000, 1.000	0.828, 1.211, 1.624	0.974, 1.390, 1.819	0.263
Optimization	0.787, 1.049, 1.427	0.743, 1.014, 1.439	1.000, 1.000, 1.000	0.926, 1.341, 1.770	0.253
Reduction	0.787, 1.081, 1.476	0.675, 0.900, 1.276	0.691, 0.933, 1.374	1.000, 1.000, 1.000	0.224

TABLE VIII. LOCAL WEIGHT AND PAIR-WISE COMPARISON MATRIX OF "CYBER-PHYSICAL PRODUCTION SYSTEMS"

Sub-factors	Collaboration	Detects Production System	Decision-Making Processes	Visibility and Traceability	Synchronization	Intelligent	Weights
Collaboration	1.000, 1.000, 1.000	0.746, 1.010, 1.325	0.541, 0.734, 1.000	0.590, 0.783, 1.049	0.943, 1.333, 1.754	1.061, 1.498, 1.970	0.147
Detects Production System	1.060, 1.423, 1.831	1.000, 1.000, 1.000	0.612, 0.819, 1.122	0.632, 0.884, 1.236	1.112, 1.579, 2.053	1.063, 1.498, 1.955	0.174
Decision-Making Processes	1.226, 1.667, 2.140	1.106, 1.541, 1.998	1.000, 1.000, 1.000	0.970, 1.378, 1.835	1.138, 1.596, 2.134	1.024, 1.433, 1.890	0.214
Visibility and Traceability	1.216, 1.650, 2.108	0.976, 1.394, 1.900	0.638, 0.900, 1.301	1.000, 1.000, 1.000	1.220, 1.693, 2.183	1.116, 1.589, 2.079	0.209
Synchronization	0.741, 0.998, 1.352	0.572, 0.752, 1.053	0.513, 0.720, 1.020	0.504, 0.671, 0.939	1.000, 1.000, 1.000	0.957, 1.463, 1.970	0.142
Intelligent	0.579, 0.797, 1.118	0.621, 0.833, 1.150	0.621, 0.866, 1.199	0.524, 0.705, 1.008	0.524, 0.711, 1.122	1.000, 1.000, 1.000	0.115

TABLE IX. INNER DEPENDENCE WEIGHT OF THE FACTORS

Main Factors	Internet of Things	Cloud Manufacturing	Big Data Analytics	Additive Manufacturing	Cyber-Physical System
Internet of Things	1.000	0.444	0.493	0.402	0.396
Cloud Manufacturing	0.186	1.000	0.187	0.160	0.102
Big Data Analytics	0.461	0.365	1.000	0.353	0.362
Additive Manufacturing	0.201	0.104	0.192	1.000	0.139
Cyber-Physical System	0.152	0.087	0.129	0.085	1.000

TABLE X. TOTAL WEIGHT OF MAIN FACTORS AND SUB-FACTORS

Factors	Interdependent weights	Ranking	Sub-factors	Local weights	Ranking	Global weights	Ranking
Internet of Things (IoT)	0.3198	1	Monitoring	0.2718	2	0.0869	4
			Tracking	0.3067	1	0.0981	3
			Information	0.1647	4	0.0527	7
			Automation	0.2569	3	0.0822	5
Cloud Manufacturing (CMg)	0.1382	4	Security	0.097	5	0.0134	22
			Resource as Service	0.226	2	0.0313	14
			Orchestration	0.214	3	0.0296	15
			Resource management	0.275	1	0.0379	8
			Utilization	0.188	4	0.0260	16
Big Data Analytics (BDA)	0.2963	2	Predictive	0.1243	4	0.0368	10
			Data Collection	0.3342	2	0.0990	2
			Data Driven	0.3600	1	0.1067	1
			Accuracy	0.1815	3	0.0538	6
Additive Manufacturing (AM)	0.1417	3	Predictive	0.2597	2	0.0368	11
			Data Collection	0.2633	1	0.0373	9
			Data Driven	0.2526	3	0.0358	12
			Accuracy	0.2243	4	0.0318	13
Cyber Physical Systems (CPS)	0.1041	5	Collaboration	0.1466	4	0.0153	20
			Detects Production System	0.1735	3	0.0181	19
			Visibility and Traceability	0.2140	1	0.0223	17
			Synchronization	0.2088	2	0.0217	18
			Intelligent	0.1418	5	0.0148	21
				0.1153	6	0.0120	23

The decision-makers performed pairwise comparisons for main factors and sub-factors, which were then analyzed using fuzzy ANP. According to the findings, the "Internet of Things" was the most important factor, with an interdependent weight of 31.98 percent. The second most important factor, with a weight of 29.63 percent, was "Big Data Analytics", while "Additive Manufacturing," "Cloud Manufacturing," and "Cyber-Physical Systems" had interdependent weights of 14.17, 13.82, and 10.41 percent, respectively. In terms of important sub-factors, the results showed that "Data-Driven" was the most important sub-factor that influenced decision-makers, with a global weight of 10.67 percent. Next, "Data Collection" was ranked second with a global weight of 9.90 percent, followed by "Tracking," "Monitoring," and "Automation," with global weights of 9.81, 8.69, and 8.22 percent, respectively. The bottom five sub-factors in terms of importance were "Detects Production," "Collaboration," "Synchronization," "Security," and "Intelligent," with global weights of 1.81, 1.53, 1.48, 1.34, and 1.20 percent, respectively. Therefore, these sub-factors had less influence on the decision-maker when selecting industry 4.0 technologies for their production management.

V. DISCUSSION

According to the findings of this study, the Internet of Things (IoT) is the most important because it can be linked to machines or equipment in the automated manufacturing process, such as the Automated Guided Vehicle (AGV) for loading raw materials into the production line. Robots and packaging equipment must operate in line with production flow to improve work efficiency, productivity, cost reduction, and human error. Furthermore, IoT may also be used to build interactions or data transmission amongst equipment to maintain production running smoothly and in line with standards. Meanwhile, traceability and real-time data exchange can help manufacturing be more efficiently monitored and planned. Because the electronics industry typically uses just-in-time manufacturing methods, raw materials or parts must be arrived on time to meet production plans in both quantity and quality. For this reason, the IoT is used to connect production data with suppliers to control and track the flow of production parts to ensure continuity by predefined production plans against real-time targets. This enables the manufacturer and its suppliers to have access to the same data sources and use data to boost productivity while also storing big data for analysis and intelligent decisions. In terms of inventory management, the IoT can perform quick counts and control the right amount of inventory levels to ensure reliable raw material delivery.

Big data analytics is an important secondary factor in managing big data both inside and outside the organization for analytics to enhance decision-making, machine maintenance predictions, data modeling for summary reporting, data connecting across the manufacturing process, predictive analytics, and data linking between suppliers and customers. Overall, big data analytics can use the information gleaned from data analysis to assist all relevant departments in standardizing and systematically receiving the same information, resulting in more efficient work. By creating prototypes, additive manufacturing is now beginning to play an important role in both product development and manufacturing processes. New product prototypes are created during the stages of concept, prototype development, testing, and production for presenting customers with the product appearance, making decisions, and understanding the product details more easily. Furthermore, additive manufacturing enables manufacturers to more easily and quickly adjust parts to meet customer needs, reducing the time and cost spent on modifying prototype parts and allowing for greater flexibility in product development.

Cloud manufacturing is crucial for connecting accurate and up-to-date data with suppliers and customers. Additionally, cloud computing manages data collection and services both inside and outside the organization by carrying out manufacturing operations over the Internet that responsible is for the supervision of the organization's IT department. Moreover, Electronic Data Interchange (EDI) is used for data exchange between suppliers and customers to reduce errors and duplication of documents. Meanwhile, EDI enables faster and more accurate data transfer, as well as making papers easier to search and available only to authorized users. It also makes use of real-time correlation and efficient data exchange. The cyber-physical system is the least important of the main factors in this study. Robots or automated machines, for example, are pre-programmed for control in a manufacturing process. Subsequently, data obtained from machine or robot operations are not sent back and forth between the physical and cyber worlds for automatic control of machines or robots in the physical world. The design and development of cyber-physical systems in the electrical appliance business demands numerous aspects, as well as the challenges of designing software that analyzes and operates entire systems. Therefore, organizations must invest more effort and finances in developing the software.

In terms of sub-factors, the findings of this study have indicated that data-driven is the most important sub-factor because the electrical appliance industry has a diverse range of models and clearly defined production lines. It is also a type of just-in-time production (JIT) in which raw materials and spare parts from various suppliers are processed into a large number of production lines in a specific time frame. To ensure continuity and accuracy, it is critical to be data-driven, which means that production planning data must be aligned with market demand. While production model sequencing must be consistent with the availability of quality data, raw materials, and spare parts. Moreover, data on the availability of machines and equipment on the production line require predictive maintenance to avoid malfunctions during production. As stated above, data-driven can significantly improve the manufacturer’s production efficiency. Another important sub-factor in collecting data from various production activities is data collection. Large amounts of accurate data must be collected throughout the manufacturing process to analyze it and make decisions quickly and precisely on time. In terms of the significance of data collecting, if a decision is delayed or made incorrectly, the production will not be able to operate as planned. Meanwhile, production costs will rise when manufacturing time is extended. Furthermore, the following manufacturing plan will be interrupted and delayed, resulting in the corporation failing to deliver products on time to customers. Therefore, data collection must be accurate and real-time to meet as several customer requirements as possible.

Traceability is an important sub-factor for tracking the flow of parts and raw materials from suppliers to the production line. Traceability also allows the inspection of parts with serial numbers, lot numbers, and manufacture dates to be rapidly tracked back and standardized, which is very useful in the case of a problem. To keep planning on track and build trust with customers, it is necessary to track and monitor each manufacturing process to assess the availability of all spare parts and raw materials before production begins. Monitoring requires reporting the production situation in real time and comparing it to the target by connecting the data via the internet network. Meanwhile, it displays the operational status of machines and equipment in the production line, as well as performance reports in the manufacturing process as compared to the plan. Consequently, monitoring is an essential component for having a real-time overview of the production situation and managing production efficiently. Automation is crucial for driving the production of electrical appliances to reduce costs and increase manufacturing efficiency. Besides, it can also help to automate the primary and secondary production lines as well. However, the manufacturer must first determine which production processes, such as production line systems or packaging systems, require automation. Finally, automation will aid in the faster and more consistent improvement of production processes, providing customers with confidence.

For less important sub-factors, this study has discovered that the detects production system monitors a variety of parameters due to its connection with machines or equipment and manufacturing processes. Fully automated systems necessitate significant capital investments for ongoing improvement, which compels careful consideration of improvement priorities. For collaboration and synchronization, they collaborate with the physical and cyber worlds to integrate systems in production processes that are time-consuming to improve. By synchronizing communication with machines and equipment, it is necessary to prepare various equipment to support the connection between the cyber-physical system and the production process, making it more convenient and efficient in monitoring and controlling the production process. Furthermore, electrical appliance production activities involve complex multiple steps in production processes that require employee and machine integration. The security of the operating system during the manufacturing process must be stable and free of cyber threats. Only on-premise operating systems or private clouds will be used by electrical appliance manufacturers and business partners for internal storage and services. Therefore, operating system risks require data security countermeasures against accidental data leakage and data theft. For another sub-factor, intelligence is the least important as manufacturers prioritize process automation and robotics to improve manufacturing processes to be fast, low-cost, and data-driven for precision and effective decision-making. As a result, intelligent technology is a self-determining intelligent technology that requires the preparation of a large data structure to drive intelligent manufacturing, which requires the implementation of a continuous development plan.

VI. Conclusion

The fourth industrial revolution is currently posing challenges for many industries, particularly the consumer electronics industry, and IoT is one of the key tools for this change because it can improve and connect machines and equipment on the production line to automate and optimize production efficiency while lowering costs. On the other hand, companies that want to use Industry 4.0 technology, must think carefully due to the high capital investment required. As a result, this research investigates the factors influencing the application of Industry 4.0 technology for electrical appliance manufacturers so they can reap the full benefits of this Industry 4.0 technology, such as increased revenue, profit, productivity, and efficiency. as well as cost savings.

The internet of things, cloud manufacturing, big data analytics, additive manufacturing, and cyber-physical systems were identified as five factors influencing the appliance industry's efforts to adopt Industry 4.0 technologies in this study. The Internet of Things is the most important factor in the application of Industry 4.0 technologies, followed by big data analytics, additive manufacturing, cloud computing, and cyber-physical systems in descending order of importance. Data-driven, data collection, tracking, monitoring, and automation are the top five sub-factors influencing appliance manufacturers in implementing Industry 4.0technologies, while detecting production systems, collaboration, synchronization, security, and intelligence have less influence on decision-makers in applying Industry 4.0technologies to their appliance manufacturing. Based on the study's findings, electrical appliance manufacturers can use factors and sub-factors to select the best industrial technology for improving production management and company performance both financially and profitably.

According to the study's findings, they have identified the factor of the Internet of Things (IoT) as the most important because the IoT can be connected to machines and equipment for production continuity. Furthermore, IoT can track and present real-time data to improve the speed and efficiency of manufacturing. Therefore, IoT capabilities can connect existing machines and devices to new equipment outfitted with IoT systems to improve production and warehouse management performance. It is also critical for big data analytics to manage production resources using data from operating systems. Furthermore, data from sensors, devices, and machines is continuously collected and stored as big data for analysis and process planning, as well as manufacturing to achieve operational precision throughout the procurement of production equipment. It is crucial for just-in-time production planning, which demands high precision in terms of production time and raw material supply cycle in order to deliver products to consumers on time. Additive manufacturing is an important part of new product development because it can reduce the steps and costs associated with prototyping for customers. This makes it easier for customers to understand the product and allows them to quickly modify the prototype to meet their needs, providing flexibility in developing new products. Therefore, it can minimize the cost of new product development and launch products to market faster. Cloud computing is considered as the operating systems used within the enterprise, supplier, and customer networks to ensure the stability and security of real-time connections and data relationships in cloud computing. While cyber-physical systems connect the physical and cyber worlds. Thus, manufacturers must consider numerous dimensions when integrating the entire system, which necessitates adequate personnel and budget planning for continuous development.

In terms of the significance of sub-factors, data-driven is a sub-factor that requires a lot of attention. Because the electrical appliance industry produces a wide range of products and employs just-in-time production systems, manufacturers must manage a large amount of data related to suppliers and customers continuously and in real-time. By connecting to the Internet of Things system, machines and devices will send important data for processing and analyzing big data to monitor the availability of raw materials and spare parts to ensure that manufacturers can produce as planned. Data collection is considered for accurate analysis and decision-making. Because the supply chain in the electronics manufacturing industry is complex, each process generates unique data that is linked both inside and outside the organization, necessitating careful consideration of data importance. Traceability requires tracking the flow of parts, raw materials, and goods to build customer trust and provide real-time production data linked to production processes, resulting in more efficient production management. However, automation is now very important in the production of electrical appliance manufacturers to meet the needs of

Industry 4.0, which requires developing automated machines to work instead of more humans. Improved production lines were required to automatically assemble parts for faster, more accurate, and standardized operations.

In implications for management, this research benefits electrical appliance manufacturers in terms of utilizing the factors in this study to appropriately determine the application of Industry 4.0 technology in their production. Because manufacturers have limited budgets, it is necessary to prioritize and select cost-effective and appropriate Industry 4.0 technologies used in production to increase the enterprise's productivity and competitiveness. In terms of research limitations, the sample size of this study is mostly medium to large-sized companies, tier 1st parts manufacturers, and electrical appliance manufacturers that have the potential to apply Industry 4.0 technology at the moment, whereas the sample size of SMEs is small, and they face obstacles in applying Industry 4.0 technology due to limited funding. However, small, and medium-sized enterprises (SMEs) are numerous and play an important role in driving the country's economy, both in terms of income generation and job creation. Consequently, future research will concentrate on studying problems and obstacles in the application of Industry 4.0 technology by SME businesses for the benefit of SME production development, as well as improving SMEs' competitiveness to compete with other large companies in the market.

References

[1] M. Ghobakhloo, "Industry 4.0, digitization, and opportunities for sustainability," Journal of Cleaner Production. Vol. 252, April 2020.

[2] N. G. P. Carvalho, O. Chaim, E. Cazarini, M. C. Gerolamo, "Manufacturing in the fourth industrial revolution: A positive prospect in sustainable manufacturing," Procedia Manufacturing. Vol. 21, pp. 671-678, January 2018.

[3] S. Bag, S. Gupta, S Kumar, "Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development," Internal Journal of Production Economics. Vol. 231, January 2021.

[4] S. Gierej, The Framework of Business Model in the Context of Industrial Internet of Things. Procedia Engineering, Vol. 182, pp. 206-212, April 2017.

[5] Y. A. Fatimah, K. Govindan, R. Murniningsih, A. Setiawan, "Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: a case study of Indonesia," Journal of Cleaner Production. Vol. 269, October 2020.

[6] L. Atzori, A. Iera, G. Morabito, "The internet of things: A survey," Computer networks. Vol. 54, pp. 2787-2805, May 2010.

[7] S. Mittal, M. A. Khan, D. Romero, T. Wuesta, "A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs)," Journal of Manufacturing Systems, Vol. 49, pp. 194-214, October 2018.

[8] K. N. Qureshi, S. Din, G. Jeon, F. Piccialli, "Link quality and energy utilization based preferable next hop selection routing for wireless body area networks. Computer Communications, Vol. 155, pp. 382-392, January 2020.

[9] J. C. Bendul, H. Blunck, "The design space of production planning and control for industry 4.0," Computers in Industry. Vol. 105, pp. 260-272, February 2019.

[10] S. Doh, B. Kim, "Government support for SME innovations in the regional industries: The case of government financial support program in South Korea," Research Policy, Vol. 43, No. 9, pp. 1557-1569, November 2014.

[11] M. Ghobakhloo, "Industry 4.0, digitization, and opportunities for sustainability," Journal of Cleaner Production. Vol. 252, April 2020.

[12] S. Bag, S. Gupta, S Kumar, "Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development," Internal Journal of Production Economics. Vol. 231, January 2021.

[13] M. S. Bhatia, S. K. Jakhar, S. K. Mangla, K. K. Gangwani, "Critical factors to environment management in a closed loop supply chain," Journal of Cleaner Production. Vol. 255, May 2020.

[14] Z. Hassan, H. A. Ali, M. M. Badawy, "Internet of Things (IoT): Definitions, Challenges and Recent Research Directions," Vol. 128(1), pp. 37-47, October 2015.

[15] S. I. Shafiq, C. Sanin, E. Szczerbicki, C. Toro, "Virtual engineering factory: creating experience base for industry 4.0, Cybernetics and Systems," Vol. 47, No. 1, pp. 32-47, Febuary 2016.

[16] Schoenherr, T. and Speier-Pero, C. (2015) Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential, Journal of Business Logistics, 36(1), 120-132

[17] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Generation Computer Systems. Vol. 29, No. 7, pp. 1645-1660, September 2013.

[18] H. M. Pereira, S. Ferrier, M. Walters, et al., "Essential Biodiversity Variables," Vol, 339, No. 6117, pp. 277-278, Jan 2013.

[19] M. S. Bhatia, S. K. Jakhar, S. K. Mangla, K. K. Gangwani, "Critical factors to environment management in a closed loop supply chain," Journal of Cleaner Production. Vol. 255, May 2020.

[20] M. Javaid, A. Haleem, "Impact of industry 4.0 to create advancements in orthopaedics," Journal of Clinical Orthopaedics and Trauma. Vol. 11, No. 6, pp. 491-499, March 2020.

[21] J. L. Hopkins, "An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia," Computers in Industry Vol. 125, No. 2, pp. 1-20, February 2021.

[22] N. Harikannan, S. Vinodh, "Sustainable industry 4.0 - an exploratory study for uncovering the drivers for integration," Journal of Modelling in Management, Vol. 16, No. 1, pp. 357-376, April 2021.

[23] G. Büchi, M. Cugno, R. Castagnoli, "Smart factory performance and Industry 4.0," Technological Forecasting and Social Change. Vol. 150, January 2020.

[24] S. E. Hamdi, M. Oudani, A. Abouabdellah, A. Sebbar, "Fuzzy approach for locating sensors in industrial internet of things," Procedia Computer Science, Vol.160, pp. 772-777, November 2019.

[25] R. Vasja, M. Maja, K. Alojz, "A Complex View of Industry 4.0", SAGE Journals, pp. 1-11, June 2016.

[26] K. Zhou, T. Liu, L. Zhou, "Industry 4.0: Towards future industrial opportunities and challenges" 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), January 2016.

[27] L. Ardito, A. M. Petruzzelli, U. Panniello, A. C. Garavelli, "Towards Industry 4.0: mapping digital technologies for supply chain management-marketing integration," Business Process Management Journal. Vol. 25, No. 2, pp. 323-346, March 2019.

[28] E. Manavalan, K. Jayakrishna, "A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements," Computers and Industrial Engineering, Vol. 127, pp. 925-953, January 2019.

[29] J. Zhu, H. Zhou, C. Wang, L. Zhou, S. Yuan, W. Zhang, A review of topology optimization for additive manufacturing: status and challenges. Chinese Journal of Aeronautics.

[30] H. Zhong, S. Y. Nof, "The dynamic lines of collaboration model: collaborative disruption response in cyber-physical systems," Computere and Industrial Engineering, Vol. 87, pp. 370-382. September 2015.

[31] S. Subashini, V. Kavitha, "A survey on security issues in service delivery models of cloud computing," Journal of Network and Computer Applications. Vol. 34, No.1, pp. 1-11, January 2011.

[32] E. Hofmann, M. Rusch, "Industry 4.0 and the current status as well as future prospects on logistics," Computers in Industry, Vol. 89, pp. 23-34, August 2017.

[33] J. Schlechtendahl, M. Keinert, K. Kretschmer, A. Lechler, A. W. Verl, "Making existing production systems Industry 4.0-ready," Production Engineering. Vol. 9, No. 1, pp. 1-6. February 2014.

[34] Q. Zhang, L. Cheng, R. Boutaba, "Cloud Computing: State-Of-The-Art and Research Challenges," Journal of Internet Services and Applications, No. 1, pp. 7-18, April 2020.

[35] H. P. Breivold, K. Sandstrom, "Internet of Things for Industrial Automation Challenges and Technical Solutions," IEEE International Conference on Data Science and Data Intensive Systems, pp. 532-539, December 2015.

[36] Ahuett-Garza H. and Kurfess T. "A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing," Manufacturing Letters, Vol. 15, pp. 60-63. January 2018.

[37] A. Alharthi, V. Krotov, B. Michael, "Addressing barriers to big data," Business Horizons, Vol. 60, No. 3, pp. 285-292. February 2017.

[38] M. D. Ryan, "Cloud computing privacy concerns on our doorstep," Communications of the ACM, Vol. 54, No.1, 36-38, Junuary 2011.

[39] K. Popovic´, Z. Hocenski, "Cloud computing security issues and challenges," The 33rd International Convention MIPRO, May 2010.

[40] R. Henzel, C. Ellwein, G. Herzwurm, O. Riedel "Cloud manufacturing: Theoretical localization within production theory," Procedia CIRP, Vol. 99, pp. 555-560, 2021.

[41] Y. Ji, P. Liu, Y. Li, B. N. Bekele, "A modified toxicity probability interval method for dose-finding trials," Chin. Trials, Vol. 7, No. 6, pp. 653-663, October 2020.

[42] L. Ren, L. Zhang, F. Tao, C. Zhao, "Cloud manufacturing: from concept to practice," Enterprise Information Systems, Vol. 9, No. 2, pp. 186-209, June 2013.

[43] B. H. Li, L. Zhang, S. L. Wang, F. Tao, et al., "Cloud Manufacturing: A New Service-Oriented Networked Manufacturing Model," Computer Integrated Manufacturing Systems, Vol. 16, No. 1, pp. 1-7, January 2010.

[44] X. V. Wang, X. W. Xu, "An interoperable solution for Cloud manufacturing," Robotics and Computer-Integrated Manufacturing, Vol. 29, No. 4, pp. 232-247, August 2013.

[45] X. Xun, "From cloud computing to cloud manufacturing," Robotics and Computer-Integrated Manufacturing, Vol. 28, No. 1, pp. 75-86, February 2012.

[46] F. Tao, L. Zhang, V. C. Venkatesh, Y. Luo, Y. Cheng, "Cloud manufacturing: a computing and service-oriented manufacturing model," Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, Vol. 225, No. 10, August 2011.

[47] A. Sanders, C. Elangeswaran, J. Wulfsberg, "Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing," Journal of Industrial Engineer and Management, Vol. 9, No. 3, pp. 811-33, 2016.

[48] M. Pflanz, M. Schirrmann, H. Nordmeyer, "Drone based weed monitoring with an image feature classifier," 28th German Conference on Weed Biology and Weed Control, No. 458, pp. 379-384, March 2018.

[49] P. M. Vergara, E. A. de la Cal Marin, J. Villar, V. M. Gonzalez, "An IoT Platform for Epilepsy Monitoring and Supervising," Journal Sensors, Vol. 17, pp. 1-18, July 2017.

[50] S. R. Prathibha, A. Hongal, M. P. Jyothi, "IoT based monitoring system in smart agriculture," International Conference on Recent Advances in Electronics and Communication Technology, pp. 81-84, March 2017.

[51] M. Lezoche, J. E. Hernandez, M. M. E. Alemany, H. Panetto, "Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture," Computers in Industry, Vol. 117, pp. 103-187, March 2020.

[52] A. Adauto, S. Khan, M. A. da Silva, J. A. G. Neto, G. Picasso, M. D. P. T. Sotomayor, "Synthesis, characterization and application of a novel ion hybrid imprinted polymer to adsorb Cd(II) in different samples," Environmental Research, Vol. 187, No.1, pp.1-10, August 2020.

[53] D. Trabucchi, T. Buganza, "Data-Driven Innovation: switching the perspective on Big Data," pp. 1-22, January 2018.

[54] N. Santhosh, M. Srinivsan, K. Ragupathy, "Internet of Things (IoT) in smart manufacturing," IOP Conf. Series: Materials Science and Engineering, Vol. 764, pp. 1-14, September 2019.

[55] H. Kagermann, "Change through digitization-Value creation in the age of Industry 4.0," Management of Permanent Change, pp. 23-45, December 2015.

[56] J. Zhu, H. Zhou, C. Wang, L. Zhou, S. Yuan, W. Zhang, "A review of topology optimization for additive manufacturing: status and challenges," Chinese Journal of Aeronautics, Vol. 34, No. 1, pp. 91-110, January 2021.

[57] F. Tao, Y. Cheng, L. D. Xu, et al., "CCIoT-CMfg: Cloud Computing and Internet of Things-Based Cloud Manufacturing Service System," IEEE Transactions on Industrial Informatics,Vol. 10, No. 2, pp. 1435-1442, May 2014.

[58] C. G. Hidalgo, D. Hidalgo, L. R. Sanchez, et. al., "IoT Heterogeneous Mesh Network Deployment for Human-in-the-Loop Challenges Towards a Social and Sustainable Industry 4.0," IEEE Access, Vol. 6, pp. 28417-28437, May 2018.

[59] C. Cimini, F. Pirola, R. Pinto, S. Cavalieri, "A human-inthe-loop manufacturing control architecture for the next generation of production systems," Journal of Manufacturing Systems, Vol. 54, pp. 258-271, January 2020.

[60] F. Rengier, A. Mehndiratta, H. von Tengg-Kobligk, et al., "3D printing based on imaging data: Review of medical applications," International Journal of Computer Assisted Radiology and Surgery, Vol. 5, No. 4, pp. 335-341, May 2010.

[61] R. Weller1, K. Schmidt1, K. Teinilä, R. Hillamo, "Natural new particle formation at the coastal Antarctic site Neumayer," Atmospheric Chemistry and Physics, Vol. 15, No. 19, pp. 11399-11410, October 2015.

[62] S. M. Khajavi, J. Holmström, J. Partanen, "Additive manufacturing in the spare parts supply chain: hub configuration and technology maturity," Rapid Prototyping Journal, Vol. 24, pp. 1178-1192, October 2018.

[63] M. Rehnberg, S. Ponte, "From smiling to smirking? 3D printing, upgrading and the restructuring of global value chains," Global Networks, Vol. 18, No. 1, pp. 57-80. June 2017.

[64] L. Monostori, Cyber-physical production systems: roots, Expectations and R&D challenges, Procedia CIRP, Vol. 17, pp. 9-13, July 2014.

[65] M. J. Mazzei, D. Noble, "Big Data Dreams: A Framework for Corporate Strategy," Business Horizons, Vol. 60, No. 3, pp. 405-414, June 2017.

[66] H. F. Cervone, "Organizational considerations initiating a big data and analytics implementation," Digital Library Perspectives, Vol. 32. No. 3, pp. 137-141, August 2016.

[67] M. Garetti, L. Fumagalli, E. Negri, "Role of Ontologies for CPS Implementation in Manufacturing," Management and Production Engineering Review, Vol. 6, No. 4, pp. 26-32, December 2015.

[68] T. Yamane, "Statistics: An introductory analysis," New York, 1967.

[69] L. A. Zadeh, "Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems," Advances in Fuzzy Systems – Applications and Theory, Vol. 6, pp. 394-432, May 1996.

[70] A. Taweesangrungroj, R. Rattanabanchuen, S. Sinthupinyo. "A Decision-Making Model of Technological-Focused Government Agency Selection of Technological Start-Up Businesses. Trends in Sciences, Vol. 19, No.1, pp. 1749-1749, January 2022.

[71] A. Taweesangrungroj, R. Rattanabanchuen, S. Sinthupinyo, "Decision-making process of Thai government agent for selection of technological startup companies in pitching of concept ideas," Asian Journal of Information and Communications, Vol.11, No.2, 2019.

[72] S. Sinrat, W. Atthirawong, Integrated Factor Analysis and Fuzzy Analytic Network Process (FANP) Model for Supplier Selection Based on Supply Chain Risk Factors. Research Journal of Business Management, Vol. 9, pp. 106-123, October 2014.